J Bus Econ (2019) 89:125–153
https://doi.org/10.1007/s11573-018-0905-9

ORIGINAL PAPER

The impact of acquisitions on Chinese acquirers' innovation performance: an empirical investigation of 1545 Chinese acquisitions

Christian Fisch[1,2] · Jörn Block[1,2] · Philipp Sandner[3]

Published online: 13 April 2018

Abstract Acquisitions by Chinese firms have increased markedly in recent years. So far, we know little about the effects of these acquisitions on the acquirer's innovation performance. Our paper focuses on two interrelated research questions. First, to what extent can Chinese firms increase their patent output following an acquisition? Second, which factors influence the post-acquisition patent output? Using a comprehensive dataset of 697 publicly listed Chinese firms in the manufacturing sector that conducted 1545 acquisitions from 2000 to 2012, we find no significant overall effect of acquisitions on patent output. However, we find that several acquisition-specific factors have a positive effect on the post-acquisition patent output (e.g., size of the acquired knowledge base, relatedness of the acquired knowledge base, cross-border acquisitions). Our study extends prior research on post-acquisition innovation performance to the context of Chinese acquirers.

Keywords Acquisitions · China · Patents · Innovation · Absorptive capacity · State-owned enterprises · Catch-up

✉ Christian Fisch
cfisch@uni-trier.de

Jörn Block
block@uni-trier.de

Philipp Sandner
p.sandner@fs.de

1 Faculty of Management, Trier University, 54296 Trier, Germany

2 Erasmus Institute of Management (ERIM), Erasmus University Rotterdam, P.O. Box 1738, 3000 DR Rotterdam, The Netherlands

3 Frankfurt School of Finance and Management, Sonnemannstraße 9-11, 60314 Frankfurt Am Main, Germany

JEL M16 · O33 · O34 · P30

1 Introduction

Only 15 years before, Chinese applicants filed 2% of the patents they filed in 2014. While Chinese entities increased their applications 50-fold since then, applications by US applicants grew twofold and applications by Japanese applicants even decreased by 3% (WIPO 2017). The development of China in terms of innovation is particularly intriguing and recent. China now faces the follow-up challenge of transitioning from an imitation-based to an innovation-based economy in order to complete its attempt to catch up to further developed countries (Kim 1997; Hu and Mathews 2008). Past economic growth in China was largely driven by cheap labor and physical capital. These drivers, however, raise questions about the sustainability of this development and on whether a similar development is possible in terms of innovation (Wu 2001).

Chinese companies are aware of this problem. Acquisitions are one vehicle for companies to access and exploit previously unexplored knowledge (Ahuja and Katila 2001; Cloodt et al. 2006). Acquisitions by Chinese firms have surged in recent years. In 2014, Chinese companies announced 4502 acquisitions, an increase of 33% over the previous year. Access to technology is cited as an important reason for Chinese acquisitions (e.g., Deng 2004; Morck et al. 2008; Buckley et al. 2014) and is frequently portrayed in the media. Chinese acquisitions, particularly those where the target is located in a developed country, are often associated with the fear of knowledge drains and a potential negative effect for the acquired companies.

So far, however, we know little about the effects of acquisitions on the Chinese acquirer's innovation performance. Although prior research has investigated these effects in developed countries, it is unclear whether the results obtained in a Western context also apply to an emerging market context such as China (Zhao et al. 2011; Ramasamy et al. 2012; Barkema et al. 2015). In this regard, prior research has questioned the ability of Chinese firms to successfully integrate the acquired knowledge because they lack absorptive capacity (Rugman and Li 2007; Anderson et al. 2015). Thus, we investigate the post-acquisition patent output of Chinese acquirers drawing on absorptive capacity theory. In spite of some caveats, patents are one of, if not *the* most frequently utilized proxy to measure innovation in innovation research.

We study two interrelated research questions. First, to what extent can Chinese firms increase their patent output following an acquisition? Second, which acquisition-specific factors influence the post-acquisition patent output? Our study uses a comprehensive dataset of 1545 acquisitions by publicly listed Chinese manufacturing firms from 2000 to 2012. Overall, we find no significant effect of acquisitions on patent output of Chinese acquirers. Assessing deal-specific variables, we find that a larger absolute size of the acquired knowledge base, technological relatedness, and cross-border acquisitions have a positive effect on post-acquisition patent output. In contrast, a larger relative size of the acquired knowledge has a negative effect. Prior acquisition experience and ownership status (state-owned versus private companies) have no effect on the post-acquisition patent output.

The contribution of our study is twofold. First, we extend the literature on the effects of acquisitions on post-acquisition innovation performance (e.g., Ahuja and Katila 2001; Cloodt et al. 2006; Desyllas and Hughes 2010). In particular, our study builds on prior work by Ahuja and Katila (2001) and Cloodt et al. (2006) and can be seen as an extended replication study of these studies. Replication studies have recently received renewed interest in management research and are crucial for establishing reliable results (Ethiraj et al. 2016). Prior research on post-acquisition innovation performance draws on absorptive capacity and organizational learning frameworks to explain increases in patent output, with scholars frequently stressing the need to better understand the contextual dimension surrounding the phenomenon (Muehlfeld et al. 2012; Argote 2013). We contribute to this line of research by introducing the unique context of Chinese acquirers. Previous research has relied on samples and firms from developed countries, and it is unclear whether the post-acquisition effects for Chinese acquirers are similar. Additionally, the applicability of theoretical frameworks developed in a Western context (i.e., absorptive capacity) to an emerging market context is unclear and has previously been questioned (e.g., Murray et al. 2005; Zhao et al. 2011; Barkema et al. 2015). We show that certain previous findings apply to the Chinese context, while others do not. Second, we add to the increasing and current literature on innovation in China. Previous studies have empirically analyzed the explosive increase in patenting by Chinese entities and its antecedents (e.g., Hu and Mathews 2008; Li 2012; Boeing et al. 2016). Although there are studies that analyze Chinese acquisitions with regard to financial performance (Deng 2009; Zhao et al. 2011; Buckley et al. 2014), an in-depth empirical investigation of the effects on innovation output and its antecedents is still lacking. This is particularly intriguing because access to technological know-how is one of the main reasons for Chinese acquisitions (e.g., Deng 2004; Morck et al. 2008; Anderson et al. 2015). Our study is also relevant from a practical standpoint. Managers from acquiring firms in emerging markets might find our results interesting because they inform them about important deal characteristics that facilitate learning from acquisitions. Policymakers in China and Western countries might find our results interesting and relevant because they indicate that acquisitions can be a profitable catch-up strategy with regard to innovation performance.

The remainder of this study is structured as follows: Sect. 2 describes the theoretical framework and derives hypotheses about the effect of acquisitions on the acquirer's innovation performance. Section 3 describes the dataset and variables. Section 4 presents the results of our descriptive and multivariate analyses, while Sect. 5 discusses the findings and concludes.

2 Theory and hypotheses

2.1 Theoretical framework

Absorptive capacity is the theoretical framework of choice in most studies analyzing the acquirer's post-acquisition innovation performance (e.g., Ahuja and Katila 2001; Cloodt et al. 2006; Kotabe et al. 2011). Absorptive capacity describes a company's ability to value, assimilate, and apply new knowledge to commercial ends. A higher absorptive capacity thus enables a company to better understand and subsequently capture the value of external information (Cohen and Levinthal 1990) leading to a higher innovation output. Sun and Anderson (2010) describe absorptive capacity as an example of organizational learning that concerns how an organization integrates and makes use of new external knowledge.

Within the absorptive capacity literature, research on knowledge transfer between organizations has gained substantial momentum in recent years (e.g., Hitt et al. 2000; Argote 2013). This research stream analyzes whether an organization can benefit from the experience of other organizations in order to realize productivity gains and increase its innovation output. Investigated determinants and drivers that facilitate knowledge transfer between organizations include characteristics of the acquired knowledge base, cultural proximity, or previous acquisition experience (e.g., Ahuja and Katila 2001; Muehlfeld et al. 2012).

Our study builds on absorptive capacity theory. We use the theory to describe under which circumstances we expect acquisitions to have an effect on the acquirer's post acquisition innovation performance. Specifically, we assume that acquisitions have an impact on the acquirer's absorptive capacity (a stock variable), which in turn determines whether the acquirer can realize gains in post-acquisition patent output (a flow variable).

