How Chinese firms employ open innovation to strengthen their innovative performance

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Abstract: China became the second-largest economy behind the USA in 2010. While there is quite some macroeconomic research documenting the technological catching-up of China as a nation, there is only little research studying how individual Chinese firms are catching up. This paper draws on the open innovation perspective to explore how Chinese firms improve their innovative performance. Our empirical analysis is based on a sample of 91 native Chinese firms in high-tech industries. The results indicate that Chinese
firms widely implement an open innovation approach to strengthen their innovative performance. These firms use:

1. technology in-licensing agreements to obtain access to technologies
2. long-term alliances with foreign partners to access state-of-the-art technologies
3. collaboration with local universities and R&D institutes to broaden their technological strengths
4. collaboration with the local industrial community to deepen their technological skills.

**Keywords:** open innovation; innovative performance; technology in-licensing; China.


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Nadine Roijakkers obtained her PhD in Collaborative Innovation from UNU-MERIT, Netherlands in 2002. For two years, she worked as a Policy Researcher for the EC. From 2004 to 2007, she was an Assistant Professor of Open Innovation at Eindhoven University of Technology, Netherlands. From 2007 to 2009, she worked as a Strategy Consultant at KPMG, Netherlands advising companies on how to profit from their innovation/alliance strategies. Since 2009, she has been working at Hasselt University, Belgium to develop the theory and practice of open innovation. Outlets for her research include *Long Range Planning*, *Harvard Business History Review*, *Research Policy*, *European Management Journal*, *Technological Forecasting and Social Change*, and *British Journal of Management*.

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Jin Chen is Professor and Deputy Director of the National Institute for Innovation Management at Zhejiang University. In 1998, he was a Visiting Scholar at Alfred Sloan School of Management (MIT). His research interests
How Chinese firms employ open innovation


1 Introduction

Since the late 1970s China has successfully experienced an economic transformation from a centrally planned, closed economy to one of the world’s most dynamic and globally integrated market economies. In 2010, China overtook Japan as the second-largest economy in the world behind the USA. The recent literature on economic development has debated the relative importance of institutions, policy, globalisation, and technological change as competing determinants of China’s economic growth (Hung, 2009; Liu, 2010). Firms are the major determinants of China’s rapid economic growth and yet compared with the burgeoning literature on the achievements of the Chinese economy there is little known about how Chinese firms obtain access to advanced technology, how they learn, and finally, how they improve their innovative performance.

Most documented insights about the innovation activities of firms in developing countries are drawn from various economies that have been successful in catching-up. Examples are South Korea, Singapore, Taiwan, and Hong Kong (Hobday, 1995; Kim and Nelson, 2000; Lall, 2000). Central questions pertaining to technology-lagging firms that are trying to improve their innovative performance are: how do they obtain access to external technology; how do they learn; and ultimately, how do they integrate the acquired technologies into their own knowledge bases in order to innovate and compete successfully with their global counterparts (Hobday, 1995; Kim, 1999)? This view on technological development in developing countries is characterised by three features: international technology diffusion as the main channel of innovation; reversed product life cycle as a learning process; and domestic technological efforts to improve innovative performance. Technology development in developing countries starts with the diffusion of international technology (usually mature/obsolete technology) from developed countries. Companies in developing countries then gradually upgrade their technological skills and move from mature to emerging technologies (through different stages, including acquisition, assimilation, and improvement). Eventually, the performance of these technological activities relies heavily on the technological efforts exerted by firms in developing countries (such as absorptive capacity) (Bell and Pavitt, 1993; Hobday, 1995). The catching-up strategies of technology-lagging firms have been considered as a matter of relative speed in a race along a particular track, and technology development is understood as an accumulative unidirectional process with emphasis on the role of technological capability building in the later stages of the catching-up process (Perez and Soete, 1988). This model is also labelled the staged model of technological catching-up (Chen and Qu, 2003).
Some authors suggest that the staged model, which has been applied to the newly industrialised economies, such as South Korea, can be applied to China as well (Fan, 2006; Jin and von Zedtwitz, 2008; Xie, 2004). Fan (2006), for instance, argues that innovative capability and self-developed technologies have been crucial to the successful catching up by domestic firms in China’s telecom-equipment industry. He furthermore suggests that domestic firms should prioritise building innovative capability from the very earliest stages of the catching-up process – and not (as the staged model suggests) only at the later stages. By examining the development process of China’s colour TV industry, Xie (2004) comes to the conclusion that the learning process occurring in this industry is intrinsically the same as that of other newly industrialising economies (NIEs) although there are also some noteworthy differences as a result of the huge domestic market in China. Jin and von Zedtwitz (2008) observe that some practices to improve innovative performance in Chinese manufacturing companies appear to be in disagreement with the staged model, and go on to provide an addition to Kim’s (1980) model where they distinguish between three stages of performance improvement: acquisition, assimilation, and improvement.

