# Inward FDI spillovers and innovation capabilities in Chinese business: exploring the moderating role of local industrial externalities

**Abstract:** It is generally believed foreign direct investment (FDI) has spillover effects which can affect the innovation capabilities of local firms in host countries. Comparatively little, however, is known about the contingent local contextual factors that influence how these FDI spillovers can be captured. Integrating the literature on FDI knowledge spillovers with that on inter and intra-industrial externalities we explore how local industrial agglomeration moderates the effect of FDI knowledge spillovers on innovation in the emerging market context of China. Empirical estimates, based on panel data of 1,610 listed indigenous Chinese firms recorded between 2000 and 2010, indicate that such spillovers are more easily captured in industrially diverse settings. By contrast, industrial specialization negatively moderates this relationship. We explore the implications of these findings, considering their relevance for emerging market policy-makers grappling with the challenges of navigating their economies through the 'middle-income-trap' to high-income status by promoting more innovative local firms.

**Keywords:** FDI, specialization, diversity, innovation capability, moderating effect, China

## 1 Introduction

The growth of FDI to emerging markets, coupled with their rapid industrialization and concomitant evolution in industrial structure are two marked and important features of emerging markets. Yet comparatively little is known about how FDI inflows and domestic industrial externalities interact with one another in these markets. Purported advantages of industrial externalities, such as Marshall-Arrow-Romer (MAR) externalities of specialization, include those of scale, lower transportation costs and intra-sector knowledge spillovers of tacit or codified specialized knowledge that flows more easily among clustered firms of the same sector. Industrial diversity, by contrast, also known as Jacobs externalities, include the advantages of size and the potential to tap multiple knowledge bases within a general geographic cluster. Do these different types of industrial externalities interact with inward FDI and what impact do they have on the innovation capabilities of host country emerging market (EM) firms, currently aspiring to rapidly catch-up with their developed market (DM)counterparts (Awate, Larsen & Mudambi, 2012, 2014; Tan & Mathews, 2014)?

The question of how EM firms develop innovation capabilities is of central importance to Chinese policy-makers. As the Chinese economy rapidly approaches middle-income levels growth is predicted to slow. Transition to a more innovative society is considered the key challenge in overcoming the '*middle-income-trap*' (World Bank, 2013). Indeed, China has declared its intention of moving from being a '*global manufacturer*' to a leader in global innovation (Abrami et al., 2014). The upgrading and adjustment of regional industrial structures, moreover, is a process that is being led in part by the Chinese government, through among other things its control of key state-owned business groups (Nolan, 2013).

Exploring how FDI and industrial externalities interact to influence Chinese firm-level innovation has potentially important policy implications, as well being of theoretical interest (Li et al., 2013a; Li et al., 2013b). Here we focus on the moderating role of the local industrial context as a facilitator (or otherwise) of innovation. So far the debate on the role of industrial agglomeration on growth and innovation remains inconclusive, with methodological and contextual factors believed to be important reasons for this inconclusiveness (Beaudry and Schiffauerova, 2009). Most empirical and theoretical research, however, has concentrated on DM, not EM contexts. Further research on the effect of industrial specialization and diversity on firm innovation in China, therefore, may be helpful in advancing our understanding of MAR and Jacobs industrial externalities as well as the conditions under which innovation in EM firms benefits from inward FDI. Given it is also widely believed EM firms adopt different innovation strategies to DM firms, this is an interesting question (Awate, Larsen and Mudambi, 2012, 2014; Mathews, 2006). Our paper therefore aims to make a contribution to extend the aforementioned debates on FDI knowledge spillovers, industrial externalities, and EM firm innovation strategies by examining how these factors interact with each other and exert an effect on the innovation capabilities of EM firms.

The remainder of this paper is organized as follows. The theoretical background and empirical hypotheses are developed in section 2, data and methodology are reported in section 3. Section 4 reports the results of descriptive analysis and panel regression estimations. Theoretical and practical implications of findings are discussed in the section 5.

## 2 Theoretical background and hypothesis development

### 2.1 FDI, industrial externalities and firm innovation

FDI is generally believed to have positive knowledge spillover effects for domestic firms in both DM and EM recipient countries (Buckley et al., 2002; Kinda, 2010; Padilla-Pérez, 2008). International business (IB) research suggests FDI brings not only capital but also advanced technology, new ideas, and further access to international markets for host country firms (Buckley et al., 2002; Crespo and Fontoura, 2007; Kokko et al., 1996). EM firms may not only benefit from acquisition of superior foreign technical knowledge, they may also improve their management capabilities through learning from other MNEs, both of which are critical for their development (Fu, 2012). Recent studies have increasingly emphasized, however, that FDI spillovers are conditional on a number of factors (Li et al., 2013a; Yuan et al., 2008). From the perspective of the FDI source, for example, FDI that originates from OECD countries is more likely to be accompanied by positive spillover effects on the innovation of indigenous firms. This is particularly so in technology-intensive sectors. Investments from Hong Kong, Macao and Taiwan, by contrast, are generally considered to be more concentrated in labor-intensive sectors and thus bring fewer benefits (Buckley et al., 2007b). Such investments typically exploit low labour and land costs, rather than searching for new markets using advanced technologies. By contrast, MNEs from OECD countries have a propensity to focus on new and emerging sectors, or high technology industries. These MNEs launch new products using advanced knowledge which they exploit to compete against local counterparts in host markets (Buckley et al., 2007b). At the firm-level, moreover, absorptive capacity is deemed an important factor determining whether successful absorption of advanced knowledge available via knowledge spillovers from FDI may be realized (Ferragina and Mazzotta, 2013; Girma, 2005). Durham (2004), for example, showed that firms with higher levels of absorptive capacity can more easily gain technical opportunities from foreign presence. This evidence is supported by studies conducted in both developed and developing countries (Zhang et al., 2010). Though many prior studies have drawn attention to a variety of internal and external factors that condition how FDI spillovers may be captured little is yet known about the interplay between FDI spillovers and local agglomeration economies in affecting innovation capabilities in indigenous firms.

This is surprising, as the topic of agglomeration economies, like FDI, has also attracted considerable academic interest (Asheim and Isaksen, 1997; De Groot et al., 2009; Duranton and Puga, 2004; Henderson, 1997; Li et al., 2012; Neffke et al., 2010). The majority of these studies have investigated the impact of two dimensions of industrial structure: the specialization and diversity of regional economic composition in affecting economic performance and innovative capabilities (Beaudry and Schiffauerova (2009). On the one hand, based on the seminal work of Marshall (1890), a series of studies provide empirical evidence related to the question of whether agglomeration economies are beneficial for economic development or not (see De Groot et al. (2009) for a review of this literature). Glaeser et al. (1992) coined the term 'Marshall-Arrow-Romer externalities', or MAR externalities, to refer to specialization. On the other hand, Jacobs (1969) suggested that a city with multiple disciplines is more likely to have a strong knowledge base and local innovators may more easily develop fresh ideas and novel technologies in such environments. This argument has become increasingly popular in recent years as increasing demand for variety has led to rapid changes in consumer demand. Product innovation, it is argued, is more closely related to the integration of cross disciplinary knowledge (Nieto and Santamaría, 2007; Tatikonda and Rosenthal, 2000).

