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How to cite this publication

Please cite the final published version:

Muratova, Y., Rigamonti, D., & Wulff, J. (2019). The effect of acquisitions on exploration and exploitation in China. *Journal of Strategy and Management*, 12(2), 174-188.

<https://doi.org/10.1108/JSMA-10-2018-0124>

Publication metadata

Title:	The effect of acquisitions on exploration and exploitation in China
Author(s):	Yulia Muratova; Damiana Rigamonti & Jesper N. Wulff
Journal:	<i>Journal of Strategy and Management</i> , 12(2), 174-188
DOI/Link:	10.1108/JSMA-10-2018-0124
Document version:	Accepted manuscript (post-print)

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STRUCTURED ABSTRACT

Purpose

The mechanisms of knowledge acquisition and their impact on innovation are particularly relevant in the context of rapidly growing emerging markets. This paper investigates the relationship between firm acquisition characteristics and postacquisition knowledge exploration and exploitation in the Chinese domestic acquisition market.

Design/methodology/approach

By using patent and company data of 188 domestic Chinese deals completed between 2002 and 2013, the paper replicates the measurements and analytical methods of the US-based study by Phene, Tallman, and Almeida (2012) to address the acquirer's opportunity to explore and/or exploit external knowledge, its ability to absorb and effectively assimilate such knowledge and thus establish innovations in new technologies.

Findings

The paper finds support for a positive effect of knowledge uniqueness of the target on the bidder's postacquisition exploration. The findings also support that the postacquisition exploitation is facilitated by the commonality of technological knowledge between the bidder and the target, a result that, although expected, was not supported in the US-based study.

Originality/value

This paper qualifies the generalizability of US-based findings about postacquisition exploration and exploitation in the context of China. It also responds to the call for China-focused knowledge management research by capturing innovation capability building by Chinese firms through domestic acquisitions. Finally, it contributes to the nascent literature on replication in management studies.

Keywords: Mergers & Acquisitions; Exploration/Exploitation; Emerging Market Strategies; Replication.

THE EFFECT OF ACQUISITIONS ON EXPLORATION AND EXPLOITATION IN CHINA

INTRODUCTION

Building up firm innovation capacity through knowledge exploration and exploitation by means of corporate acquisitions has been a centerpiece of strategy research for over two decades (Calipha et al., 2018; Choi and McNamara, 2017). The study by Phene, Tallman, and Almeida (2012) provides a comprehensive overview of the conditions under which acquisitions lead to either exploration or exploitation of a target's technological knowledge stock. These conditions include the acquirer's opportunity to explore and/or exploit external knowledge and its ability to absorb and effectively assimilate such knowledge, and thus establish innovations in new technologies. While the study has important theoretical merits, it draws its conclusions from a sample of US firms without questioning whether the effect of the conditions for knowledge exploration and exploitation in question is generalizable to different economic and institutional contexts.

To understand the extent to which the mechanisms discussed in Phene et al. (2012) are context-free, we replicate the study on a sample of Chinese firms. Replication studies are fundamental in management research to test whether particular findings are consistent when the context changes, i.e. generalizable (Bettis et al., 2016). We focus on China for three reasons. First, China is the second largest economy in the world, surpassed only by the US. China aims to completely revamp its industry towards a ubiquitous use of advanced technologies in the manufacturing industry by 2025 (Kennedy, 2015). Thus, China's hunger for innovation represents an empirically important context for testing the theoretical assumptions underlying the findings by Phene et al. (2012). Second, an acquisition strategy is the preferred growth and innovation driver of Chinese firms (Chan, 2009). In December 2001, China entered

the World Trade Organization (WTO). Opening its borders to more foreign firms had a tangible impact on domestic companies (Liu and Chen, 2014). The intensified competition, in fact, revealed many operational deficiencies of Chinese firms, whose survival became dependent on how fast they could develop their capabilities (Deng, 2009). The Chinese government emphasized and supported quick firm restructuring, which led to a four-fold growth of the number of large domestic mergers and acquisitions (M&As) between 2002 and 2010 (Tang and Metwalli, 2012). Third, prior work on Chinese acquisitions has shed light on their multiple idiosyncrasies that make them distinctly different from acquisitions completed in a US context. In the context of Chinese state capitalism, firm ownership matters for access to critical resources required for firm growth. While state-controlled firms enjoy slack resources, private firms scramble to get access to bank credit and information, which forces them to become more efficient and make do with the resources at hand. Often, state-owned and private firms with political connections conduct acquisitions, not for strategic business purposes, but rather to fulfill social goals, such as acquiring a bankrupt company that is a major employer in the region, or to align themselves with various other interests of the government (Arnoldi and Muratova, 2018). Finally, against the backdrop of fast economic development, relative weakness of corporate practices, underdeveloped market institutions, and various non-business related reasons for acquisitions, the ability of Chinese firms to integrate a target firm and thereby absorb its knowledge has been further questioned, albeit in the context of cross-border acquisitions (Liu and Woywode, 2013). The presence of these contextual factors may alter the way in which the mechanisms described in Phene et al. (2012) function in the Chinese market for acquisitions.