Previous research indicates that the effect of acquisitions on the acquirer's subsequent innovation performance fundamentally depends on multiple characteristics of the acquisitions (e.g., Ahuja and Katila 2001; Cloodt et al. 2006). Our study can be considered as an extended replication study in this context. Table 6 (Appendix) provides a comparison between the works of Ahuja and Katila (2001), Cloodt et al. (2006) (which is an extended replication study of Ahuja and Katila (2001)), and this study. While the concepts and variables used in our study closely relate to those used in previous studies, we extend previous findings to the context of China, where their applicability is unclear. In particular, while H1 as our baseline hypothesis assumes an overall positive effect of acquisitions on innovation performance in the catch-up process of Chinese acquirers, we also explore several deal- and company-specific characteristics that shape this outcome. Specifically, we assume that the effect of an acquisition on the acquirer's post-acquisition patent output depends on the size of the acquired knowledge base, the relatedness of the acquired knowledge base, and on several firm characteristics of the acquirer.

2.2 Hypotheses

2.2.1 Overall effect of acquisitions on Chinese acquirers' post-acquisition patent output

Acquisitions constitute a very prominent way for firms to access external knowledge (Ahuja and Katila 2001). Generally, firms try to increase their absorptive capacity and subsequent innovation performance by acquiring and utilizing the experiences of others (Cloodt et al. 2006). Specifically, it is assumed that firms can enhance their absorptive capacity by acquiring other firms and their knowledge bases (Ahuja and Katila 2001; Anderson et al. 2015). The acquisition of new knowledge bases can lead to potential economies of scale and scope, which may benefit an acquirer's capacity to produce (valuable) innovation output (Henderson and Cockburn 1996; Ahuja and Katila 2001).

The external acquisition of knowledge through acquisitions is particularly attractive for companies with limited capabilities that are looking to expand their absorptive capacity and knowledge base quickly (Hitt et al. 2000; Zhao et al. 2011). China is a prominent example of a transition economy that still suffers from the rigidities of a planned, closed market economy in which innovation was often neglected and is trying to extend its innovation-related capabilities quickly (Peng 2003; Zhao et al. 2011).

Our baseline hypothesis is that acquisitions help Chinese firms to increase their absorptive capacity and shall have a positive effect on the innovation output. The following hypothesis applies:

H1 Chinese acquirer's patent output will increase following an acquisition.

2.2.2 Size of the acquired knowledge base

Characteristics of the information being transferred are likely to affect the acquirer's post-acquisition patent output. In particular, the absolute and relative size of the acquired knowledge base have been shown to influence the post-acquisition innovation performance (e.g., Lubatkin 1983; Ahuja and Katila 2001).

Absolute size of the acquired knowledge base Firms can enhance their absorptive capacity by acquiring knowledge bases, hence enabling initially limited Chinese firms to increase their innovation outputs. This effect is assumed to be larger with a large size of the acquired knowledge base. This is because the integration of a knowledge base leads to potential economies of scale and scope (Henderson and Cockburn 1996; Ahuja and Katila 2001). Following Schumpeterian logic, innovations are often a result of the recombination of existing elements of knowledge (Ahuja and Katila 2001; Cloodt et al. 2006). Thus, the number of potential recombinations increases with an increasing knowledge base. If an acquired company has a very small or non-existent knowledge base, this suggests that access to technology was not a major motive for the acquisition and should thus not positively influence post-acquisition patent output (Ahuja and Katila 2001).

Previous research has assumed the post-acquisition innovation performance to increase linearly with the acquisition of knowledge bases with a larger absolute size (e.g., Ahuja and Katila 2001; Cloodt et al. 2006). However, the degree to which a company can integrate acquired knowledge and thereby increase its absorptive capacity and benefit from it is likely to suffer from diminishing returns. This is because the integration of very large knowledge bases demands considerable efforts and resources on the part of an acquirer. Indeed, previous research has indicated an inverted U-shaped relationship between increases in absorptive capacity and resulting innovation performance (Stock et al. 2001; Nooteboom et al. 2007). Therefore, we expect the relation between the absolute size of the acquired knowledge base and innovation output to be non-linear and follow a curvilinear form, in that it will be positive but with diminishing returns:

H2a The absolute size of the acquired knowledge base will be positively related to a Chinese acquirer's post-acquisition patent output, but with diminishing returns.

Relative size of the acquired knowledge base Before recombination benefits can be achieved, the acquired information and knowledge needs to be processed by the acquiring company. This process, however, depends crucially on the acquirer's own knowledge base. A large *relative size of the acquired knowledge base* indicates that the firm acquires more patents in the acquisition than it currently has. This is the case, for example, when a company that owns ten patents acquires a company that has 1000 patents.

If the acquirer has little or no own knowledge, the acquisition of external knowledge and the integration of this knowledge into the acquirer's organization and process will be complex and (in the short run) not necessarily lead to increases in innovation output. Thus, it is not only the absolute size of the acquired knowledge base that matters but also its *relative size* compared to the acquirer's existing knowledge base. If the relative size of the acquired knowledge base is too large, the acquiring firm will have to devote a comparatively large amount of resources to integrate the acquired knowledge base, leading to fewer resources being available to perform actual innovation activities. Additionally, disruption of existing routines is likely because the acquiring company is faced with a comparatively large amount of new information and routines, which require substantial adaption on the part of the acquiring firm (Ahuja and Katila 2001; Cloodt et al. 2006). We thus hypothesize the following negative effect:

H2b The relative size of the acquired knowledge base will be negatively related to a Chinese acquirer's post-acquisition patent output.

2.2.3 Relatedness of the acquired knowledge base

In addition to the size of the acquired knowledge base, previous research underlines that the relatedness of the acquired knowledge base is crucial for the post-acquisition innovation performance (Ahuja and Katila 2001; Cloodt et al. 2006; Muehlfeld et al. 2012). Knowledge bases can be related in multiple ways. To grasp this diversity, we measure the technological relatedness of the acquired knowledge base, whether the acquired firm operated in a similar or unfamiliar industry to the acquirer, and whether the acquisition was a cross-border acquisition or a domestic acquisition. We expect technological and industry relatedness to have a positive effect on innovation output. Also, we expect cross-border acquisitions to have a positive effect because they enable Chinese acquirers to access knowledge that is often further advanced.

Technological relatedness of the acquired knowledge base The relatedness of the acquired knowledge base reflects the content of the acquired knowledge. Based on absorptive capacity theory, we shall argue that related knowledge enables Chinese firms to more easily apply new information to new environments, thus facilitating integration of the acquired knowledge base (Cohen and Levinthal 1990; Makri et al. 2010). With regard to innovation, relatedness leads to common skills and a shared technical language. In contrast, innovation routines tend to be different if they originate from unrelated technological fields, thus rendering the integration of the knowledge bases more difficult and resource consuming (Cohen and Levinthal 1989; Cloodt et al. 2006). However, unrelated knowledge can benefit the organization by providing new approaches to solve old problems or by allowing it to better process external information.

Because both arguments are valid, previous research has shown that the combination of knowledge bases with a moderate degree of relatedness provides benefits of increasing variety, while still providing enough common ground to build upon (Ahuja and Katila 2001; Cloodt et al. 2006). For example, Ahuja and Katila (2001) find evidence for a non-monotonic and U-shaped relationship. The authors argue that performance will increase with increasing relatedness, but will decrease beyond a certain point. This effect has been confirmed by Cloodt et al. (2006). Applying a more fine-grained approach to measuring technological relatedness and complementarity, Makri et al. (2010) show that technological complementarity is an important factor in stimulating innovation output, while they also find knowledge similarities to have no effect on innovation quantity or quality. The authors argue that while integration is facilitated, these similarities are not enough to spark innovation performance. Similar results are obtained by Cassiman et al. (2008). Thus, we expect a non-linear relationship that is positive, but with diminishing returns:

H3a Technological relatedness will be positively related to a Chinese acquirer's post-acquisition patent output, but with diminishing returns.

Acquisition in a similar industry The industrial context is an important factor that may influence an acquisition's outcome. Barkema and Vermeulen (1998) argue that a firm operating in multiple industries might profit from the increased diversity in terms of knowledge. For example, the firm will be able to gain more experience because it has to deal with a more diverse set of demands, rivals, and partners than a firm only operating in one industry. Also, a firm that is active in multiple industries may be able to realize economies of scale and scope and may thus profit more from its innovations.