Both industrial specialization and diversity are highlighted in prior studies for their specific effects in different settings. As yet, however, there is no consensus on the question of which type of industrial structure is more conducive for innovation. According to Beaudry and Schiffauerova (2009) only four studies focus on the effect of industrial specialization in developing countries, with none on China. Six studies have examined the role of diversity in emerging markets, with one of these focused on China. To the best of our knowledge, moreover, no research has explored the contingent role of industrial specialization and diversity, despite their very close relations to both economic and innovation activities (De Groot et al., 2009). Here we look to bridge this gap by integrating the two aforementioned literature streams and considering our findings also in the context of research on EM firm' innovation strategy, so as to further probe inside the spillover 'black box' (Desrochers and Leppala, 2011: 844).

### 2.2 Foreign presence and indigenous firm innovation

The FDI of multinational enterprises (MNEs) may bring considerable opportunities for indigenous firms, including opportunities for collaboration, entry to the supply chain or involvement as a commercial agent. Collaborations with MNEs may help indigenous firms to learn both managerial and technical knowledge from the MNEs' regional subsidiaries (Jindra et al., 2009). Since the technical gap between most indigenous EM firms and foreign enterprises is considerable, indigenous firms may look to imitate their foreign counterparts through cooperation in R&D or via participation in the DM MNE supply network (Glass and Saggi, 1998). For instance, foreign firms may care about their influence on the environment and may require their host suppliers to obtain international recognized quality standards (Javorcik, 2004). As well as collaboration, indigenous firms may also become locked in competition with foreign invested enterprises (FIEs) in their domestic markets. Indeed, as overseas investors often aim to explore new markets in host countries, intensified competition is also a typical outcome (Meyer and Sinani, 2009). Products launched by foreign firms are highly competitive, since their products usually incorporate advanced technologies, high levels of quality supported by stronger brands than their domestic market counterparts (Chang and Park, 2012). To take up the challenge posed by foreign firms, indigenous firms may attempt to imitate foreign firms' products or develop their own competitive products via further investment in their own R&D capabilities (Buckley et al., 2007a; Xiao et al., 2013).

Since implementation of the '*Reform and Opening Up*' policy, and particularly during the 1990s and onward, foreign firms have rapidly become far more important players in the Chinese economy. FDI has not only significantly enriched and enlarged the Chinese domestic market, it has also brought with it significant challenges for indigenous firms. In particular, the huge volume of overseas' investment that have poured into China since 2002 (when China became a formal member of the WTO) numerous key industrial sectors been opened up to the competition of foreign firms (He and Wang, 2012). Chinese indigenous firms remain hugely important contributors to the remarkable development processes of economic development and also the main industry players (Tian and Estrin, 2008). These firms, moreover, have benefitted considerably from the presence of foreign investment, in numerous ways. In general, therefore, it is argued inward FDI has led to significant improvements in the innovation capabilities of indigenous Chinese firms.

**Hypothesis 1:** Inward FDI is positively related to the innovation capabilities of Chinese firms.

2.3 The moderating role of local industrial structures: how do Chinese firms capture FDI spillovers?

Diversified industrial structures allow firms to obtain knowledge from multi-disciplinary knowledge bases which in turn may promotes innovation (Jacobs, 1969). As innovation is a process of knowledge recombination and recreation (Cohen and Levinthal, 1990), access to multiple knowledge bases may provide the platform for innovators to communicate and transfer their ideas, findings, breakthroughs, and applications (Beaudry and Schiffauerova, 2009). Successful innovation requires expertise or knowledge of multiple technological fields and subjects: 'a more diverse industrial fabric in close proximity fosters opportunities to imitate, share and recombine ideas and practices across industries' (Beaudry and Schiffauerova, 2009: 319). These knowledge spillovers from a diversified industrial structure may enable firms to conduct effective R&D and innovate and are commonly known as Jacobs externalities.

Prior studies suggest that in-house R&D is full of uncertainties and resource restrictions. Firms are encouraged to conduct open innovation through which they may benefit from collaboration with external partners (Chesbrough, 2003). This idea has been shown to be a useful way for both process innovation and product innovation (Chesbrough and Crowther, 2006). Technology purchases or licensing are found to be useful for firms in undertaking technological upgrading and innovation, especially in developing countries (Wang and Zhou, 2013). Cross disciplinary knowledge transfer and diffusion are conducive for firms to conduct both incremental and radical innovations. Or, as Desrochers and Leppala (2011: 846) optimistically put it, the argument for Jacobs spillovers is 'commonsensical in light of what is known about human creativity, at least inasmuch as, innovations are always the results of new combinations of pre-existing know-how, skills, ideas, processes materials and artifacts'. The frequent communication between knowledge workers in different economic actors can therefore facilitate knowledge diffusion and integration, which in turn may provide opportunities for indigenous firms to gain positive knowledge spillovers from FDI. Additionally, foreign firms in a diversified region are capable of utilizing the local knowledge base for complementing their understanding of host markets through collaborating with indigenous firms (Dunning, 2001; Liu et al., 2009). This offers indigenous firms valuable opportunities to learn from their foreign collaborators and in turn improve their R&D capability.

The ability of EM firms to more efficiently capture FDI spillovers in the presence of a more diversified technological base may also be a result of their specific technological-catch up strategies (Mathews, 2006; Awate, Larsen and Mudambi, 2012,2014). Strategies employed by EM firms typically look to exploit their 'advantages of backwardness' and the historical specificity of late-industrialization – namely the abundance and availability of foreign technologies, often traded on the international technology markets (Amsden and Hikino, 1994). As Desrochers and Leppala put it in their investigation of Jacobs externalities, 'from an economic perspective developing new applications for one's existing expertise has always been a more sensible (if not always successful) proposition than developing a new product or expertise from scratch' (Desrochers and Leppala 2011: 848). EM firms, following this logic, have evolved learning strategies to firstly imitate and then subsequently to improve upon foreign technologies (Mathews, 2006; Awate, Larsen and Mudambi, 2012,2014; Hennart, 2012).

There are very strong incentives for EM firms to acquire foreign technologies of all kinds and a diverse industrial environment may facilitate these acquisition processes. EM firms can leverage low domestic production costs and potentially out compete foreign rivals in their home market owing to preferential access to complementary local resources (i.e. government contracts, lower costs of capital etc.) and greater familiarity with it (i.e. lower psychic distances) (Hennart, 2012; Luo and Tung, 2007). Their domestic markets are often in the early stages of development with large market potential. Intellectual property right (IPR) laws, moreover, are often weakly enforced, guaranteeing prolonged use of any successfully acquired technology. Thus, over time, EM firms develop strong firm-level capabilities to unbundle foreign technologies - a process that has been referred to as the development of 'project execution capabilities' (Amsden and Hikino, 1994). EM firms also develop strong capabilities to work with and learn from foreign MNEs, in doing so also exploiting these relationships to rapidly acquire their technologies (Mathews, 2006; Tan and Mathews, 2014). For many EM firms, moreover, the capability to acquire foreign technologies is often internalized within business groups, which itself may lead to firm-level diversification strategies (Amsden and Hikino, 1994). Inherent, therefore, in many EM firms, is the tendency towards the potential for the cross-fertilization of ideas that the pursuit and acquisition of all sorts of foreign technologies may bring. The capability to imitate foreign technologies, moreover, may also subsequently lead to innovation via further incremental process and product driven innovations building upon the acquired foreign technologies (Williamson and Yin, 2013). This leads to our second hypothesis.

**Hypothesis 2**: Regional industrial diversity positively moderates the relationship between the innovation capabilities of Chinese firms and inward FDI.