By using patent and company data of 188 domestic Chinese deals completed between 2002 and 2013, we closely replicate the measurements and analytical methods used by Phene et al. (2012) to test their original hypotheses. Our findings show that we can successfully replicate one out of four significant results of the US-based study. Specifically, we confirm that the technological uniqueness of the target

facilitates postacquisition knowledge exploration. Furthermore, we confirm the hypothesized positive effect of common technological knowledge between the two firms on exploitation, which was not supported in the US-based study.

Our study make several contributions. First, we qualify the findings of the original study, thereby offering an empirical contribution to the literature on postacquisition innovation. Second, we shed light on domestic acquisitions as a mechanism to access strategic assets and improve the absorptive capacity of Chinese firms. Third, our findings clearly demonstrate that the results of an analysis are not always generalizable beyond the particular sample investigated (Gelman, 2015) and studies in the management field need replication.

The article is structured as follows: In the next section, we summarize the arguments and the hypotheses of Phene et al. (2012). In the subsequent sections, we describe our data, methods, and results. Finally, we critically discuss the findings of our replication with reference to the original study.

THE LOGIC OF PHENE ET AL.'S THEORETICAL PROPOSITION

Phene et al. (2012) build their hypotheses drawing on organizational learning theory, according to which a firm's strategy, including innovation, is inherently path dependent, and its evolvement is a function of a delicate balance between exploration (or distant search) and exploitation (or local search) of new knowledge. They argue that a firm engages in exploration if it collects and absorbs unique technological knowledge that is new to the firm, whereas exploitation refers to building upon the same technological areas that the firm already possesses. New knowledge, either distant or local, does not reside within the firm, hence, a firm acquisition may be an efficient mechanism of knowledge acquisition. The authors suggest that three factors are important for determining whether a given firm acquisition facilitates

exploration or exploitation: the opportunity for exploration or exploitation, the ability of the acquiring firm to absorb the target's knowledge, and the level of control necessary for efficient knowledge transfer.

The access to new knowledge is key for a firm wishing to engage in exploration. In such a case, an acquiring firm would likely select a target that holds largely new knowledge, i.e. a target offering high technological uniqueness. This, however, is not desirable when a firm seeks to excel in the technological areas it already knows well. A target's technological uniqueness would then create a barrier inhibiting recognition of any familiar knowledge it might store. Moreover, it might push a firm to explore rather than exploit and thus diverting its strategy. Therefore, a firm wishing to build on its current knowledge stock should avoid acquiring targets that feature a large degree of technological uniqueness. Hence,

H_{1A}: The extent of target firm technological uniqueness is positively related to exploration by the acquirer firm.

H_{1B}: The extent of target firm technological uniqueness is negatively related to exploitation by the acquirer firm.

The ability of a firm to assimilate or absorb knowledge from the target is dependent on the degree of common knowledge shared by the two firms. The degree of overlap of knowledge stocks provides common ground in at least three important dimensions: technological capabilities; stable architectural knowledge and engineering skills; mind-set & language, allowing better coordination of activities between the two firms, thereby facilitating knowledge exploitation. Moderate knowledge overlap, or some degree of technological proximity, may also intensify knowledge exploration. The overlap could serve as a backdrop condition allowing a more nuanced recognition of unique knowledge as well as facilitating its absorption due to better coordination of activities. Thus,

H_{2A}: The extent of common technological knowledge between acquirer and target firms positively moderates the effect of target technological uniqueness on exploration by the acquirer firm.

H_{2B}: The extent of common technological knowledge between acquirer and target firms is positively related to exploitation by the acquirer firm.

The ability to recognize and absorb knowledge is also dependent on the geographical proximity of the two firms. Professional relationships are embedded in social networks. Locational proximity is paramount for building and maintaining social relations among actors, and those social relations intensify the informal knowledge flow and promote better understanding. Hence, geographical proximity is vital for transferring knowledge and it facilitates the absorption of unfamiliar knowledge and intensifies exploitation.

H_{3A}: The extent of common geographic bases between acquirer and target firms positively moderates the effect of target technological uniqueness on exploration by the acquirer firm.

H_{3B}: The extent of common geographical bases between acquirer and target firms is positively related to exploitation by the acquirer firm.

