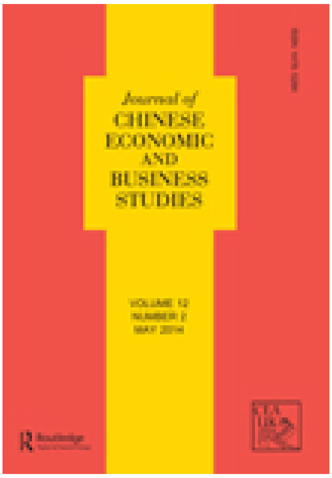

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Technology licensing and innovation performance: evidence from Chinese latecomers in high-tech industries

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Technology licensing and innovation performance: evidence from Chinese latecomers in high-tech industries

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As a catalyst for endogenous technological change, inward technology licensing (ITL) can improve a firm's innovation performance. This paper investigates the effect of learning by licensing and choice of licensed-in technologies on innovation performance. We extend the ITL strategy to the latecomer context, addressing two critical factors: (1) number of licenses and (2) age of licensed-in technology. We hypothesize about the relationship of the licensee's innovation performance with the number of licenses and age of licensed-in technology, as well as the moderating effect of the licensee's absorptive capacity. Based on a sample of 154 Chinese high-tech firms, empirical evidence is found in support of our arguments. This study is the first to consider the significance of the age of licensed-in technology to innovation performance and found that the number of licenses has a curvilinear (an inverted U) relationship with innovation performance. We also confirmed the significant moderating effect of absorptive capacity on the above two relationships.

Keywords: inward technology licensing; licenses; technology age; latecomer; absorptive capacity

1. Introduction

The phenomenal rise in the number of latecomers from emerging economies who have become fast followers and caught up with industry leaders has drawn the attention of researchers. Inward technology licensing (ITL) has been emphasized as one of the most important strategies that latecomers use to build up their competitive advantage, especially in technology-intensive industries (Fosfuri 2002, 2006; Johnson 2002; Laursen, Leone, and Torrisi 2010; Teece 1986). Successful ITL is associated with the process of identifying a licensing opportunity, making a licensing decision, and adopting licensed-in technologies. Earlier studies have investigated the determinants of opportunity identification and licensing decisions, and have identified three categories, namely firm characteristics, management perceptions, and external environment (Atuahene-Gima 1993). However, the adoption of licensed-in technologies has received less attention. Thus, this study aims to identify the important factors in adopting licensed-in technologies and reveal their relationships with innovation performance.

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The stream of research exploring the relationship between firms' ITL strategy and their subsequent innovation performance has shown mixed results. Álvarez, Crespi, and Ramos's (2002) findings underscored the significance of ITL strategy for accelerating a latecomer's technological catching-up. Ahuja and Katila (2001) examined the size of technology acquisitions and determined that size had a positive impact on a firm's innovation performance. On the contrary, Johnson's (2002) study showed that inward licensing experience had a negative impact on innovation performance. Although Johnson's (2002) work showed a firm's internal R&D to be an important factor influencing the association between licensing inputs and innovation performance, recent findings by Tsai and Wang (2009) have raised doubts about this association and showed that ITL expenditure did not contribute significantly to innovation performance in Taiwan, even under the moderating effect of internal R&D. Thus, the precise means by which inward licensing experience affects innovation performance is still inconclusive. Each of these studies furthered our understanding of the micro-foundation of licensing, but did not shed much light on the determinants of purposeful ITL strategy.

This study attempts to resolve the above mixed results by investigating the learning by licensing effect among Chinese latecomers.[1] Given Chinese latecomers' remarkable technological catching-up over the last decade, their learning is likely to have relied on technology transferred through licensing. Based on data from the World Bank (2013), Figure 1 shows how Chinese latecomers' licensing expenditure grew slowly from 1998 to 2003 and then dramatically increased from mid-2004 to 2012. Similarly, according to the State Intellectual Property Office of China (SIPO) data (SIPO 2013) on the number of licensing agreements as shown in Figure 2, the number of patent licensing deals increased dramatically from 1998 to 2012. During the period 1995–2008, it was reported that China contributed 22.9% of the total number of patents filed with the World Intellectual Property Organization (WIPO 2011), ranking third in the world for patenting after Japan and USA. Some Chinese latecomers such as Huawei, ZTE and Haier, even ranked among top patent applicants in their particular fields (WIPO 2011). Thus, investigating the licensing activities of Chinese latecomers will certainly help uncover the ITL strategies that promote innovation.

Considering the nature of latecomers' inferior resources, the two critical factors that can promote innovation performance are (1) the number of licenses and (2) the age of licensed-in technology; these represent the ITL strategic choice embedded in the overall strategy of the firm. The number of licenses is a direct measure of licensing activities and represents the extent of ITL, while the age of licensed-in technology is an

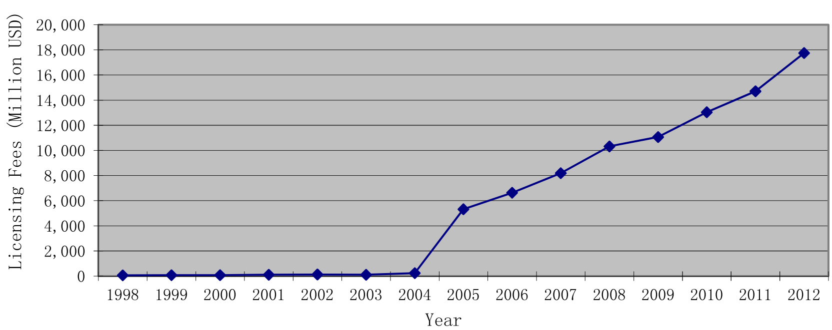

Figure 1. Licensing expenses in China (World Bank 2013).

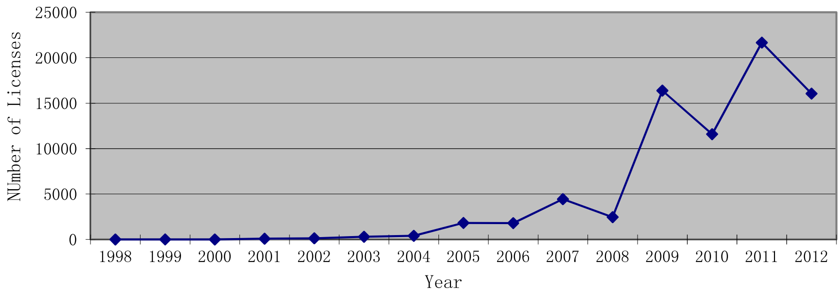

Figure 2. Number of licenses in China (SIPO 2013).

important measure of its value. Although Rockett (1990a, 1990b) extended the licensing literature to cover the role of technology age in outward licensing, there is a lack of research investigating this important factor in the post-adoption stage of ITL. By focusing on the above two factors, the main goal of this study is to investigate the strategic choice of ITL on the growth of innovation in the post-adoption stage. This study borrows from organizational learning theory[2] and examines the respective impacts of the number of licenses and the age of licensed-in technology on the subsequent innovation performance of a licensee, as well as the moderating effect of absorptive capacity on the above two relationships.

