Management and Organization Review

CAMBRIDGE UNIVERSITY PRESS

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Journal:	*Management and Organization Review*
Manuscript ID	MOR-GIC-19-191.R4
Manuscript Type:	Article
Keywords:	Technology ladder, Market ladder, Catch-up, Technological learning, Emerging markets

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ABSTRACT

The influence of technological learning on industry-level catch-up has long drawn substantial attention in the catch-up research field. However, the underlying mechanisms of technological learning and the unique catch-up context in large emerging economies are much less explored. To explain the technological learning processes of latecomers that face the technology gap and strive to build differentiated competitive advantage, this study builds on the absorptive capacity perspective and deconstructs technological learning processes into two mechanisms: technology decomposition and technology recombination. The former entails decomposing advanced technologies into pieces, parts, or modules, while the latter entails the process of capturing market opportunities through recombining knowledge from diverse sources into commercial products through localized innovations and adaptations. Then, we propose a~~n~~ unique "ladder-like" catch-up context (i.e., technology ladder and market ladder) and investigate how the technological learning process and ~~such a~~the unique catch-up context jointly affect industrial catch-up performance in China. Using~~ a~~ seven-year panel data from Chinese manufacturing industries, the results indicate that only technology recombination has a significantly positive relationship with ~~the ~~industrial catch-up performance. In addition, the market ladder strengthens the positive impact of technology recombination on ~~the ~~industrial catch-up, while the technology ladder weakens the positive impact of technology decomposition on ~~the ~~catch-up.

KEYWORDS: Technological learning, technology ladder, market ladder, catch-up, emerging markets

INTRODUCTION

Due to the accelerated economic development in countries such as China and India in past decades, the ~~catching~~catch-up experience of large emerging economies has attracted ~~enormous~~ great attention in the extant literature (Chatterjee & Sahasranamam, 2018; Guo & Zheng, 2019; Lee, Park, & Krishnan, 2014; Xiao, Tylecote, & Liu, 2013). One primary stream of research highlighted the role of technological learning in the catch-up of latecomers and demonstrated that ~~the~~ effective technological learning processes are associated with increasing the development of absorptive capability, which facilitates latecomers in accumulating innovative capability and achieving technological catch-up (Chung & Lee, 2015; Figueiredo & Cohen, 2019).

Despite a considerable focus on latecomer technological learning in the literature, several issues remain unsettled. First, substantial catch-up studies have exclusively emphasized that latecomers largely rely on external knowledge acquisition from foreign firms (Chen, 2009; Ray, Ray, & Kumar, 2017; Tzeng, 2018), ~~whereas~~ while little is known about the underlying learning-related mechanisms that could clarify how these latecomers absorb ~~the~~ acquired knowledge and create new knowledge (Figueiredo & Cohen, 2019; Lewin, Massini, & Peeters, 2011). However, reality has shown that not every latecomer that began learning from foreign firms ~~ended up~~ successfully achieved ~~in~~ industrial catch-up (Vind, 2008; Yap & Truffer, 2019). Therefore, to better understand industrial catch-up, it is essential to analyze the underlying learning-related mechanisms that allow industries to absorb knowledge and learn quickly (Chatterjee & Sahasranamam, 2018; Liefner, Si, & Schafer, 2019). Absorptive capacity, which ~~is~~ goes beyond knowledge acquisition and has been refined as a multidimensional construct involving knowledge acquisition, assimilation, transformation, and exploitation, offers a useful lens to deconstruct the technological learning process and address this gap (Lane, Koka, & Pathak, 2006; Zahra & George, 2002).

Second, the technological learning process is highly context-dependent (Figueiredo & Cohen, 2019; Lee & Malerba, 2017). In this regard, the unique contexts of large emerging economies cannot be ignored because these ~~will~~ significantly shape the effectiveness of technological learning. Previous studies have investigated technology-related contexts, such as technological regimes (Lee, Gao, & Li, 2017; Li, Capone, & Malerba, 2019), and market-related contexts, such as market size and market segmentation, for catch-up success (e.g., Mu & Lee, 2005; Wei, Wang, & Liu, 2018). However, we argue that systematic discussions of large emerging economies' structural aspects are still nascent (Brandt & Thun, 2016; Thun, 2018). This is important because large emerging economies normally have a "ladder-like" context: a highly segmented market structure on the demand side (i.e., from price-sensitive and good-enough markets to price-tolerant and high-quality markets) (Buckley & Hashai, 2014; Li et al., 2019) ~~that is simultaneously supplied by~~and diverse levels of technologies on the supply side (i.e., from low-end technologies to high-end advanced technologies)~~: a "ladder-like" context~~. Specifically, each market segment is a crucial rung on the market ladder, and each technology building block is a rung on the technology ladder (Brandt & Thun, 2016). We contend that applying the notion of a ladder to both the technology and the market contexts demonstrates the~~a~~ multilevel nature of the catch-up contexts of large emerging economies (Brandt & Thun, 2016; Thun, 2018), and such concepts are key to understanding how large emerging economies adopt learning processes to reduce technological gaps and compete with leading foreign firms (Brandt & Thun, 2016).

To address the aforementioned gaps, this study first deconstructs the technological learning process into technology decomposition and technology recombination. We then discuss how the unique catch-up context in terms of the technology ladder and market ladder shapes the impact of technological learning on industrial catch-up performance. More specifically, our destruction of technological learning is theoretically related to the absorptive capacity perspective, which emphasizes four main aspects of the learning process ~~as~~: knowledge acquisition, assimilation, transformation, and exploitation (Zahra & George, 2002). We deconstruct the technological learning process into technology decomposition and technology recombination. Technology decomposition corresponds to knowledge acquisition and assimilation, especially in terms of decomposing advanced technologies acquired externally into pieces, parts, or modules; through this, latecomers can significantly mitigate the technology gap between themselves and leading foreign competitors. Technology recombination corresponds to knowledge transformation and exploitation, aiming to capture market opportunities by recombining technologies and knowledge acquired from diverse sources into commercial products with localized innovations and adaptations (Guo & Chen, 2013; Guo & Zheng, 2019). We argue that both technology decomposition and technology recombination are crucial learning mechanisms for latecomers to catch up with industrial leadership because they leverage limited knowledge and resources to create something from nothing (Liu, Ying, & Wu, 2017). We believe this deconstruction of the technological learning process illustrates how latecomers with limited resources can progress from low-tier (or productive) skills to high-tier innovation (Miao, Song, Lee, & Jin, 2018).

We further introduce the concepts of the industry-level technology ladder and market ladder to capture the unique structural features of large emerging economies engaged in catch-up. The technology ladder refers to the degree of technological continuity among different levels of a given industry and its constituent firms. The market ladder refers to the degree of continuity of market segments for all firms in a given industry. A more seamless technology ladder or market ladder ~~will~~ enables latecomers to make full and efficient use of their capabilities and greatly reduce the technological threshold requirements when engaging in catch-up (Li et al., 2019; Wei et al., 2018). Specifically, a continuous technology ladder increases the availability of knowledge and may serve as a substitute for technology decomposition. A continuous market ladder gives latecomers specializing in technology recombination more opportunities to capture market share and profit through localized innovations. We argue that the technology ladder weakens the positive impact of technology decomposition on industrial catch-up performance, while the market ladder strengthens the positive impact of technology recombination on industrial catch-up performance.

Using an industry-level sample of Chinese manufacturing industries during the period of 2001 to 2007, we conducted a panel data analysis to validate our research hypotheses. The choice of Chinese manufacturing industries is justified for two reasons. First, as ~~one~~ a large emerging economy, China has made great achievements in terms of industrial catch-up and has enjoyed significant growth in the manufacturing sector over four decades (Brandt, Biesebroeck, & Zhang, 2012; Brandt & Thun, 2016). Second, even in the present China still faces a lack of core technologies as a whole and the challenge of catching up with foreign industry leaders (Wei et al., 2018). According to an evaluation of China's technological development level by the Ministry of Science and Technology of China in 2016, among the 1,350 technologies in 13 important technical fields, 17% were at the cutting-edge international level, 31% reached the parallel level, and 52% were still lagging behind,~~at the following level,~~ relative to international ~~standards~~ levels (Minister of S&T of People's Republic of China, 2016). Therefore, it is necessary to examine the unique learning-related mechanisms underlying technological learning processes to understand why some industries have become globally competitive, while others have not. Chinese manufacturing industries provide an appropriate context to test how technology decomposition and technology recombination, interplayed with the technology and market ladders, can explain the ~~a~~cross-industry variations ~~on~~in catch-up performance in large emerging economies for the benefit of policymakers and practitioners.

This study contributes to the latecomer technological learning and catch-up literature in the following ways. First, through the lens of the absorptive capacity perspective, we unpack the underlying technological learning process by deconstructing it into technology decomposition and technology recombination, which is an approach that has been largely ignored in previous studies. Based on this, our study empirically confirms that only technology recombination significantly affects industry-level catch-up performance. Second, going beyond prior studies that mainly emphasize the generic characteristics of the catch-up context in the developing countries, the notion of the technology ladder and market ladder in our study systematically illustrates the structural traits of catch-up contexts in large emerging economies. Furthermore, the joint effects of technology decomposition, technology recombination and catch-up context enriches our understanding of why different industries have heterogeneous catch-up performance under similar catch-up contexts (e.g., technology gap and speed of technology development).