The Marshall-Arrow-Romer (MAR) model suggests that manufacturers clustered in the same or similar industrial sectors can reap benefits from spatial proximity (Viladecans-Marsal, 2004). The short geographic distance between cluster members, for example, enables them to reduce transportation costs and in turn increase their profits. Although a highly specialized industrial structure is beneficial for the cluster members, it may potentially create barriers for innovation when local firms are also trying to benefit from FDI knowledge spillovers. Highly centralized regional industrial structures are associated with vertical linkages of firms within supply chains that are strong and stable. External actors may face fewer opportunities to take a leadership position in a specialized sector if they invest into that sector. This may prohibit potential foreign presence because one of the objectives of foreign investment is to search and occupy new markets in host countries (Dunning, 2001; Luo, 2003). Moreover, specialized clusters are more likely to be locked-into specific technologies, which impedes cluster members from absorbing and utilizing new ideas and knowledge from fields outside of their main their R&D activities (Beaudry and Schiffauerova, 2009; Boschma and Iammarino, 2009; Neffke et al., 2010). New knowledge spillovers from FDI may therefore be incompatible with the knowledge base of a highly specialized industrial structure, limiting the scope of potential benefits. For example, some very large companies in a specialized industrial structure play important roles as key innovators[1]. These firms have incentives to defend their considerable influence over other cluster members and also to prevent knowledge leakages. In other words, indigenous firms could facilitate technology transfer of their R&D outputs to compete with foreign companies rather than imitate or learn the spillover technologies from regional foreign counterparts. These have been referred to as '*defensive*' or '*offensive*' technology strategies (see Xiao et al. (2013) and Freeman (1992)).

MAR, in contrast to Jacobs externalities, take place when tacit or codified knowledge can be shared among cluster members more easily. This, it is argued, is done within the same sector as transmission costs are lower. More specialized regions, however, may also develop more specialized knowledge bases than diversified regions. As a result they may also be more prone to lock-in in their areas of expertise because the probability of local absorptive capacity 'being compatible with foreign technologies are less for specialized regions than for diversified ones' (Wang et al. 2014: 13). Similarly, more diversified regions have broader knowledge bases and these can play 'a crucial role in absorbing technology spillovers from local MNEs' (Wang et al. 2014: 13). We argue on this basis that a region with highly specialized industrial structure will impede the positive effect of FDI spillovers. Hence,

**Hypothesis 3:** Regional industrial specialization negatively moderates the innovation capabilities of Chinese firms and inward FDI.

## 3 Data and method

3.1 Data

Chinese publicly listed companies (PLCs) play a dominant role in the Chinese economy (Tian and Estrin, 2008) and most PLCs are key players within their corresponding industrial sectors. For instance, SINOPEC in the oil and gas sector and SANY in the construction machinery sector are important players (Chen, 2004). Moreover, the financial data of PLCs are comparatively reliable, since they have to obey stricter accounting rules and are under the supervision of the China Securities regulatory commission (CSRC) (Ching Chi Heng and Noronha, 2011). We therefore use a panel dataset based around data from Chinese publicly listed companies (PLCs) for the period of 2000 to 2010. Specifically, the annual accounting and corporate governance information of all *A*-share firms listed on the Shanghai and Shenzhen stock exchanges are obtained from the China Stock Market Accounting Research (CSMAR) database. Regional data was also collected from various issues of *The China Statistical Yearbook on Science and Technology*, *The China Industry Economy Statistical Yearbook*, and *The Database of China Main S&T Index (DCMSTI)*. The statistical yearbooks are official publications compiled by National Bureau of Statistics of China (NBSC) and State Intellectual Property Office (SIPO). The DCMSTI is compiled by the Ministry of Science and Technology (MOST). Contrasting with previous research that relies mostly on the *China Statistical Yearbook* (Fu, 2008; Huang et al., 2012), the DCMSTI and MOST data provide more fine grained detail on the local economic and S&T indicators, such as R&D expenditures, S&T personnel and regional GDP growth.

As the CSMAR dataset includes no information on firm patenting activities we manually collected the number of patent registrations of each firm from the website of the China State

[1]The '*key innovators*' refer to those giant firms in a cluster with power and ambitions to amplify their influence through allocating resources and/or proposing production and technological standards.

Intellectual Property Office (SIPO)[2]. We match the accounting information with the patent data for each firm as well as the local characteristics. Firms operating in service sectors are dropped because most of them have never applied for patents and have few R&D activities. We also deleted those records with missing values and firms that had some degree of foreign ownership, since our research objective is to examine the role of FDI knowledge spillovers on innovation in indigenous Chinese firms. The final unbalanced panel covers the period from 2000 to 2010 with 9,596 firm-year observations for 1,610 firms with 124,200 successfully granted patents.

3.2 Variables measurements

*3.2.1 Dependent variable*

*Innovation capability (IC)*: we used patent counts to indicate innovation capability. This is a proxy showing the extent to which an innovator creates new knowledge. There are three advantages of using patents as the dependent variable. First, the procedures and criteria for assessing patents are reliable and respected(Griliches, 1990). SIPO is the only authority in China evaluating patent applications and issuing patent grants (Kroll, 2011; Xiang et al., 2013). The patent system in China, moreover, has experienced significant development since China entered the WTO in 2001 (Li, 2012). The number of Chinese patents granted has considerably increased, from 105,345 in 2000 to 814,825 in 2010[3]. Patent number counts have become a core index of the competitiveness evaluation system at both regional and firm-levels in China (Kroll, 2011). Chinese firms realize the importance of patenting as an indicator of innovativeness. Using the patent number count as the dependent variable also allows for further comparative analysis as a number of studies use this measure (for example,Choi et al. (2011)).

*3.2.2 Explanatory variable*

*FDI (fdi)*: To test the relationship between FDI spillovers and innovation capability in indigenous firms we employ the proportion of total industrial product value contributed by foreign invested enterprises (FIEs) in a region (in this study the regional unit of analysis is the province-level) to measure the presence of FDI. This followsBuckley et al. (2002) andTian (2006).

*Industrial specialization (spe)*: Inspired by the work ofGlaeser et al. (1992) and Gao (2004), a local industrial specialization indicator was constructed to measure MAR externalities. This reflects the extent to which a region's industrial structure is specialized relative to economic activities in the country as a whole(Wang et al., 2014). It is defined as follows:

$$S_i = \sum_{j=1}^{n} \frac{E_{ij}}{\sum_{j=1}^{n} E_{ij}} \left[ \left( \frac{Y_{ij}}{\sum_{j=1}^{n} Y_{ij}} \right) / \left( \frac{\sum_{i=1}^{m} Y_{ij}}{\sum_{i=1}^{m} \sum_{j=1}^{n} Y_{ij}} \right) \right] \quad (1)$$

where $Y_{ij}$ is industrial output of industry $j$ in region $i$, $E_{ij}$ is the number of employees of industry $j$ in region $i$, $n$ and $m$ are the numbers of industry and region respectively, $E_{ij} \Big/ \sum_{j=1}^{n} E_{ij}$ is an assigned weight to each industry $j$'s relative prominence in the total industrial employment in region $i$. A higher value of $S_i$ indicates a greater degree of specialization in

[2] The search platform of SIPO patent is available at http://www.sipo.gov.cn/zljs/.

[3] The details of the huge surge of Chinese patenting can be referred at the website of SIPO (http://www.sipo.gov.cn/).

region $i$ .