2. Theory and hypothesis

A wide range of studies have identified licensing as one of the most important mechanisms of technology transfer (Arora and Gambardella 2010; Chesbrough 2003; Davidson and McFetridge 1985; Fosfuri 2002). This strategy adds additional inputs to a licensee's technology landscape and this inward flow of technology has the potential to help the licensee build competitive advantage by integrating internal R&D and external technologies (Grant 1996). Leone et al. (2009) found that firms who undertake ITL have better innovation performances compared to non-licensing firms. Furthermore, Álvarez, Crespi, and Ramos (2002) claimed that technology acquisition by ITL is a potentially significant means for latecomers to accelerate their technological catching-up.

There are both environmental drives and internal motivations for latecomers to adopt ITL. Rapid technology change, aggressive competition in technological capability, and strengthened intellectual property protection create catching-up barriers for latecomers who want to access and adapt technological advances (Grant 1996; Lee 1996; Leone et al. 2009). However, licensing from industry leaders allows latecomers to tap into external resources. In addition, ITL helps latecomers leverage their initial competitive advantage to enjoy the free-rider effect (Lee and Lim 2001; Mathews 2002), which further promotes their internal motivations for ITL. The internal motivations for latecomers' ITL can be categorized as passive or active. The conventional research (Atuahene-Gima 1993; Chatterji 1996; Kollmer and Dowling 2004; Lubatkin 1983; Roberts and Berry 1984) treated ITL as new product development or a market entry strategy to reduce the financial risk of R&D and time-to-market. Due to their initially weak technological capability and the entry order disadvantage (Mathews 2002), ITL by latecomers has been traditionally viewed as a passive reaction to compensate for technological shortcomings or a means to break the industry's entry barrier (Hill 1997; Lowe and Taylor 1998). However, recent research has viewed ITL as a means to open up learning opportunities (Cohen and Levinthal 1989; Pitkethly 2001) and spur inventive activities (Leone et al. 2009). ITL has become a popular strategy for speeding up a licensee's endogenous technology change and technological capability development over time (Johnson 2002; Tsai and Wang 2009). By relying on a licensing channel to possess proven technology, latecomers can focus more on their own potentially superior or competing technology (Hill 1997). Hence, ITL is widely accepted as a potential means for latecomers to build competitive advantages by adopting licensed-in technologies (Grant 1996).

According to organizational learning theory, the adoption of licensed-in technology can be viewed as a learning process (Davidson and McFetridge 1985; Laursen, Leone, and Torrisi 2010). The technologies available in the market are potential learning opportunities for licensees (Johnson 2002; Pitkethly 2001). Learning by licensing is associated with a firm's ability to identify and acquire licensed-in technology, and then process it into innovation. Moreover, it demands that licensees' R&D efforts act not only as a direct input to innovation performance, but also as a means of absorptive capacity (Cohen and Levinthal 1990). Licensed-in technologies enlarge the licensee's pool of existing knowledge stock (Vanhaverbeke, Beerkens, and Duysters 2004), and thus indirectly favors the absorptive capacity of the licensee (Katrak 1997). If they possess a certain absorptive capacity, licensees may sense the potential of licensed-in technology to generate innovation by recombining the knowledge (Henderson and Cockburn 1994). This knowledge recombination benefits from alternative technology inputs via ITL and is regarded as an important strategy for latecomers to catch up on their technology (Kim 1997; Kodama 1995). Thus, learning by licensing is a viable strategy to promote innovation for the licensee (Johnson 2002; Mathews and Cho 1999). In practice, not all licensees can successfully carry out the learning by licensing because the potential technological benefits depend on effective learning and implementation (Dahlman, Ross-Larson, and Westphal 1987). Obtaining external technologies by purchasing patents together with relevant support, such as experience, expertise, and R&D inputs, is required to realize the benefits of these technologies. Without adequate capability, licensees will have a hard time identifying technology opportunities and making full use of licensed-in technologies. The catching-up literature (Winiecki 1987) also exposed the failure of Soviet-type economies' technology acquisitions and highlighted the difficulties in adopting licensed-in technologies thereby, visualizing the importance of strategic management in ITL adoption.

The effectiveness of ITL adoption, along with subsequent innovation performance, has been widely studied. Research by Lee (1996) and Willmore (1991) presented the alleged positive effect of licensing on internal R&D. Johnson (2002) captured the positive relationship between inward licensing experience and patent generation by a licensee. Indeed, ITL has been proven to play an important role in influencing the innovation performance of a licensee, albeit most likely with a time lag (Fabrizio 2009; Xie and Wu 2003). Empirical evidence by Mansfield et al. (1982) indicated that the average 'start-up lag' for international technology transfer is two years. This implies that licensees cannot immediately improve their innovation performance; rather, it results from the period of learning. Therefore, we use subsequent patent generation (within three years immediately after licensing) as a measurement of the innovation output of ITL strategy. This study objectively analyzes patent generation by Chinese latecomers who adopted ITL in high-tech industries where knowledge is highly intensive, markets are difficult to penetrate, cost advantages are minimal, and strategies of linkage and leverage are important. Since all latecomers from China share a similar regulatory environment and experience roughly the same environmental forces (Xie and Wu 2003), we are able to focus on the factors of strategic management in ITL adoption. This study does not assert that these ITL factors are the only source of heterogeneity among licensees, only that they are the most important. This is further discussed in the following paragraphs.