However, most prior studies show that firms pursuing related, intra-industry acquisitions outperform unrelated, inter-industry acquisitions (e.g., Muehlfeld et al. 2012; Haleblian and Finkelstein 1999). This is because of larger synergies: Firms can more likely build on existing practices and routines if the new industrial environment is similar to the environment in which prior knowledge was obtained and developed. In contrast, a transfer of routines may be impossible if knowledge is predominantly novel and characterized by different dominant logics which have to be learned. Companies can thus generalize their experience more easily if there is a greater similarity (Cohen and Bacdayan 1994; Barkema and Vermeulen 1998; Finkelstein and Haleblian 2002; Desyllas and Hughes 2010). Conceptually, the argumentation follows Huff (1982), who argues that “shared concepts”, for example on how a firm successfully operates, are developed within an industry and are not accessible for outsiders. Empirical evidence on how the industrial context guides strategic thinking was initially put forward by Spender (1987). Also, Barkema and Vermeulen (1998) describe that high levels of diversification force a firm to adapt a more fragmented organizational structure that will prevent learning when knowledge is acquired.

With particular regard to the post-acquisition innovation performance, previous research indicates that R&D synergies are harder when two firms operate in different industries and that more diversified firms tend to be less innovative (Hoskisson and Hitt 1988; Ahuja and Katila 2001; Hagedoorn and Duysters 2002). We thus presume that Chinese acquirers tend to benefit more from related acquisitions in which the acquirer operates in a similar industry:

H3b An acquisition in a related versus unrelated industry will be positively related to a Chinese acquirer’s post-acquisition patent output.

Cross-border acquisition The geographic context is an important factor shaping acquisition outcomes. Previous studies have often highlighted that cross-border acquisitions pose several obstacles to the acquiring firm that hinder post-acquisition performance. In contrast to domestic acquisitions, cross-border acquisitions often involve different legal systems, different national cultures, and higher transportation costs which can be major obstacles to achieving integration benefits (Olie 1994; Vaara 2003; Björkman et al. 2007; Dikova et al. 2010). Also, differences in languages are a common source of friction (e.g., Muehlfeld et al. 2012). Cultural similarity, which is assumed to be greater in domestic than cross-border acquisitions, eliminates a common source of friction by facilitating negotiations (Adair and Brett 2005) and the integration of the acquired company (Björkman et al. 2007). Another factor is the regulatory framework (Clougherty 2005), which is also more similar in a domestic acquisition, thus reducing the complexity of an acquisition. All these factors limit the transfer of knowledge in an acquisition. We could therefore assume a domestic acquisition will be more beneficial than a cross-border acquisition because of a greater relatedness.

However, cross-border acquisitions provide opportunities. With particular regard to innovation performance, Barkema and Vermeulen (1998) argue that an exposure to geographical diversity may lead to higher innovation levels because it exposes a firm to different environments, enabling it to profit from different experiences by getting access to new sources of knowledge. This information leads to a richer knowledge structure and stronger technological capabilities (Ghoshal 1987; Barkema and Vermeulen 1998). A similar argument is put forward by Ahuja and Katila (2004), who find that firms expanding beyond national markets develop unique innovation search paths as a response to the changing environment. While a performance enhancing effect of domestic acquisitions is shown in some studies (e.g., Muehlfeld et al. 2012), other studies find negative or no effects (e.g., Ahuja and Katila 2001; Desyllas and Hughes 2010), prompting Björkman et al. (2007) to describe the empirical evidence as inconclusive.

Companies from emerging markets such as China frequently lag behind companies from developed countries in terms of strong intangible resources (e.g., technological know-how). Thus, Chinese firms might particularly benefit from cross-border acquisitions instead of domestic acquisitions to address this comparative disadvantage and access further developed knowledge. This access to knowledge from developed countries has frequently been described as one of the more important motivations for Chinese acquisitions (e.g., Deng 2004; Morck et al. 2008; Buckley et al. 2014). Therefore, we suggest that cross-border acquisitions positively influence a Chinese acquirer's patent output.

H3c A cross-border versus a domestic acquisition will be positively related to a Chinese acquirer's post-acquisition patent output.

2.2.4 Characteristics of the acquirer

Finally, previous research has shown that several characteristics of the acquirer influence the acquirer's post-acquisition innovation performance (Haleblian and Finkelstein 1999; Ahuja and Katila 2001; Muehlfeld et al. 2012). Here, we focus on the acquirer's previous acquisition experience as well as a characteristic that is unique to the Chinese context, namely whether the acquiring company is state-owned or not.

Previous acquisition experience Previous acquisition experience should positively influence the outcome of an acquisition (Lubatkin 1983; Haleblian and Finkelstein 1999). This is because it is often assumed that an organization's acquisitions are similar to each other. Therefore, past acquisition experience can be applied to following acquisitions. The rationale behind this widespread assumption is based on the learning curve, which rests on the assumption of positive effects by learning through repetition. In this regard, positive returns through the accumulation experience are a robust finding in organizational learning research (Muehlfeld et al. 2012).

Following this argumentation, it is likely that previous acquisitions will also facilitate the integration of acquired knowledge. Even though the effects of previous acquisition experience have been studied extensively in acquisition studies it is surprisingly rarely investigated regarding its effect on innovation performance. Following the learning arguments posited above, we assume a positive influence of previous acquisitions on the acquirer's post-acquisition performance. We hypothesize:

H4a Previous acquisition experience will be positively related to a Chinese acquirer's post-acquisition patent output.

State-owned vs. private acquirers In transition economies, the institutional environment is often characterized by strong governmental interference. This is particularly true for China, where governmental constraints and incentives influence M&A decisions in a major way (Deng 2009). Often, corporate strategic decisions are influenced by political motives (Tsui et al. 2004). For example, the Chinese government has been stimulating Chinese companies to become competitive MNCs by formulating a series of policies for the acquisition of foreign knowledge (e.g., value-added taxes, favorable financing) (Deng 2004, 2009). By this, various firms have become international players through aggressive international expansion. While this referred to strong manufacturing firms in the past, China now specifically encourages investment in R&D to enhance innovation capability and by focusing more on acquisition of intangible assets such as technology and managerial capabilities from global giants (Deng 2009).

The Chinese corporate landscape is very different from Western countries because the Chinese economy has been dominated by state-owned enterprises (Wang et al. 2007; Boeing et al. 2016). In contrast to other former socialist countries, China never underwent a mass privatization. Thus, the share of enterprises directly or indirectly owned by the state is still large (albeit decreasing) (Wang et al. 2007; Boeing et al. 2016).

The boundaries separating these companies from the state are often blurred (Tsui et al. 2004). Chinese state-owned enterprises are typically large, resourceful, and heavily subsidized corporations. Previous research has characterized them as lacking dynamism, passive, less learning-, and not performance-oriented (White 2000; Peng 2003; Wang et al. 2007; Boeing et al. 2016). Traditionally, state-owned enterprises relied on innovations that were administratively directed to them (White 2000). Overall, these attributes indicate lower levels of absorptive capacity and lesser capabilities to incorporate knowledge, compared to private firms. State ownership should thus lead to a negative effect on the acquirers' patent output. In contrast, a private organization should possess a larger absorptive capacity and should be able to profit from acquisitions to a larger extent.

H4b Compared to private acquirers, state-owned acquirers will profit less from acquisitions with regard to their post-acquisition patent output.

3 Data and variables

3.1 Data

Studies on post-acquisition innovation performance often impose a range of restrictions on the sample, for example, with regard to industry, company size, deal value, or shares acquired (e.g., Makri et al. 2010; Desyllas and Hughes 2010). Because the Chinese context remains unexplored so far, we keep our sample as unrestricted as possible and merge three databases: Compustat (company data), SDC Platinum (acquisition data), and PATSTAT (patent data). Our final sample includes 697 acquiring companies that conducted 1545 acquisitions and filed patents from 2000 to 2013.[1]

[1] Several companies conducted more than one acquisition during the sampling period.

Company data Initially, we draw a sample of potential acquiring firms from Compustat international. Compustat includes all listed Chinese firms, is one of the most comprehensive databases on firm data, and has been used frequently used in related studies (e.g., Ahuja and Katila 2001; Cloodt et al. 2006; Laamanen and Keil 2008; Sears and Hoetker 2014). Using Compustat effectively excludes smaller firms, which is however consistent with previous acquisition research focusing on large and publicly listed firms (Ahuja and Katila 2001; Desyllas and Hughes 2010; Makri et al. 2010). Consistent with previous research, we focus on manufacturing firms (SIC codes 20–39) (e.g., Puranam et al. 2006; Sears and Hoetker 2014), which are also more prone towards formal IP protection and particularly patents (e.g., Block et al. 2015). Due to data unavailability prior to 2000, we draw all data available for the period from 01.01.2000 until 31.12.2012. In total, this leads to an unbalanced panel of 1726 companies with 13,858 company/year observations. This sample includes both acquiring and non-acquiring firms.