The ability of a firm to explore or exploit the knowledge stock of a target firm varies with the level of control obtained in the target through one of the three main forms – merger or acquisition of majority interest, acquisition of partial interest, and acquisition of minority interest in the form of acquisition of assets. Prior research shows that the loss of autonomy wrenched by the acquisition of majority rights leads to the disruption of a target's routines, resulting in the loss of its innovative capability. This might be particularly detrimental for the exploration of the target's knowledge stock. Hence, when fulfilling this purpose, acquiring a minority or a partial stock prevents the disruption of the target's activities and

keeps the base for knowledge exploration intact. Contrarily, majority ownership facilitates better coordination between the two firms and, thus, higher efficiency of knowledge transfer, when the sole interest of an acquiring firm is the exploitation of the common technological areas.

H_{4A}: Acquisition of a majority equity interest or a merger is negatively related to exploration by the acquirer.

H_{4B}: Acquisition of a majority equity interest or a merger is positively related to exploitation by the acquirer.

H_{5A}: Acquisition of a partial equity interest is positively related to exploration by the acquirer.

H_{5B}: Acquisition of a partial equity interest is negatively related to exploitation by the acquirer.

METHODS

Sample

Our sample consists of 188 domestic acquisitions completed by Chinese companies over the period 2002-2013. The sample was collected as follows. First, from Zephyr (a comprehensive M&A deals database provided by *Bureau Van Dijk*), we identified the entire population of domestic deals completed by listed Chinese firms. We selected the year 2002 as a starting point for our collection because China's entrance into the WTO in December 2001 had substantial consequences for Chinese firm behavior. In fact, the intensification of competition from foreign companies forced the domestic firms to become more competitive by restructuring their operations and changing their business practices (Deng, 2009). Second, the context of our study is the manufacturing industry. The limited number of Chinese deals solely within the semiconductor industry, which is the focus of Phene et al. (2012), does not make such a tailored study possible. For this reason, we decided to address the whole

manufacturing industry, i.e., the acquiring companies involved in the deals should have a Standard Industrial Classification (SIC) code within the range 20 to 39. Although we could not focus on the semiconductor industry only, this classification range means that the acquiring firms in our sample operate within the main high-technology manufacturing areas, such as electronic components, communication systems, computers and electrometrical equipment. Out of the total sample of 188 deals, 164 (about 87% of the sample) involve high-tech acquirers. In line with the US-based study, the target companies were, however, allowed to span all possible industrial sectors.

The third and most stringent criterion for our sample collection strategy was the selection of innovative companies based on patent filing (Baron and Spulber, 2018). For each deal, both the acquirer and the target must have filed at least one patent in the three years before the acquisition, in line with Phene et al. (2012). This is a necessary condition for the calculation of exploration and exploitation measures. We decided to adopt a three year span, instead of five years as implemented in the original work, in order to align the investigation with the market conditions characterizing the Chinese economy and patenting process (He et al., 2018). In China, it takes between one and a half and two years to process an invention patent application (Fu, 2008; IPR, 2017), which is considerably shorter than in the US, where the average processing time is about three years (USPTO, 2017). For each firm, data related to patent stocks, e.g. filing year and area of technology, have been retrieved from Orbis (a database also provided by *Bureau Van Dijk*) and cross-checked against Derwent World Patents Index (DWPI, a Thomson Reuters' database containing patent applications and grants).

Finally, the Orbis database was also used to obtain financial indicators and controls, which were cross-checked against the firms' annual reports in the case of missing data. Due to the issues in retrieving corporate data of unlisted Chinese firms (see, e.g., Le and O'Brien, 2010), both the acquirers and the

targets included in our sample are publicly listed companies on the Shanghai, Shenzhen, and Hong Kong Stock Exchanges.

Dependent variables

We measured the dependent and independent variables by closely following the original study. For each acquiring company, our exploration and exploitation measures were based on the comparison between the patent portfolio of the acquirer three years before and three years after the acquisition. More precisely, for each company, the comparison relied on the identification of the firms' core technological areas. In agreement with the original study, our definition of core areas at the three-digit technology class level was based on the proportion of each technology class in a firm's patent portfolio, measured as the ratio of the number of patents in a technology class to the total number of patents across all technology classes in the period of analysis. Subsequently, the core technology classes were identified as those that contributed more to the firm's patent portfolio than a specific cutoff threshold. In line with Phene et al. (2012), we used a 3 percent cutoff to determine core technology classes for the acquiring and the target firms. According to the reference methodology, we also allowed the cutoff to increase to 20 percent for small companies with a lower level of patenting.

Hence, *exploration by the acquirer* was defined as a postacquisition shift by the acquirer into those technological fields that were the unique cores of the target before being acquired, i.e., those technological classes that represented core areas for the target, but not for the acquirer in the three years before the acquisition date. Then, the exploration by the acquirer was calculated as the increase in the number of patents filed by the acquirer after the acquisition (comparing the three years after to the three years prior to the deal) in the target's unique core technology areas, divided by the deflator index. The deflator index is a useful method to distinguish real acquirer patenting growth from the inflationary

tendencies that could be attributed to general increases in patenting activity over time. We adapted the deflator suggested by Phene et al. (2012) to the manufacturing context. Specifically, for each year included in our analysis (2002-2013) and for each of the 20 sub-sectors of the manufacturing industry, tracked at two-digits, we counted the total number of patents filed by Chinese companies in the three years before and the three years after the acquisition. Then the deflator was constructed as the total number of patents filed in each specific sector in the post-deal period divided by the number of those filed in the preacquisition period.