THEORETICAL BACKGROUND AND HYPOTHESES

Technology Decomposition and Technology Recombination

Technology decomposition and technology recombination are based on the absorptive capacity perspective. Absorptive capacity was originally defined as the ability "to recognize the value of new, external information, assimilate it and apply it to commercial ends" (Cohen & Levinthal, 1990: 128). After decades of development, the absorptive capacity literature has acknowledged that technological learning processes consist of four dimensions: knowledge acquisition, assimilation, transformation, and exploitation (Figueiredo & Cohen, 2019; Lane, Koka, & Pathak, 2006). However, the existing literature on latecomer technological learning pays significant attention to how latecomers acquire external advanced knowledge (Bell & Figueiredo, 2012; Lee & Malerba, 2017; Zahra & George, 2002) while neglecting the learning mechanisms pertinent to other dimensions, such as assimilation, transformation, and exploitation. ~~Despite~~ Although external advanced technologies can be brought by foreign firms to provide opportunities for catching up, the extent to which such opportunities ~~can be~~are used depends greatly on the ~~latecomer's adopted~~ learning strategy the latecomer adopts (Kim, 1998; Tzeng, 2018). In addressing this issue, we propose an analytical framework of latecomer technological learning processes to reveal how latecomers in the ~~catching-~~catch-up process absorb external knowledge and use knowledge.

The technological learning process in this study is divided into two mechanisms: technology decomposition and technology recombination. As different actors in a given industry collaborate, technology decomposition and technology recombination may intertwine and relate to each other (Carlile & Rebentisch, 2003). In addition, these two mechanisms are not necessarily sequential because defining where one begins or ends is difficult in practice (Carlile & Rebentisch, 2003). For example, when acquired technical knowledge is relatively simple and therefore can be smoothly assimilated, technology decomposition may be unnecessary, and only recombination may occur.

Technology decomposition entails comprehensively understanding the architecture and principles embodied by a given technological component and its modules (Chen & Liu, 2005; Guo & Chen, 2013; Henderson & Clark, 1990; Ulrich, 1995). The existing literature generally emphasizes that knowledge acquisition is distinct from knowledge assimilation, whereby externally acquired information is analyzed and understood (Kim, 1997; Zahra & George, 2002). However, the technology gap between latecomers and industry forerunners may impede knowledge assimilation, and previous studies have failed to demonstrate how latecomers should adapt their learning processes in response. To address this problem, this study introduces the concept of technology decomposition based on the absorptive capacity perspective, which can clarify the methods by which latecomers decode the architecture and design principles embodied in external technologies. Through technology decomposition, latecomers can overcome obstacles to knowledge assimilation. Technology decomposition typically entails (but should not be limited to) gradual participation in collaborative product development among system vendors and suppliers of materials, components, and equipment; gradual extension from peripheral to core subsystems or from parts to product modules and system products; and adaptive and/or localized technology improvement (Choung, Hwang, & Song, 2014; Guo & Chen, 2013).

The tension between the resource-consuming feature of catching ~~-~~up and the severe resource deficiencies faced by latecomers makes efficient and effective knowledge transformation and exploitation processes critical. An effective way for latecomers to address such constraints is technology recombination. Extending the conceptualization of knowledge transformation and knowledge exploitation ~~on the basis of~~based on the absorptive capacity perspective, technology recombination refers to the process through which latecomers in large emerging economies fully capture the business opportunities in domestic markets. Through this ~~such~~ process, technology recombination ~~thereby~~ effectively facilitates the ~~accumulating~~ accumulation of the financial resources from market returns to sustain long-term efforts to catch ~~ing~~ up. ~~catchin~~Specifically, the characteristics of domestic demands in large emerging economies are different from those in developed markets. For example, some market segments in large emerging economies do not necessarily require the most sophisticated technology and may value the price–value ratio highly (Brandt & Thun, 2016; Thun, 2018). With a more intuitive understanding of the domestic market ~~compared to~~than foreign firms, latecomers can effectively recombine knowledge to satisfy particular domestic market segments, such as the more price-sensitive low-end segments at the initial catch-up stage or the growing middle segments that require "good-enough" products and innovation (Brandt & Thun, 2016; Gadiesh, Leung, & Vestring, 2007; Thun, 2018). ~~Especially~~In particular, technology recombination enables latecomers to capture domestic market opportunities through reconfiguration and localized innovation, resulting in a favorable cost–quality ratio that satisfies domestic market segments (Thun, 2018). In contrast, knowledge transformation denotes the combining of existing knowledge with newly acquired and assimilated knowledge, and knowledge exploitation denotes the new application of knowledge (Zahra & George, 2002), setting aside the distinctive activities of technology recombination for targeting particular market segments to formulate differentiated competitive advantage in large emerging economies. Technology recombination typically entails (but should not be limited to) the integration of local and ~~hyper-local~~hyperlocal technologies and expertise from diverse sources, the collaborative development of product designs and manufacturing processes, the fusion of different technical routines and standards, the exploitative reconfiguration of local technological expertise, and the recombination of familiar components in new ways (Arts & Veugelers, 2014; Guan & Yan, 2016; Guo & Chen, 2013).

In addition, we note that some concepts in existing studies share a similar focus on recombination: for example, ~~the~~ “combinative capability” proposed by Kogut and Zander (1992) and the “composition-based view” (CBV) proposed by Luo and Child (2015). Given this shared focus, we believe technology recombination can be regarded as a specific extension of the combinative capability proposed by Kogut and Zander (1992). The concept of combinative capability is a more generic concept that ~~emphasizing~~emphasizes the intersection of the capability to synthesize and apply current and acquired knowledge in a competitive environment (Kogut & Zander, 1992). Technology recombination is useful in the context of large emerging economies because latecomers can recombine domestic knowledge inputs to provide the exact level of quality products and innovations required by the domestic market and further build differentiated competitive advantage (Brandt & Thun, 2016; Thun, 2018).

The CBV attributes ~~a~~ firms’~~’s~~ competitive advantage to being able to “identify a set of resources available in the market that they can purchase and to combine them in a way that is creatively and speedily adaptive to market requirements” (Luo & Child, 2015: 379). However, the CBV does not treat the possession of knowledge as a superior resource, and it exclusively emphasizes the creative use of resources available for sale in the open market (e.g., technology, brand, services, channels) to satisfy mass consumption (Luo & Child, 2015). By contrast, our study of technology recombination highlights knowledge as a special resource—some knowledge cannot be purchased in the market, such as tacit knowledge about certain products and technologies. To further support and clarify our position, in Appendix I, we summarize the key theoretical arguments in the existing literature on concepts related to technology decomposition and technology recombination.

Technology Decomposition, Technology Recombination, and Catch-up Performance

Technology decomposition can mitigate or overcome the potential negative influence of a large technology gap between foreign forerunners and latecomers, thus facilitating the catch-up process (Lee, Cho, & Jin, 2009). The technological gap represents ~~“a~~ great promise~~”~~ ~~(Gerschenkron, 1962)~~ because it provides latecomers with the opportunity to imitate and use more advanced technology elsewhere (Fagerberg, Srholec, & Knell, 2007). To take advantage of this learning opportunity, latecomers must overcome obstacles in the path of assimilating external technology—specifically, a knowledge threshold in certain sectors or technology fields must be crossed (Jang, Lo, & Chang, 2009). Otherwise, large technology gaps can frustrate attempts to catch up (Haddad & Harrison, 1993). As such, technology decomposition is helpful in dividing advanced technologies into knowledge subsets that are much easier to learn and understand as well as in accelerating assimilation of external knowledge through better use of externally accessible expertise (Chen & Liu, 2005). Technology decomposition is therefore crucial for ~~greatly decreasing~~ lowering the learning threshold for latecomers aspiring toward a higher rung on the technology ladder and improved mass production (Mathews & Cho, 1999). Moreover, technology decomposition can help latecomers greatly reduce the cost and time associated with understanding information obtained from external sources, thus accelerating ~~the~~ capability-building ~~process~~ during the catch-up process. Thus, we propose the following:

Hypothesis 1: Technology decomposition is positively related to catch-up performance.

On the one hand, in the process of technology recombination, latecomers can recombine technologies and expertise from a wide variety of external sources or recombine these technologies with existing expertise into new technology and product developments (Keupp & Gassmann, 2013). On the other hand, they can localize or adapt technologies acquired to meet specific demands in the highly segmented domestic market and new market segments created by technological changes, or they can transplant the technical expertise arising from~~built in~~ technology decomposition into new market segmentations or applications (Li et al., 2019; Thun, 2018; Wei et al., 2018). Hence, technology recombination is not only a learning and knowledge-creation process in which latecomers' technological capability is built and enhanced but also a moderator for latecomers to take advantage of market opportunities to increase the possibility of and efficiency in obtaining market returns (Guo & Chen, 2013). These market returns allow latecomers to accumulate sufficient capital for further investments in research and development (R&D)—the key to being capable of upgrading their technological capabilities (Wei et al., 2018). By upgrading their technological capabilities, latecomers are more likely to achieve sustainable catch-up (Li et al., 2019). Therefore, we propose the following:

Hypothesis 2: Technology recombination is positively related to catch-up performance.

Large Emerging Market contexts: Technology Ladder and Market Ladder

The contexts of large emerging economies, especially Brazil, Russia, India, and China (the BRICs~~ economies~~), may differ from those in newly industrialized economies (such as Singapore, Korea, and Taiwan) or other developing countries with relatively small populations ~~size~~ and domestic ~~market~~markets (Brandt & Thun, 2016; Wei et al., 2018). The empirical studies on emerging ~~markets~~market contexts are summarized in Appendix II.