Acquisition data Data on the acquisition activity of the sampled firms are obtained from SDC Platinum. SDC Platinum is one of the most comprehensive databases on acquisitions and has been frequently used in previous studies (e.g., Makri et al. 2010; Valentini 2012; Sears and Hoetker 2014). We draw a sample of all completed deals between January 1, 2000 and December 31, 2012 in which the acquirer is a Chinese company. Next, we match the data obtained from SDC and Compustat semi-manually based on the SEDOL number. Entries that could not be matched based on the SEDOL number were matched manually after conducting an in-depth search on the respective company homepage. In total, 1545 acquisitions could be matched to 697 companies.

Patent data Patent data is obtained from PATSTAT, one of the most comprehensive databases on patents to date that is provided by the EPO. PATSTAT comprises data from over 100 countries and contains more than 110 million patent documents. Furthermore, PATSTAT has been described as the most comprehensive database for Chinese patents (Liegsalz and Wagner 2013). We use the version of March 2015. Because not all patents are immediately registered in PATSTAT, we only include patents applied for before 31.12.2013 (because we use a lag of one year, we can only include company and acquisition data until 31.12.2012). We identify patent documents in which one of the acquired or acquiring companies is listed as applicant or assignee. A particular problem of identifying Chinese patents refers to the often flawed and inconsistent depiction of the names of the applicants and their translation from Chinese to English. Therefore, we generated search patterns that included variant spellings, abbreviations, and applicant names. The search patterns were refined in several iterations to improve the identification and matching of relevant patents. More specifically and in contrast to previous studies, we use the measure of patent families to avoid an overrepresentation of patents filed at multiple patent offices (Li 2012). We use the earliest application within each patent family to determine the date of the patent, as it is closest to the date of the actual innovation.

3.2 Variables

Dependent variable Our dependent variable is the number of new patent applications per year, which measures a firm's *patent output*. Patents are frequently used to measure innovation output and are the most commonly used indicator to analyze post-acquisition innovation performance (e.g., Ahuja and Katila 2001; Valentini 2012). This is because patents are related to inventiveness, are an externally validated measure of technological novelty, and are of economic significance (Ahuja and Katila 2001).[2]

Independent variables To measure the overall effect of an acquisition on post-acquisition patent output (H1), we include a dummy variable (*deal dummy*) that captures whether a company conducted an acquisition in the respective year (=1) or not (=0).

To analyze H2a, we measure the *absolute size of the acquired knowledge base* by aggregating the patents of the acquired firm in the five years preceding its acquisition. For H2b, the *relative size of the acquired knowledge base* is calculated by dividing the absolute size of the acquired knowledge base by the knowledge base of the acquiring firm. This variable takes a value of zero if the acquiring firm did not file any patents.

We measure the *technological relatedness of the acquired knowledge base* (H3a) by the difference between the proportion of patents filed in each IPC class between the acquiring and acquired firms patent portfolio in a given year. A large value indicates a low relatedness. To measure technological equality, we further include a dummy variable that takes a value of 1 if the acquired and acquiring company filed their patents in the same IPC classes, and 0 otherwise. The measurement of the variables follows the approach of Ahuja and Katila (2001) and Cloodt et al. (2006). The data is obtained from PATSTAT. To account for an acquisition of a company in a similar industry, we construct a dummy variable that takes a value of 1 if the acquired company operates in the *same superordinate industrial category* (2-digit SIC code), and 0 otherwise (H3b). To analyze H3c, we include a variable that captures whether the deal is a cross-border (=1) or domestic (=0) acquisition.

To assess H4a, we measure the acquirer's *previous acquisition experience* by including the number of acquisitions conducted previous to the respective deal. Finally, we include a dummy variable that measures whether the acquiring company is *state-owned* (H4b) or not. Because there is no consensual approach about how to measure state ownership in the literature, we used information available in CSMAR. To validate these data, we manually searched two online databases that included information on state ownership (sina.com and cmbchina.com). If all three sources stated that the company is state-owned, this variable takes a value of 1, and 0 otherwise.

[2] Most prior studies utilize the number of successful patent applications (patents granted) as a dependent variable. Due to data limitations, we used the number of all patent applications (see Sect. 5).

Control variables We control for several variables that might influence patent output. We approximate a company's age by including the *time since its IPO*. Also, we control for a company's size by including its *total revenue (log.)*. Larger firms tend to be able to produce higher innovation outputs. More profitable firms should be able to devote more resources to innovation, which we want to control for by including the company's *return on assets*. To rule out the possibility our post-acquisition results are solely driven by a higher pre-acquisition innovativeness, we control for a firm's innovativeness by including its patenting intensity in logged form. *Patenting intensity* is constructed by dividing a firm's patents by its total assets per year and is a suitable replacement for the usually used R&D intensity, which was not available in Compustat (e.g., Sandner and Block 2011). Also, we include the volume of *shares* acquired in the deal. Comparatively large acquisitions should facilitate knowledge transfer. To account for inter-industry differences, we include *industry dummies* (2-SIC). To account for time differences, we include *year dummies*. Also, there are large regional differences across China (e.g., Fisch et al. 2016; Li 2012). To account for these differences, we also include a set of dummy variables that capture the *province* in which the acquirer is located.

4 Results

4.1 Descriptive statistics

Table 1 provides a detailed description of our variables. Table 2 shows descriptive statistics, correlations, and variance inflation factors (VIFs). Values are reported per company per year. For example, companies filed 13.78 patents per year while the average return on assets is 5%. On average, the acquired firms applied for 9.4 patents in the five years preceding the acquisition. Interestingly, only 5% of the acquisitions were cross-border (78 of 1545), whereas 47% of the acquisitions were conducted in a similar or the same industry. Finally, 41% of the acquisitions were carried out by state-owned enterprises. Correlations and VIFs indicate that multicollinearity should not distort our results.

4.2 Multivariate statistics

Because our dependent variable *patent output* is a count variable with only non-negative integers, we use count data regressions as our main method of analysis. The results are reported in Tables 3 and 4. Following Pollock et al. (2008) and Muehlfeld et al. (2012), we account for within-firm variation by clustering standard errors at company level. This is similar to a random-effects regression and addresses a potential bias caused by multiple acquisitions by the same firm in the same year.[3] Previous

[3] In line with previous research, this enables us to include multiple acquisitions carried out by the same company in the same year. To circumvent a bias caused by the inclusion of these observations, we also control for the number of previous acquisitions of each acquirer.

Table 1 Description of variables

Variable	Description
Patent applications	Number of new patent applications per year, recorded at the patent family level
Deal dummy	Measures whether the company did an acquisition in the respective year
Time since IPO	Measures the time since the acquirer's IPO (in years)
Total revenue (log)	Logarithmized total revenue (million USD)
Return on assets	Acquirer's return on assets
Patent intensity (log)	Logarithmized patent intensity, measured by a firms' patents divided by its total assets per year over the last 3 years
Shares acquired	Volume of shares acquired in the respective deal
Absolute size of acquired knowledge base	Absolute size of acquired knowledge base, measured by aggregated patents of acquired firm in 5 years preceding its acquisition
Relative size of acquired knowledge base	Relative size of acquired knowledge base, measured by absolute size of acquired knowledge base divided by knowledge base of the acquiring firm
Technological relatedness of acquired knowledge base	Technological relatedness of acquired knowledge base, measured by difference between proportion of patents filed in each IPC class between acquiring and acquired firms patent portfolio in a given year
Acq. in similar industry	= 0, if acquired company does not operate in same superordinate industrial category, = 1, if acquired company operates in same superordinate industrial category
Cross-border acquisition	= 0, if domestic acquisition, = 1, if cross-border acquisition
Previous deals	The number of acquisitions the acquirer performed before the respective deal
Acq. by state-owned ent.	= 0, if acquiring company is not state-owned = 1, if acquiring company is state-owned.

We also include year dummies, industry dummies, and province dummies in our models. Compustat, SDC Platinum, PATSTAT (version: March 2015)

research has shown that an acquisition's impact on the acquiring firm's innovation performance is not immediate (e.g., Ahuja and Katila 2001; Cloodt et al. 2006). Thus, we include all covariates with a lag of 1 year, which is in line with previous studies (e.g., Desyllas and Hughes 2010) and enables us to keep more data points, as the most recent year would have to be excluded otherwise.