Similarly, the second dependent variable, *exploitation by the acquirer*, was measured as the change in the number of patents granted to the acquirer in its core technology classes three years before and three years after the acquisition. Again, the increase in the number of patents was divided by the deflator index. Both for the case of exploration and exploitation, a decrease in the patents count when comparing the periods before and after the acquisition was associated with a value of 0. Finally, exploration and exploitation measures were constrained to assume only non-negative integer values.

Independent variables

Regarding the independent variables, the *target technological uniqueness* was measured as the number of core technology classes unique to the target, i.e., the number of classes that represented a core for the target, but not for the acquirer in the three years prior to the acquisition. *Common technological knowledge* between the acquirer and the target was measured as the number of core technological classes common to the acquirer and the target in the three years prior to the acquisition.

We could not follow Phene et al. (2012) as closely as we did above in the construction of the two variables *common geographic bases* between acquirer and target and *level of control*. In the first case, the reason was that we could not retrieve the inventors' location, used by Phene et al. (2012) as an

indicator of physical proximity because this information was not available in the sources available to us. After careful consideration, we decided to use the province location of a target and acquirer as the best proxy of physical proximity between the companies. As Chinese provinces have important institutional differences and are subject to trade barriers, we assume that inventors in the R&D unit, as a critical corporate activity, are co-located within the firm's headquarters. Therefore, our measure of *common geographical bases* between acquirer and target is in substance similar to Phene et al. (2012), and we do not expect that the departure from the original measure should be of any significance. This variable was a dummy equal to 1 if the two firms were located in the same province; 0 – otherwise.

Regarding the *level of control*, the original study classifies three categories: (a) acquisition of assets, (b) acquisition of partial interest, and (c) acquisition of majority interest and mergers. However, our data source did not provide the “acquisition of assets” option in the acquisition type classification. Still, the definition of an asset can be very broad if left without further specification, as assets can range from equipment and facilities to buildings and to intangible assets (Villalonga and McGahan, 2005). Thus, it is not clear how to estimate the level of control that the acquirer can exercise after such acquisitions, when no detailed information is provided about the size, absolute or relative, of the acquired assets. For this reason, we decided to proceed as follows: First, we collected the exact percentage of interest acquired. Then, to be coherent with Phene et al. (2012), we used the acquired percentage as a base for the construction of a set of three dummy variables representing the three control classes. Specifically, we followed the definition of control proposed in the corporate governance literature (Claessens et al., 2000; Faccio and Lang, 2002) and identified *acquisition of minority interest* when the interest acquired was below 20 percent, *acquisition of partial interest* when the interest acquired was between 20 and 50 percent, and *acquisition of majority interest* when the interest acquired was above 50 percent. The reliability of this segmentation was then tested after the analysis.

Controls

We followed Phene et al. (2012) in defining and measuring also the control variables that might influence the acquirer's exploration and exploitation. *Acquirer knowledge stock* and *target knowledge stock* were measured as the total number of patents filed by the acquirer and the target, respectively, in the three years prior to the acquisition.

Acquirer size was measured as the log of the total assets one year prior to an acquisition. *Acquirer R&D intensity* was measured as the percentage of R&D expenditure to sales one year prior to an acquisition. *Acquirer performance* was proxied by return on sales (ROS), i.e., the ratio of the operating profit to firm sales one year before an acquisition, taken in percentage form. The *number of prior acquisitions* made by the acquirer in the two years prior to the focal acquisition was also controlled for. We were not able to retrieve the acquirer's number of prior alliances. However, in the original study, this variable had a coefficient close to zero and was omitted from several of the robustness checks. This made us confident that the lack of this control would not affect the results of our analysis. Also, we did not control for foreign acquirers, as our focus was limited to the Chinese domestic deals. Again, we are confident that this difference in the data collection between our sample and the original one (which included a proportion of foreign acquirers limited to 8%) does not have an effect on the results of the study. Finally, a control for the acquisition year was included as well.

Model

In order to test our hypotheses, we followed the original study and modeled our dependent variables using negative binomial regression models. Count models, such as the negative binomial, are well-suited for estimating variables that count the number of patents after an acquisition event (Blevins et al., 2015).

For each model, we estimated the degree of overdispersion to test whether the negative binomial is preferred over the Poisson model. After the analysis, we further considered the zero-inflated negative binomial as an alternative.