In contrast, a new research stream points out that the traditional staged model for improving innovative performance – mainly drawn from NIEs – is not applicable to China and that an alternative model is needed (Chen and Qu, 2003). In this new model companies integrate operational, tactical, technological, and strategic learning. Using information technology as a facilitator, this new technological learning has multiple objects, multiple sources, multiple subjects, and multiple methods. Liu (2005) documents that Japan’s and Korea’s technological catching-up model is relatively closed. They imported foreign technology but did not innovate together with foreign companies. They focused on the development of in-house R&D to gradually improve acquired and mature foreign technology. Meanwhile they did not simply rely on foreign technology for new products. In the case of China, Liu provides an alternative model, which he labels the ‘open model’. In this new model, firms can access the latest technology to undertake innovation and do not wait for technologies to become mature before importing them and making incremental innovations. Chinese firms increasingly ally with technologically advanced foreign partners. Simultaneously, China’s capabilities in technology and science have increased strongly over time, which may largely support learning by Chinese firms. Finally, Chinese firms could obtain easy access to the latest technologies because of the presence of high-quality inward foreign direct investment (FDI). Findings from recent studies of FDI flows also contradict proposals based on the product life cycle theory (Athreye and Cantwell, 2007). Many new technologies have been shipped to developing countries for commercialisation and multinational firms have been further developing technologies in R&D labs located in developing countries (Dunning and Lundan, 2009). Liu (2005) concludes that Chinese firms are much more open in their innovative activities than companies in NIEs during their transition periods.

In general, Chinese firms employ a variety of sources to improve their innovative performance, including technology licenses (Liu et al., 2006), alliances (Duysters et al., 2009), knowledge spillovers from high-quality FDI (Quan, 2010), collaborations with universities and R&D institutes (Chen and Qu, 2003), and outward FDI (Huan and Ghauri, 2008). These routes to improved innovative performance employed by Chinese firms are in line with the imperatives of open innovation proposed by Chesbrough (2003). Open innovation can be defined as: ‘the use of purposive inflows and outflows of knowledge to accelerate internal innovation, and to expand the markets for external use
of innovation, respectively’ [Chesbrough et al., (2006), p.1]. The basic premise of open innovation lies in the wide use of external knowledge sources to accelerate the innovation process and strengthen internal technological capabilities. At the same time, open innovation encourages companies to search for ways to monetise internal technologies that do not fit with their business models and they do not commercialise themselves. Since Chesbrough’s pioneering work, open innovation research has burgeoned and now represents a strong and vibrant literature stream (Huizingh, 2011; Dahlander and Gann, 2010).

In this study we draw on the open innovation perspective to explore how Chinese firms employ the open innovation approach to improve their innovative performance. The open innovation approach is represented by our focus on technology in-licensing, alliances with foreign partners, and collaborations with universities, R&D institutes, and community members. More specifically, we investigate how these different open innovation modes to source external technology influence the innovative performance of Chinese high-tech firms. To the best of our knowledge, empirical studies that investigate technological catching-up at the level of individual Chinese firms are scarce or non-existent. Most studies conducted at the macroeconomic level are case-based (Chen and Qu, 2003; Jin and von Zedtwitz, 2008; Liu and Wang, 2003). The current study makes use of an extensive firm-level database and provides new insights to better understand the innovative activities of Chinese firms. It also contributes to the literature on open innovation, which has been studied almost exclusively in the context of technologically advanced countries and has not yet been properly examined in developing countries (Chesbrough, 2011).

The paper is structured as follows. In the following section we discuss the major theories underlying our set of hypotheses. Next, we describe the data, sample, variables, and statistical method in a methods section. In a subsequent section we present the main results of the empirical analysis. We discuss these results and draw conclusions on the basis of our findings in the final section of this paper.

2 Theory and hypotheses

Since the publication of Chesbrough’s seminal book on open innovation (2003) the concept has become one of the hottest topics in the field of innovation research. A search in Google Scholar on open innovation provides over 1.8 million hits and the above-mentioned book has gathered more than 2,000 citations in just seven years (Google Scholar, http://scholar.google.com/). Open innovation scholars observe that the knowledge landscape has become widely distributed as a result of the efforts of universities, technological institutions, national labs, and small and medium-sized enterprises (SMEs). In this new knowledge landscape, firms are increasingly using external knowledge to foster their innovations and accumulate competencies in a world where knowledge is increasingly ubiquitous and dispersed (Chesbrough, 2003; Vanhaverbeke and Cloodt, 2006). Open innovation can be split into inbound and outbound flows of knowledge. Inbound open innovation is when firms tap into external sources of knowledge to accelerate their own innovation. Sourcing happens through in-licensing agreements, spin-ins, mergers and acquisitions, and alliances. Accessing external knowledge has long been recognised as a significant factor in successful
innovations (Rothwell, 1994). According to the study by Laursen and Salter (2004), firms in general draw upon different sources of external knowledge. Likewise, outbound open innovation is when firms reveal internal knowledge to outsiders to achieve commercialisation in other markets or in other applications. Outbound open innovation is related to out-licensing, spin-outs, and other strategies. Through outbound open innovation firms can increase the productivity of their R&D efforts, leverage their investments in R&D, and partner with actors adept at bringing inventions to the market (Chesbrough, 2003).