In the latecomer context, one key factor embedded in the overall strategy of a licensee is the number of licenses. The number of licenses is a direct link to the extent of ITL and financial exposure of the latecomer. Since latecomers lack resources (Mathews 2002), the limitations of R&D inputs and existing capability constrain the number of licenses and hinder the learning effect in ITL adoption. A larger number of licenses means that more licensed-in technologies can be translated into learning opportunities for the licensee. Moreover, licensing-in technologies can enlarge the internal knowledge base and extend the innovation scope by boosting knowledge recombination (Ahuja and Katila 2001; Katrak 1997; Kodama 1995). This positive effects through exploring licensed-in technologies will be limited if the level of internal exploitative learning capability is low (Cohen and Levinthal 1990). It is because the trade-off between exploration and exploitation in a learning process needs to be balanced (Cohen and Levinthal 1990). It has been found that the marginal utility of learning efficiency from exploration remains low in firms whose capability to exploit is relatively scarce (Lichtenthaler 2009; Zahra and George 2002), which is case of latecomers. Beyond a certain level, latecomers face difficulties to absorb a large number of licensed-in technologies (Pitkethly 2001) due to their inferior technological capability; an excessive number of licensed-in technologies may hamper the efficiency of learning (March 1991). This is because adopting more licensed-in technologies requires more R&D efforts to spur effective learning, including human and financial capital support. The extra effort required is unsustainable for latecomers who often suffer resource constraints. For instance, internal intelligences are important assets for realizing both tangible and intangible technology transfers by cooperating with licensors (Atuahene-Gima 1993; Fleisher, Li, and Zhao 2010). The fact is that these intelligences are always in short supply for latecomers in emerging economies due to the lack of human capital accumulation (Liu 1998). Moreover, latecomers rarely have sufficient financial capital for external hires. Thus, it is difficult for latecomers to benefit from a large number of licensed-in technologies. Even worse, too much reliance on ITL may affect internal R&D development because it diminishes the staff's motivation to innovate themselves (Pillai 1979). If a licensee only uses licensed-in technologies as they are, or does not bother to adapt or customize the technologies according to its own needs, the benefits of learning cannot be optimized to develop its innovative capability. Therefore, we believe that excessive ITL impedes a licensee's subsequent innovation performance and propose Hypothesis 1:

H1: The number of licenses has a curvilinear (an inverted U) effect on the subsequent innovation performance of a licensee.

Considering the limited resources allocated to ITL, latecomers should carefully select the technology to be licensed to ensure that innovation can be achieved. It is because this possible technology change triggered by licensing-in decisions can be incorporated to the production and thus affects the productivity in the post-licensing stage (Nelson, 1964). As emphasized by Fosfuri (2002) and Ziedonis (2007), ITL is an important instrument of strategic choice regarding the vintage of technology (or the equivalent quality in their research) beyond a simple entry mode (or the right to use the technology). To examine the quality of technology, technology age was first proposed by Rockett (1990a, 1990b) as an important determinant that licensors can use to extract rents from licensees. We argue that technology age can be used by a licensee as a measure to capture returns on innovation from ITL.

Technology age has been stressed as a critical factor affecting knowledge recombination and, as a result, innovation performance (Nerkar 2003). All technologies depreciate in value as they grow old (Perez and Soete 1988; Tanaka, Iwaisako, and Futagami 2007). Since old technologies have been extensively used by competing firms for extended periods and have likely been replaced by new technologies, they are less valuable as inputs that contribute to innovation (Katila 2002). In contrast, recent technologies offer promising technological opportunities, and thus they are more interesting sources for knowledge recombination (Kim 1997; Sorensen and Stuart 2000).

In addition, recent technologies can help latecomers maintain a good fit between themselves and the competitive environment (Sorensen and Stuart 2000). In high-tech industries where the technology life cycle is short, new technologies may quickly become outdated. Besides endogenous technology development, latecomers can update their patent portfolios by importing recent patents. These recent patents can facilitate a market entry to an emerging technological field (Fosfuri 2002). During the early development of a technological field, every firm is new to the area and the relevant patents available in the technology market are likely to be very recent. As the technology matures, latecomers who license the recent technology enjoy the learning curve advantages (Nelson 1995; Shane 2001). The learning curve embodies the initial difficulty of learning; the possible returns of learning come after the initial familiarity are gained (Ritter and Schooler 2002). The initial learning takes latecomers some time, possibly years, to absorb the licensed-in technology to the level where they can generate innovation based on the accumulation of learning-by-doing (von Hippel 1988). If the licensed-in technology is recent, it is more likely to be advantageous even after ITL adoption.

Based on the above arguments, we propose Hypothesis 2:

> H2: The age of licensed-in technology has a negative effect on the subsequent innovation performance of a licensee.

Few prior studies have examined possible contingent factors that may moderate the impact of ITL on licensees' innovation performance. The moderating effect of Internal R&D has been examined by a number of prior studies (Johnson 2002; Tsai and Wang 2009), but the results are conflicting. Johnson (2002) found that licensing-in experience can provide a strong impetus to innovation only when combining with internal R&D inputs. However, Tsai and Wang (2009) claim that there is no synergistic effect between licensing-in experience and internal R&D on innovation development. We posit that internal R&D is only a partial proxy measure of a wider construct – existing technological capability that is likely to moderate the effect of ITL on innovation performance.

To cultivate an in-house technological capability can be critical for maximizing the learning outcomes of ITL adoption. Song, Bij, and Weggeman (2005) pointed out that internal R&D efforts have a significant effect on the adoption of technology. Sen and Rubenstein (1990) claimed that the cumulative efficiency of past technology learning could increase the effectiveness of external technology adoption. In other words, by adding R&D inputs over time, technological knowledge can be accumulated (Drejer 2000; Schoenecker and Swanson 2002). Accumulative technological knowledge (as the notion of existing technological capability in this study) represents a licensee's absorptive capacity to recognize the value of technology, assimilate it, and apply it to innovation (Cohen and Levinthal 1990; March 1991; Hall, Jaffe, and Trajtenberg 2001). A number of scholars, e.g. Stock, Greis, and Fischer (2001) and Cohen and Levinthal (1990), have hypothesized that a high level of accumulative technological knowledge can lead to inertia and rigidity, resulting in an inward-looking tendency. However, we do not expect this factor to be important in this study, which focuses on latecomers from China. Unlike firms in advanced countries, all of the latecomers covered in our study still have relatively low level of technological knowledge accumulation. Interestingly, a recent study of Taiwanese high-tech firms (Tsai and Wang 2009) has also found a net positive moderating effect of accumulative technology capability. Given that the Taiwanese firms generally have higher level of knowledge accumulation than the Chinese firms (both samples in the same high-tech sector of electronic and telecommunications), we can safely infer that the inertia/rigidity factor is unlikely to be a significant factor for the latecomers in this study. Therefore, the well-established technological capability can improve the absorption of imported technologies from ITL and enhance the effectiveness of learning on latecomers' innovation performance (Gambardella 1992; Grünfeld 2003; von Hippel 1988; March 1991; Mowery, Oxley, and Silverman 1996). It implies that the existing level of the technological capability determines the extent to which the licensee can efficiently adopt licensed-in technologies. When the number of licenses is certain, the strong existing technological capability may boost the effectiveness of adopting licensed-in technologies and result in a better innovation performance. If the number is uncertain, weak existing technological capability may limit adoption to a very small number of licenses due to the low level of absorptive capacity.