RESULTS

Table 1 presents the descriptive statistics of the original and the replication studies. There are some differences between the two samples. First, the Chinese sample contains a couple of firms with much higher exploration values than the US sample. This skews the mean of the Chinese sample, making it appear much larger. For instance, removing the firm with an exploration value of 755 yields a mean of 6.9, and removing the four firms with the largest exploration values reduces the mean to 2.2, which is close to the original sample. Second, the Chinese sample has more non-zero values than the original sample, which also contributes to a higher mean. A similar pattern is evident with respect to technological uniqueness and common technological knowledge. For instance, about 90 percent of the Chinese firms have technological uniqueness values between 0 and 2. Removing the firms with values above 2 reduces the mean to 0.8, which also indicates a larger number of non-zero values than in the US sample. In general, the Chinese firms are larger, invest less in R&D, have fewer prior acquisitions and are more similar in terms of performance.

Insert Table 1 and Table 2 about here

Table 2 presents the correlations of the replication sample. If compared to the correlation table of Phene et al. (2012), uniqueness is notably weaker in our sample, and target knowledge stock is notably

stronger correlated with exploration. In general, the Chinese sample shows smaller correlations between covariates, thus reducing possible multicollinearity issues.

Exploration

Tables 3 and 4 summarize the results from the negative binomial regressions with exploration (Models 1-6) and exploitation (Models 7-12) as dependent variables. Model 1 acts as a control model, Models 2-5 correspond to the main hypotheses, and Model 6 is the comprehensive model closely mimicking the sequence in the original study. In terms of likelihood-based measures, our control model (Model 1) compares favorably to the control model in the original article. In all our models, α and the associated likelihood ratio clearly indicate overdispersion, hence the appropriateness of the negative binomial regression model.

Phene et al. (2012) find support for H_{1A} in Models 2 and 6, suggesting that exploratory innovation increases with the target's number of unique areas of technological expertise. Specifically, their full model (Model 6) shows an estimated coefficient of 1.97. The estimated coefficient increases considerably in size when looking at their Model 2, where they report that for a one-unit increase in unique patents, the log of the expected exploration increases by 7.39, which results in an expected change in the incident rate of about 1,619. Given the excessive size of this result, we suspect that the authors are fitting a too complicated model to a dataset that is too sparse. We estimate a much weaker positive association in our Chinese sample. Our Model 2 shows a significant positive relationship of 0.952 (standard error (s.e.) = 0.38) between uniqueness and exploration, while Model 6 shows a significant positive relationship of 0.78 (s.e. = 0.4). In terms of null hypothesis significance testing, our results show support for H_{1A} , but are substantially smaller in terms of effect sizes compared to the original study.

Based on the level of the p-values associated with their model coefficients, Phene et al. (2012) conclude mixed results regarding the effects of knowledge commonalities (H_{2A}). Our findings show that the interaction between uniqueness and knowledge commonalities is negative and nonsignificant. These results are largely consistent with the results from Model 6. In summary, our data do not show support for H_{2A} of the original study.

The findings of the original study also show that common geographic bases of acquirer and target positively moderate the effect of uniqueness on exploration. However, the Chinese firms exhibit a behavior that does not support H_{3A} . We observe a nonsignificant interaction term, which is negative in Model 4, but close to zero in Model 6. Together, these results do not support H_{3A} .

Lastly, Phene et al. (2012) conclude that H_{4A} and H_{5A} are not supported. In line with the results from the original study, we find that majority interests tend to facilitate a greater exploration than the two minor control alternatives in Models 5 and 6, but the coefficients are nonsignificant. In Model 5, partial interests acquisitions are nonsignificant and positively related to exploration, whereas they are nonsignificant and negatively related to exploration in Model 6. In sum and similar to the original study, our results about the impact of the level of control on exploration are not in line with H_{4A} and H_{5A} .

Insert Table 3 about here

Exploitation

Table 4 summarizes the results of our models with exploitation as the dependent variable. Again, α and the associated likelihood ratio confirm that the negative binomial models are preferable compared to the Poisson model. The control model (Model 7) is again in line with the original study, with the addition that now it supports the expected positive impact of the acquirer's R&D intensity on

exploitation. Firms investing in R&D are, in fact, expected to better absorb and integrate the acquired technology, leading to higher outcomes (Cassiman and Veugelers, 2006).