The literature on open innovation has proliferated and focused mainly on the enhancement of the open innovation framework and the establishment of its general validity (e.g., Dahlander and Gann, 2010; Laursen and Salter, 2006; Lichtenthaler and Ernst, 2007). For instance, one line of research strives to extend the national context of the USA, the country where open innovation originates, to other developed nations, such as the UK, the Netherlands, and Germany (e.g., Laursen and Salter, 2006). In developing countries, as we mentioned before, some pioneering researchers have observed that technological laggards, for example in China, are increasingly widening their external sources of technology in line with open innovation (Liu, 2005). Although this is an important observation, there is still almost no empirical evidence to show how firms in developing countries implement the open innovation approach to strengthen their innovative performance. The subject of how latecomer firms can benefit from open innovation is still underexplored in current studies of open innovation. Prior studies of technological developments by latecomers are dominated by the channels of international technology transfers (Liu and White, 1997). A few recent studies utilise cases to describe new channels that are opened by open innovation, such as alliances with foreign partners (Duysters et al., 2009) and co-inventions with universities and R&D institutes (Chen, 2004). In this study, we conduct a comprehensive examination of how Chinese firms employ various inbound open innovation approaches to strengthen their innovative performance. Specifically, we explore how technology licensing, alliances, and collaborations with universities, R&D institutions, and community members lead to a higher innovative performance by Chinese high-tech firms.

3 Foreign technology in-licensing

A technology licensing agreement implies that the owner of intellectual property rights grants another organisation permission to use the intellectual property on the basis of agreed terms and conditions (Grindley and Teece, 1997). Being a licensee provides a Chinese firm with the following benefits which could further foster its innovative performance:

1. The licensee can integrate part of the licensor’s knowledge into its own knowledge base, which provides the potential to achieve economies of scale and scope in innovation, and results in a larger knowledge base (Fleming, 2001; Lin, 2003). Previous studies have suggested that knowledge creation is a recombinatory process and that novel innovations often result from a recombination of existing components of knowledge into new syntheses (Henderson and Cockburn, 1996). Similarly, Chinese firms recombine licensed technology with their own knowledge to broaden and renew their technology base. Technology in-licensing will thus increase the
number of novel combinations that a licensee can create on the basis of combined knowledge bases.

2 The licensee may increase its R&D efforts or other activities aimed at absorbing and developing the licensed-in technology. Such R&D efforts will most likely include extensive lab testing, quality control, hiring new scientists and engineers, adapting the new technology to local demands, etc. These innovative activities reinforce a licensee’s technological capabilities and are also likely to enhance innovative output (Lee and Lim, 2001). As a result, technology licensing is likely to produce more innovations. In line with this argumentation we develop the following hypothesis:

Hypothesis 1 Foreign technology licensing by Chinese firms has a positive impact on their innovative performance.

4 Strategic alliances with foreign partners

A strategic alliance refers to an agreement between two or more partners where this cooperative mode has the common aim of sharing necessary resources as well as coordinating activities (Hagedoorn, 1993; Narula and Hagedoorn, 1999). Strategic alliances have become increasingly popular since the 1970s, particularly for undertaking technological development activities (Narula and Hagedoorn, 1999). In general, strategic alliances facilitate technological learning and provide opportunities to access foreign markets, share the cost of investment such as R&D, and access resources such as complementary technology. Firms in developing countries benefit in several ways from establishing strategic alliances with partners in advanced countries (Hobday, 1995). First of all, through alliances with foreign firms, universities or research institutes, indigenous firms in developing countries obtain a unique and valuable opportunity to gain access to state-of-the-art technologies and learn about the latest technological developments (Chatterji and Manuel, 1993; Mansfield et al., 1982). Secondly, by being partners of foreign companies in developing countries, domestic firms become a node in the global networks of these foreign firms. This provides local firms with important inputs such as information on international quality standards and market trends. Particularly, foreign parties that seek to enter domestic markets may even consciously support their domestic partners’ technological learning by training research personnel, sharing information, and maintaining their previous technology transfers, joint R&D, and financial support (Chen and Sun, 2000; Hobday, 1995). The above arguments lead us to formulate the following hypothesis:

Hypothesis 2 Alliances with foreign partners have a positive impact on the innovative performance of Chinese firms.