To analyze H1, which assumes a positive effect of an acquisition on the acquirer's post-acquisition patent output, we use the full sample. This includes years in which a company conducted and acquisition as well as years in which the company did not conduct an acquisition. Model 1 includes the base model. Model 2 shows that, overall, an acquisition does not have a statistically significant effect on patent output

Table 2 Descriptive statistics, correlations, and VIFs. Data sources: Compustat, SDC Platinum, PATSTAT (version: March 2015)

Variables	Mean	SD	Min.	Max.	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	VIF
(1) Patent applications	13.78	51.74	0.00	1233													1.34
Control variables (t − 1)																	
(2) Time since IPO	16.13	6.16	5.00	33.00	0.06*												1.20
(3) Total revenue (log)	7.52	1.53	0.00	12.98	0.33*	0.19*											1.57
(4) Return on assets	0.05	0.11	−0.82	1.00	−0.01	0.02	0.04										1.01
(5) Patent intensity (log)	0.73	1.55	0.00	19.11	0.23*	−0.18*	−0.10*	0.00									1.19
Deal-specific variables (t − 1)																	
(6) Shares acquired	0.59	0.34	0.00	1.00	−0.00	0.00	0.04	−0.02	−0.04								1.01
(7) Absolute size of acq. KB	9.42	111.35	0.00	3633	0.25*	0.03	0.07*	−0.02	0.05	0.04							1.14
(8) Relative size of acq. KB	0.53	2.99	0.00	53.21	−0.03	0.04	0.04	−0.01	−0.05	0.01	0.22*						1.12
(9) Technological relatedness	0.32	–	0.00	1.00	0.19*	−0.14*	0.23*	0.04	0.22*	−0.02	0.11*	0.18*					1.25
(10) Cross-border acquisition	0.05	–	0.00	1.00	0.13*	0.00	0.15*	−0.06*	−0.01	0.05*	0.01	0.04	0.014				1.04
(11) Acq. in similar industry	0.47	–	0.00	1.00	0.04	−0.07*	0.12*	0.02	0.05	0.02	0.05	0.07	0.19*	−0.02			1.06
(12) Previous acq. experience	2.33	1.93	1	16	0.20*	0.14*	0.34*	−0.01	−0.05*	0.01	0.04	−0.03	0.11*	0.03	0.03		1.17
(13) Acq. by state-owned ent.	0.41	–	0.00	1.00	0.08*	0.31*	0.39*	−0.01	−0.12*	0.033	0.03	−0.03	0.03	0.02	0.11*	0.10*	1.29

N = 1545

KB Knowledge base, *VIF* Variance inflation factors

*$p < 0.05$

Table 3 Focus on the overall deal-effect. Data sources: Compustat international, SDC Platinum, PATSTAT (version: March 2015)

Variables	Hyp.	Model 1		Model 2	
		Coeff.	(SE) p-value	Coeff.	(SE) p-value
Control variables (t – 1)					
Time since IPO		–0.032	(0.007)*** 0.000	–0.032	(0.007)*** 0.000
Total revenue (log)		0.744	(0.033)*** 0.000	0.742	(0.033)*** 0.000
Return on assets		0.536	(0.300)* 0.074	0.523	(0.300)* 0.081
Patent intensity (log)		0.738	(0.095)*** 0.000	0.739	(0.095)*** 0.000
Deal-specific variables (t – 1)					
Deal dummy	*H1 (+)*			0.060	(0.044) 0.178
Year dummies		Yes		Yes	
Industry dummies		Yes		Yes	
Province dummies		Yes		Yes	
N (Companies)		6925	(697)	6925	(697)
Pseudo R^2		0.178		0.178	
Alpha		1.607		1.607	

Results of the negative binomial regression analysis (dependent variable: patent applications per year)

Standard errors clustered at company level

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

(*deal dummy*), indicating that the increase in patent output is not significantly larger a year after an acquisition than it is in years that do not follow an acquisition. Thus, the general assumption that an acquisition always leads to knowledge gains for a Chinese acquirer cannot be supported.

The following models introduce the independent, deal-specific variables and also shift our analysis to the deal level. In contrast to Table 3, we now exclude observations in which no deal was carried out to explore the variance between the acquisitions in more detail. The results of this deal-specific analysis are displayed in Table 4. We enter the variables stepwise. The following paragraph focusses on the most robust Model 4.

With regard to H2a, we find that a higher *absolute size of the acquired knowledge* base has a highly significant and positive effect on the acquirer's post-acquisition innovation performance. We also find that this effect decreases at higher levels, as indicated by the significant squared term. We also find support for H2b:

Table 4 Focus on deal-specific variables. Results of a negative binomial regression analysis (dependent variable: patent applications per year). Data sources: Compustat international, SDC Platinum, PATSTAT (version: March 2015)

Variables	Hyp.	Model 1		Model 2		Model 3		Model 4	
		Coeff.	(SE) p-value	Coeff.	(SE) p-value	Coeff.	(SE) p-value	Coeff.	(SE) p-value
Control variables (t − 1)									
Time since IPO		−0.029	(0.009)*** 0.002	−0.029	(0.010)*** 0.003	−0.030	(0.010)*** 0.003	−0.025	(0.010)** 0.010
Total revenue (log)		0.734	(0.041)*** 0.000	0.711	(0.041)*** 0.000	0.765	(0.039)*** 0.000	0.693	(0.040)*** 0.000
Return on assets		0.471	(0.382) 0.218	0.480	(0.404) 0.234	0.455	(0.390) 0.243	0.467	(0.390) 0.231
Patent intensity (log)		0.759	(0.110)*** 0.000	0.756	(0.114)*** 0.000	0.801	(0.117)*** 0.000	0.711	(0.107)*** 0.000
Deal-specific variables (t − 1)									
Shares acquired		−0.132	(0.103) 0.200	−0.070	(0.106) 0.508	−0.082	(0.108) 0.446	−0.112	(0.104) 0.281
Absolute size of acq. KB	*H2a* (+)	0.004	(0.002)** 0.019					0.003	(0.001)*** 0.026
Absolute size of acq. KB^2	*H2a* (−)	−0.000	(0.000)** 0.044					−0.000	(0.000)* 0.079
Relative size of acq. KB	*H2b* (−)	−0.088	(0.019)*** 0.000					−0.101	(0.020)*** 0.000
Technological relatedness	*H3a* (+)			0.474	(0.468) 0.311			0.811	(0.461)* 0.078
Technological $relatedness^2$	*H3a* (−)			0.048	(0.535) 0.928			−0.294	(0.523) 0.575

Table 4 (continued)

Variables	Hyp.	Model 1		Model 2		Model 3		Model 4	
		Coeff.	(SE)	Coeff.	(SE)	Coeff.	(SE)	Coeff.	(SE)
			p-value		p-value		p-value		p-value
Acq. in similar industry	*H3b* (+)			−0.001	(0.075)			0.019	(0.073)
					0.994				0.797
Cross-border acquisition	*H3c* (+)			0.357	(0.131)***			0.406	(0.122)***
					0.006				0.001
Previous acq. experience	*H4a* (+)					−0.002	(0.035)	−0.008	(0.035)
							0.951		0.812
Acq. by state-owned ent.	*H4b* (−)					−0.036	(0.115)	−0.066	(0.114)
							0.756		0.560
Year dummies		Yes		Yes		Yes		Yes	
Industry dummies		Yes		Yes		Yes		Yes	
Province dummies		Yes		Yes		Yes		Yes	
N (Companies)		1535	(697)	1535	(697)	1535	(697)	1535	(697)
Pseudo R^2		0.175		0.175		0.170		0.180	
Alpha		1.131		1.139		1.186		1.077	

Standard errors clustered at company level

KB Knowledge base

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

A higher *relative size of the acquired knowledge base* is associated with a lower post-acquisition innovation output.

With regard to H3a, we find that *technological relatedness of the acquired knowledge* base positively influences patent output ($p = 0.078$). However, we do not find evidence for a non-linear relationship. With regard to the industrial context, we assumed that *intra-industry deals* have a positive effect on post-acquisition patent output (H3c). Our empirical analysis does not support this hypothesis. H3c suggests differences between cross-border and domestic deals and suggests a positive effect of *cross-border acquisitions*. Compared to a domestic deal, an international deal increases patent applications in subsequent years ($p = 0.001$).

Finally, we find no support for H4a and H4b, which assumed differences in the acquisition consequences of experienced versus inexperienced acquirers or state-owned versus private acquirers.

4.3 Robustness checks

In addition to our main analysis, we perform several robustness checks that are displayed in Table 5.