*Industrial diversity (div)*: to identify the impact of increased local diversity of industries (Jacobs externalities), we construct this diversity variable following the work of (Gao, 2004; Henderson, 1997). Let $Y_{ij} \Big/ \sum_{j=1}^{n} Y_{ij}$ be industry $j$ 's share of the total industrial output in region $i$ . $y$ is the industrial output. We then subtract $D_i$ from 1 to allow a higher value of it to reflect higher diversity. It is defined as follows:

$$D_i = 1 - \sum_{j=1}^{n} (Y_{ij} \Big/ \sum_{j=1}^{n} Y_{ij})^2 \text{, } i\text{=1, 2, 3,…, n} \quad (2)$$

where $D_i$ is the diversity index. The higher the value of $D_i$ , the more diversified the local industrial structure is in region $i$ .

*3.2.3Control variables*

We take into account both firm features and local characteristics when examining the specific effect of explanatory variables (Wang and Lin, 2013; Zahra et al., 2014). We control for possible effects of firm features.

Firm R&D intensity (*frd*): R&D investment is found as one of the main drivers for firm R&D capability, prior studies show high R&D intensities lead to innovation outputs(Laursen and Salter, 2006). Contrary to international accounting standards, annual reports of publicly listed firms in China do not include R&D investment expenditure records. To overcome this deficiency, we followDong and Gou (2010) that the item of "*Cash Paid for the Business Related Activities*" reported in firms' financial statement is equivalent to R&D investment in China. It includes the development and design cost, technology development cost and research cost. We therefore used the ratio of a firm's R&D investment against its sales as a proxy for the firm's R&D intensity.

Firm age (*age*): innovation is found to be closely related to a firm age (Thornhill, 2006). Both firms' R&D investment and innovation highlights are varied in different phase of a firm's life cycle. We therefore used the number of years since the firm's establishment as a proxy for the firm's age.

Firm size (*size*): prior studies suggest that bigger firms may have more resources to conduct R&D activities(Cohen and Klepper, 1996). The natural log of a firm's total assets at the end of the fiscal year was used as a proxy of the firm's size.

Firm leverage (*leverage*): a high debt to equity ratio will impact on the R&D investment decisions as higher leveraging increases the likelihood of bankruptcy (Choi et al., 2012). We thus used the percentage of a firm's percentage of total debt over total equity as a proxy of the firm's leverage rate.

Firm return on asset (*ROA*): a firm with higher profitability is more likely to invest in R&D resources in inventive activities (Choi et al., 2012), we thus used a firm's return on assets as a proxy of the firm's profitability.

Firm performance (*Tobin's Q*): better performing firms will invest more in innovation and set up long term R&D plans to ensure their competitiveness. Following prior studies, we use the market value of assets over book value of assets (Tobin's Q) as a proxy of the firm's performance (Talke et al., 2011).

Local characteristics that are closely related to innovative activities are taken into account as well[4].Regional human capital (*hrc*): the availability of human capital is essential to

[4]The 'local' or 'regional' in this research refers to the provincial level in China. Advantages for using this spatial level are discussed in Li (2009).

enhance innovation capability as it represents the capability to absorb and recognize external knowledge (Fu, 2008; Mankiw et al., 1992; Wang, 2010). The *hrc* in this research is calculated as the ratio of residents with tertiary degrees divided by regional total inhabitants. Moreover, the regional scale is closely related to inventive output as increasing returns to scale yield externalities (Feldman and Audretsch, 1999). To account for such impacts, we use the natural logarithm of the number of total employees (*lscale*) in a region as a proxy for the economic size of the region (Rodríguez-Pose and Crescenzi, 2008). We also expect that R&D activities thrive in regions with a high rate of economic and industrial growth since regions with higher pace of development may attract more foreign and indigenous investment for innovation and grow faster (Fu et al., 2011). We thus use regional GDP growth rate *(gdpg)* as a proxy to control for the effect of local economic growth potential across regions and sectors (Cheung and Lin, 2004). The definition, operationalization and data source of each variable are summarized in Table 1 below.

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3.3 Model specification

As the dependent variable in this study is a patent count variable and takes only nonnegative integer values, linear regression is inappropriate. This is mainly because the distribution of residuals of the dependent variable will be heteroscedastic and nonnormal. Poisson regression is recommended to model count data (Hausman et al., 1984). The Poisson distribution, however, requires that the mean and variance of the sample data are equal, which is a strong assumption that usually cannot be achieved as patent data often displays overdispersion, where the variance exceeds the mean (Hausman et al., 1984). As the descriptive statistics show in Table 2, the standard variation (S.E.=123.50) of firms' patent number is much greater than the mean (Mean=12.47), indicating that our patent data is over-dispersed.

Though the coefficients will be estimated consistently in the presence of over-dispersion, their standard errors will generally be underestimated which produces spurious high levels of significance (Cameron and Trivedi, 1986). Extant empirical studies suggest an alternative method, i.e., negative binomial regression, to deal with the over-dispersion problem of patent data (Almeida et al., 2002; Chang et al., 2006; Choi et al., 2011; Schilling and Phelps, 2007). As Hausman et al. (1984) suggests, the negative binomial model is a generation of the Poisson model which allows over-dispersion by incorporating an individual, unobserved effect into the conditional mean. In other words, we relax the variance restrictions of the underlying Poisson model. Blundell et al. (1995) suggested the conditional probability density function in the Poisson model for firm$_{i,t}$ is:

$$\Pr(Y_{it} = y_{it} \mid X_{it}) = \frac{e^{-\lambda_{it}} \lambda_{it}^{y_{it}}}{y_{it}!} \tag{3}$$

In line with prior studies (Almeida et al., 2002; Chang et al., 2006; Choi et al., 2011), individual, unobserved effect was introduced into a conditional mean as follows:

$$E[Y_{it}] = \lambda_{it} = \exp(\mu_t + \beta x_{it} + \gamma z_i + \alpha_i + \varepsilon_{it}) \tag{4}$$

where $\exp(\varepsilon_{it}) \sim \Gamma[1, \alpha]$, which means the error term is assumed to have a *gamma* distribution. The subscripts $i$ and $t$ mean that the parameter λ is allowed to vary across individuals ($i$=1, 2, …, n) and year ($t$=1, 2, …, m). The parameter α is estimated directly from the data and captures overdispersion.

The dynamic count data model of patent data on firms' innovation capability was adopted, and we applied the negative binomial panel models with fixed effects to examine both the direct and interactive effects of foreign presence ($fdi_{i,t-1}$), specialization ($spe_{i,t-1}$) and diversity ($div_{i,t-1}$) on innovation capability. The log-linear function of all covariates of this study can be showed as the following.

$$\begin{aligned}\log \lambda_{it} &= \alpha_i + \beta_1 frd_{i,t-1} + \beta_2 age_{i,t-1} + \beta_3 size_{i,t-1} + \beta_4 leverage_{i,t-1} \\ &+ \beta_5 ROA_{i,t-1} + \beta_6 Tobin's Q_{i,t-1} + \beta_7 hrc_{i,t-1} + \beta_8 gdpg_{i,t-1} \\ &+ \beta_9 \mathrm{lscal}e_{i,t-1} + \beta_{10} fdi_{i,t-1} + \beta_{11} spe_{i,t-1} + \beta_{12} div_{i,t-1} \\ &+ \beta_{13}(fdi_{i,t-1} \times spe_{i,t-1}) + \beta_{14}(fdi_{i,t-1} \times div_{i,t-1})\end{aligned} \tag{5}$$

As FDI knowledge spillovers take time to be absorbed and to have an effect on a firm's innovation capability, we use a one year lag for all independent variables in our regression estimations (as shown in formula (5) above). Another advantage of lagging all independent variables by a year is that this procedure can remove possible endogeneity in the model (Fu, 2008; Usai, 2011). Given that the length of gestation for inventive activities is varied, we additionally use two and three year lags for all independent variables in our estimations, which also serves as robustness tests for our results(Choi et al., 2011; Schilling and Phelps, 2007).