During the course of technology utilization, the post-licensing innovation performance may also be enhanced by knowledge recombination in an integrated knowledge pool (Fleming 2001; Henderson and Cockburn 1996; Kogut and Zander 1996). An enlarged knowledge pool can be created via external technology acquisition channels, i.e. ITL in our context. Licensed-in technologies can add to the existing knowledge pool and serve as sources of possible knowledge recombination for renewed innovations. Furthermore, a sizeable existing knowledge base (strong existing technological capability in this study) increases the possibilities for licensed-in technologies to be combined with existing technologies (Cohen and Levinthal 1989, 1990; Fleming 2001; Henderson and Cockburn 1996; Kogut and Zander 1996; Vanhaverbeke, Beerkens, and Duysters 2004). The above arguments imply that, if a licensee imports a greater number of technologies, its subsequent innovation performance will only improve when it has a competent existing technological capability.

In addition, existing technological capability allows licensees to enjoy direct benefits from the vintages of licensed-in technologies, such as technology age. Old technology has limited value for innovation, while recent technology has greater potential (Katila 2002; Perez and Soete 1988; Tanaka, Iwaisako, and Futagami 2007). However, only firms with competent technological capability can realize the potential benefits of recent technology. As the level of existing technological capability increases, more technological opportunities embedded in the recent technology can be identified and explored (Cohen and Levinthal 1990; Fabrizio 2009; Hall, Jaffe, and Trajtenberg 2001). Therefore, the more recent technologies a licensee imports, the better its subsequent innovation performance will be when it has a strong enough existing technological capability.

In summary, the above arguments lead to the following hypotheses regarding the moderating role of a licensee's existing technological capacity:

H3: A licensee's existing technological capability positively moderates the relationship between the number of licenses and the subsequent innovation performance.

H4: A licensee's existing technological capability negatively moderates the relationship between the age of licensed-in technology and the subsequent innovation performance.

3. Data and methodology

3.1. Sample and data

This study uses a licensing data-set obtained from the SIPO, which includes both domestic and international licenses obtained by Chinese licensees from 1998 to 2009. Each record contains the licensor's name, licensee's name, name, and application number of the licensed-in patent and the registration date of licensing. This sample focuses on patent licensing transactions by Chinese firms in the high-tech sector[3] of electronic and telecommunications, including telecommunications, mobile, IT, and consumer electronics industries, completed during the observation period from 1998 to 2005. This provides an initial set of 'licensing-in data points' for 154 firms.

The extra patent data for each licensee is also collected from SIPO. Additional information about each licensee, such as the year established and number of employees, is retrieved from the company website, annual reports, or public media. This additional information allows us to cross-link the original data-set with other sources of information that are necessary for our analysis. The extended data for three firms is unavailable, so they are not included in the empirical test.

3.2. Variables

3.2.1. Dependent variable

Innovation performance: the number of patents has been widely used as a measurement of innovation performance in prior empirical research (Ahuja and Lampert 2001; Hall, Jaffe, and Trajtenberg 2001; Kim 1997). Thus, we adopt this variable and use patent generation as a proxy indicator of the innovation performance for each licensee. We count the number of patents applied for by each licensee within three, four, or five years after the licensing year. If the licensee has multiple licensing years, we average the patent counts. The average number of patents generated by each licensee within three years after licensing is considered as the dependent variable. The number of patents generated within four or five years is used to construct the variables that we use to check the robustness of the outcomes.

3.2.2. Independent variables

Number of licenses: this independent variable is the total number of licensing agreements for each licensee over the period 1998–2005. It includes both international patent licensing and domestic patent licensing.

Age of licensed-in technology: this independent variable is the time lag between the application year of the patent licensed in and the registration year of the licensing agreement from SIPO. First, we compute the time lag for each licensing agreement. Next, we average the time lags for each licensee over the period 1998–2005.

3.2.3. Moderating variable

Existing technological capability: because existing knowledge stock may influence the absorptive capacity for learning (Laursen, Leone, and Torrisi 2010; Perez and Soete 1988), we use each licensee's existing patent stock in SIPO to measure this moderating variable. First, we count the number of patents applied for by each licensee during the five years prior to licensing at the level of each licensing agreement. Next, we average the cumulative number of patents during the five years prior to licensing for each licensee. This value is treated as the measurement of existing technological capability.

3.2.4. Control variables

Age of internal technology: theoretical research about learning (Katila 2002; Nerkar 2003; Sorensen and Stuart 2000) suggests that technology age in the existing knowledge stock has a significant impact on innovation. Thus, the average age of internal technology is a variable that should be controlled for. Using data about each licensee's existing patent stock for the five years prior to licensing, this variable is calculated by computing the time lag between the application year of the patent and the first licensing year in SIPO.

Diversity age of internal technology: the impact of the diversity of the age of internal technology is also considered an important factor (Cohen and Levinthal 1989; Katila 2002). Thus, we use a standard division of the age of the internal patent stock to measure the age of the licensee's internal technology.

Firm age: since the number of years of operations can influence innovation performance, we include firm age as a control variable to capture prior experience in technology development activities. Firm age is defined as the number of years from the establishing year of the licensee to 2009.

Firm size dummy: many studies have reported that firm size influences innovativeness in learning (Cohen and Levinthal 1989; Henderson and Cockburn 1996). The number of employees has been widely used as a measure of firm size (Calof 1994; Ettlie and Rubenstein 1987). To determine the size of each licensee, we count its employees. Since less than one-third of the firms' employee numbers are listed and the numbers for private firms are unreliable, we transformed this variable into a dummy variable. In line with the Institute Für Mittelstandsforschung (Small Business Research Institute) and United Nations Conference on Trade and Development, firms with less than 500 employees are defined as Small and Medium Enterprises and those with more than 500 employees are large enterprises (Commission of the European Communities 1985; Corsten 1987; Neelameghan 1992). Thus, a value of 1 represents a large enterprise with more than 500 employees. If the employee number is equal to or less than 500, the value is coded as 0.

Regional dummy: prior research has shown that regional institutional policies, geographical knowledge spillover, business ties, and local competition affect how firms acquire products and process knowledge (Barney 1991; Koschatzky 1998). Therefore, a regional dummy is added as a control variable. We control this effect by identifying the Chinese province that each licensee is located in and sorting them based on the total number of patents from their province over the period 1985–2009. Since the number of 1000,000 patents is about the average accumulated patent number of the province that our sample firms located, we use this average number as a benchmark to measure this dummy variable. The value of this variable is set to 1 for licensees located in Chinese provinces where the total number of patents is equal to or greater than 1000,000 and 0 for licensees located in Chinese provinces where the total number of patents is less than 1000,000.

Licensor dummy: we control the interrogate linkage between the licensor and licensee using this dummy variable, as nearly 80% of the licensees only had one licensor over the period 1998–2005. If the licensee has a sole licensor, meaning all of its patents are licensed from just one licensor, the value of licensor dummy is coded as 0. Otherwise, it is coded as 1.