For latecomers, catch-up is essentially a process of learning how to improve product quality and technological capability to narrow the economic distance from industry leaders (Guo, Zhang, Dodgson, & Gann, 2019b). A highly segmented technology and market structure ~~strongly~~ implies~~y~~ that latecomers in large emerging economies must select an appropriate entry point in the range~~,~~ from low-end to high-end technology and market segments according to their existing learning processes and mechanisms~~,~~ and then keep moving up the ladder. Nonetheless, the empirical evidence remains ~~scanty~~scant on how latecomers implement learning-related mechanisms in different technology- and market-related contexts for industrial catch-up in large emerging economies. A typical exception is Figueiredo and Cohen (2019), who explored how Brazil's forestry and pulp industry responded to opportunities for early entry into path-creation technological catch-up. For this reason, a more systematic and empirically grounded understanding of the conditions under which latecomers with different learning mechanisms achieve catch-up is still needed (Miao et al., 2018). Specifically, this study introduces the concepts of the technology ladder and market ladder to capture the unique structural features of catch-up contexts in large emerging economies. An industry's technology ladder reflects the degree of continuity of technology-level distribution in that industry, and its market ladder reflects the degree of continuity of market segments in that industry. Heeding the call by Miao et al. (2018), we argue that the ladder-like contexts ~~are the moderating effects on~~serve as contingencies ~~on~~in the relationships between technological decomposition, recombination, and industrial catch-up performance because such interactions ~~will~~ significantly influence the possibility and cost of leveraging external resources and opportunities, resulting in divergent catch-up performances.

Specifically, technology decomposition corresponds to knowledge acquisition and assimilation, aiming to mitigate the technology gap that frustrates knowledge assimilation. A continuous technology ladder increases the availability of knowledge and decreases the difficulty of knowledge acquisition and assimilation. Therefore, we mainly postulate that the technology ladder may serve as a substitute for technology decomposition in improving industrial catch-up performance. In addition, technology recombination mainly corresponds to knowledge transformation and exploitation, with the aim of capturing market opportunities by recombining diverse technologies and knowledge into commercial products. Therefore, we purposively focus on the contingent role of the market ladder between the relationship of technology recombination and industrial catch-up performance.[1]

The moderating effect of the technology ladder

In a given industry, the level of continuity in the technology ladder ~~will~~ greatly affects the quantity of available knowledge and the difficulty involved with knowledge acquisition. The higher the level of continuity of the technology ladder is, the greater the availability of knowledge, which may induce a substitute for the impact of technology decomposition on catch-up performance. Within such industries, no matter which technology tiers the latecomers are in (even for local latecomers with relatively weak capabilities), it is easy for them to meet many other firms from ~~an~~ adjacently higher technology tiers, and they have ~~more~~ many opportunities to benefit from the foreign advanced technology imported by the top rungs in the ladder, especially in the context of large emerging economies (Brandt & Thun, 2016).

In China, the presence of a large number of firms ensures continuity in the distribution of technology and capability levels across firms within a given industry. Due to the technological superiority of foreign firms relative to domestic firms, foreign firms often occupy the top end of the technology ladder in China (Zhang, Li, Li, & Zhou, 2010). As a typical case, Mu and Lee (2005) illustrated how knowledge was acquired from the Bell Telephone Manufacturing

[1]We also noted that the technology ladder may moderate the relationship between technology recombination and catch-up performance. However, due to the little theoretical relevance and unclear underlying mechanisms, we decided not to discuss this issue in this paper to avoid diluting the focus of the study. In addition, we empirically tested such an assumption and obtained nonsignificant moderation results (results available upon request).

Company by Shanghai Bell (a Sino–foreign joint venture), then by domestic firms, such as Huawei. ~~When drawing~~As an analogy between technology development and ladder climbing, the more rungs domestic latecomers face and the more consecutive the rungs are, the ~~easier they~~more easily the latecomers can climb the ladder (Brandt & Thun, 2016). Missing rungs at any point can impede the development process for ~~those~~ climbers at low levels. As a consequence, the difficulty and cost involved in absorbing external knowledge tend to decrease, and such a favorable knowledge environment may weaken the facilitating role of technology decomposition by reducing the learning threshold for catching up. Even latecomers with a relatively weak level of technology decomposition can acquire external knowledge because they can easily find learning targets ~~easily~~ and establish linkages with advanced targets. These latecomers may source knowledge from these linkages through various acquisition channels, such as labor turnover; technology cooperation agreements; licensing; interaction among customers, producers, and technology developers; and learning by imitation (~~Guo & Guo, 2011;~~ Hansen & Lema, 2019; Xiao et al., 2013). Such a continuous technology ladder allows domestic firms to gradually assimilate advanced technology through using spillovers from a set of actors in the catch-up process, and it ensures the continuity of the capability-building process at the industry level (Lee & Ki, 2017; Li et al., 2019).

Moreover, the high continuity of a technology ladder may greatly reduce the need for local latecomers to develop and innovate technologies internally (Awate, Larsen, & Mudambi, 2012; Xiao et al., 2013). Internal development is often perceived as ~~more risky or~~riskier or more uncertain than acquiring technology from elsewhere. Therefore, we propose the following substitute effect hypothesis:

Hypothesis 3: The more continuous the technology ladder is at the industry level, the weaker the positive impact of technology decomposition on catch-up performance.

The moderating effect of the market ladder

Previous studies revealed that large emerging economies (especially the BRICs) often have several typical economic features, such as a large potential domestic market (Guennif & Ramani, 2012; Mu & Lee, 2005; Wei et al., 2018) and a highly segmented market structure (Buckley & Hashai, 2014; Gadiesh et al., 2007; Li et al., 2019). A highly segmented market comprises a market ladder from the low-end to the high-end segments, in which the technology and capability requirements are different across different segments. This is especially important for latecomers in manufacturing sectors because the ~~huge~~ large domestic market ~~size~~ in large emerging economies is more likely to make each market segment ~~big~~large enough to provide economies of scale. Each market segment in the domestic market serves as a rung on the developmental ladder. ~~In s~~Specifically,~~:~~ demand in the low-end—the first rung on the ladder—provides latecomers with an “incubation space” in which they can start with low-level capabilities, develop capabilities, and increase sales volumes. In addition,~~;~~ demand in medium- and higher-end market segments enables latecomers to learn about consumers’ preferences in these segments and to justify the sizable investments in R&D, personnel, and equipment that upgrading entails (Brandt & Thun, 2016; Li et al., 2019).

In a market ladder with a high level of continuity, local latecomers specialized ~~at~~ in technology recombination, on the one hand, may have a greater chance of capturing market opportunity through localized innovations. Notably, products designed domestically are most often introduced first in the domestic market rather than in global markets (Butollo & Ten Brink, 2018; Mu & Lee, 2005). Latecomers widely employ the market strategy of targeting lower-end markets or niche markets, especially in their early stages of development (Lee, Lim, & Song, 2005). With a continuous market ladder, an industry specialized in technology recombination can easily find market segment targets matching the existing technology and capability levels. This provides a space to survive and develop (Wei et al., 2018; Zeschky, Widenmayer, & Gassmann, 2011). As capability develops, latecomers can continuously use recombination strategies to seize market opportunities with local requirements and ~~to~~ become strikingly innovative in manufacturing and product designs (Butollo & Ten Brink, 2018). After observing and analyzing products or technologies~~y~~ in different market segments (usually in higher-level market segments), latecomers can sometimes integrate the knowledge and technology learned into their own product developments.

On the other hand, for latecomers specialized ~~at~~in technology recombination, a market ladder with a high level of continuity ~~will make~~facilitates profiting from local markets~~ easier~~. For example, latecomers can offer "good-enough" quality at lower costs to meet the demands of price-sensitive market segments (Thun, 2018; Wei et al., 2018). A continuous market ladder can provide more opportunities to ~~take~~ adopt the above development strategy and keep improving, which is likely a necessary condition for latecomers to climb the market ladder. In addition, a continuous market ladder can help latecomers with strong recombination capabilities anticipate new technological developments and capabilities, which in turn incentivize them to invest more profit into capability improvement. Consequently, latecomers with strong recombination capabilities ~~will~~ benefit from the learning curve and thus achieve higher levels of catch-up performance.

Hypothesis 4: The more continuous the market ladder is, the stronger the positive impact of technology recombination on catch-up performance.

METHOD

Data and Sample

We used the industry, not the firm, as the unit of analysis and created an industry–year dataset. Our data cover ~~China's~~ all two-digit Standard Industrial Code (SIC) manufacturing industries in China for the period between 2001 and 2007.[2] This was a period when China ~~continued~~

[2] We excluded three of the 29 manufacturing industries from our analysis because of strict government regulations or incomplete data, i.e., Tobacco Processing, Petroleum Processing, and Other Manufactures (Guo, 2008).

~~to~~was transitioning from a central planning system to a market-oriented system, and the country made numerous national policies to promote technological upgrades. Specifically, the Chinese central government released the 10th Five Year Plan (2001–2005), which ushered in the national technological upgrading initiative that continued through the 11th and 12th Five Year Plans. In 2005, the Chinese central government released its National Medium-and Long-Term Program for Science and Technology Development, prioritizing the policy of "indigenous innovation". During this period of technological upgrading, the Chinese government ~~is~~ was quite open to bottom-up experimentation and learning (Heilmann, 2018, p173), and such an embrace of local experimentation stimulated diverse trial-and-error experiments among different industries. This provide~~s~~d a beneficial context for our empirical test. Our data show that for most industries, the productivity gap between local firms and foreign firms hosted in China persisted during the period of our study. Notably, according to the mean values of catch-up performance in each year (2000-2007), only five industries achieved a level surpassing that of their foreign competitors; the average productivity gap is 49,686 Yuan per capital and the largest gap is 151,605 Yuan per capital (the Raw Chemical Materials and Chemical Products industry) (see Appendix III). If the foreign competitors hosted in developed countries were taken as the reference, the gap could be even greater.~~We excluded three industries of the 29 manufacturing industries from our analysis because of strict government regulations or incomplete data, i.e., Tobacco Processing, Petroleum Processing, and Other Manufactures (Guo, 2008).~~

Our dataset combines five different secondary data sources. Four were compiled by China's National Bureau of Statistics (CNBS): the Annual Industrial Survey Database (AISD), the Industrial Product Production Capacity Database (IPPCD), the China Statistical Yearbook, and the China Statistical Yearbook on Science and Technology (S&T Yearbook). The AISD and IPPCD provide detailed firm-level financial and operational information for all state-owned and nonstate-owned industrial enterprises above the designated size of five million RMB in revenue, foreign firms included. These firm-level data are aggregated to measure the two industry-level variables—the technology ladder and the market ladder. The China Statistical Yearbook and S&T Yearbook provide aggregated data at the industry level for most other variables. The fifth source is the marketization index compiled yearly by the National Economic Research Institute in China (Fan, Wang, & Zhu, 2010). Due to~~Because~~ the limitation of the IPPCD~~ contains data only from 2000 to 2006~~, this study set up ~~a ~~seven-year panel data, with a one-year lag between the independent variables (from 2000 to 2006) and the dependent variables (from 2001 to 2007).