5 Collaborations with domestic universities and research institutes

The traditional source of technology for Chinese firms is importing new technologies from abroad – mainly through technology in-licensing – and this route continues to play a crucial role. For many years, more than two-thirds of R&D expenditures by large and medium-sized Chinese companies have been directed towards importing foreign
technologies (Liu, 2005). Strategic alliances represent another important catalyst that helps Chinese firms learn and improve their innovative performance. This effect has its strongest impact when the strategy is focused on low-cost production by Chinese companies and fast-growing domestic markets. Apart from these two important sources, the next most important open innovation approach for Chinese firms in terms of expenditure is collaboration with local universities and research institutes. As Liu (2005) points out, contracting out research to domestic universities and R&D institutes is one of the key channels of technology sourcing by Chinese firms. The capabilities of NIEs in science and technology were poor during the 1960s and 1970s when compared to developed countries. By contrast, there are several strong capabilities in science and technology in China today and these are recognised by multinationals from developed countries as they set up new R&D labs in the vicinity of domestic universities or research labs. Chinese firms can take advantage of these capabilities to support their technological learning and to strengthen their innovative performance (Chen and Kenney, 2007). By interacting formally and informally with universities and research institutes, firms can acquire new scientific knowledge to benefit their product or process innovations (Caloghirou et al., 2004). Spencer (2003) argues that a firm that acquires technological knowledge from universities and research institutions may speed up its innovations. This leads us to develop the following hypothesis:

Hypothesis 3 Collaboration with domestic research institutes has a positive impact on the innovative performance of Chinese firms.

6 Collaboration with the local industrial community

A firm’s exposure to knowledge within its environment will affect its future innovative performance (McGrath et al., 1995). In light of the open innovation approach, firms acquire knowledge from different sources in their environment to capture a synergic effect and the diversity of these sources significantly influences their innovative performance (Zahra and George, 2002). One of the striking features of Chinese firms lies in their limited internal R&D efforts (Liu, 2005). This fact drives Chinese firms to be more open in their technological capability building. Technology in-licensing provides them with the visible and accessible technologies; alliances with foreign partners offer them access to the latest technological developments; collaborations with local universities and research institutes enable them to widen their technological skills. Meanwhile, Taiwanese firms also set up collaborations with suppliers, customers, and competitors that enable them to deepen their existing technological skills (Tsai and Wang, 2009). This is related to the concept of the industrial community, which emphasises the interdependence of different partners seeking to commercialise certain technologies. This is also consistent with the premise of open innovation, which suggests that a firm’s suppliers, users, and competitors can be a potentially beneficial source of new ideas and innovations. Therefore, Chinese firms that collaborate with industrial community members import distinct knowledge elements from a large number of different sources. This in turn facilitates a firm’s ability to create new types of technological knowledge (Ahuja and Katila, 2001) and further improves its innovative performance. We thereby hypothesise that:
Hypothesis 4  Collaboration with local industrial community members has a positive impact on the innovative performance of Chinese firms.

7 Methods

7.1 Data and sample

In the stream of research on the technological catching-up of China most empirical research is based on data at the macroeconomic level (Fei and Zhang, 2009; Girma et al., 2009; Guo, 2008; Li, 2009). This study proceeds differently, with a focus on the microeconomic level, and employs a unique but underexplored dataset recording the identity and characteristics of licensing agreements.

In China, the State Intellectual Property Office (SIPO) is in charge of recording licence agreements. SIPO’s records enable us to obtain detailed data about licensing agreements, that is, information about the licensor, licensee, and licensed patent names, as well as contracting dates and patent numbers. More specifically, a record tells us who licenses which patents to whom in which year. SIPO has recorded and published this information since the end of the 1990s. The records from 1998–2009 have been made available for public use. In 1998 and 1999, however, there were many missing records. As a result, we make use of the data from 2000 onwards.

In light of our research purpose, we focus on the most innovative industry – the high-tech industry. According to the Chinese National Bureau of Statistics the Chinese high-tech industry consists of five main industrial sectors (i.e., medical and pharmaceutical products, aircraft and spacecraft, computers and office equipment, medical equipment and meters, electronic equipment and communications equipment) with several high-tech sub-sectors in each of these sectors. Based on the technology licensing data, this study includes native Chinese firms operating in these high-tech sectors with license records from 2000 to 2003. This period is chosen because it allows sufficient time for firms to have learnt from the licensed-in technology and for this learning experience to have an effect on their innovative performance. In total, there are 98 firms during this period, but we excluded 7 of these firms from our dataset because these companies were no longer operating due to bankruptcy or merger and acquisition. Finally, we base our analysis on a sample of 91 firms active in technology in-licensing during the period 2000-2003.