Year dummy: this dummy variable indicates a particular licensing year recorded in SIPO over the period 1998–2005. The year is set to 1998 by default. As there are not enough observations from 1999 to 2001, we combine the year dummy 1 (1999), year dummy 2 (2000), and year dummy 3 (2001) together and control for these years as year dummy 123. Year dummy 4, 5, 6, and 7 refer to the particular years 2002, 2003, 2004, and 2005, respectively.

3.3. Methods

This section describes the econometric approach used to conduct the empirical analysis in this study. Because the dependent variable is a count variable – number of patents, this study uses a negative binomial regression analysis. The count data usually exhibits overdispersion and has only non-negative integer values (Maddala 1983). To analyze the count data, the linear regression model based on the assumption of homoscedasticity is violated to explain the normally distributed errors. The appropriate models for the count data are built on the Poisson probability distribution (Cameron and Trivedi 1998; Greene 2008). However, the basic Poisson model only applies to count data that has the same mean and variance. The Poisson model does not fit well for this study because the count data – number of patents – differs across observations (heterogeneity) and its variance usually exceeds the mean.[4] Thus, the negative binomial regression model is the standard choice for data overdispersion of countable patents (Hausman, Hall, and Griliches 1984; Kennedy 1998). The negative binomial regression model also has the advantage of capturing both observed and unobserved heterogeneity in the analysis, whereas only observed heterogeneity is captured in the Poisson regression model (Long 1997). To avoid the negative value of the dependent variable, the negative binomial regression model parameterizes the independent variables as an exponential function (Long 1997):

$$Y_j = \exp\left(\alpha X_{1j} + \beta * X_{2j} + \ldots \gamma * C_j + \varepsilon_j\right)$$

where Y_j is the number of patents generated by a firm j, X_{nj} is the vector of the acquisition variables to be tested, and C_j is the vector of the control variables affecting Y_j. This specification implies that the number of patents by a firm in any year is randomly distributed following the negative binomial model.

Based on the theoretical expectations regarding innovation performance and the determinants of the number of licenses, age of licensed-in technology and existing technological capability, the above model is used in this study to explain a licensee's innovation performance in terms of number of patents. Furthermore, this study adopts a firm-level analysis rather than a firm-year panel due to an inherent problem with the data provided by the data source – SIPO. Specifically, in the period of observation, the number of inward licensing deals are not made available for every year, but are instead lumped together across several years, resulting in zero entries for some years and very high figures for certain years. Indeed, for many of the sampled firms,[5] their licenses appear only in one particular licensing year, with zero entries for all other years. Because of this problem of data aggregation across multiple years, a firm-year panel analysis would not be appropriate. Indeed, we have run a firm-year panel test and found the results to be poor due to the violation of the pooled analysis assumption of equal population variances. Thus, we adopt a firm-level negative binomial analysis. In addition, a sensitivity analysis is carried out later to test the robustness of the results.

4. Results

The descriptive statistics and correlations between variables are presented in Table 1. The coefficients reveal that the analysis does not suffer from multicollinearity in the interaction terms between existing technological capability, number of licenses, and age of licensed-in technology. Table 2 shows the results of the regression analysis on the effects of the number of licenses and age of licensed-in technology, as well as the moderating effect of the existing technological capability, on the innovation performance of a licensee. Model 1 presents the base model with all control variables. The age of internal technology has an inverted U relationship with innovation performance, which is similar to the results of prior work by Katila (2002). The impacts of the firm size and regional dummy turn out to be significant for the innovation performance. The effect of the licensor dummy is insignificant, which means that whether a firm has a sole licensor or many licensors does not have a strong impact on the innovation performance.

Model 2, Model 3, and Model 4 test Hypotheses 1 and 2. Model 2 shows that the estimated coefficient of number of licenses does not have a significant effect on the innovation performance of a licensee, but Model 4 verifies the inverted U shape effect ($p < 0.05$). The age of licensed-in technology has a negative impact on innovation performance. The results in Model 3 and Model 4 show that age of licensed-in technology has a significant negative effect on the innovation performance of a licensee (as expected, $p < 0.01$).

Thus far, the study focuses on the individual effects of the number of licenses and age of licensed-in technology on the subsequent innovation performance. The rest of the models examine the moderating effect of existing technological capability on the above two relationships, which is visualized in Figure 3.[6] Model 5 shows that the moderating variable of existing technological capability has a positive impact on the subsequent innovation performance. Model 6 and Model 8 examine the moderating effect of existing technological capability on the effect of the number of licenses on innovation performance. The results from Model 6 show that existing technological capability has an alleviating effect on the relationship between the number of licenses and innovation performance ($p < 0.05$): the interaction term with the linear term of number of licenses is negative, while that of the squared term is positive. To gain additional insights, we further draw the interaction plots in Set A, Figure 3, in support of Hypothesis 3. This figure, based on Model 8 and 90 percentiles of the data, shows that there are two different ITL strategies that promote the post-licensing innovation. In the case of adopting only a few licenses, the licensee still needs to rely on its own R&D in order to achieve a better innovation performance. However, a licensee can obtain the benefits of a large number of licenses by internalizing licensed-in technologies. When importing many external technologies, it would not make sense for the quantity to affect the post-licensing innovation performance, only for the existing capability of the licensee to absorb the imported technologies. Model 7 and Model 8 investigate the interaction effect

Table 1. Descriptive statistics – mean, standard deviation, and correlations.

Variables	Mean	Standard deviation	1	2	3	4	5	6	7	8	9	10
1. Innovation performance	149.53	954.633	1									
2. Number of licenses	19	79.285	−.025	1								
3. Age of licensed-in technology	7.87	2.709	−.098	.094	1							
4. Existing technological capability	10.80	62.951	.438**	−.031	−.066	1						
5. Age of internal technology	.613	1.335	.266**	−.051	−.099	.127	1					
6. Diversity age of internal technology	.175	.469	.176*	−.018	−.101	.144	.640**	1				
7. Firm age	13.91	7.122	.061	−.075	.131	.183*	.138	.286**	1			
8. Firm size dummy	.36	.483	.191*	−.109	−.036	.216**	.108	.188*	.275**	1		
9. Regional dummy	.95	.225	.037	.043	.177*	.040	−.069	.025	−.051	−.005	1	
10. Licensor dummy	.29	.456	−.067	.084	−.022	.067	.048	.082	.063	.060	.022	1

Notes: Year dummies were included in the analysis but not shown in this table.
Number of observations (N) = 151.
**Correlation is significant with a p value of 0.01 (2-tailed, significant at 10%).
*Correlation is significant with a p value of 0.05 (2-tailed, significant at 5%).