The AISD is recognized as the most comprehensive firm-level dataset, ~~counting~~accounting for approximately 90% of the total output in most Chinese industries (Wang & Li, 2014); it has become an important and accurate source for academic research because it has achieved a level of consistency in data collection across time, industries~~y~~, and regions (e.g., Park, Li, & Tse, 2006; Zhou, Gao, & Zhao, 2017). Its sample size was more than 120,000 in 2000 and~~,~~ ~~which ~~increased to nearly 280,000 in 2006. It contains firm-level statistical indicators such as industrial output, value-added, employment, subsidy, and industry code (at the four-digit level). Each firm is identified by an invariant code in the dataset, based on which the AISD and IPPCD are combined. The IPPCD includes production capacity data by product code. The data collected from the China Statistical Yearbook include the following: number of firms, number of employees,~~ the~~ original value of microelectronics-controlled equipment, sales revenue from the principal business, profit, fixed-asset investment, and industrial value-added of both all firms and foreign firms in each industry. Data from the S&T Yearbook include (a) industry-level aggregates of large- and medium-sized enterprises (LMEs): number of firms, number of employees, sales revenue, new product sales, intramural expenditure on science and technology (S&T) activities, expenditure on technology import, technology absorption and domestic technology purchase, number of invention-type patent and total patent applications, and funding amount obtained for S&T activities from four different sources; and (b) industry-level aggregates of universities and public research laboratories: number of S&T personnel, number of scientists and engineers, and intramural expenditure on S&T activities. All monetary variables are deflated by taking 2000 as the base year, with the producer price index for manufactured goods taken from the China Statistical Yearbook.

Variable Measurements

Dependent variable: Catch-up performance

This study used domestic firms' improvement in labor productivity to reflect an industry's catch-up performance (Jung & Lee, 2010; Lyu, Lin, Ho, & Yang, 2019). Catch-up performance is shown in terms of increasing labor productivity when industry firms climbed the ladder of value chains toward higher value-added activities (Lee, 2013). Labor productivity can be measured easily and compared clearly across different contexts. Specifically, labor productivity was calculated by the industry-level value-added per capita, excluding foreign firms in the industry. *Catch-up performance* was measured as the labor productivity difference between the prior year and the focal year. Because the amount variable is highly skewed, we computed the natural logarithm.

Independent variables: Technology decomposition and technology recombination

As an industry-level ~~research~~study, we measured technology decomposition and technology recombination using statistical data at the industry level from the China S&T Yearbook. According to our theory, technology decomposition involves dividing advanced technologies into knowledge subsets, which facilitates the assimilation of advanced knowledge. Therefore, expenditure on technology absorption of the acquired technology is a good indicator available in the CNBS ~~aggregated level~~ dataset at the aggregate level to reflect firms' efforts in technology decomposition activities. Taking ~~a~~the Chinese leading air separator system manufacturer HASSMC ~~for~~as an example, it imported a medium- and low-pressure turbo-compressor manufacturing technology in ~~terms~~ the form of technical blueprints from Hitachi Corporation (Japan) in 1981. In 1987, HASSMC signed a contract with Demag Company (German) to import the design and manufacturing technology for medium- and high-pressure turbo-compressors ~~in terms of~~through cooperative production. To assimilate the foreign advanced technology, HASSMC invested ~~many expenditures on~~heavily in these activities, which afterwards served as a critical foundation for HASSMC's self-development of new compressor technologies in the sixth and seventh generations of air separator systems since 1996 (Guo & Chen, 2013). Therefore, we measured technology decomposition using the following: (a) absolute assimilation intensity,~~:~~ the ratio of expenditure on technology absorption to sales revenue from the principal business,~~;~~ and (b) relative assimilation intensity,~~:~~ the ratio of expenditure on technology absorption to the total expenditure on S&T activities.[3]

Following our theory of technology recombination, domestic firms usually recombine diverse technologies and knowledge to yield products quite different from those of foreign firms to capture market opportunities (Guo & Chen, 2013). R&D ~~lets~~allows firms to generate new ideas, ~~new~~ blueprints, and ~~new~~ models, part of which will eventually facilitate knowledge recombination and application (Hagedoorn & Cloodt, 2003). Latecomer firms usually have to conduct more R&D to support recombination activities because they ~~could~~ can no longer use reengineering as a strategy to catch up as market-oriented reforms progress~~ed~~ (Guennif & Ramani, 2012). HASSMC, for example, ~~it~~ made many adaptive changes ~~through~~by redesigning the product's parameters and restructuring the production engineering details~~,~~ to better fit the specific manufacturing conditions and localized domestic market demands. By investing in R&D, the company was able to reconfigure existing technological expertise into new product

[3]Intramural expenditure on S&T activities represents the real expenditure for firms to deploy internal S&T activities and includes compensation for labor, raw material expenditure, expenditure on the purchase of fixed assets and spending for new products.

fields and ~~integrating~~integrate it with newly acquired expertise through trial ~~-~~and ~~-~~error~~,~~; it rapidly ~~fulfilled~~ achieved expertise transplantation from air separator systems to cold ethylene boxes~~,~~ and seized market opportunities from the petrochemical industry. Therefore, we adopted data on new product development and internal technology development to measure technology recombination (Liu & White, 1997). Patent application was used as a ~~supplement~~supplemental indicator since it can reflect firms' accumulation ~~on~~of economically valuable knowledge to prepare for potential market opportunities. Specifically, we calculated (a) output intensity on new product: the ratio of new product sales to sales revenue in the principal business, (b) output intensity on patent: the ratio of invention-type patent application count to sales revenue from the principal business, and (c) input intensity on S&T activities: the ratio of intramural expenditure on S&T activities to sales revenue from the principal business.

To assess the convergent and discriminant validity of our measures, we conducted an exploratory factor analysis (EFA). We included the two technology decomposition items and three technology recombination items. Our EFA indicated a distinct two-factor solution. Our three technology recombination indicators loaded on Factor 1, and the two technology decomposition indicators loaded on Factor 2 (see Table 1). Each factor had an eigenvalue above 1.0 (2.426 and 1.498, respectively). The two factors explained 78.48% of the variance. This pattern of results confirmed both the convergent and discriminant validity of our indicators. Therefore, the first three indicators were used to generate technology recombination, and the last two were used for technology decomposition. Owing to the difference in scale among indicators, the indicators were first transferred proportionally into a value range [0, 5], and then their arithmetic means were calculated as the variable scores.

****** INSERT TABLE 1 ABOUT HERE ******

Moderators: Technology ladder and market ladder

The *technology ladder* of an industry reflects the degree of continuity of technology-level distribution for all the firms in that industry. The calculation procedure for a given industry was as follows: (1) each firm's labor productivity (value-added per capita) was calculated as the proxy for the technology level; (2) based on the values of technology level for all firms in the industry, a value range [min, max] was set up and divided into k intervals with the same length[4]; (3) all firms in ~~this~~ the industry were classified into one of the k intervals according to their technology level; (4) the number of firms in each interval (N_i) was then counted, and the ratio of each interval (as one group) to all the k intervals (the whole industry) in the firm number was calculated: $R_i = {N_i}/{\sum_1^K N_j}$; and (5) based on a widely used measure of concentration, the Herfindahl–Hirschman Index (Acar & Sankaran, 1999), the technology ladder was measured by $1 - \sum_1^k {R_i}^2$. The higher the value was, the more continuous the technology ladder. To ~~both~~ avoid the potential effect of outliers and save more samples, ~~the~~ firms with labor productivity lower than the 5th percentile or higher than the 95th percentile were dropped in measuring the technology ladder (~~please find~~ similar treatment was adopted in ~~(~~Balasubramanian & Lieberman~~,~~ (2010)). The measurements based on samples across the range [~~the~~ 1st percentile, ~~the~~ 99th percentile] were used as alternatives in the robustness tests.

The *market ladder* of an industry reflects the degree of continuity of market segments (i.e., the so-called quality level distribution) for all the firms in that industry. We first calculated each firm's product price as a proxy for the quality level,[5] which was measured as industrial output value divided by production capacity. Similar to the technology ladder, the market ladder was calculated by replacing the value of the technology level with the quality level.

[4] The [min, max] is a value range based on the sample excluding outliers, and K is set to 10. Ten value ranges are constructed, i.e., ~~i.e.~~ [min, min + Δ), [min + Δ, min + 2Δ], …, [min + 9Δ, max], where Δ = (max-min)/10.