We then gathered some complementary information for all the Chinese in-licensing companies in our sample: the founding date of the firm; number of employees; and main location. This information was gathered from annual reports, telephone calls, emails, company websites, search engines (e.g., Google, Baidu), and newspapers. Relevant patent applications by firms at the provincial level were collected from SIPO. The firms in the sample are based in 17 different Chinese provinces and municipalities in the developed regions of eastern China and the economically most important provinces in the centre and west of the country. Most of the best-known Chinese firms are included, such as Huawei, ZTE, TCL, Haier, and BYD.
8 Measurement of variables

8.1 Dependent variable

Innovative performance (IP): This variable measures the innovative output of the focal firms using Chinese patent counts. Patent counts have been widely used to measure innovative performance in previous studies (Henderson and Cockburn, 1996; Trajtenberg, 1990). In the present study, we measure innovative performance using the number of patents granted within a five-year period after the licensing year. Our choice for a five-year time span is based on previous work by Leone et al. (2009), Ahuja and Katila (2001), Cloodt et al., (2006).¹

8.2 Independent variables

- Licence experience (LE): This variable was obtained by checking all SIPO-registered foreign technology in-licensing agreements of Chinese companies. A licence agreement covers at least one patent. We counted the number of licensed-in patents in a given year to construct this variable.

- Alliance experience (AE): This variable was constructed as follows. First, by reviewing company publications, including annual reports of public companies, we found 21 firms in our sample with prior international alliances. We consider a five-year time period to record this experience, that is, the licensing year, two years before and two years afterwards. Second, for the rest of the mostly private firms in our sample we conducted a careful examination of websites and newspapers and we called some companies to check whether they established alliances with foreign partners during the five-year period mentioned above. We constructed this variable as a dummy; when firms have prior foreign alliance experience this variable takes the value of 1 and 0 otherwise. We believe that the dummy variable is more reliable than a count variable because the various sources for this variable tend to overlap.

- Collaboration with universities and research institutes (CURI): To measure the experience of firms with this aspect of open innovation, we counted the number of joint patents with domestic universities and research institutes during the above-mentioned five-year period.

- Collaboration with industrial community (CIC): In a similar manner, we calculated this variable as the number of local industrial partners in firms’ co-patenting portfolios during the five-year period.

8.3 Control variables

We control for several variables, which according to the literature are likely to influence the innovative performance of firms. Absorptive capacity (AC) is calculated as the cumulative number of Chinese patent applications within five years prior to the time of licensing [see Cohen and Levinthal (1989), Kim and Inkpen (2005), Nooteboom et al. (2007), and Vanhaverbeke et al. (2002) who also use accumulated patent counts as a
measure of absorptive capacity). To represent firm size (FS), we use the number of firm employees (natural logarithm form). Firm age (FA) is defined as the number of years from a firm’s founding to the licensing year. Technology age (TA) is the average number of years from the licensed-in patent filing year in SIPO to the year of licensing by Chinese firms. It should be noted that for foreign technologies, this is not exactly equivalent to measuring age because foreign companies have not been consistent in registering and applying for patents in SIPO, unlike in foreign patent offices. For province patent stock (PPS) we use the average number of patent applications per million people prior to the licensing year for the provinces where the sample firms are based. The variable ownership of firms (OF) is a dummy variable where the value of 1 represents state-owned firms and the value of 0 represents private firms. Finally, we control for potential effects of the industry to which the firms belong on innovative performance by including five dummies that specify firms’ industrial activities in our analysis. We follow the Chinese National Bureau of Statistics’ high-tech industrial classification system that we referred to previously to classify our sample firms into the five main industrial sectors and related sub-sectors [see for example Liu and Buck (2007) and Li and Wu (2010) for studies that similarly make use of this industrial classification]. Based on this classification scheme we find that 92% of our sample firms are located in electronic equipment and communications equipment and its various sub-sectors. We therefore distinguish the following six groups of companies. The first five groups of companies are firms that operate in one of the sub-sectors of electronic equipment and communications equipment and these groups of firms are represented in the analysis by means of the following dummy variables. We distinguish between manufacturers of communications equipment (D2), manufacturers of broadcasting and TV equipment (D3), manufacturers of electronic components and other electronic equipment (D4), manufacturers of domestic TV sets and radio receivers (D5), and manufacturers of electronic appliances (default category). The last group consists of isolated companies that operate in the various sub-sectors of medical and pharmaceutical products, aircraft and spacecraft, computers and office equipment, and medical equipment and metres. We lumped these firms together in a residual category (D1).

9 Method

The dependent variable in this study – patent counts – is a count variable. Models for count data have been prominent in economics and management using the Poisson regression (Hausman and Griliches, 1984). However, there is an implicit restriction on the distribution of observed counts in the Poisson model: the variance of the random variable is constrained to equal the mean. In patent-based studies, this condition is seldom met because of overdispersion in the data (i.e., the variance largely exceeds the mean, see Table 1) and therefore scholars frequently use the negative binomial model, which is the standard choice for patent count data (Hausman and Griliches, 1984; Stuart, 2000). A Hausman specification test is used to determine the choice between a random- and fixed-effects modelling approach. We take the negative binomial method as the analytical procedure for our study (the Hausman tests indicate that a random-effects model is appropriate for this analysis, see Table 2).
### Table 1
Descriptive statistics and correlations