# 4 Results

4.1 Descriptive analysis

Table 2 shows the mean, standard deviation, and correlations of all variables. Most of the correlation coefficients for the independent variables are smaller than 0.10, indicating that the specific effects of explanatory variables will not be seriously affected by other control variables. Given that the biggest correlation value is -0.47 between regional human capital and scale, the Variance Inflation Factors (VIF) are computed. The VIF value for each independent variable is reported (Table 3).The average VIF value for each estimation are smaller than 2.0. The mean of all VIF values is 1.31, smaller than the recommended threshold of 10 (Belsley, 1980). Multicollinearity is therefore not a serious concern.

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4.2 Estimation results

Following prior studies, we use negative binomial panel regressions with fixed effects and report several fitness values of each model (e.g., Log Likelihood, Wald chi2, and VIF). Following Schilling and Phelps (2007), we also report estimates using negative binomial panel regressions with random effects as robustness tests (shown in the Appendix). To decrease any potential multicollinearity we standardize both the predictor (FDI) and moderator variables (specialization and diversity) before creating the interaction terms (Aiken and West, 1991). Moreover, as we explore a moderating effect in the empirical framework, we use the estimates of the full model (as shown in Equation (5)) to test if the interaction term is significant (Dawson, 2013).

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Table 3 shows estimates for the three dependent variables ($Patents_{it+1}$; $Patents_{it+2}$; $Patents_{it+3}$). The results of the negative binomial regressions are reported separately for the three dependent variables. Models 1-3 report the results using a one-year lag between all independent variables and firm patenting ($Patents_{it+1}$). Models 4-6 report the results using a two-year lag between all independent variables and firm patenting ($Patents_{it+2}$). Models 7-9 report the results using a three-year lag between all independent variables and firm patenting ($\mathrm{Patents}_{it+3}$). For each dependent variable, the first models (i.e. 1, 4, 7 in Table 3) include firm and local characteristics only, the second models (2, 5, 8) add the direct effects of foreign presence (*fdi*), and the third model adds the interaction term, $fdi \times spe$ and $fdi \times div$ (i.e. 3, 6, 9).

In hypothesis 1, we predicted FDI knowledge spillovers have a positive effect on innovation capability in indigenous firms. Table 3 shows that the main effect of FDI spillovers (*fdi*) is positive with a significance at 0.01 level ($\beta$=0.227, $p$<0.01, model 3 ($Patents_{it+1}$)). This positive influence on firms' patenting can also be found in longer year lagged settings ($\beta$=0.256, $p$<0.01, model 6 ($Patents_{it+2}$); $\beta$=0.252, $p$<0.01, model 9 ($Patents_{it+3}$)), indicating that knowledge spillovers of FDI are beneficial for indigenous firms' innovation capability and this argument is robust in various year-lagged settings. Therefore, hypothesis 1 is supported.

In hypothesis 2, we predicted a positive effect of the interaction of foreign presence and diversity on firm patenting. In the one-year lagged model, the interaction term ($fdi \times div$) is positive and highly significant ($\beta$=0.232, $p$<0.01, model 3 ($Patents_{it+1}$)). Moreover, the coefficient for $fdi \times div$ is positive and statistically significant in models using both two- and three-year lags ($\beta$=0.202, $p$<0.01, model 6 ($Patents_{it+2}$); $\beta$=0.155, $p$<0.01, model 9 ($Patents_{it+3}$)). Therefore, hypothesis 2 receives strong support in models using different year lags.

In hypothesis 3, we predicted a negative effect between the interaction of FDI and industrial specialization on innovation capability of firms. In the one-year lagged model, the interaction term, $fdi \times spe$, is negative and is highly significance ($\beta$= -0.139, $p$<0.01, model 3 ($Patents_{it+1}$)). Moreover, the coefficient for $fdi \times spe$ is negative and statistically significant in models using both two- and three-year lags ($\beta$= -0.154, $p$<0.01, model 6 ($Patents_{it+2}$); $\beta$= -0.091, $p$<0.01, model 9 ($Patents_{it+3}$)). Therefore, hypothesis 3 received strong support in the models using different year lags.

To illustrate the patterns of the significant moderating effects that support hypotheses 2 and 3, in Table 3 we plot the effect of the interactions using $Patents_{it+1}$ as the dependent variable, illustrated in Figure 1 below. For ease of illustration and to help better interpret the results, the log-linear form of the negative binomial models in Table 3 was adopted to calculate interactive effects.

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INSERT FIGURE 1 ABOUT HERE

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Figure 1 shows the interaction plot of FDI knowledge spillovers and specialization (plot A) and FDI knowledge spillovers and diversity, respectively (plot B) in $Patents_{it+1}$. We use one standard deviation below and above the mean to denote the high and low levels of the moderating variables respectively. In plot (a) of Figure 1, the slope of "*low specialization*" (blue and solid line) is steeper than the slope of "*high specialization*" (red and dashed line). This is consistent with Hypothesis 3, indicating that firms in a local industrial structure with a lower level of specialization gain more benefits from the FDI knowledge spillovers in terms of their improved innovation capabilities. Similarly, in plot (b) of Figure 1 the slope of "*high diversity*" (red and dashed line) is greater than the slope of "*low diversity*" (blue and solid line), implying that industrial diversity enhance the positive relationship between foreign presence and indigenous firms' innovation capability, consistent with hypothesis 2.

## 5 Discussion and conclusions

Both FDI spill-overs and industrial externalities are believed to be crucial knowledge sources for spurring innovation. Here we explore the question of the potential interaction between FDI and industrial externalities on the innovation outputs (as captured by patent counts) of indigenous firms. We have shown that the effect of FDI knowledge spillovers is contingent on the degree of industrial specialization and diversity. By integrating three streams of literature, namely that on FDI knowledge spillovers, agglomeration economies, and EM firm innovation strategies, we contribute to the important question of how EM firms develop innovation capabilities. After controlling for the possible impacts of firm and local characteristics on innovation capability, we find that the positive effect of FDI knowledge spillovers is significant and robust in models with different time-lag specifications. More importantly, the moderating roles of industrial specialization and diversity are significant for different year-lag specifications in our estimations. These results not only provide robust support for our predictions, but also indicate that local agglomeration economies are a crucial factor impacting on the association between FDI knowledge spillovers and indigenous Chinese firms' innovation capability. Our results suggest EM firms can more easily capture FDI spillovers in diverse industrial environments and that specialized industrial structures, by contrast,retard the capacity of EM firms to capture innovation spillovers.

How do we explain these findings, which contrast with many studies for DM firms, which mostly have found that DM firms actually benefit from specialization? Beaudry and Schiffauerova's (2009) review of 67 empirical studies (mostly of developed markets) exploring MAR and Jacobs externalities, for example, shows approximately 70% of these studies found a positive significant impact of MAR externalities on innovation. While many studies have also found negative impacts of one or both externality, the negative impacts are indeed more pronounced for MAR externalities, albeit only 27% of the 67 studies have found negative impacts for MAR (compared with only 3% of the 67 for Jacobs externalities). This leads Beaudry and Schiffauerova (2009: 320) to conclude the solely negative influence for MAR externalities is found 'much more often'. An implication of our findings is that indigenous Chinese firms may find it hard to benefit from FDI spillovers in the presence of local industrial specialization, which is insignificant in various year lag model settings. Our estimates for industrial diversity, by contrast, suggest it exerts positive externalities on indigenous firm innovation capability, indicating that indigenous firms can benefit from a multidisciplinary knowledge base at the local level. This result supports the findings drawn from many other countries (i.e. de Lucio et al. (2002) and Neffke et al. (2010)) which have generally found positive outcomes for Jacobs externalities. Beaudry and Schiffauerova's (2009) review, for example, found positive significant impact of MAR externalities on innovation or growth in 75% of the 67 studies reviewed in the case of Jacobs externalities.