[5] Firms that produce a single category of product are used as the sample to calculate firms' product price level. Because the AISD reports only the total industrial output value for each firm, only ~~those~~ firms with one measurement unit of product price (e.g., Yuan per ton) can be processed. This processing method is similar to the measurement of product market fragmentation based on the share of products by firms operating in single submarket niches by Gambardella and Giarratana (2013), which indicates that the higher product market fragmentation is, the more pronounced the specialization advantages are and the higher the probability that firms operate in single submarket niches.

When firms in one industry had two or more measurement units (e.g., Y~~y~~uan per ton, Y~~y~~uan per meter), we calculated the values of the market ladder separately based on the subsamples that contained the most firms and the second-most firms according to their measurement units. When two values of the market ladder based on different subsamples occurred in an industry, we chose the larger value or the value calculated based on many more subsamples (e.g., ~~its~~ with a sample size ~~was~~ more than 10 times that of the other group). The average value of the two values of the market ladder was also calculated and used as an alternative in the robustness tests.

Control variables

Sectoral factors: (1) *Foreign direct investment (FDI) spillover*. We used the ratio of foreign firms' value-added to the total value-added in an industry to control for the FDI spillover effect. Previous literature has argued that FDI investment can create positive or negative externalities on domestic firms through knowledge diffusion, provision of public goods, or a crowding-out effect (Spencer, 2008). (2)

~~*Technology level of P*~~*public research institution*~~*s*~~ *competence*. Universities and public research laboratories have been important agents of the innovation systems supporting economic catch-up (Fischer, Schaeffer, & Vonortas, 2019; Mazzoleni & Nelson, 2007). Based on their technology competence from basic and applied scientific research, they play the role of technology gatekeepers and enablers in the catch~~ing~~-up process of domestic firms and the development of domestic capabilities by helping collect foreign information on advanced technology, promoting technology transfer, solving related problems in external knowledge absorption and application, and making R&D project evaluations (Chen, 2009; Mazzoleni & Nelson, 2007). Five indicators were used to operationalize the technology level of public research institutions in a given industry: (a) the ratio of the number of employees in public research institutions to the number of firm employees; (b) the ratio of the number of S&T

personnel in public research institutions to the number of firm employees; (c) the ratio of the number of scientists and engineers in public research institutions to the number of firm employees; (d) the ratio of intramural expenditure on S&T activities in public research institutions to that in firms; and (e) the ratio of intramural expenditure on S&T activities in public research institutions to firms' sales revenue from the principal business. An orthogonal factor analysis (with varimax rotation) of these five indicators yielded one significant factor (with an eigenvalue above 4 and all factor loadings over 0.8). Thus, these five indicators were first transformed proportionally into scores within a value range [0, 5], and then their arithmetic means were calculated to generate the technology level value of public research institutions.

(3) *Technological complexity*. The complexity of technological knowledge can affect the ease of learning and act as a distinct barrier to imitation (Cohen & Levinthal, 1990; Ryall, 2009)~~,~~ and thus to catch-up performance. On the one hand, to assimilate and exploit complex knowledge, firms must accumulate more prior knowledge and undertake more internal R&D. ~~There will be~~ This entails an increase in the requirement for capital and time consumption, which are usually scarce in a world characterized by rapid and unpredictable change and global market competition. On the other hand, firms ~~will~~ run the risk of failing to receive a payoff when their innovations involve more complex technology because more potential change is likely to arise during the knowledge exploitation process. In this study, *technological complexity* was measured as the original value of microelectronics-controlled equipment divided by sales revenue from the principal business.

(4) *Industry competition***.** Competition pressures an industry's firms to cut costs and provides incentives for more exploratory activities and innovation (Abebe & Angriawan, 2014). ~~At the same time~~In addition, industry competition may make it difficult for firms to receive appropriate returns from innovation. In this study, *industry competition* was measured as the natural logarithm of the total ~~firm~~ number of firms in a given industry.

Industry-average firm features~~-related ~~: (1) ~~*Industry-average f*~~*Firm size***.** Industry-average firm size strongly influences industrial catch-up performance. It reflects the necessary firm size required ~~by~~ to gain~~gaining~~ from economies of scale as well as an industry's entry barrier. A larger average firm size usually involves more skilled labor, resources, and slack, and firms in such industries are ~~more~~ capable of undertaking technological innovation with a lower risk of failure. We measured *firm size* as the total ~~employee~~ number of employee ~~of~~ in a given industry divided by the total firm number (Lee, 2013; Park et al., 2006). (2)

Investment intensity. Given the potential influence of fixed-asset investment on economic growth and productivity (Zheng, Barbieri, Di Tommaso, & Zhang, 2016), fixed-asset investment per capita at the industry level was included as one of the control variables (Park et al., 2006). (3)

Fund source diversity. Firms obtain funds for innovation activities from different sources, including self-raised funds, bank loans, government funds, foreign funds, and others. We first calculated the source concentration by using the Herfindahl–Hirschman Index; we then used one minus that value to reflect the fund source diversity.

(4) *Profitability***.** Profitability was measured as the total profits divided by the sales revenue from the principal business.

Institutional factors: (1) *Institutional development*. Previous studies in economics, finance, and international business have extensively used the marketization index to measure institutional development in different regions in China (Zhou et al., 2017), which the National Economic Research Institute compiles yearly (Fan et al., 2010). Because this study is at the industry level, the exposure to different marketization environments of each industry-year observation was measured as the sum of marketization scores across all provinces in the given year, weighted by the percentage of industry output reported in a given province over the total industry output for the focal year. Therefore, a high value indicates that~~d~~ the industry's main output in a given year was from well-developed provinces. (2)

~~*Foreign direct investment (FDI) spillover*. We used the ratio of foreign firms' value-added to the total value-~~

~~added in an industry to control for the FDI spillover effect. Previous literature has argued FDI investment can create positive or negative externalities on domestic firms through knowledge diffusion, provision of public goods, or a crowding-out effect (Spencer, 2008).~~

State ownership. The resources, objectives, and governance of state-affiliated firms differ significantly from those of private firms (Cui & Jiang, 2012). We used the ratio of state-affiliated firms to the total number of firms for each industry to control for the role of state capitalism~~'s role~~ in China. (3)

Subsidy. We used the average subsidy amount per firm in an industry to control for the role of government support~~s~~. Governments in emerging economies ~~hold~~ have a significant influence on regulatory policies and control ~~over~~ key resources in the restructuring of the economy, and subsidies are~~y is~~ a typical type of government sponsorship (Du & Mickiewicz, 2016).

Estimation Method

We adopted the Breusch-Pagan Lagrange multiplier test to decide whether the pooled ordinary least squares approach or the panel data method was more appropriate ~~As our data has a panel structure, we conducted the Hausman test and the Breusch and Pagan Lagrangian multiplier (BP-LM) test to choose the appropriate models~~ (Breusch & Pagan, 1980). The results of the test show that the latter is better since there were unobserved individual effects in the data. Next, the Hausman test ~~was~~was~~is~~ used to choose between fixed-effect and random-effect models for the panel data method. The results suggest~~ed~~ that fixed--effect panel models ~~should be used, because explanatory variables were correlated with the unobserved effects~~were more appropriate (see results in Table 3).~~Based on the results, the fixed effects model is selected for every regression model (see Table 3 and 4).~~ Heteroskedasticity, autocorrelation, and cross-sectional dependence of panel data were tested for every regression model, and the results (in Tables 3 and 4) showed that there were heteroskedasticity and autocorrelation for many models, e.g., Model 5 of Table 3 ($\chi2(26)$=10337.48, *p*=0.00; F(1,25)=4.699, *p*=0.04). Regressions with Driscoll-Kraay standard errors were implemented to cope with these problems (Driscoll &

Kraay, 1998). To reduce the potential multicollinearity due to interaction terms (*Technology decomposition * Technology ladder, Technology recombination * Market ladder*), these independent variables were centered before calculating the product terms. All independent variables were lagged one year to mitigate potential endogeneity problems in the models. In addition, we examined the variance inflation factor (VIF) in the models. The maximum VIF was 4.83, and the mean VIF was 2.40, which is substantially less than the standard rule of 10, indicating that multicollinearity was not a significant concern.

RESULTS

Descriptive Statistics and Regression Analysis

Table 2 reports descriptive statistics and correlation coefficients for all variables. As shown in Table 2, labor productivity declines in a few cases (i.e., catch-up performance is negative), which indicates ~~the~~that labor productivity does not always improve for every industry. The market ladder has a wider variation than the technology ladder among different industries. Regarding the correlation matrix of the main variables, the correlation between technology decomposition and technology recombination is significant and positive (β = 0.38, p = 0.00). Technology decomposition, technology ladder, and market ladder are all significantly positively correlated with catch-up performance. Because the state-owned ratio is highly related to institutional development (β = -0.71, p = 0.00), a robustness test was done by deleting the state-owned ratio (please find the results in the following section).

****** INSERT TABLE 2 ABOUT HERE ******

Table 3 reports the regression results. Model 2 includes all variables, excluding two interaction terms, and Models 3 and 4 add one interaction separately. The results indicate that technology recombination has a positive and ~~statistically~~ significant effect on catch-up performance (β = 1.86, p = 0.04, in Model 2; and β = 2.65, p = 0.02, in Model 5), but the direct effect of technology decomposition is not statistically significant. Thus, Hypothesis 2 ~~has~~

~~been~~is supported, ~~whereas~~ while Hypothesis 1 ~~has not received support~~is not. In terms of effect size, holding all other factors constant, ~~an~~a 1% increase ~~of~~in technology recombination increases catch-up performance by 1.85%.