Table 2. Negative binomial regression (dependent variable = innovation performance).

Variables	Model 1	Model 2 H1	Model 3 H2	Model 4 H1, H2	Model 5 H1, H2	Model 6 H3	Model 7 H4	Model 8 H3, H4
Age of internal technology	2.712*	3.203**	2.479**	3.825**	4.967***	4.379***	5.052***	4.519***
	(1.599)	(1.620)	(1.187)	(1.583)	(1.377)	(1.167)	(1.415)	(1.179)
Age of internal technology ^2	−.387*	−.451**	−.433**	−.625***	−.900***	−.776***	−.918***	−.812***
	(.225)	(.227)	(.1808)	(.229)	(.215)	(.192)	(.220)	(.190)
Diversity age of internal technology	−.613	−.959	.410	−.559	−1.913	−2.212	−1.569	−1.648
	(1.960)	(2.075)	(1.724)	(2.164)	(1.675)	(1.354)	(1.764)	(1.443)
Firm age	.122	.125	.109	.118	.0586	.0608	.0618	.0571
	(.0925)	(.0876)	(.0768)	(.0723)	(.0492)	(.0471)	(.0492)	(.0477)
Firm size dummy	2.160*	1.738	1.980**	1.869**	−.0168	−.335	.132	−.110
	(1.139)	(1.125)	(.889)	(.825)	(.640)	(.601)	(.638)	(.599)
Regional dummy	3.653*	3.907**	4.319**	5.320***	4.042**	3.818**	4.014**	3.769**
	(2.030)	(1.956)	(1.790)	(1.888)	(1.651)	(1.559)	(1.643)	(1.541)
Licensor dummy	−.497	−.651	.302	.417	.790	1.139*	.840	1.276**
	(1.169)	(1.084)	(.855)	(.855)	(.647)	(.624)	(.649)	(.622)
Year dummy 123	−1.943	−1.930	−2.261**	−1.734	−1.221	−.858	−1.067	−.763
	(1.290)	(1.271)	(1.114)	(1.138)	(1.015)	(.930)	(.984)	(.946)
Year dummy 4	−.814	−1.015	−1.917**	−1.719**	−1.208	−1.096	−1.166	−1.119
	(1.093)	(1.018)	(.903)	(.840)	(.749)	(.675)	(.724)	(.709)
Year dummy 5	−.904	−1.034	2.332***	−2.949***	−.838	−1.081	−.600	−.565
	(1.000)	(.956)	(.773)-	(.807)	(.754)	(.730)	(.777)	(.785)
Year dummy 6	.124	.628	−.725	−.277	−.975	−.524	−.960	−.690
	(.918)	(1.037)	(.743)	(.705)	(.601)	(.635)	(.595)	(.621)
Year dummy 7	.388	.255	.594	−.0094	.0280	.195	.109	.243
	(1.396)	(1.222)	(.960)	(.886)	(.811)	(.721)	(.795)	(.731)
Constants	−3.152	−3.775	1.665	.940	−.606	−.897	−1.028	−1.338
	(2.984)	(3.012)	(2.537)	(2.616)	(2.162)	(2.003)	(2.142)	(2.022)

(Continued)

Table 2. (*Continued*).

Variables	Model 1	Model 2 H1	Model 3 H2	Model 4 H1, H2	Model 5 H1, H2	Model 6 H3	Model 7 H4	Model 8 H3, H4
Number of licenses		.0758		.0952**	.0775**	.0586*	.0780**	.0624**
		(.0913)		(.0439)	(.0359)	(.0316)	(.0353)	(.0310)
Number of licenses ^2		−.00041		−.00048**	−.00042***	−.00031**	−.00043***	−.00034**
		(.00038)		(.00019)	(.00016)	(.00015)	(.00016)	(.00015)
Age of licensed-in technology			−.629***	−.782***	−.442***	−.400***	−.413***	−.362***
			(.129)	(.152)	(.136)	(.120)	(.139)	(.124)
Existing technological capability					.0428***	.130***	.201***	.366***
					(.0106)	(.0461)	(.0798)	(.101)
Existing technological capability * number of licenses						−.0394**		−.0598***
						(.0189)		(.0199)
Existing technological capability * number of licenses ^2						.0037**		.0050***
						(.0017)		(.0017)
Existing technological capability * age of licensed-in technology							−.0249**	−.0289***
							(.0114)	(.0092)
Pseudo R^2	0.0627	0.0678	0.0879	0.0980	0.1258	0.1317	0.1273	0.1358
Log likelihood	−336.076	−334.237	−327.017	−323.415	−313.439	−311.335	−312.912	−309.861

Notes: Standard errors in bracket.
***$p < 0.01$.
**$p < 0.05$.
*$p < 0.1$ (2-tailed) $N = 151$.

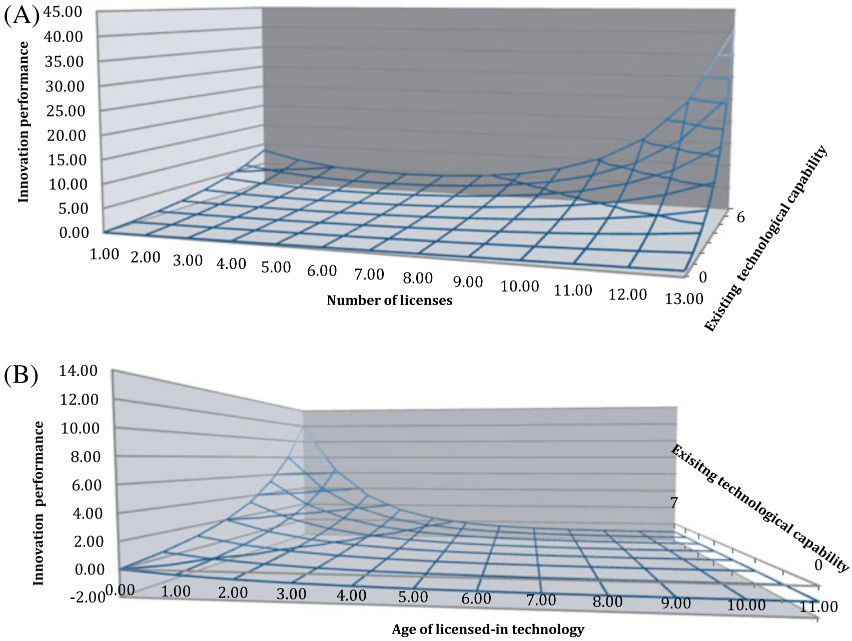

Figure 3. Interaction plots. Set (A): interaction of number of licenses and existing technological capability. Set (B): interaction of age of licensed-in technology and existing technological capability.

between age of licensed-in technology and existing technological capability on the innovation performance of the licensee. The results show that the licensee's existing technological capability negatively moderates the relationship between the age of licensed-in technology and innovation performance ($p < 0.01$), which supports Hypothesis 4. In other words, the absorptive capacity of the firm has a smaller positive impact on the subsequent innovation performance as the technology age increases. The interaction is plotted in Set B, Figure 3, based on Model 8 and 90 percentile of the data. The pattern is in line with the prediction that, with a high existing technological capability, latecomers can take greater advantage of recent licensed-in technologies. The positive effect on innovation performance only appears when the licensee acquires new technologies. Even with a strong existing technological capability, technologies that are more than 4.5 years old prior to licensing seem to have no value for subsequent innovation. This finding disagrees with the wisdom that 'old is gold' (Nerkar 2003) when exploring the value of internal knowledge.