First, the acquisition of knowledge may not always be the main motive for an acquisition. Some acquisitions, for example, might aim to access resources, or gain market share. Previous research has dealt with this issue by only focusing on acquisitions in which the acquired company filed at least one patent five years to being acquired (e.g., Ahuja and Katila 2001). In Model 1 (Table 5), we thus reduce our sample accordingly. While our sample is reduced to 452 acquisitions by 290 firms, the findings of our main analysis remain robust. Still, this robustness check cannot completely rule out differences in target selection or different acquisition motives.

Second, our sample includes several companies that performed more than one acquisition in a given year. While we account for the number of previous acquisitions for every observation and also cluster the standard errors on the company level, it is hard to disentangle the effect of each acquisition on the acquirer's cumulative patent output. Therefore, we excluded companies that conducted more than one acquisition in a single year from our sample. As Model 1 (Table 5) shows, this restriction severely decreases our sample to 679 acquisitions carried out by 478 companies. In spite of the decreased sample, the findings with regard to H2a and H2b remain robust. Due to the decreased sample size, however, the cross-border effect becomes insignificant.

Third, our main model uses a lag of 1 year for all covariates. By this, we account for a delay in the effect of an acquisition on the acquirer's patent output. However, different lag structures have been used in previous literature. For example, Ahuja and Katila (2001) as well as Cloodt et al. (2006) include the independent variables with no lag, and a lag of 1–3 years simultaneously. Their results show that, while there are differences between the different lag structures, the overall effects remain similar. In order to validate our results, we thus estimate our main model with a lag of 3 years. While this leads to a severe drop in observations to 894 acquisitions (we had to exclude the two most recent years), all results remain robust.

Table 5 Robustness checks. Results of a negative binomial regression analysis focusing on deal-specific variables (dependent variable: patent applications per year). Data sources: Compustat international, SDC Platinum, PATSTAT (version: March 2015)

	Hyp.	Model 1		Model 2		Model 3		Model 4	
Description		Only acquired firms that filed at least one patent		Acquirers with multiple acquisitions in one year excluded		All covariates lagged by 3 years		Observations excluded where relative size = 0	
		Coeff.	(SE)	Coeff.	(SE)	Coeff.	(SE)	Coeff.	(SE)
Variables			p-value		p-value		p-value		p-value
Control variables (t − 1)									
Time since IPO		−0.009	(0.015)	−0.024	(0.011)**	−0.038	(0.013)***	−0.022	(0.013)*
			0.548		0.030		0.003		0.087
Total revenue (log)		0.681	(0.065)***	0.664	(0.054)***	0.745	(0.056)***	0.722	(0.060)***
			0.000		0.000		0.000		0.000
Return on assets		−0.740	(0.408)	0.886	(0.556)	−1.144	(0.406)***	−0.630	(0.404)
			0.070		0.111		0.005		0.119
Patent intensity (log)		0.573	(0.155)***	0.754	(0.112)***	0.605	(0.103)***	0.548	(0.123)***
			0.000		0.000		0.000		0.000
Deal-specific variables (t − 1)									
Shares acquired		−0.061	(0.173)	−0.121	(0.137)	−0.066	(0.152)	−0.022	(0.180)
			0.725		0.377		0.665		0.904
Absolute size of acq. KB	H2a (+)	0.004	(0.001)***	0.021	(0.007)***	0.005	(0.001)***	0.004	(0.002)***
			0.009		0.006		0.000		0.038
Absolute size of acq. KB^2	H2a (−)	−0.000	(0.000)**	−0.000	(0.000)**	−0.000	(0.000)***	−0.000	(0.000)*
			0.030		0.030		0.000		0.075
Relative size of acq. KB	H2b (−)	−0.136	(0.029)***	−0.117	(0.032)***	−0.326	(0.057)***	−0.123	(0.023)***
			0.000		0.000		0.000		0.000
Technological relatedness	H3a (+)	8.167	(1.418)***	0.554	(0.615)	1.959	(0.693)***	5.346	(1.760)***

Table 5 (continued)

	Hyp.	Model 1		Model 2		Model 3		Model 4	
Description		Only acquired firms that filed at least one patent		Acquirers with multiple acquisitions in one year excluded		All covariates lagged by 3 years		Observations excluded where relative size = 0	
		Coeff.	(SE)	Coeff.	(SE)	Coeff.	(SE)	Coeff.	(SE)
Variables			p-value		p-value		p-value		p-value
			0.000		0.368		0.005		0.002
Technological relatedness^2	H3a (−)	−5.264	(1.072)***	−0.064	(0.711)	−1.504	(0.792)*	−3.320	(1.253)***
			0.000		0.928		0.058		0.008
Cross-border acquisition	H3b (+)	0.626	(0.279)**	0.141	(0.171)	0.641	(0.164)***	0.276	(0.212)
			0.025		0.411		0.000		0.192
Acq. in similar industry	H3c (+)	0.039	(0.111)	0.062	(0.100)	−0.027	(0.103)	0.120	(0.103)
			0.727		0.537		0.792		0.245
Previous acq. experience	H4a (+)	0.012	(0.057)	0.020	(0.063)	−0.152	(0.071)**	−0.012	(0.045)
			0.832		0.748		0.033		0.785
Acq. by state-owned ent.	H4b (−)	−0.027	(0.163)	−0.151	(0.133)	−0.020	(0.145)	0.164	(0.150)
			0.870		0.257		0.889		0.275
Year dummies		Yes		Yes		Yes		Yes	
Industry dummies		No		Yes		Yes		Yes	
Province dummies		No		Yes		Yes		Yes	
N (Companies)		452	(290)	679	(478)	894	(439)	398	(251)
Pseudo R^2			0.184	0.173		0.189		0.197	
Alpha			0.857	1.037		1.248		0.572	

Standard errors clustered at company level

KB Knowledge base

* $p<0.10$, ** $p<0.05$, *** $p<0.01$

Finally, we calculated the relative size of the acquired knowledge base by dividing the absolute size of the acquired knowledge base by the knowledge base of the acquiring firm. If the acquired firm did not file any patents, the variable takes a value of 0. Because a very small value should indicate a very large difference between the two knowledge bases, this is not necessarily the case if the acquirer has 1 patent and the acquired firm has 0 patents. Therefore, we exclude all observations in which the variable takes a value of 0 in Model 3 (Table 5). Again, this decreases our sample by a large extent. However, the significant findings with regard to the *relative size of the acquired knowledge base* remain robust.

5 Discussion and conclusion

We analyze the effect of acquisitions on the acquirer's post-acquisition innovation performance in the emerging market context of China. We draw on absorptive capacity theory and find no significant overall effect of acquisitions on the patent output of Chinese acquirers. Yet, several deal-specific variables, such as characteristics of the acquired knowledge base and cross-border acquisitions do influence the post-acquisition patent output. Our findings extend the previous literature on the effect of acquisitions on post-acquisition innovation performance (e.g., Ahuja and Katila 2001; Cloodt et al. 2006; Desyllas and Hughes 2010). Additionally, we contribute to the increasing literature on innovation in China. Previous studies have empirically analyzed the explosive increase in patenting by Chinese entities and its antecedents (e.g., Hu and Mathews 2008; Li 2012).

Previous research has assumed that emerging market firms may not profit from acquisitions because they lack the absorptive capacity to successfully exploit acquired knowledge (Narula 2012; Anderson et al. 2015). However, we identify several deal-specific characteristics that significantly influence the post-acquisition patent output. Unsurprisingly, we find that a higher absolute knowledge base of the acquired firm increases post-acquisition patent output. Although this linear effect has been identified in previous research, our findings suggest that the effect is non-linear and decreases at higher levels. We explain this in the acquisition context previously unexplored finding through the significant requirements that the integration of a very large knowledge base poses for an acquiring firm. Although potentially providing a huge potential to increase their own absorptive capacity, companies may be overwhelmed by very large knowledge bases. This implies that the most attractive targets for Chinese acquirers may not necessarily be firms with the largest possible knowledge base; rather, it should be more beneficial to choose targets with a moderate knowledge base.

In line with H3c, we find that Chinese companies profit from international acquisitions. This indicates that Chinese firms successfully draw on the often more developed knowledge in technologically and culturally distant countries. Because a successful integration of more distant and potentially more advanced knowledge often requires a considerable amount of absorptive capacity, this finding largely contradicts the argument that Chinese firms lack absorptive capacity. Additionally, this finding supports the notion that Chinese companies use cross-border acquisitions to transition to an innovation-based economy and to catch up to developed countries (Morck et al. 2008; Anderson et al. 2015). An additional explanation for this finding could be that the Chinese patents acquired in domestic acquisitions are of comparatively low value (Fisch 2016). This notion of a lower patent value is supported by recent research which indicates that Chinese patents are less valuable than from the US or other developed economies (e.g., Boeing and Mueller 2016; Fisch et al. 2017). Even though the overall patent value of Chinese patents might be increasing in recent years, it is thus not surprising that the acquisition of more valuable, international patents has a larger effect on post-acquisition patent output of Chinese acquirers.