Regarding the interaction effects, the interaction of technology recombination and the market ladder is positive and ~~statistically~~ significant (β = 8.48, p = 0.00, in Model 5), ~~whereas~~ while the interaction of technology decomposition and the technology ladder is negative and ~~statistically~~ significant (β = -24.64, p = 0.02, in Model 5). Hence, Hypotheses 3 and 4 receive support. In terms of effect size, holding all others at their means, when the technology ladder is at the high level (i.e., the mean plus one standard deviation), ~~an~~a 1% increase ~~of~~ in technology decomposition decreases catch-up performance by 0.73%. However, when the technology ladder is at a low level (i.e., the mean minus one standard deviation), ~~an~~a 1% increase in technology decomposition increases catch-up performance by 0.74%. When the market ladder ~~was~~ is set at the low level (i.e., the mean minus one standard deviation)~~, middle level (i.e., mean value)~~ and the high level~~ respectively~~ (i.e., the mean plus one standard deviation), ~~an~~a 1% increase ~~of~~in technology recombination increases catch-up performance by 1.57%~~, 2.69%~~ and 3.82%~~ correspondingly~~, respectively.

****** INSERT TABLE 3 ABOUT HERE ******

To better understand the moderation results~~results~~, we plotted the moderation effects following Meyer, van Witteloostuijn and Beugelsdijk (2017). Figure 1 (Figure 2) gives the 95% confidence ~~range~~interval for the moderating ~~line~~effect, which shows the marginal effect of technology decomposition (technology recombination) on catch-up performance for the full range ~~of possible scores~~values of the technology ladder (market ladder). Figure 1 shows that although the average moderating effect ~~turn out to be~~is significantly negative in the regression model, there is a middle range (approximately from 0.754 to 0.807) for the technology ladder for which the effect is insignificant, and the effect of technology decomposition on catch-up performance is positive for low values of the technology ladder and negative for high values of the technology ladder. Figure 2 illustrates that the positive moderating effect, i.e., the marginal effect of technology recombination on catch-up performance, is significant only after the value of the market ladder is approximately 0.508. ~~Figure 1 shows that compared with industries with high levels of continuity in the technology ladder (i.e., mean plus one standard deviation), the effect of technology decomposition on catch-up performance is more positive in industries with low levels of continuity in the technology ladder (i.e., mean minus one standard deviation), indicating Hypothesis 3 receives support. As shown in Figure 2, the positive effect of technology recombination on catch-up performance is stronger in industries with high levels of continuity in the market ladder (i.e., mean plus one standard deviation) when compared with industries with low levels of continuity in the market ladder (i.e., mean minus one standard deviation). Hence, Hypothesis 4 is supported.~~

****** INSERT FIGURE 1 AND FIGURE 2 ABOUT HERE ******

Robustness Tests

We ran a set of robustness tests. Their estimates all showed that our results are robust when using a variety of alternative measurements of the key variables (i.e., technology ladder and market ladder) in the estimating equation (Model 1 and 2 of Table 4) and when the state-owned ratio was deleted because of its highly correlated relationship with institutional development (Model 3 of Table 4). As discussed in the Variable Measurements section, we adopted alternative measurements of the technology ladder and market ladder. First, the range (i.e., [~~the~~ 5th percentile, ~~the~~ 95th percentile]) of firm-level data used in calculating the technology or market ladder can be ~~set wider~~widened to increase the sample size by deleting fewer outliers. In Model 1 of Table 4, the technology ladder and market ladder were calculated with the firm-level data included in the range [~~the~~ 1st percentile, ~~the~~ 99th percentile]. Second, the market ladder was calculated with the average of the market ladder values based on two separate subsamples (firm groups with different measurement units) in one industry, and the corresponding robustness test results are reported in Model 2 of Table 4.

****** INSERT TABLE 4 ABOUT HERE ******

DISCUSSION AND CONCLUSION

In this study, we ~~have~~ examined how technological learning (in terms of technology decomposition and technology recombination) and catch-up context (in terms of the market ladder and technology ladder) jointly determine industrial catch-up performance. With industry-level data on a sample of Chinese manufacturing industries, we find that technology recombination increases industry-level catch-up performance, ~~whereas~~ while the empirical results ~~have not confirmed~~ do not confirm the existence of a direct effect of technology decomposition on industry-level catch-up performance. Moreover, we find that the influence of technological learning in terms of technology decomposition and technology recombination is contingent on the levels of continuity in the technology ladder and market ladder. Specifically, continuity in the market ladder strengthens the positive influence of technology recombination on industry-level catch-up performance, ~~whereas~~ while continuity in the technology ladder weakens the positive influence of technology decomposition on industry-level catch-up performance.

This study contributes to the literature on latecomer technological learning in the following aspects. First, few analytical frameworks explore how latecomers absorb acquired external knowledge and create new knowledge to achieve industrial catch-up (Figueiredo & Cohen, 2019). Latecomers are normally dislocated from the technological frontier, and they must implement unique technological learning mechanisms to build their own capabilities (Chung & Lee, 2015; Figueiredo, 2003; Figueiredo & Cohen, 2019). This study divides technological learning into two mechanisms, technology decomposition and technology recombination~~,~~ as derived from the absorptive capacity perspective, to explain how technological learning processes lead to ~~a~~cross-industry variation in industry-level catch-up performance when latecomers face large technology gaps. Despite the potential catch~~ing~~-up opportunities offered by advanced foreign technologies, latecomers still face a large technology gap in the technology ladder, and technology decomposition may help ~~latecomers~~ mitigate ~~such a large~~this gap and accelerate the assimilation of external knowledge by dividing external technologies into knowledge subsets. In addition, technology recombination helps latecomers conduct architectural innovation to capture the demand characteristics of diverse domestic market segments~~'~~ ~~demand characteristics~~ in large emerging economies and balance products' cost–quality ratio (Thun, 2018), achieve competitive advantage and specialize in core capabilities, and sustain technological ~~catching-~~catch-up through continuously profiting from localized innovations (Guo & Chen, 2013). The empirical results indicate that technology recombination has a significantly positive relationship with industry-level catch-up performance. The results are in line with previous research that emphasizes how technological learning processes facilitate catch-up in latecomers (Figueiredo, 2003; Figueiredo & Cohen, 2019), and the results ~~help us gain~~offer further insight into direct assessments of learning-related mechanisms constituting absorptive capacity (Lewin et al., 2011). However, the proposed relationship between technology decomposition and industry-level catch-up performance is not significant. A possible explanation is that the decomposed knowledge may not be used or may be stored for later use (rather than used immediately) due to a lack of markets or complementary technologies (Garud & Nayyar, 1994). In this regard, technology decomposition may not necessarily influence the next year's industry-level catch-up performance. In addition, technology decomposition may frustrate latecomers to some degree when conducting domestic innovation. As stated, technology decomposition is likely to lower the learning threshold for latecomers to assimilate the acquired knowledge. When technology decomposition is at a high level, even latecomers with weak technological capability may be reluctant to pursue production and process innovation internally. Consequently, technology decomposition may not significantly affect industry-level catch-up performance in large emerging economies.

Second, our study confirms that both the technology ladder and market ladder play important contingent roles in shaping the relationship between technological learning and industry-level catch-up performance. Unlike previous catch-up studies that mainly emphasize the role of generic characteristics of the catch-up context for developing countries (e.g., technology gap, technology life cycle, and technology complexity and uncertainty) (Park et al., 2006; Wang, Roijakkers, & Vanhaverbeke, 2014), we purposely focus on the structural featured traits of catch-up contexts in large emerging economies (i.e., the technology ladder and market ladder). The technology ladder indicates the extent to which latecomers can leverage technological opportunities and resources, ~~hence~~ thereby ~~easing~~ reducing the technology gap (Brandt & Thun, 2016; Jefferson & Rawski, 1994; Thun, 2018); the market ladder enables latecomers to better understand the domestic market, effectively satisfy diverse market demands, and further facilitate the upgrading process (Brandt & Thun, 2016; Wei et al., 2018). This study captures a better understanding of the unique characteristics of catch-up contexts~~' unique characteristics~~, which reflect the structural nature of the technology level and the quality/price level at the industry level in large emerging economies. We believe that such findings can help us better understand the catch-up context differences between large emerging economies and other emerging countries.

Third, the present study empirically validates how the interactions between technology decomposition, technology recombination, and catch-up context affect industry-level catch-up performance. The existing literature has paid significant attention to the direct effects of both technological learning and catch-up contexts on catch-up performance~~s~~. However, less empirical validation has been made concerning the interactive effects of technological learning and the catch-up context on industrial catch-up performance. The technology ladder and market ladder, as unique features of the catch-up contexts in large emerging economies, signify the extent to which technological and market opportunities and resources can be leveraged at the industry level, and ~~some recent research has~~recent studies have demonstrated that industry-level catch-up performance depends on the interactions between technological learning processes and available opportunities and resources (Figueiredo & Cohen, 2019; Jung & Lee, 2010). To advance this line of inquiry, the empirical evidence from our study reveals that technological decomposition, technology recombination, and catch-up context jointly and distinctively affect industry-level catch-up performance. Specifically, a substitute effect is found between technology decomposition and the technology ladder, ~~whereas~~ while a complementary effect is found between technology recombination and the market ladder. The results extend the work of Figueiredo and Cohen (2019) and Lee and Lim (2001) ~~as well as~~ and provide a new research angle for us to understand the interindustry difference in catch-up performance in the context of large emerging economies.