Several robustness tests confirm the accuracy of the results. First, we add the industry dummy into the model. This shows the similar results as reported above. Second, we change the dependent variable of innovation performance in the analysis of the full models by adjusting the period of patent counts to three years, four years, and five years after licensing. The estimated coefficients maintain similar empirical results, which support hypotheses H1 to H4.

5. Discussion and summary

The existing literature has paid little attention to latecomers' ITL strategy for technological capability development. However, as a significant number of Chinese latecomers have successfully become top patent generators, this research topic deserves greater attention. Due to their weaker resources, it is important for latecomers to learn from forerunners and innovate effectively. Due to the dramatic increase in ITL activities that has been observed in China over the last decade, there is an urgent need to investigate the ITL strategy behind the success stories of Chinese latecomers. By treating ITL as an integral part of technological strategic management, this study explores how latecomers can make proactive management decisions to minimize the risk of licensing and maximize their innovation performance.

This study explores ITL strategy for latecomers by focusing on two critical factors: (1) the number of licenses and (2) the age of licensed-in technology. We found that the age of licensed-in technology is a critical factor for the subsequent innovation performance of the licensee. As technology becomes old, its value for inward licensing depreciates. The age of licensed-in technology also negatively affects the positive impact of existing technological capability on innovation performance, indicating that older technology is less valuable for implementing a catching-up strategy. By considering the factor of age of licensed-in technology, this study reconciles the contradictory research findings about the impact of prior licensing experience and determines there is an inverted U relationship between the number of licenses and the subsequent innovation performance. Thus, latecomers should strive to achieve an optimal rate of ITL. More importantly, this relationship is positively moderated by a licensee's existing technological capability. That is, without complementary technological capability, excessive licensing impedes a licensee's learning. Our findings on the moderating effect of absorptive capacity (H3 and H4) highlight the need for firms to maintain a dynamic balance between internal R&D capability development and external technological leverage through ITL in their technological catching-up process, and the need to avoid becoming overly dependent on external technology. The above empirical results support the resource-based approach for determining what technology latecomers should license in, and help explain why some latecomers' innovation performance outshines others. This study provides important empirical support for the recent trend of inward licensing as a strategy for latecomers to achieve technological catching-up.

Based on the above findings, the age of licensed-in technology is predicted as a hidden factor that influences the effectiveness of learning by licensing. Due to the concern over the mixed results of the linear relationship between licensing-in experience (number of licenses in this study) and subsequent innovation performance (Álvarez, Crespi, and Ramos 2002; Ahuja and Katila 2001; Johnson 2002; Tsai and Wang 2009), this study further tests the moderating effect of the age of licensed-in technology on the above linear relationship. The analysis is conducted in line with the same set of variables in Table 2, and the results are shown in Table 3. Model 1 contains the same control variable as Table 2. The results from Model 2 are consistent with the existing finding of the insignificant linear effect of licensing-in experience (number of licenses in this study) on the subsequent innovation performance (Tsai and Wang 2009). Model 3 adds the variable – age of licensed-in technology. Like the results from Table 2, Model 3 shows the same negative relationship between the age of licensed-in technology and the subsequent innovation performance. Ultimately, Model 4 employs all the variables and tests the interaction effect of the number of licenses and the age of licensed-in technology. The results from Model 4

Table 3. Negative binomial regression (dependent variable = innovation performance).

Variables	Model 1	Model 2	Model 3	Model 4
Age of internal technology	2.712*	2.386	2.434**	3.257**
	(1.599)	(1.536)	(1.203)	(1.555)
Age of internal technology ^2	−.387*	−.359*	−.428**	−.551**
	(.225)	(.214)	(.182)	(.227)
Diversity age of internal technology	−.613	−.169	.444	.161
	(1.960)	(1.933)	(1.722)	(2.140)
Firm age	.122	.1082	.108	.109
	(.0925)	(.0898)	(.0772)	(.078)
Firm size dummy	2.160*	2.214*	1.987**	1.918**
	(1.139)	(1.133)	(.891)	(.841)
Regional dummy	3.653*	3.441*	4.282**	4.319**
	(2.030)	(2.064)	(1.801)	(1.790)
Licensor dummy	−.497	−.745	.270	.518
	(1.169)	(1.159)	(.870)	(.887)
Year dummy 123	−1.943	−2.060	−2.278**	−2.139*
	(1.290)	(1.273)	(1.118)	(1.171)
Year dummy 4	−.814	−.765	−1.905**	−1.864**
	(1.093)	(1.082)	(.910)	(.909)
Year dummy 5	−.904	−1.012	−2.316***	−2.556**
	(1.000)	(.995)	(.777)	(.783)
Year dummy 6	.124	−.0543	−.735	−.724
	(.918)	(.951)	(.749)	(.730)
Year dummy 7	.388	.720	.647	.138
	(1.396)	(1.443)	(1.004)	(.990)
Constants	−3.152	−2.514	1.685	2.720
	(2.984)	(2.971)	(2.539)	(2.768)
Number of licenses		−.0125)	−.0013	−.0802*
		(.0134	(.0065)	(.0433)
Age of licensed-in technology			−.621***	−.811***
			(.134)	(.176)
Number of licenses * age of licensed-in technology				.0081*
				(.0045)
Pseudo R^2	0.0627	0.0648	0.0880	0.0925
Log likelihood	−336.076	−335.322	−326.997	−325.360

Note: Standard errors in bracket.
***$p < 0.01$.
**$p < 0.05$.
*$p < 0.1$ (2-tailed) $N = 151$.

reveal that the age of licensed-in technology positively moderates the relationship between the number of licenses and the subsequent innovation performance with a p-value of 0.071. The linear relationship between the number of licenses and the subsequent innovation performance turns out to be significantly negative ($p < 0.1$), while the negative relationship between the age of licensed-in technology and the subsequent innovation performance remains the same ($p < 0.01$).