Finally, we do not find significant differences in the post-acquisition patent output between state-owned and private firms. We expected the innovation-hampering aspects to overwhelm in state-owned companies: inefficient structures, the absence of managerial knowledge and unhealthy ties between government and businesses (Choi et al. 2011). However, previous literature also indicates that state-owned enterprises could be more innovative (Choi et al. 2011). For example, the successful catch-up of Taiwan and South Korea has been partially attributed to state-driven technological development aimed at fostering innovation capabilities. A similar effect could be expected for China because the government's long-term orientation and substantial financial support might lead to a better environment for innovation.

In conclusion, our results show that Chinese companies seem to be able to successfully exploit acquisitions to increase their patent output under certain circumstances (e.g., in cross-border acquisitions). This contradicts studies assuming a comparatively limited absorptive capacity of Chinese firms (Rugman and Li 2007; Anderson et al. 2015). A potential explanation lies in the transformative process China undergoes and the adaptability this process demands from companies, particularly in changing environments, such as during a transformation from imitation to innovation. For example, the industrial and institutional environment in China is highly dynamic and uncertain. This is because the transformation process leads to a variety of unique and often experimental industrial policies (Luo and Peng 1999; Murray et al. 2005). This forces firms to adapt their products and strategies very quickly. Thus, this reality might prepare them for the hurdle of acquisitions and enable them, despite a potentially worse initial situation, to profit from acquisitions. Another explanation is that Chinese firms often exhibit a very inactive role when integrating acquired firms, which is contrary to public belief. Several studies indicate that Chinese firms often grant acquired firms considerable autonomy following an acquisition. This passive strategy aims to minimize integration problems while simultaneously keeping an acquired firm as functional as possible, for example by keeping the old management in place (Liu and Woywode 2013; Anderson et al. 2015). This not only enables the Chinese firm to profit from the acquired firm as much as possible but also contradicts the public image of Chinese firms only acquiring firms to drain their knowledge.

This study is not without limitations. First, previous studies often try to consolidate companies and their subsidies, for example, using Dun and Bradseet's "Who Owns Whom" database (e.g., Valentini 2012). This is helpful when trying to grasp a company's patent portfolio. However, the Chinese company landscape is very opaque and there is no common source for consolidation. To account for this, we generated and refined our search patterns in multiple iterations and are confident that we have identified an accurate patent portfolio through this process. A second limitation concerns our dependent variable (patent output). Patents suffer from the idiosyncrasies of the patenting process and other limitations. Despite these potential drawbacks, patents are by far the most frequently used measure of innovative performance in an acquisition context (e.g., Ahuja and Katila 2001; Desyllas and Hughes 2010). Finally, the acquisition of knowledge is not always the main motivation for an acquisition. If an acquisition is carried out, for example, to gain access to resources or market share, a subsequent effect on the innovation performance is unlikely. Controlling for different acquisition motives is a frequently discussed issue in previous literature (e.g., Ahuja and Katila 2001) and we try to account for it in our robustness checks to some extent. Still, this issue provides a fruitful avenue for future research. Finally, our study is closely related to the studies of Ahuja and Katila (2001) and Cloodt et al. (2006). Extending these studies, we explore multiple independent variables that have remained unexplored so far. However, these prior studies utilize the number of successful patent applications as a dependent variable. Successful patent applications might give a better impression of a firm's actual innovation output because patents of low quality or trivial patents are often not granted and therefore filtered out. However, we could not use the number of successful patent applications because this information was only partially available in the Chinese context and would have led to a major loss in observations.

Additionally, we focus on acquisitions, which is only one option for inter-firm knowledge transfer, albeit an important one. Thus, further research might examine other mechanisms of knowledge acquisition, such as strategic alliances or joint ventures in the specific context of China (e.g., Kale et al. 2000; Duso et al. 2010). Second, various contributions have highlighted the fact that the increase of China's innovative capacity is remarkable in terms of quantity, but questionable in terms of quality (e.g., Li 2012). Future research might find it interesting to assess patent quality in more detail. Due to the limitation in Chinese patent data, it might be interesting to assess patent quality in an already established context in which data are reliably available, such as the US. Third, cross-border acquisitions are a particularly interesting subgroup of acquisitions. It might be interesting to analyze how country-specific variables affect the post-acquisition innovation performance. For example, it could be analyzed whether there is a difference in the effect on the acquirer's innovation performance when US firms or European firms are acquired. Finally, more refined ways of analysis could be used to ensure the robustness of our results. For example, future research could approach the development of the acquirer's post-acquisition innovation performance using a differences in differences setup.

Acknowledgements We thank participants of the G-Forum (2015) and participants of a research seminar at the Universities of Luxemburg, Düsseldorf, and Heilbronn for their insightful comments.

Appendix

See Table 6.

Table 6 Comparison of our study with previous studies

Study	Title	(Main) conceptual framework	Dependent variable	Hypotheses (Findings)	Sample
Ahuja and Katila (2001)	Technological acquisitions and the innovation performance of acquiring firms: A longitudinal study	Absorptive capacity	Number of successful patent applications by the acquiring firms 4 years following the acquisition	Number of non-technological acquisitions (ns), absolute size of acquired knowledge base (+), relative size of acquired knowledge (−), relatedness of acquired knowledge base(−) [squared (−)], number of technological acquisitions where patents unavailable (+)	72 leading firms the chemicals industry (30 European, 26 American, 16 Japanese) that conducted 534 acquisitions between 1980 and 1991
Cloodt et al. (2006)	Mergers and acquisitions: Their effect on the innovative performance of companies in high-tech industries	Absorptive capacity	Number of successful patent applications by the acquiring firms 4 years following the acquisition	Number of non-technological M&As (−), absolute size of acquired knowledge base (−), relative size of acquired knowledge base (−), technologically related and technologically unrelated M&As (+) [squared (−)]	347 firms from high-tech industries (256 North American, 45 European, 46 Asian) that conducted 2429 M&As between 1985 and 1994

Table 6 (continued)

Study	Title	(Main) conceptual framework	Dependent variable	Hypotheses (Findings)	Sample
This study	The impact of acquisitions on Chinese acquirers' innovation performance: An empirical investigation of 1545 Chinese acquisitions	Absorptive capacity	Number of patent applications by the acquiring firms in every year following the acquisition	Absolute size of acquired knowledge base (+) [squared (−)], relative size of acquired knowledge base (−)[squared (−)], technological relatedness (+)[squared (ns)], acquisition in similar industry (ns), cross-border acquisition (+), previous acquisition experience (ns), acquisition by state-owned enterprise (ns)	697 firms from manufacturing industries (Chinese) that conducted 1545 acquisitions and filed patents between 2000 and 2013

ns not significant

References

Adair WL, Brett JM (2005) The negotiation dance: time culture, and behavioral sequences in negotiation. Organ Sci 16:33–51

Ahuja G, Katila R (2001) Technological acquisitions and the innovation performance of acquiring firms: a longitudinal study. Strateg Manag J 22:197–220

Ahuja G, Katila R (2004) Where do resources come from? The role of idiosyncratic situations. Strateg Manag J 25:887–907

Anderson J, Sutherland D, Severe S (2015) An event study of home and host country patent generation in Chinese MNEs undertaking strategic asset acquisitions in developed markets. Int Bus Rev 24:758–771

Argote L (2013) Organizational learning: creating, retaining and transferring knowledge. Springer Science & Business Media, New York

Barkema HG, Vermeulen F (1998) International expansion through start-up or acquisition: a learning perspective. Acad Manag J 41:7–26

Barkema HG, Chen XP, George G, Luo Y, Tsui AS (2015) West meets East: new concepts and theories. Acad Manag J 58:460–479

Björkman I, Stahl GK, Vaara E (2007) Cultural differences and capability transfer in cross-border acquisitions: the mediating roles of capability complementarity, absorptive capacity, and social integration. J Int Bus Stud 38:658–672

Block JH, Fisch C, Hahn A, Sandner PG (2015) Why do SMEs file trademarks? Insights from firms in innovative industries. Res Policy 44:1915–1930

Boeing P, Mueller E (2016) Measuring patent quality in cross-country comparison. Econ Lett 149:145–147

Boeing P, Mueller E, Sandner P (2016) China's R&D explosion: analyzing productivity effects across ownership types and over time. Res Policy 45:159–176