Our findings provide new insights for policymakers in large emerging economies. First, policymakers must understand the positive effects of technological recombination on industry-level catch-up performance. Industrial policies should be made to improve domestic technological capabilities ~~through policy measures~~ (e.g., increasing the intramural expenditure on S&T activities) and to encourage latecomers to be more open and collaborative for innovation; this would further enable latecomers to recombine knowledge from diverse sources into commercial products with localized innovations. Second, policymakers should identify the level of continuity in the technology ladder and market ladder ~~levels in~~of a given industry ~~in a domestic catch-up context~~ ~~as well as~~ and carry out relevant policy initiatives to facilitate appropriate technological learning processes and patterns to improve catch-up performance. Specifically, an industry with a high market ladder level should conduct more technology recombination, whereas an industry with a low technology ladder level should carry out more technology decomposition. Third, this study’s findings demonstrate the importance of market ladder continuity in improving catch-up performance. A demand-side policy, such as public procurement, should be ~~paid~~given more attention during industrial policymaking. By doing so, a more continuous market segment structure can be formulated for latecomers in a given industry.

Several limitations also exist in this study. First, this study ~~has~~ used industry-level Chinese manufacturing industries as ~~its~~ the research sample. Although China is a typical ~~of a~~ large emerging economy, future studies are needed to examine whether the findings in this ~~research~~ study can be generalized ~~into~~ to broader contexts (e.g., other large emerging economies, such as Brazil and India). Second, given that this study purposefully focuses on industry-level analysis, further research based on case studies and regional-level or firm-level empirical studies (when conditions permit) can explore whether similar, identical, or different results might be found. Researching antecedents of catch-up performance at different research levels will definitely garner new insights into Chinese manufacturing industries. Third, we did not directly observe and thus measure technology decomposition and technology recombination based on firm-level data. Instead, we used archival data regarding the input or output highly related to these technology learning activities as proxy measurements. Future ~~study~~studies could comprehensively measure technology decomposition and technology recombination by using available microl~~micro-l~~evel data~~ available. Lastly~~. Finally, additional research would shed more light on catch-up theory by investigating whether institutional contexts change the moderating effect of the technology ladder and market ladder on the relationship between technology decomposition, technology recombination, and industrial catch-up performance in large emerging economies.

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Table 1. Factor analysis of technology decomposition and technology recombination

Indicators	Factor 1	Factor 2
Output intensity on new product	**0.889**	0.024
Output intensity on patent	**0.647**	0.094
Input intensity on S&T activities	**0.915**	0.124
Relative assimilation intensity	-0.083	**0.963**
Absolute assimilation intensity	0.335	**0.899**
Eigenvalue	2.426	1.498
Cumulative % of variance explained	43.29	78.48

Table 2. Descriptive statistics and correlation coefficients (*N* = 182)

	Variable	Mean	Std.Dev.	Min	Max	1	2	3	4	5	6
1	Catch-up performance (*Ln*)	8.487	3.663	-10.76	11.33						
2	Technology decomposition	0.881	0.754	0	4.352	0.150*					
3	Technology recombination	1.438	0.86	0.158	3.863	0.027	0.375***				
4	Technology ladder	0.791	0.03	0.687	0.87	0.157*	0.053	-0.053			
5	Market ladder	0.648	0.129	0.282	0.865	0.144	-0.098	-0.382***	0.160*		
6	FDI spillover	0.35	0.151	0.047	0.796	-0.281***	-0.172*	0.053	-0.244***	-0.277***	
7	Public research institution competence	0.654	0.801	0	3.931	-0.099	0.037	0.275***	-0.173*	-0.315***	-0.170*
8	Technological complexity	0.05	0.047	0.001	0.31	0.107	0.103	0.06	0.201**	-0.052	-0.184*
9	Industry competition	6.474	0.784	4.263	7.934	0.137	0.248***	0.361***	-0.240**	-0.056	-0.195**
10	Firm size	6.944	0.4	5.993	8.619	0.052	0.004	0.088	-0.109	0.138	-0.132
11	Investment intensity (*Ln*)	1.904	0.543	0.809	3.304	0.141	0.213**	0.199**	-0.038	-0.072	-0.518***
12	Profitability	0.052	0.02	-0.002	0.114	0.13	0.216**	0.085	-0.089	-0.179*	-0.054
13	Fund source diversity	0.261	0.099	0.037	0.547	-0.203**	-0.048	-0.002	0.046	0.066	-0.096
14	State-owned ratio	0.164	0.117	0.008	0.58	-0.085	-0.160*	0.131	-0.033	-0.071	-0.235**
15	Institutional development	7.329	1.341	4.093	9.942	0.078	0.073	-0.046	-0.302***	-0.229**	0.393***
16	Subsidy	2.65	0.988	0.636	7.365	0.031	0.418***	0.478***	-0.031	-0.003	-0.339***

	Variable	7	8	9	10	11	12	13	14	15
8	Technological complexity	-0.122								
9	Industry competition	0.051	-0.088							
10	Firm size	-0.288***	-0.104	0.035						
11	Investment intensity (*Ln*)	0.017	0.393***	0.147*	0.262***					

12	Profitability	0.094	0.173*	-0.002	-0.186*	0.197**				
13	Fund source diversity	0.257***	-0.078	0.253***	-0.284***	-0.152*	-0.186*			
14	State-owned ratio	0.563***	0.145	0.051	-0.293***	0.133	0.169*	0.270***		
15	Institutional development	-0.363***	0.032	0.059	0.115	-0.037	0.114	-0.279***	-0.713***	
16	Subsidy	0.072	0.113	0.284***	0.329***	0.588***	-0.036	0.018	0.098	-0.238**

* p < 0.05; ** p < 0.01; *** p < 0.001.

~~Table 2. Descriptive statistics and correlation coefficients (N = 182)~~

—	Variable	Mean	Std.Dev.	Min	Max	1	2	3	4	5	6
1	Catch-up performance (*Ln*)	8.487	3.663	-10.760	11.330						
2	Technology decomposition	0.881	0.754	0.000	4.352	0.150*					
3	Technology recombination	1.438	0.860	0.158	3.863	0.027	0.375***				
4	Technology ladder	0.791	0.030	0.687	0.870	0.157*	0.053	-0.053			
5	Market ladder	0.648	0.129	0.282	0.865	0.144	-0.098	-0.382***	0.160*		
6	Technological complexity	0.050	0.047	0.001	0.310	0.107	0.103	0.060	0.201**	-0.052	
7	Industry competition	6.474	0.784	4.263	7.934	0.137	0.248***	0.361***	-0.240**	-0.056	-0.088
8	Firm size	6.944	0.400	5.993	8.619	0.052	0.004	0.088	-0.109	0.138	-0.104
9	Investment intensity (*Ln*)	1.904	0.543	0.809	3.304	0.141	0.213**	0.199**	-0.038	-0.072	0.393***
10	public research institution Competence	0.654	0.801	0.000	3.931	-0.099	0.037	0.275***	-0.173*	-0.315***	-0.122
11	Profitability	0.052	0.020	-0.002	0.114	0.130	0.216**	0.085	-0.089	-0.179*	0.173*
12	Fund source diversity	0.261	0.099	0.037	0.547	-0.203**	-0.048	-0.002	0.046	0.066	-0.078
13	FDI spillover	0.350	0.151	0.047	0.796	-0.281***	-0.172*	0.053	-0.244***	-0.277***	-0.184*
14	State-owned ratio	0.164	0.117	0.008	0.580	-0.085	-0.160*	0.131	-0.033	-0.071	0.145
15	Institutional development	7.329	1.341	4.093	9.942	0.078	0.073	-0.046	-0.302***	-0.229**	0.032
16	Subsidy	2.650	0.988	0.636	7.365	0.031	0.418***	0.478***	-0.031	-0.003	0.113

—	Variable	7	8	9	10	11	12	13	14	15
8	Firm size	0.035								
9	Investment intensity (*Ln*)	0.147*	0.262***							
10	public research institution Competence	0.051	-0.288***	0.017						
11	Profitability	-0.002	-0.186*	0.197**	0.094					
12	Fund source diversity	0.253***	-0.284***	-0.152*	0.257***	-0.186*				
13	FDI spillover	-0.195**	-0.132	-0.518***	-0.170*	-0.054	-0.096			
14	State-owned ratio	0.051	-0.293***	0.133	0.563***	0.169*	0.270***	-0.235**		
15	Institutional development	0.059	0.115	-0.037	-0.363***	0.114	-0.279***	0.393***	-0.713***	
16	Subsidy	0.284***	0.329***	0.588***	0.072	-0.036	0.018	-0.339***	0.098	-0.238**