The finding of the significant moderation effect further supports the predication that the age of licensed-in technology is an important hidden factor that affects the effectiveness of licensing-in experience at promoting innovation. It is found that latecomers can import a large number of older technologies and internalize them to generate innovation. This finding can be explained by two underlying reasons. First, licensing is an important tool used by latecomers to break an industry's entry barriers. The fundamental technologies that emerge together with an industry's development are often old and thus the patents are available in the market. These patents are generally filed by the pioneers in the industry who often set the dominant designs or industry standards. For newcomers to the industry, it is impossible to circumvent the technical barriers to trade their products without licensing the fundamental technologies. For example, the two Chinese latecomers in telecommunications industry who have become the industry leaders, i.e. Huawei and ZTE, are in the list of licensees in the data-set. The patents that Huawei and ZTE licensed are mainly fundamental ones from the firm that set the industry standards – Quantum Telecom.

The second reason explaining why latecomers can make use of imported old technologies to generate innovation relates to the business model which is about how to make use of the technology. The old licensed-in technology itself may not contribute much to the upcoming innovation by latecomers; however, the business model which uses the old technology for the development of good-enough products to meet the needs of a low-end or new group of customers is favorable. It is reasonable that latecomers choose not to compete directly with incumbents for technology leadership, but to enter the market first and gradually accumulate the technological capability. In this way, how advanced or new of a technology maybe does not matter much for latecomers trying to innovate quickly, because the specific innovation trajectory may enable the imported old technologies to become visible in the market and favored by a certain group of the customers.

The results of this study reveal latecomer strategies for successful learning by licensing and have important managerial implications. It discloses that latecomers' ITL strategy is not only about how much learning can be achieved from licensing, but also about identifying the right technology resources to learn. The direct implication is that ITL enables latecomers to enlarge their knowledge pool in a short period of time, although extra time and resources are required to fully absorb licensed-in technologies. Licensed-in technologies can serve as seeds that spur internal R&D development, but resource allocation to internal R&D development is critical in the long run. In the case where competitors are not willing to license out some of their core technologies, latecomers must accumulate technological capability to compensate for the shortage of technology available in the market. Thus, latecomers need to optimize their resource allocation between ITL and internal R&D development.

The other important implication of this study is for the long-term planning of technological capability development. Latecomers may not be fully motivated to purchase patents to compensate for their technology shortfalls, but building them into their patent portfolios is the best approach for promoting their technological capability development. In high-tech fields, licensing as a fast track to transfer technology may spur a firm's technological learning and innovation for competency building. Furthermore, learning from the latest technology rather than older technology has prominent advantages, especially for latecomers who have been accumulating absorptive capacity. Instead of passive licensing to fill technology gaps, updating their technology portfolios by strategically importing the right technology is a wiser way for latecomers to grow steadily and achieve technological catching-up.

Finally, we would like to acknowledge several caveats in this study. First, due to limitations of the data sources, a cross-sectional data-set rather than panel data was used to conduct the empirical testing. Although we added in the year dummy as a control variable, this may have captured the limited differences between years when analyzing the firm level data, rather than the firm year panel. Second, besides the quantitative aspect, it would be interesting to test the qualitative aspect of the licensed-in technologies. However, the widely used measurement of weighted citation cannot be tested based on the SIPO database as there is citation data missing from 2004 to 2007 in the database. The missing citation data in SIPO precluded us from examining the more quality aspects such as the value of technologies in this study. Due to the above concerns, more research along these lines is warranted.

Notes

1. Latecomer firms, as defined by Matthew (2002), are those firms who enter late in the industry by historical necessity not by their own choice. Typically, the high-tech firms from emerging economies are often treated as latecomers relative to that from developed economies, which share the following common characteristics: (1) late entrants in an industry; (2) initial resource poor; (3) strategic focus of catch up; and (4) some competitive advantages by leveraging the position in the industry of choice (Mathews 2002; Mathews and Cho 1999). In this study, the latecomers are Chinese firms operating in high-tech industries that are catching up with existing incumbents from developed economies.
2. The concept of organizational learning theory is initiated by Cangelosi and Dill (1965) and origins from behavior and psychology theory (Cyert and March 1963; Weick 1979). The organizational learning theory studies models and theories about the way an organization learns and adapts. There are two levels of analysis of organizational learning theory, namely individual level and organizational level. In this study, we mainly focus on the organizational level. An organization is seen as an adaptive system that has the ability to sense the changes from its environment (both internal and external) and adapt accordingly in the organizational learning theory. The effectiveness of organizational learning is found strongly associated with absorptive capacity (Cohen and Levinthal 1990), which is the part we mainly adopted from organizational learning theory. The absorptive capacity of an organization is treated as a trade-off between the efficiency of internal communication and the ability to explore and exploit information from other organizations or the environment (Cohen and Levinthal 1990).
3. The widely adopted definition of high-tech industries was established by the Organization for Economic Co-operation and Development (OECD) in 1986. The high-tech industries were identified based upon their high R&D intensities (R&D spending as a percentage of production) relative to other manufacturing industries. Based on the OECD classification (Hatzichronoglou 1997), the high-tech industries are cataloged by Chinese government into five sectors, namely pharmaceuticals, aircraft and spacecraft, electronic and telecommunications, computers and office machinery, and medical equipment and meters. Among the five sectors, electronic and telecommunications has been the most developed sector and has performed the most innovation related activities in China. According to China Statistics Yearbook (2011), the sector of electronic and telecommunications had the best output value, the highest expenditure of new product development and the most patenting activities in the past decade. Thus, this study focuses on this high-tech sector.
4. We calculate the Lagrange Multiplier (LM) test for overdispersion in this study. The LM test is used in the Poisson model versus the negative binomial model (Cameron and Trivedi 1998; Johansson 1995). The results indicate that the effects of overdispersion are statistically significant, which is against the Poisson assumption of the equality of the mean and variance. Thus, the negative binomial model that can accommodate overdispersion is more appropriate than the Poisson model.
5. For example, Shenzhen Shanling Electronics Ltd, one of our sample firms, had 726 licensing-in deals registered in 2005; Dongwan DaXin Science and Technology Ltd had 542 licensing-in deals only in the year of 2005; and Shenzhen Huajia Digital Ltd had 368 licensing-in deals recorded in 2005.
6. Based on the coefficients of the negative binomial regressions in Table 2, we calculate how existing technological capability changes the likelihood that a licensee will successfully generate innovation by adopting licensed-in technologies (so-called incidence-ratio −1). The surfaces in both figures – Set A and Set B –show the impact of existing technological capability on the chance that a firm will successfully adopt licensed-in technologies (under the measure of the number of licenses and age of licensed-in technology).

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