Addressing the first hypothesis, Phene et al. (2012) find a significantly negative impact of uniqueness on exploitation. However, the coefficients that we find in both Models 8 and 12 show a still negative, but much weaker and nonsignificant relationship between the two variables. Thus, H_{1B} is not supported. With regard to knowledge commonality (H_{2B}), Phene et al. (2012) find a positive relationship, but their coefficients of 0.8 (Model 9) and 0.41 (Model 12) are nonsignificant. This makes them conclude that common technological areas do not seem to facilitate exploitation. In our replication, we find a positive and significant coefficient of 0.34 (s.e. = 0.16) in Model 9 and of 0.38 (s.e. = 0.14) in Model 12. These results are in line with H_{2B} . Regarding H_{3B} , we find a positive and nonsignificant relationship concerning common geographic base between the acquirer and the target firm in Model 10. However, the coefficient is significant in Model 12. The sizes of our estimated coefficients are about half of those in the original study. Using the same decision rules as in the original study, we conclude mixed support for H_{3B} . Finally, Phene et al. (2012) determine that exploitation is not sensitive with regard to the level of control. Our results show the opposite sign, but are also nonsignificant. Thus, hypotheses H_{4B} and H_{5B} are not supported neither in the original study nor in our study.

Insert Table 4 about here

Robustness checks

We conducted several tests to determine whether our replication results are sensitive to certain differences in the samples between the original study and our study. First, we reran the models without the outliers mentioned in the descriptive statistics section. For instance, we explored the impact of

running our models excluding exploration and exploitation values above 144 and uniqueness above 3, to make our maximum values more comparable to the original study. As the excluded firms constitute a very small part of our sample, neither the model coefficients nor the p-values changed substantially, which was not surprising.

Second, we included industry controls to check whether our broader industry focus had any effect on our results (Jensen-Vinstrup et al., 2018). We also ran our models using only the firms belonging to high-tech sectors. None of these tests indicated substantial changes compared to the results reported in this study. Moreover, we compared the means of the variables used in the analyses between firms in the semiconductor industry (SIC 3671-3679) and other firms in the sample and found no significant differences.

Third, as negative binomial models are non-linear models, we followed the approach suggested in the literature to graphically examine the interactions included in Models 3 and 4 (Wulff, 2015). These plots do not change the conclusions about H_{2A} and H_{3A} . For that reason they are not included in the paper, but available upon request.

DISCUSSION AND CONCLUSION

This paper replicates the measurements and analytical methods of the US-based study by Phene et al. (2012) on postacquisition knowledge exploration and exploitation in the context of China. Table 5 reports the support to the hypotheses established in the original and in this paper, respectively.

Insert Table 5 about here

Of the four hypotheses supported in the original study, we find evidence only for the positive effect of the target's technological uniqueness on the bidder's postacquisition exploration and partial evidence for

the hypothesis that geographical proximity facilitates exploitation. Hence, only one of the proposed mechanisms can be conclusively said to be context-free. Moreover, in contrast to the original study, we reveal that the technological knowledge shared between the target and the acquirer encourages postacquisition exploitation. Regarding the other five hypotheses that were not supported in the original study, we find coherent results, fleshing out the need for further clarification of the mechanisms involved in postacquisition knowledge integration with respect to these specific factors.

Our study contributes to several strands of research. First, we contribute to the literature on postacquisition innovation. We confirm the positive impact of the technological uniqueness of the target on postacquisition exploration. The effect size of the technological uniqueness obtained in our model is smaller than the one obtained in the original study. The target's uniqueness above certain levels is typically detrimental (Ahuja and Katila, 2001) if the acquirers do not have the absorptive capacity necessary for the effective integration of new knowledge, due to, for example, underdeveloped knowledge integration systems or weak managerial practices and skills compared to the US firms. Similarly, the employees' opposition to changes may stifle the ability of the acquirer to integrate the novelty (King et al., 2003). The reason could also be lower information transparency in the Chinese market for acquisitions, which does not allow detailed appreciation of the knowledge stock prior to an acquisition, ultimately making the absorption of extra knowledge more difficult. The fact that the full extent of new knowledge typically remains underutilized can also help explain why we did not find that technological uniqueness is negatively related to exploitation by the acquiring firm.

Our study also confutes Phene et al.'s (2012) rejection of the hypothesis about the positive effect of common technological knowledge on postacquisition exploitation. This can be explained by Chinese firms' efficiency in integrating familiar knowledge leading to incremental innovation (Puga and Trefler, 2010). Regarding the hypothesis that commonality of knowledge facilitates the transfer of the target's

technological uniqueness for exploration purposes, our results are coherent with Phene et al. (2012): Our replication provides evidence that this hypothesis does not hold irrespective of the contexts. Furthermore, in line with Phene et al. (2012), we cannot find support for the two hypotheses on the degree of a bidder's control over its target. We argue that the level of control may not be a sufficient proxy for the disruption of a target's activities. For example, in the case of China, not all acquisitions, not even those involving the transfer of majority ownership rights, imply significant disturbances in the target's daily operations (Liu and Woywode, 2013). The acquirer's experience in conducting similar acquisitions is also known to affect the transition period for the target (Haleblian and Finkelstein, 1999), which is a relevant factor for the Chinese sample. In the light of this, we posit that further investigation into the effect of the level of ownership rights on postacquisition innovation is necessary.