Digging inside the 'black box' of the firm to trace spillovers is generally considered an impossible task: 'Knowledge spillovers are invisible and "leave no paper trail by which they may be measured or tracked" (Krugman, 1991, p.53) (Beaudry and Schiffauerova, 2009: 321). Or, as Desrochers and Leppala (2011: 844) put it, spillovers are the convenient black-box that provides 'an escape route to avoid studying the specific mechanisms at play'. We can, however, speculate here as to why diversification may facilitate innovation in theEM context. The international business literature argues EM firms are inherently different to DM firms, and in large part this is because of their innovation strategies (Awate, Larsen and Mudambi, 2012, 2014). As 'late-industrializers' looking to 'catch-up', EM firms engage in different kinds of strategies when learning from DM MNEs. In contrast to DM MNEs, EM firms initially look to intensively and opportunistically learn from foreign competitors and exploit an existing stock of knowledge. They may do so via linkage, leverage and learning, the so-called LLL model (Mathews, 2006; Tan and Mathews 2014). This differentiates them from DM firms. Part of the EM strategy, therefore, at least in the initial stages, involves imitation of existing foreign technologies, including product and process related practices (Amsden and Hikino, 1994; Awate, Larsen and Mudambi, 2014; Mathews, 2006). EM firms are comparatively indiscriminate in the technologies they look to acquire. In this scenario, industrial diversity provides a greater opportunity for technology acquisition owing to the elevated volume of opportunities made available to EM firms. Moreover, after the initial imitation stages subsequent innovation may also take place, often in an incremental manner building from the acquired foreign technology. Willamson and Yin (2013), for example, discuss what they refer to as ‘cost’, ‘application’ and ‘business model’ innovation in Chinese firms, which are in essence related to the further exploitation of a diverse range of foreign technologies. In later stages, therefore, they argue efforts to indigenously innovate take place (Willamson and Yin, 2013). This can also start with recombinant forms of the foreign technologies. In contrast to EM firms, moreover, the comparative evidence also suggests that DM firms generally find industrial specialization more favorable for their innovation strategies (Beaudry and Schiffauerova, 2009: 321). DM firms look to push technological boundaries and make breakthrough discoveries, rather than engage in the intensive imitative behaviors of EM firms (Awate, Larsen and Mudambi, 2014; Williamson and Yin, 2013; Tan and Mathews, 2014). Owing to the different strategies and endowments of both DM and EM firms, therefore, we can speculate as to why we find diversified industrial structures more appropriate in supporting EM firms to capture spillovers from FDI and what, therefore, may lie inside the ‘black box’ of the firm (Desrochers and Leppala, 2011).

We can also draw some practical implications for both policy-makers and business practitioners. Firstly, with a relatively recent dataset of Chinese firms, the findings of this research demonstrate the positive role of FDI spillovers in affecting indigenous firm’ innovation capability (at least in terms of patenting activity). Policy-makers are thus suggested to not only attract FDI, but also establish diversified local industrial structures which are more likely to amplify the positive effects of FDI knowledge spillovers for indigenous firms’ innovation capability. Indigenous innovators will find it harder to gain advance knowledge or technical opportunities from a specialized industrial structure (Jiang et al., 2011; Kang and Jiang, 2012). Local governments may look to reshape local agglomeration economies. This may play an important role in helping Chinese firms improve their innovative capabilities and facilitate transition beyond the middle-income levels (and avoidance of the much discussed ‘middle-income-trap’ (World Bank, 2013)).In regions with low levels of FDI, policy-makers may consider promoting indigenous innovation in local firms by increasing the degree of industrial diversity.

Finally, the limitations in this study may be addressed in future research. Firstly, we used only Chinese publicly listed companies for our estimations. While this approach is used in many previous studies, (e,g., Choi et al. (2011)) in future enlarged datasets that encompass both listed and unlisted firms would be desirable. The comparative analyses of the roles of FDI knowledge spillovers and industrial structure in affecting different types of indigenous firms will extend the findings of this research. Secondly, we used the number of patents as the proxy for innovation capability. Other indicators, such as new product sales and total factor productivity are recommended in future research to verify these findings. Further, studies on MAR and Jacobs externalities are riven by problems concerning the appropriate unit of analysis (i.e. over what size of region should the spillovers be looked for?). Our approach follows fairly conventional procedures. Studies employing alternative approaches will be useful in corroborating or otherwise the reliability of the observed relationships .Finally, we mainly focus on the interaction between FDI knowledge spillovers and industrial externalities on indigenous firm innovation capability. We do not account for a number of firm-level characteristics, such as absorptive capacity, ambidexterity of innovation, organizational culture and the like. Future studies may further examine how these firm-level attributes interact with industrial externalities and FDI to influence innovation.

## Appendix

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Table 1 Definition and description of variables for firm level study

| Variable | Acronym | Operationalization | Source |
|---|---|---|---|
| Firm patent | $patent_{i,t}$ | Firm $i$'s patent count in year $t$ | SIPO website |
| Firm R&D intensity | $frd_{i,t-1}$ | Firm $i$'s R&D spending/sales in year $t-1$ | CSMAR database |
| Firm age | $age_{i,t-1}$ | Year $t$ minus firm $i$'s establishment year | CSMAR database |
| Firm size | $size_{i,t-1}$ | Nature log of firm $i$'s total assets at the end of fiscal year $t-1$ | CSMAR database |
| Firm leverage | $leverage_{i,t-1}$ | Firm $i$'s percentage of total debt over total equity in year $t-1$ | CSMAR database |
| ROA | $ROA_{i,t-1}$ | Firm $i$'s return on assets in year $t-1$ | CSMAR database |
| Tobin's $Q$ | $Tobin'sQ_{i,t-1}$ | Firm $i$'s market value of assets over book value of assets in year $t-1$ | CSMAR database |
| FDI intensity | $fdi_{i,t-1}$ | Firm $i$'s regional FIEs' product value/total product value in year $t-1$ | China Statistical Yearbook |
| Specialization | $spe_{i,t-1}$ | Firm $i$'s regional industrial specialization in year $t-1$, calculated using formula (1) | China Industry Economy Statistical Yearbook |
| Diversity | $div_{i,t-1}$ | Firm $i$'s regional industrial diversity in year $t-1$, calculated using formula (2) | China Industry Economy Statistical Yearbook |
| Human capital | $hrc_{i,t-1}$ | Proportion of residents with a tertiary degree of the region where firm $i$ located in year $t-1$ | China Statistical Yearbook on Science and Technology |
| GDP growth rate | $gdpg_{i,t-1}$ | GDP growth rate of the region where firm $i$ located in year $t-1$ | Database of China Main S&T Index |
| Scale | $lscale_{i,t-1}$ | Nature log of total employment of the region where firm $i$ located in year $t-1$ | Database of China Main S&T Index |