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<td>9 PPS</td>
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<td>-0.19</td>
<td>-0.07</td>
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<tr>
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<td>0.01</td>
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<td>-0.03</td>
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<td>-0.02</td>
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<td>-0.18</td>
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<td>16 D5</td>
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<td>0.00</td>
<td>0.04</td>
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<td>-0.02</td>
<td>0.10</td>
<td>0.20</td>
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<td>-0.15</td>
<td>-0.22</td>
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Notes: Number of observations = 101; number of firms = 91
Table 2  Analysis results

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<tr>
<th>Variables</th>
<th>Model 1</th>
<th>Model 2</th>
<th>Model 3</th>
<th>Model 4</th>
<th>Model 5</th>
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<td>IP</td>
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<tr>
<td></td>
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<td>(4.197)</td>
<td>(3.516)</td>
<td>(3.211)</td>
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<td></td>
<td>(0.026)</td>
<td>(0.027)</td>
<td>(0.019)</td>
<td>(0.017)</td>
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<td>1.513***</td>
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<td>(0.854)</td>
<td>(0.686)</td>
<td>(0.613)</td>
<td>(0.561)</td>
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<td>TA</td>
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<td>−0.171**</td>
<td>−0.156**</td>
<td>−0.145**</td>
<td>−0.105</td>
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<td></td>
<td>(0.068)</td>
<td>(0.072)</td>
<td>(0.072)</td>
<td>(0.061)</td>
<td>(0.074)</td>
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<td>1.770***</td>
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<td></td>
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<td>(0.312)</td>
<td>(0.274)</td>
<td>(0.256)</td>
<td>(0.227)</td>
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<tr>
<td>OF</td>
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<td>0.223</td>
<td>0.106</td>
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<td></td>
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<td>(0.554)</td>
<td>(0.425)</td>
<td>(0.384)</td>
<td>(0.329)</td>
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<td>0.004***</td>
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<tr>
<td></td>
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<td>(0.001)</td>
<td>(0.001)</td>
<td>(0.001)</td>
<td>(0.001)</td>
</tr>
<tr>
<td>D1</td>
<td>−1.244*</td>
<td>−1.249*</td>
<td>−1.152*</td>
<td>−0.879</td>
<td>−0.601</td>
</tr>
<tr>
<td></td>
<td>(0.747)</td>
<td>(0.753)</td>
<td>(0.643)</td>
<td>(0.595)</td>
<td>(0.705)</td>
</tr>
<tr>
<td>D2</td>
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<td>−0.071</td>
<td>−0.039</td>
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<td>0.131</td>
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<tr>
<td></td>
<td>(0.634)</td>
<td>(0.645)</td>
<td>(0.529)</td>
<td>(0.453)</td>
<td>(0.460)</td>
</tr>
<tr>
<td>D3</td>
<td>−0.076</td>
<td>−0.235</td>
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<td></td>
<td>(0.863)</td>
<td>(0.959)</td>
<td>(0.682)</td>
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<td>(0.544)</td>
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<tr>
<td>D4</td>
<td>0.179</td>
<td>0.130</td>
<td>0.224</td>
<td>0.547</td>
<td>0.763</td>
</tr>
<tr>
<td></td>
<td>(0.564)</td>
<td>(0.579)</td>
<td>(0.553)</td>
<td>(0.517)</td>
<td>(0.673)</td>
</tr>
<tr>
<td>D5</td>
<td>−0.919</td>
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<td>−0.974*</td>
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<td>(0.585)</td>
<td>(0.604)</td>
<td>(0.577)</td>
<td>(0.546)</td>
<td>(0.653)</td>
</tr>
<tr>
<td>LE</td>
<td>0.072***</td>
<td>0.021**</td>
<td>0.018**</td>
<td>0.014**</td>
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<tr>
<td></td>
<td>(0.159)</td>
<td>(0.152)</td>
<td>(0.116)</td>
<td>(0.089)</td>
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<td>AE</td>
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<td>1.230***</td>
<td>0.826**</td>
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<td></td>
</tr>
<tr>
<td></td>
<td>(0.351)</td>
<td>(0.357)</td>
<td>(0.341)</td>
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<tr>
<td>CURI</td>
<td>1.252***</td>
<td>1.428***</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.356)</td>
<td>(0.386)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>CIC</td>
<td>0.648**</td>
<td></td>
<td></td>
<td></td>
<td></td>
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<td>(0.292)</td>
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<tr>
<td>Hausman test (Chi²)</td>
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<td>15.61</td>
<td>19.81</td>
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<td>p-value</td>
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<td>0.21</td>
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<td>−387.24</td>
<td>−382.08</td>
<td>−377.20</td>
<td>−375.21</td>
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<td>Wald chi²</td>
<td>572.90***</td>
<td>597.67***</td>
<td>330.50***</td>
<td>260.26***</td>
<td>305.17***</td>
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<td>Log-likelihood ratio test</td>
<td>–</td>
<td>20.20***</td>
<td>10.32***</td>
<td>9.76***</td>
<td>3.98**</td>
</tr>
</tbody>
</table>

Notes: Standard errors in brackets. *significant at 10%; **significant at 5%; ***significant at 1%. Number of observations = 101; number of firms = 91.
10 Results

Table 1 shows the mean values, standard deviations, and correlations for all measured variables. The standard deviation of the dependent variable is several times larger than the mean, which indicates that we have to use the negative binomial method for our analysis. The independent variables are not highly correlated with each other or with the control variables (the correlations take on values below 0.50). Potential problems with multicollinearity are thus unlikely to occur.