Second, the findings of this study advance our understanding of technological upgrading by Chinese firms and contribute to the literature on innovation capabilities of firms from emerging markets. We shed light on domestic acquisitions as another viable mechanism of technological upgrading. In fact, prior studies typically focus on cross-border deals as a means of strategic assets acquisitions by Chinese firms (Zhu and Zhu, 2016). These studies show that Chinese firms face major obstacles with knowledge transfer and absorption from the targets located in advanced markets due to insufficient absorptive capacity (Liu and Woywode, 2013). With this work, we reveal that the absorption of the target's unique technology by the acquirer, albeit quite temperate, can happen in the domestic context as well. This evidences that the insufficient absorptive capacity of Chinese bidders is not limited to foreign acquisitions.

Third, we contribute to the discussion on the impact of the external environment on firm strategy. Phene et al. (2012) find that geographical proximity between the two firms facilitates the absorption of knowledge unique to the target, leading to higher postacquisition exploration. This result is not supported

in our study. One explanation can be grounded in the context-specificities of our study, such as the intervention of the state into firms' decision-making. In China, provincial governments compete against each other for higher growth rates and lower social unrest through various means, such as encouraging firms to acquire underperforming firms and to diversify into unrelated industries, thereby filling in institutional voids (Li et al., 2012). Thus, although some firms acquire targets with unique knowledge stock located in the same province, the deal might not be knowledge driven. The complexity of the definition of distance in the context of China is arguably also based on the ambiguity of the results regarding the hypothesized positive effect of geographical proximity on exploitation. On the one hand, the cooperation between an acquirer and a target active in different provinces risks being undermined by cross-province trade barriers that act as boundaries that commit both business and innovation activities to the home province (Eberhardt et al., 2013). On the other hand, because of the political program to build a knowledge-based economy in China, the effect of geographical proximity may differ between state- and privately-owned firms: The former build up their innovation capability through nation-wide acquisitions enjoying government support, whereas the latter are confined to the provincial boundaries. This, then, muddies the direct effect of common geographical bases on postacquisition knowledge transfer and offers a fruitful avenue for future research.

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TABLES

Table 1. Descriptive Statistics

Variables	Original				Replication			
	<i>M</i>	<i>SD</i>	Min	Max	<i>M</i>	<i>SD</i>	Min	Max
Exploration by acquirer	1.75	9.64	0	82	9.13	59.76	0	755
Exploitation by acquirer	238.14	457.23	0	2295	56.70	323.96	0	2841
Target technological uniqueness	0.19	0.44	0	2	1.18	1.20	0	8
Acquirer / target common technological knowledge	0.22	0.45	0	2	0.85	1.09	0	7
Acquirer / target common geographic bases	0.63	0.53	0	2	0.51	0.50	0	1
Partial interest	0.27	0.44	0	1	0.21	0.41	0	1
Majority interest	0.17	0.38	0	1	0.64	0.48	0	1
Acquirer knowledge stock	1253.61	1832.9	1	7032	102.15	382.24	0	2500
Target knowledge stock	6.88	11.39	1	79	17.09	62.38	0	646
Size of acquirer	7.30	2.32	2.70	10.86	13.61	2.31	4	24
Acquirer R&D intensity	14.24	16.27	0.49	121.54	1.86	3.01	0	18
Acquirer performance	18.92	29.03	-157.54	50.93	9.35	8.77	-22	43
Acquirer prior acquisitions	2.62	4.82	0	26	0.85	1.19	0	7

Note: Original $N = 141$ acquisitions; replication $N = 188$ acquisitions

Table 2. Correlation matrix

Replication	1	2	3	4	5	6	7	8	9	10	11	12
1. Exploration by acquirer												
2. Exploitation by acquirer	0.15											
3. Target technological uniqueness	0.20	0.01										
4. Acquirer / target common tech. knowledge	0.11	0.02	-0.02									
5. Acquirer / target common geographic bases	0.07	0.11	-0.05	0.07								
6. Partial interest	-0.07	0.04	-0.06	-0.02	-0.02							
7. Majority interest	0.05	-0.02	0.03	0.03	-0.00	-0.71						
8. Acquirer knowledge stock	0.29	0.81	0.03	0.09	0.10	-0.11	0.00					
9. Target knowledge stock	0.53	-0.02	0.27	0.31	0.06	0.11	-0.09	0.05				
10. Size of acquirer ^a	0.18	0.29	0.17	0.18	0.06	-0.03	-0.05	0.35	0.11			
11. Acquirer R&D intensity	-0.05	-0.05	-0.22	0.07	0.11	-0.14	0.10	-0.07	-0.07	-0.19		
12. Acquirer performance	0.03	-0.03	-0.07	0.03	0.05	-0.04	0.09	-0.01	-0.08	-0.11	0.33	
13. Acquirer prior acquisitions	0.13	0.21	-0.04	0.26	0.01	0.06	0.02	0.35	0.00	0.49	-0.11	-0.02