Table 2 Descriptive statistics and correlation matrix of variables for the firm level study

| | Mean | S.D. | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1. $patent_{i,t}$ | 12.47 | 123.50 | 1.00 | | | | | | | | | | | | |
| 2. $frd_{i,t-1}$ | 0.16 | 1.17 | -0.01 | 1.00 | | | | | | | | | | | |
| 3. $age_{i,t-1}$ | 10.64 | 4.48 | 0.02 | 0.03 | 1.00 | | | | | | | | | | |
| 4. $size_{i,t-1}$ | 21.46 | 1.31 | 0.15 | -0.08 | 0.10 | 1.00 | | | | | | | | | |
| 5. $leverage_{i,t-1}$ | 1.39 | 6.67 | 0.00 | 0.00 | 0.05 | 0.13 | 1.00 | | | | | | | | |
| 6. $ROA_{i,t-1}$ | 0.04 | 0.10 | 0.02 | 0.12 | -0.09 | 0.06 | -0.06 | 1.00 | | | | | | | |
| 7. $Tobin'sQ_{i,t-1}$ | 1.72 | 1.52 | -0.01 | 0.03 | 0.16 | -0.27 | -0.03 | 0.10 | 1.00 | | | | | | |
| 8. $fdi_{i,t-1}$ (%) | 39.95 | 26.97 | 0.06 | 0.01 | 0.17 | 0.12 | 0.02 | 0.05 | 0.04 | 1.00 | | | | | |
| 9. $spe_{i,t-1}$ | 0.96 | 0.34 | -0.01 | 0.00 | 0.04 | -0.01 | 0.00 | -0.00 | 0.08 | -0.20 | 1.00 | | | | |
| 10. $div_{i,t-1}$ | 0.90 | 0.04 | -0.01 | -0.01 | 0.04 | -0.04 | -0.01 | 0.04 | 0.06 | -0.11 | 0.29 | 1.00 | | | |
| 11. $hrc_{i,t-1}$ | 8.82 | 6.69 | 0.03 | -0.01 | 0.09 | 0.24 | 0.04 | 0.05 | 0.07 | 0.47 | -0.15 | -0.12 | 1.00 | | |
| 12. $gdpg_{i,t-1}$ (%) | 12.30 | 2.22 | 0.00 | 0.01 | 0.17 | 0.05 | 0.02 | 0.01 | 0.00 | 0.09 | -0.15 | 0.02 | -0.04 | 1.00 | |
| 13.$scale_{i,t-1}$ | 2932.83 | 1626.70 | 0.04 | -0.02 | 0.07 | -0.07 | -0.03 | 0.05 | 0.07 | -0.03 | -0.02 | 0.38 | -0.47 | 0.03 | 1.00 |

Note: The unbalanced panel from 2000 to 2010. Correlation (absolute) value that bigger than 0.029 is at 0.05 significance.

Table 3 Negative binomial panel regressions (fixed effects) using patent number in *t+1, 2, 3* as dependent variable

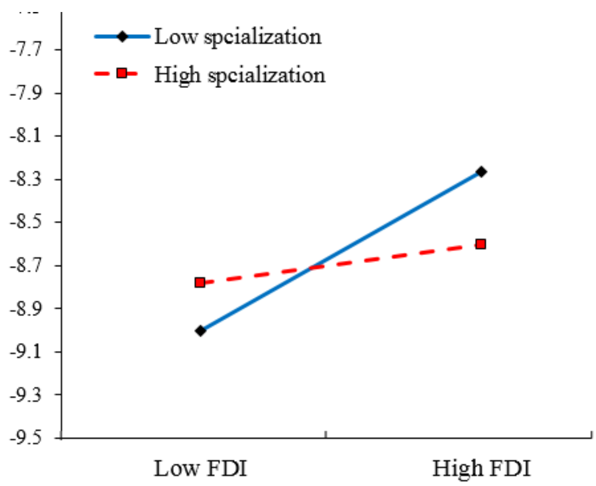
| | $Patents_{it+1}$ | | | $Patents_{it+2}$ | | | $Patents_{it+3}$ | | |
|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
| ***Firm features*** | | | | | | | | | |
| *R&D intensity* | 0.463*** | 0.451*** | 0.493*** | 0.198 | 0.199 | 0.241* | 0.270** | 0.264** | 0.293** |
| | (0.118) | (0.115) | (0.114) | (0.135) | (0.132) | (0.131) | (0.136) | (0.133) | (0.131) |
| *age* | 0.086*** | 0.079*** | 0.068*** | 0.100*** | 0.087*** | 0.078*** | 0.103*** | 0.086*** | 0.078*** |
| | (0.007) | (0.007) | (0.007) | (0.007) | (0.008) | (0.008) | (0.010) | (0.010) | (0.010) |
| *size* | 0.078*** | 0.098*** | 0.086*** | 0.058** | 0.078*** | 0.067** | 0.039 | 0.056 | 0.045 |
| | (0.026) | (0.027) | (0.027) | (0.029) | (0.029) | (0.030) | (0.037) | (0.038) | (0.038) |
| *leverage* | -0.017*** | -0.017*** | -0.017*** | 0.004 | 0.004 | 0.003 | -0.014 | -0.014 | -0.013 |
| | (0.006) | (0.006) | (0.006) | (0.005) | (0.005) | (0.005) | (0.014) | (0.013) | (0.012) |
| *ROA* | 1.003*** | 1.021*** | 0.986*** | 0.624* | 0.706* | 0.721** | 0.668* | 0.721* | 0.727* |
| | (0.342) | (0.343) | (0.341) | (0.360) | (0.365) | (0.362) | (0.399) | (0.406) | (0.404) |
| *Tobin's Q* | 0.043** | 0.053*** | 0.037** | 0.040* | 0.042* | 0.024 | 0.012 | 0.009 | -0.007 |
| | (0.017) | (0.017) | (0.017) | (0.023) | (0.023) | (0.023) | (0.031) | (0.031) | (0.032) |
| ***Regional features*** | | | | | | | | | |
| *human capital* | 0.061*** | 0.045*** | 0.051*** | 0.049*** | 0.028*** | 0.035*** | 0.040*** | 0.018** | 0.025*** |
| | (0.006) | (0.006) | (0.006) | (0.006) | (0.007) | (0.007) | (0.008) | (0.009) | (0.010) |
| *GDP growth* | 0.020** | 0.013 | 0.028*** | 0.034*** | 0.027*** | 0.039*** | 0.076*** | 0.071*** | 0.079*** |
| | (0.009) | (0.009) | (0.009) | (0.009) | (0.009) | (0.009) | (0.011) | (0.011) | (0.011) |
| *lscale* | 0.585*** | 0.558*** | 0.577*** | 0.447*** | 0.407*** | 0.450*** | 0.308*** | 0.282*** | 0.339*** |
| | (0.054) | (0.054) | (0.056) | (0.057) | (0.057) | (0.062) | (0.065) | (0.065) | (0.071) |
| ***Explanatory variables*** | | | | | | | | | |
| *fdi* | | 0.008*** | 0.227*** | | 0.009*** | 0.256*** | | 0.009*** | 0.252*** |
| | | (0.001) | (0.034) | | (0.001) | (0.037) | | (0.002) | (0.045) |
| *specialization* | | | -0.030 | | | -0.053* | | | -0.021 |
| | | | (0.032) | | | (0.030) | | | (0.033) |
| *diversity* | | | 0.175*** | | | 0.142*** | | | 0.085** |
| | | | (0.037) | | | (0.038) | | | (0.043) |
| *fdi×spe* | | | -0.139*** | | | -0.154*** | | | -0.091*** |
| | | | (0.034) | | | (0.032) | | | (0.033) |
| *fdi×div* | | | 0.232*** | | | 0.202*** | | | 0.155*** |
| | | | (0.035) | | | (0.035) | | | (0.039) |
| *Constant* | -8.732*** | -8.957*** | -8.664*** | -7.224*** | -7.295*** | -7.151*** | -5.969*** | -6.032*** | -5.967*** |
| | (0.696) | (0.702) | (0.720) | (0.751) | (0.754) | (0.780) | (0.946) | (0.945) | (0.970) |
| Log Likelihood | -10072.71 | -10053.47 | -10022.06 | -8930.82 | -8909.07 | -8884.04 | -6495.01 | -6480.26 | -6469.72 |
| Wald chi2 | 941.66*** | 964.32*** | 1029.81*** | 633.62*** | 679.99*** | 731.74*** | 435.07*** | 473.65*** | 498.99*** |
| VIF | 1.18 | 1.25 | 1.52 | 1.19 | 1.27 | 1.55 | 1.21 | 1.29 | 1.58 |
| Firms | 894 | 894 | 894 | 770 | 770 | 770 | 609 | 609 | 609 |
| Obs. | 5452 | 5452 | 5452 | 4773 | 4773 | 4773 | 3385 | 3385 | 3385 |