Table 2 presents the results of all estimated models with random effects (the Hausman tests show that the random-effects model is the appropriate method to use) as well as the outcomes of the log-likelihood tests and the Wald chi-squared tests. Model 1 presents the basic model including only control variables. The model shows that three control variables (firm size, provincial patent stock, and the firm’s absorptive capacity) have a positive effect on innovative performance. Two of the control variables (technology age and residual category) have a negative effect on innovative performance. The variables reflecting the hypothesised effects are entered into the regression in a stepwise fashion and log-likelihood ratio tests are reported for all models. Finally, Table 2 shows the full model (Model 5) that we use as the basis for testing our hypotheses.

Hypothesis 1 predicts that there is a positive relationship between foreign technology in-licensing experience in a Chinese high-tech firm and its subsequent innovative performance. The coefficient for foreign in-licensing experience in Model 5 is positive and significant ($\beta = 0.014, p < 0.05$), thus providing support for Hypothesis 1. In Hypothesis 2, we propose that there is a positive relationship between international alliance experience in a Chinese firm and its subsequent innovative performance. The coefficient for the experience with international alliances in Model 5 is positive and significant ($\beta = 0.826, p < 0.05$). We can thus accept Hypothesis 2. Hypothesis 3 predicts that there is a positive relationship between the experience in Chinese firms with collaborating with domestic universities and research institutes and their subsequent innovative performance. The coefficient for the corresponding explanatory variable in Model 5 is positive and significant ($\beta = 1.428, p < 0.01$), allowing us to accept this hypothesis. Our final hypothesis proposes that experience with collaboration with local industrial community members in Chinese firms is positively associated with subsequent innovative performance. This hypothesis is supported by the results ($\beta = 0.648, p < 0.05$).

Some findings in relation to the control variables are noteworthy. Consistent with prior literature, the innovative performance of firms is influenced by their environment; our analysis indicates that a strong provincial patent stock positively influences the innovative performance of firms. Firm size has a positive effect on innovations, that is, large firms have an advantage when strengthening their innovative outputs. Absorptive capacity has been widely discussed in the literature as having a positive effect on firms’ innovative performance. Our empirical analysis supports this view that absorptive capacity helps companies assimilate and integrate external technologies, which in turn strengthens their innovative performance.
11 Conclusions and discussion

This study is inspired by the observation that although the Chinese economy has been growing rapidly there is almost no evidence of how Chinese high-tech firms strengthen their innovative performance. Most evidence in the literature about innovation in technologically-lagging firms has been drawn from the first-tier of successful NIEs. Several critical changes have occurred in the global economic, social, and political environments since the 1960s and 1970s, when NIEs were industrialising their economies. As a result, what we know about the innovative activities in this kind of firms based on the evidence of NIEs may increasingly prove to be obsolete. For example, the so-called ‘staged model’ no longer represents how Chinese companies are improving their innovative performance. Liu (2005) states that the ‘staged model’ is characterised by a closed innovation model, whereas Chinese firms are developing technological capabilities and strengthening their innovative performance through a more open innovation model. This is consistent with Chesbrough’s (2003) observations that firms are shifting from a closed innovation paradigm to an open innovation paradigm. Therefore, we draw on an open innovation perspective to examine how Chinese firms gain access to external technologies to strengthen their internal knowledge base and increase their innovative output.

The results of the empirical analysis in this paper indicate that the innovative performance of Chinese high-tech firms is strongly influenced by reaching out to different external technology sources. Their innovative performance is not only improved by internal R&D, but also by in-licensing agreements with foreign companies to in source new technologies. This provides Chinese firms with access to new technologies, which in turn are integrated into their knowledge bases to propel the growth of their innovative output. At the same time, Chinese firms establish long-term alliances with foreign partners in developed economies in pursuit of access to the latest technologies and other knowledge spillovers from their partners. This is another external source of technology that acts as a catalyst for innovation by Chinese firms. Chinese companies also take advantage of the increasingly high quality of domestic knowledge infrastructures – such as universities and research institutes – to broaden their technological competences. Indeed, collaborations with these institutions comprise an important and rapidly growing channel for Chinese firms to boost their innovative performance. Similarly, Chinese firms deepen their existing technological strengths through collaborating with local industrial community members.