Buckley PJ, Elia S, Kafouros M (2014) Acquisitions by emerging market multinationals: implications for firm performance. J World Bus 49:611–632

Cassiman B, Veugelers R, Zuniga P (2008) In search of performance effects of (in)direct industry science links. Ind Corp Change 17:611–646

Choi SB, Lee SH, Williams C (2011) Ownership and firm innovation in a transition economy: evidence from China. Res Policy 40:441–452

Cloodt M, Hagedoorn J, Van Kranenburg H (2006) Mergers and acquisitions: their effect on the innovative performance of companies in high-tech industries. Res Policy 35:642–654

Clougherty JA (2005) Antitrust holdup source, cross-national institutional variation, and corporate political strategy implications for domestic mergers in a global context. Strateg Manag J 26:769–790

Cohen MD, Bacdayan P (1994) Organizational routines are stored as procedural memory: evidence from a laboratory study. Organ Sci 5:554–568

Cohen WM, Levinthal D (1989) Innovation and learning: the two faces of R&D. Econ J 99:569–596

Cohen WM, Levinthal D (1990) Absorptive capacity: a new perspective on learning and innovation. Adm Sci Q 35:128–152

Deng P (2004) Outward investment by Chinese MNCs: motivations and implications. Bus Horiz 47:8–16

Deng P (2009) Why do Chinese firms tend to acquire strategic assets in international expansion? J World Bus 44:74–84

Desyllas P, Hughes A (2010) Do high technology acquirers become more innovative? Res Policy 39:1105–1121

Dikova D, Rao Sahib P, Van Witteloostuijn A (2010) Cross-border acquisition abandonment and completion: the effect of institutional differences and organizational learning in the international business service industry, 1981–2001. J Int Bus Stud 41:223–245

Duso T, Pennings E, Seldeslachts J (2010) Learning dynamics in research alliances: a panel data analysis. Res Policy 39:776–789

Ethiraj SK, Gambardella A, Helfat CE (2016) Replication in strategic management. Strateg Manag J 37:2191–2192

Finkelstein S, Haleblian J (2002) Understanding acquisition performance: the role of transfer effects. Organ Sci 13:36–47

Fisch C (2016) Patents and trademarks: Motivations, antecedents, and value in industrialized and emerging markets. Dissertation, Erasmus University Rotterdam

Fisch C, Block JH, Sandner PG (2016) Chinese university patents: quantity, quality, and the role of subsidy programs. J Technol Transfer 41:60–84
Fisch C, Sandner PG, Regner L (2017) The value of Chinese patents: an empirical investigation of citation lags. China Econ Rev 45:22–34
Ghoshal S (1987) Global strategy: an organizing framework. Strateg Manag J 8:425–440
Hagedoorn J, Duysters G (2002) The effect of mergers and acquisitions on the technological performance of companies in a high-tech environment. Technol Anal Strateg Manag 14:67–85
Haleblian J, Finkelstein S (1999) The influence of organizational acquisition experience on acquisition performance: a behavioral learning perspective. Adm Sci Q 44:29–56
Henderson R, Cockburn I (1996) Scale, scope, and spillovers: the determinants of research productivity in drug discovery. RAND J Econ 27:32–59
Hitt MA, Dacin MT, Levitas E, Arregle JL, Borza A (2000) Partner selection in emerging and developed market contexts: resource-based and organizational learning perspectives. Acad Manag J 43:449–467
Hoskisson RE, Hitt MA (1988) Strategic control systems and relative R&D investment in large multiproduct firms. Strateg Manag J 9:605–621
Hu MC, Mathews JA (2008) China's national innovative capacity. Res Policy 37:1465–1479
Huff A (1982) Industry influences on strategy reformulation. Strateg Manag J 3:119–131
Kale P, Singh H, Perlmutter H (2000) Learning and protection of proprietary assets in strategic alliances: building relational capital. Strateg Manag J 21:217–237
Kim L (1997) Imitation to innovation: the dynamics of Korea's technological learning. Harvard Business Press, Boston
Kotabe M, Jiang CX, Murray JY (2011) Managerial ties, knowledge acquisition, realized absorptive capacity and new product market performance of emerging multinational companies: a case of China. J World Bus 46:166–176
Laamanen T, Keil T (2008) Performance of serial acquirers: toward an acquisition program perspective. Strateg Manag J 29:663–672
Li X (2012) Behind the recent surge of Chinese patenting: an institutional view. Res Policy 41:236–249
Liegsalz J, Wagner S (2013) Patent examination at the state intellectual property office in China. Res Policy 42:552–563
Liu Y, Woywode M (2013) Light-touch integration of Chinese cross-border M&A: the influences of culture and absorptive capacity. Thunderbird Int Bus Rev 55:469–483
Lubatkin M (1983) Mergers and the performance of the acquiring Firm. Acad Manag Rev 8:218–225
Luo Y, Peng MW (1999) Learning to compete in a transition economy: experience, environment, and performance. J Int Bus Stud 30:269–295
Makri M, Hitt MA, Lane PJ (2010) Complementary technologies, knowledge relatedness, and invention outcomes in high technology mergers and acquisitions. Strateg Manag J 31:602–628
Morck R, Yeung B, Zhao M (2008) Perspectives on China's outward foreign direct investment. J Int Bus Stud 39:337–350
Muehlfeld K, Rao Sahib P, Van Witteloostuijn A (2012) A contextual theory of organizational learning from failures and successes: a study of acquisition completion in the global newspaper industry, 1981–2008. Strateg Manag J 33:938–964
Murray JY, Kotabe M, Zhou JN (2005) Strategic alliance-based sourcing and market performance: evidence from foreign firms operating in China. J Int Bus Stud 36:187–208
Narula R (2012) Do we need different frameworks to explain infant MNEs from developing countries? Glob Strateg J 2:188–204
Nooteboom B, Van Haverbeke W, Duysters G, Gilsing V, Van den Oord A (2007) Optimal cognitive distance and absorptive capacity. Res Policy 36:1016–1034
Olie R (1994) Shades of culture and institutions in international mergers. Organ Stud 15:381–405
Peng MW (2003) Institutional transitions and strategic choices. Acad Manag Rev 28:275–296
Pollock TG, Rindova VP, Maggitti PG (2008) Market watch: information and availability cascades among the media and investors in the U.S. IPO market. Acad Manag J 51:335–358
Puranam P, Singh H, Zollo M (2006) Organizing for innovation: managing the coordination-autonomy dilemma in technology acquisitions. Acad Manag J 49:263–280
Ramasamy B, Yeung M, Laforet S (2012) China's outward foreign direct investment: location choice and firm ownership. J World Bus 47:17–25
Rugman AM, Li J (2007) Will China's multinationals succeed globally or regionally? Eur Manag J 25:333–343

Sandner PG, Block JH (2011) The market value of R&D, patents, and trademarks. Res Policy 40:969–985
Sears J, Hoetker G (2014) Technological overlap, technological capabilities, and resource recombination in technological acquisitions. Strateg Manag J 35:48–67
Spender JC (1987) Industry recipes: An enquiry in the nature and sources of managerial judgment. Blackwell, Oxford
Stock GN, Greis NP, Fischer WA (2001) Absorptive capacity and new product development. J High Technol Manag Res 12:77–91
Sun PY, Anderson MH (2010) An examination of the relationship between absorptive capacity and organizational learning, and a proposed integration. Int J Manag Rev 12:130–150
Tsui AS, Schoonhoven CB, Meyer MW, Lau CM, Milkovich GT (2004) Organization and management in the midst of societal transformation: the People's Republic of China. Organ Sci 15:133–144
Vaara E (2003) Post-acquisition integration as sensemaking: glimpses of ambiguity, confusion, hypocrisy, and politicization. J Manag Stud 40:859–894
Valentini G (2012) Measuring the effect of M&A on patenting quantity and quality. Strateg Manag J 33:336–346
Wang X, Yang B, McLean GN (2007) Influence of demographic factors and ownership type upon organizational learning culture in Chinese enterprises. Int J Train Dev 11:154–165
White S (2000) Competition, capabilities, and the make, buy, or ally decisions of Chinese state-owned firms. Acad Manag J 43:324–341
WIPO (2017) IP statistics data center. http://ipstats.wipo.int/ipstatv2. Accessed 03 Feb 2017
Wu Y (2001) Is China's economic growth sustainable? A productivity analysis. China Econ Rev 11:278–296
Zhao Y, Li Y, Lee SH, Chen LB (2011) Entrepreneurial orientation, organizational learning, and performance: evidence from China. Entrep Theory Pract 35:293–317