Note: ^a log-scale

Table 3. Negative binomial regression: Exploration

Variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
1. Target technological uniqueness (H_{1A})		0.95 (0.38)	0.79 (0.35)	1.20 (0.42)		0.78 (0.40)
2. Acquirer / target common technological knowledge			1.01 (0.28)			0.91 (0.29)
3. Target technological uniqueness $\times$ common technological knowledge (H_{2A})			-0.23 (0.31)			-0.20 (0.30)
4. Acquirer / target common geographic bases				1.09 (0.48)		0.90 (0.47)
5. Target technological uniqueness $\times$ common geographic bases (H_{3A})				-0.48 (0.72)		-0.00 (0.65)
6. Partial interest (H_{5A})					0.01 (0.91)	-0.69 (0.82)
7. Majority interest (H_{4A})					0.75 (0.77)	0.12 (0.68)
8. Acquirer knowledge stock	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)
9. Target knowledge stock	0.01 (0.00)	0.01 (0.00)	0.01 (0.00)	0.01 (0.01)	0.01 (0.00)	0.00 (0.00)
10. Size of acquirer	0.21 (0.11)	0.11 (0.11)	0.09 (0.10)	0.14 (0.11)	0.23 (0.11)	0.15 (0.10)
11. Acquirer R&D intensity	0.11 (0.09)	0.11 (0.09)	-0.11 (0.10)	0.08 (0.09)	0.15 (0.10)	-0.08 (0.10)
12. Acquirer performance	-0.01 (0.03)	-0.01 (0.03)	-0.01 (0.03)	-0.02 (0.03)	0.00 (0.04)	-0.02 (0.03)
13. Acquirer prior acquisitions	-0.08 (0.19)	0.13 (0.21)	-0.13 (0.24)	-0.02 (0.22)	-0.09 (0.20)	-0.33 (0.25)
Likelihood ratio χ^2	49.95	57.77	73.21	63.61	51.93	77.52
Pseudo R^2	0.08	0.09	0.12	0.10	0.084	0.13
α	7.76	7.09	5.88	6.66	7.56	5.59
Likelihood ratio (χ^2) of $\alpha = 0$	2388	2013	1540	1919	2291	1474

Note: $N = 188$ acquisitions. All models include year-block dummies. Standard errors are in parentheses.

Table 4. Negative binomial regression: Exploitation

Variables	Model 7	Model 8	Model 9	Model 10	Model 11	Model 12
1. Target technological uniqueness (H_{1B})		-0.16 (0.16)				-0.24 (0.17)
2. Acquirer / target common technological knowledge (H_{2B})			0.34 (0.16)			0.38 (0.14)
3. Acquirer / target common geographic bases (H_{3B})				0.47 (0.29)		0.52 (0.32)
4. Partial interest (H_{5B})					0.07 (0.50)	-0.45 (0.53)
5. Majority interest (H_{4B})					-0.03 (0.45)	-0.32 (0.44)
6. Acquirer knowledge stock	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)
7. Target knowledge stock	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)
8. Size of acquirer	0.13 (0.09)	0.15 (0.09)	0.08 (0.09)	0.16 (0.09)	0.13 (0.09)	0.10 (0.09)
9. Acquirer R&D intensity	0.13 (0.06)	0.12 (0.06)	0.12 (0.06)	0.13 (0.06)	0.13 (0.06)	0.11 (0.06)
10. Acquirer performance	-0.01 (0.02)	-0.01 (0.02)	-0.03 (0.02)	-0.01 (0.02)	-0.01 (0.02)	-0.03 (0.02)
11. Acquirer prior acquisitions	0.07 (0.16)	0.03 (0.17)	0.16 (0.18)	0.05 (0.16)	0.08 (0.17)	0.17 (0.19)
Likelihood ratio χ^2	115	116	121	118	115	127
Pseudo R^2	0.09	0.09	0.10	0.09	0.09	0.10
α	3.61	3.59	3.48	3.55	3.61	3.37
Likelihood ratio (χ^2) of $\alpha = 0$	7123	7088	6234	7053	5869	5009

Note: $N = 188$ acquisitions. All models include year-block dummies. Standard errors are in parentheses.

Table 5. Summary of support to the hypotheses established in the paper by Phene et al. (2012) and in the present paper

Phene et al. (2012) Hypotheses	Original	Replication
H_{1A}	Supported	Supported
H_{1B}	Supported	Not supported
H_{2A}	Not supported	Not supported
H_{2B}	Not supported	Supported
H_{3A}	Supported	Not supported
H_{3B}	Supported	Partly supported
H_{4A}	Not supported	Not supported
H_{4B}	Not supported	Not supported
H_{5A}	Not supported	Not supported
H_{5B}	Not supported	Not supported