Note: The panel includes Chinese PLCs in the period of 2000 to 2010. Standard errors are reported in parentheses. * p<0.1, ** p<0.05, *** p<0.01.

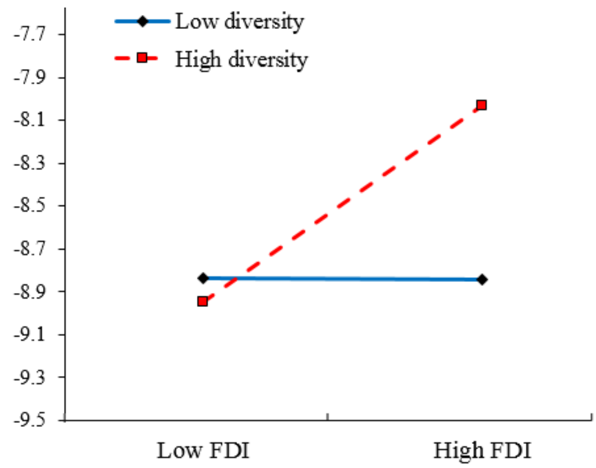
Table A1 Negative binomial panel regressions (random effects) using patent number in *t+1, 2, 3* as dependent variable

| | $Patents_{it+1}$ | | | $Patents_{it+2}$ | | | $Patents_{it+3}$ | | |
|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
| ***Firm features*** | | | | | | | | | |
| *R&D intensity* | -0.035 | -0.034 | -0.031 | -0.101 | -0.095 | -0.076 | -0.040 | -0.039 | -0.036 |
| | (0.055) | (0.052) | (0.046) | (0.114) | (0.111) | (0.103) | (0.070) | (0.066) | (0.055) |
| *age* | 0.056*** | 0.048*** | 0.035*** | 0.072*** | 0.058*** | 0.046*** | 0.067*** | 0.049*** | 0.039*** |
| | (0.006) | (0.006) | (0.006) | (0.007) | (0.007) | (0.007) | (0.009) | (0.009) | (0.009) |
| *size* | 0.083 | 0.106*** | 0.092*** | 0.074*** | 0.096*** | 0.084*** | 0.071** | 0.089*** | 0.075** |
| | (0.024) | (0.024) | (0.025) | (0.027) | (0.027) | (0.027) | (0.034) | (0.034) | (0.034) |
| *leverage* | -0.016*** | -0.016*** | -0.015*** | 0.002 | 0.001 | 0.001 | -0.012 | -0.012 | -0.011 |
| | (0.006) | (0.006) | (0.006) | (0.004) | (0.004) | (0.004) | (0.011) | (0.011) | (0.010) |
| *ROA* | 1.305*** | 1.306*** | 1.253*** | 0.962*** | 1.034*** | 1.032*** | 1.080*** | 1.117*** | 1.114*** |
| | (0.305) | (0.305) | (0.303) | (0.333) | (0.334) | (0.331) | (0.381) | (0.383) | (0.380) |
| *Tobin's Q* | 0.035** | 0.044*** | 0.024 | 0.030 | 0.032 | 0.008 | -0.016 | -0.019 | -0.045 |
| | (0.016) | (0.016) | (0.017) | (0.022) | (0.022) | (0.022) | (0.030) | (0.030) | (0.031) |
| ***Regional features*** | | | | | | | | | |
| *human capital* | 0.080*** | 0.062*** | 0.070*** | 0.063*** | 0.038*** | 0.047*** | 0.054*** | 0.027*** | 0.037*** |
| | (0.005) | (0.006) | (0.006) | (0.006) | (0.006) | (0.007) | (0.007) | (0.008) | (0.008) |
| *GDP growth* | 0.028*** | 0.019** | 0.039*** | 0.038*** | 0.030*** | 0.046*** | 0.093*** | 0.085*** | 0.097*** |
| | (0.008) | (0.008) | (0.009) | (0.008) | (0.008) | (0.009) | (0.011) | (0.011) | (0.011) |
| *lscale* | 0.821*** | 0.785*** | 0.813*** | 0.643*** | 0.587*** | 0.644*** | 0.511*** | 0.470*** | 0.540*** |
| | (0.050) | (0.050) | (0.055) | (0.054) | (0.054) | (0.060) | (0.061) | (0.061) | (0.067) |
| ***Explanatory variables*** | | | | | | | | | |
| *fdi* | | 0.008*** | 0.249*** | | 0.010*** | 0.299*** | | 0.011*** | 0.300*** |
| | | (0.001) | (0.031) | | (0.001) | (0.034) | | (0.001) | (0.041) |
| *specialization* | | | -0.003 | | | -0.042 | | | -0.011 |
| | | | (0.032) | | | (0.030) | | | (0.032) |
| *diversity* | | | 0.200*** | | | 0.179*** | | | 0.133*** |
| | | | (0.036) | | | (0.036) | | | (0.041) |
| *fdi×spe* | | | -0.143*** | | | -0.169*** | | | -0.105*** |
| | | | (0.034) | | | (0.032) | | | (0.033) |
| *fdi×div* | | | 0.295*** | | | 0.268*** | | | 0.220*** |
| | | | (0.033) | | | (0.033) | | | (0.037) |
| *Constant* | -10.57*** | -10.77*** | -10.52*** | -8.915*** | -8.826*** | -8.826*** | -8.127*** | -8.089*** | -7.997*** |
| | (0.641) | (0.646) | (0.664) | (0.704) | (0.707) | (0.734) | (0.860) | (0.859) | (0.884) |
| Log Likelihood | -15993.08 | -15965.61 | -15909.57 | -13998.61 | -13963.65 | -13919.55 | -10751.13 | -10725.32 | -10702.43 |
| Wald chi2 | 1029.9*** | 1064.6*** | 1186.3*** | 620.82*** | 695.47*** | 792.32*** | 433.41*** | 497.41*** | 552.57*** |
| Firms | 1524 | 1524 | 1524 | 1310 | 1310 | 1310 | 1175 | 1175 | 1175 |
| Obs. | 9291 | 9291 | 9291 | 8065 | 8065 | 8065 | 5965 | 5965 | 5965 |

Note: The panel includes Chinese PLCs in the period of 2000 to 2010. Standard errors are reported in parentheses. * p<0.1, ** p<0.05, *** p<0.01.



(a) Moderating role of specialization



(b) Moderating role of diversity

Figure 1 Moderating plots of specialization and diversity on the association between foreign presence and indigenous firm's innovation capability (***Patent***$_{t+1}$)