Table 3  Odds ratios of the different external sourcing modes

<table>
<thead>
<tr>
<th></th>
<th>Model 2</th>
<th>Model 3</th>
<th>Model 4</th>
<th>Model 5</th>
<th>1 standard deviation increase</th>
</tr>
</thead>
<tbody>
<tr>
<td>LE</td>
<td>1.0747</td>
<td>1.0212</td>
<td>1.0182</td>
<td>1.0141</td>
<td>1.0191</td>
</tr>
<tr>
<td>AE</td>
<td>5.1397</td>
<td>3.4215</td>
<td>2.2842</td>
<td></td>
<td>1.4989</td>
</tr>
<tr>
<td>CURI</td>
<td>3.4973</td>
<td>4.1704</td>
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<td>1.7959</td>
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<td>CIC</td>
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<td>1.9117</td>
<td></td>
<td></td>
<td>1.3128</td>
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</table>
We believe it is insightful to compare the impact of the different sourcing modes on the innovative performance of Chinese firms, but this is not possible via the coefficients in Table 2. We therefore transformed these coefficients into odds ratios. Odds ratios perform the same function as ‘standardised’ coefficients in that they generalise the unit of change. They can be obtained by exponentiation of the coefficients in Table 2. These odds ratios are represented in Table 3.

If we focus on Model 5 in Table 3 we find that all odds ratios substantially increase the innovative performance of Chinese innovating companies, but also that there are large differences between the four sourcing modes. Licence experience has the smallest impact, followed by collaboration with Chinese firms, alliance experience, and collaboration with universities and research institutes. To measure the impact of a change in these open innovation variables we work with an increase of one standard deviation relating the increase in innovative performance to the distribution of the four external sourcing modes. If we increase the use of these sourcing modes in this way we find similar improvements in firms’ innovative performance. Increasing the collaboration with industrial partners by one standard deviation results in a 31% improvement in innovative performance ($= \exp[0.648 \times 0.42]$ or 1.313). An increase of one standard deviation of the licensing experience leads to a 2% improvement and one standard deviation increase in alliance experience improves the innovative performance with 50%. Collaboration with universities and institutes is most rewarding as there is an increase in innovative performance of 79% if Chinese companies would strengthen their collaboration by one standard deviation ($= \exp[1.428 \times 0.41]$ or 1.796).

The results of our empirical analysis provide strong support for the beneficial impact of external technology sourcing on the innovative performance of Chinese companies. First, we find strong empirical support for the four hypotheses: experience with in-licensing deals, alliance experience, collaboration with universities and research labs, and collaboration with industrial partners all pay off in terms of improving the innovative performance of Chinese companies. Second, the effect of sourcing external technology is a substantial one. In other words, companies that search for new technologies beyond their organisational boundaries can actually make a difference and become more innovative than companies that choose not to do so. It appears that not collaborating is not an option for the Chinese firms in our sample, which is supportive of Liu’s (2005) argument that Chinese companies are catching-up using leading edge technology early on. We can also confirm that they source technology from several different sources. Finally, collaboration with universities and research labs clearly has the strongest impact on the innovative performance of the firms in our sample. It is not really surprising that successful collaboration with scientific partners leads to new patents. However, the relative impact of the four external sources on firms’ innovation may change when the latter is not measured in terms of patents but for instance in terms of new product introductions or share of revenues coming from new products.

The limitations of our research are diverse. They point at several interesting avenues for further research. First, our sample size is rather limited, which signals the need for empirical studies in larger samples of technology-lagging firms to back up our findings. Second, in this study we did not take into account the possible moderating effect of different levels of internal technological strength (or absorptive capacity) on the positive effect of the four external technology sourcing modes on Chinese firms’ innovative performance. Theory suggests that this effect should be positive, augmenting the effect of external technology sourcing when a firm has more internal technological skills to absorb
new technologies that are sourced through external modes. Future research could examine the potential effect of this interesting moderating variable. Third, our research shows that different types of external technology sourcing modes have significant effects on the innovative performance of Chinese high-tech firms in their attempt to catch up with competitors in developed economies. However, we did not test whether specific combinations of these external sourcing modes lead to superior performance. In other words, we did not test for complementarities between these different modes. A full blown analysis of the complementary effects of different sets of external technology sourcing modes on firms’ innovative performance would give us a first insight as to how a company can best create its optimal mix of sourcing modes to ensure superior innovative performance. To the best of our knowledge the topic of optimal mixes of external sourcing modes has remained largely unexplored in the literature so far. The fact that we find a strong positive impact of the four modes on innovative performance of Chinese companies is a strong indication that this research topic deserves more attention from researchers as well as practitioners. With clear answers on the optimal composition of the portfolio of external technology sourcing modes, companies in developing countries could catch up more rapidly.

References


How Chinese firms employ open innovation


Notes

1 One of the reviewers suggested validating our choice for a five-year time span by also conducting our analyses on the basis of different time spans. We ran additional models based on three- and seven-year time spans. The results show that there are no significant differences between the models using three-, five-, or seven-year time spans. Following the work we refer to in the main text we choose to use five-year time spans in this research.