~~* p < 0.05; ** p < 0.01; *** p < 0.001.~~

Table 3. Regression models

Variables	**Model 1**	**Model 2**	**Model 3**	**Model 4**	**Model 5**
Technology ladder	54.69*	56.12*	60.43**	38.26^{+}	43.25*
	(19.47)	(19.51)	(14.46)	(16.17)	(12.05)
Market ladder	5.910	5.342	4.155	7.851^{+}	6.604^{+}
	(3.848)	(3.917)	(3.730)	(3.390)	(3.199)
FDI spillover	1.471	3.932	0.439	4.846	1.515
	(15.53)	(17.02)	(15.51)	(15.32)	(13.72)
Public research institutions competence	-0.726	-1.052	-0.918	-0.987	-0.865
	(0.982)	(0.900)	(0.907)	(0.953)	(0.958)
Technological complexity	20.45^{+}	15.58	13.57	16.79	14.84
	(8.956)	(10.56)	(8.704)	(9.733)	(8.206)
Industry competition	-3.832*	-3.294*	-3.479^{+}	-2.834^{+}	-3.031^{+}
	(1.342)	(1.287)	(1.526)	(1.229)	(1.480)
Firm size	-2.124	-2.084	-2.203	-2.185	-2.291
	(2.704)	(2.777)	(2.709)	(2.676)	(2.598)
Investment intensity	-14.35***	-15.49***	-15.51***	-14.99***	-15.04***
	(1.708)	(1.956)	(1.923)	(1.906)	(1.857)
~~Public research institutions competence~~	~~-0.726~~	~~-1.052~~	~~-0.918~~	~~-0.987~~	~~-0.865~~
	~~(0.982)~~	~~(0.900)~~	~~(0.907)~~	~~(0.953)~~	~~(0.958)~~
Profitability	-8.904	-11.82	-20.27	-20.13	-27.64
	(30.15)	(30.84)	(31.60)	(33.94)	(33.59)
Fund source diversity	-4.707^{+}	-4.467	-4.011	-4.213	-3.797
	(2.257)	(2.468)	(2.752)	(2.661)	(2.944)
~~FDI spillover~~	~~1.471~~	~~3.932~~	~~0.439~~	~~4.846~~	~~1.515~~
	~~(15.53)~~	~~(17.02)~~	~~(15.51)~~	~~(15.32)~~	~~(13.72)~~
State-owned ratio	17.20*	20.31*	23.57*	17.24^{+}	20.46*
	(6.516)	(7.342)	(6.382)	(7.302)	(6.374)
Institutional development	-0.755	-0.212	-2.044	1.202	-0.594
	(2.253)	(1.926)	(2.094)	(1.351)	(1.633)
Subsidy	-1.168	-0.856	-0.942	-0.515	-0.614
	(1.117)	(1.012)	(0.915)	(0.839)	(0.777)
Technology decomposition		-0.000207	-0.109	0.0927	-0.0143
		(0.335)	(0.238)	(0.298)	(0.249)
Technology recombination		1.857*	1.926*	2.627*	2.652*
		(0.720)	(0.657)	(0.823)	(0.825)
Interaction items					
Technology decomposition * Technology ladder			-26.21**		-24.64*
			(6.314)		(7.432)
Technology recombination * Market ladder				8.947**	8.478**
				(1.650)	(1.543)
Constant	74.49*	67.75*	80.42*	57.22^{+}	69.68*
	(20.40)	(22.98)	(27.39)	(24.32)	(27.78)

Year dummies	Included	Included	Included	Included	Included
Fixed-effects (within) regression	F (25, 137) = 2.33**	F (25,135) =2.35**	F (25,134) =2.40***	F (25,134) = 2.21**	F (25,133) = 2.21**
Breusch and Pagan Lagrangian multiplier test for random effects	Chibar2(01) = 0.00	Chibar2(01) = 0.00	Chibar2(01) = 0.00	Chibar2(01) = 0.00	Chibar2(01) = 0.00
Hausman test	χ^2 (19) = 86.77***	χ^2 (21) = 65.45***	χ^2 (22) = 73.24***	χ^2 (22) = 90.98***	χ^2 (23) = 83.31***
Wooldridge test for autocorrelation in panel data	F (1,25) = 4.275*	F (1,25) = 5.309*	F (1,25) = 4.675*	F (1,25) = 5.463*	F (1,25) = 4.699*
Pesaran's test of cross-sectional independence	1.111	1.058	0.464	0.830	0.600
Modified Wald test for groupwise heteroskedasticity	χ^2(26) =7294.04***	χ^2(26) =5429.85***	χ^2(26) =6689.46***	χ^2(26) =8207.13***	χ^2(26) =10337.48***
F-value (regression model)	F(19,6)= 20.12***	F(21,6)=18.52***	F(22,6)=7.88**	F(22,6)= 13.39**	F(23,6)= 10.16**
Within R^2	0.3927	0.4051	0.4265	0.4294	0.4483
n	182	182	182	182	182

The t-statistics based on Driscoll-Kraay standard errors in parentheses. $^{+}$ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. The preferred model by the test statistics: Fixed-effects regression models.

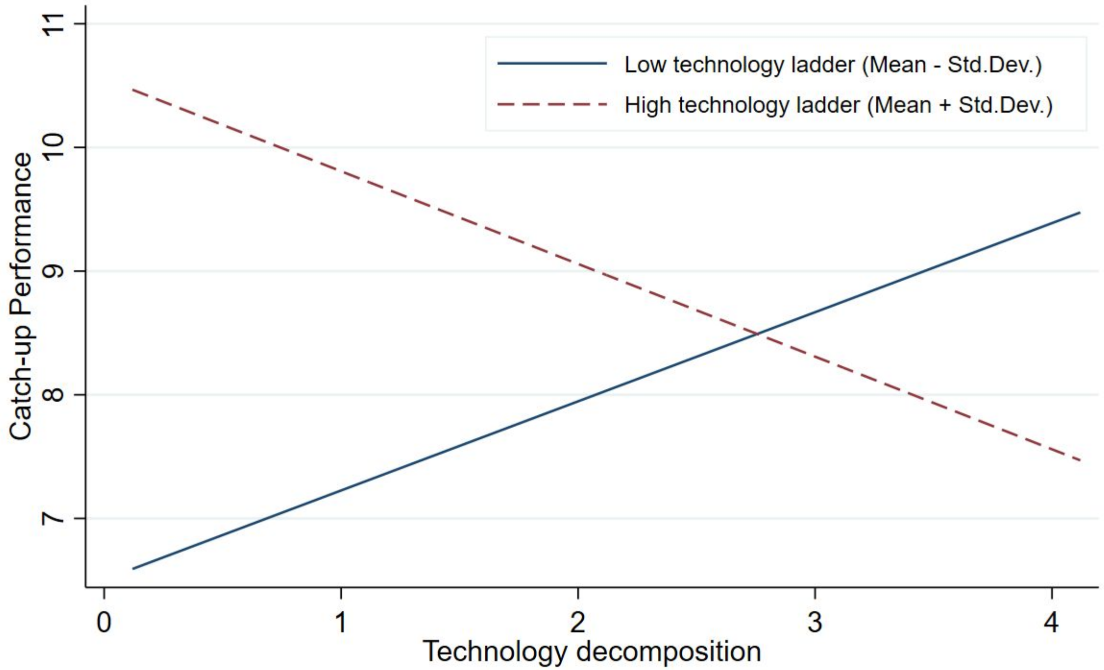
For the fixed effects estimates: within R^2. Here, only ~~reports~~ the results of FE regressions are reported due to limited space.

Table 4. Robustness tests

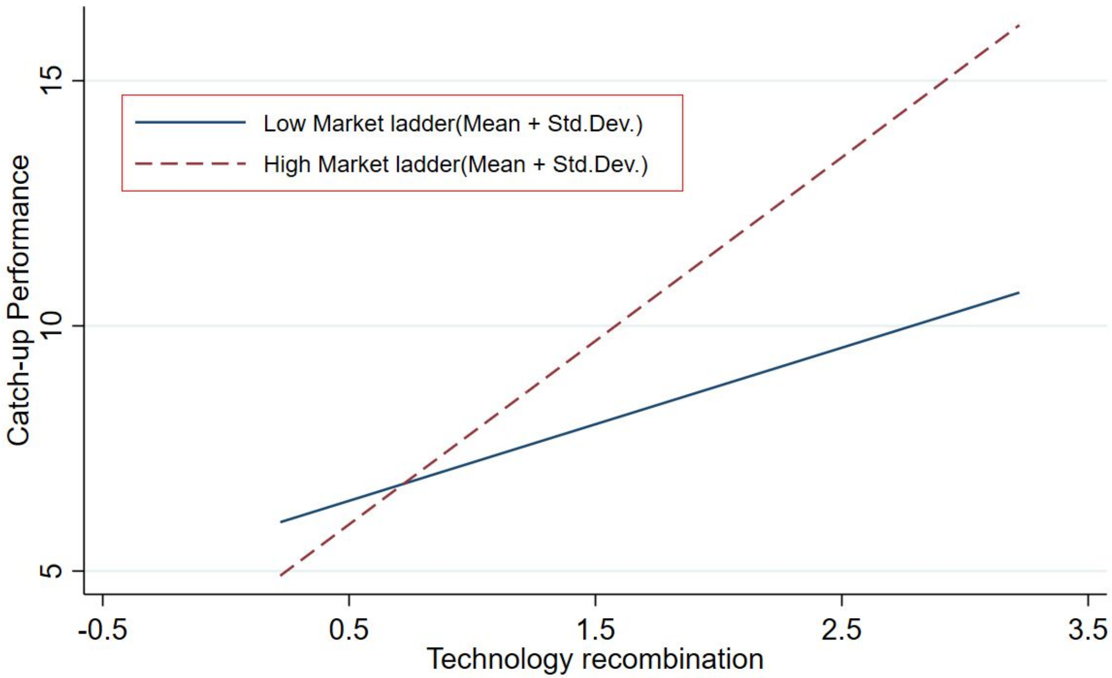
Variables	**Model 1**	**Model 2**	**Model 3**
Technology ladder	14.40*	61.04*	34.30*
	(4.939)	(16.86)	(11.97)
Market ladder	2.856	4.304	8.222+
	(2.495)	(3.112)	(3.553)
FDI spillover	1.729	0.844	-3.675
	(16.57)	(14.69)	(12.75)
Public research institutions competence	-1.435	-0.780	-0.654
	(1.150)	(0.887)	(1.023)
Technological complexity	11.74	13.51	15.42
	(8.788)	(8.578)	(8.700)
Industry competition	-3.701*	-3.062	-1.356
	(1.424)	(1.594)	(1.338)
Firm size	-1.653	-2.095	-2.113
	(3.001)	(2.811)	(2.832)
Investment intensity	-12.72***	-15.42***	-14.71***
	(1.116)	(1.816)	(1.681)
~~Public research institutions competence~~	~~-1.435~~	~~-0.780~~	~~-0.654~~
	~~(1.150)~~	~~(0.887)~~	~~(1.023)~~
Profitability	-30.29	-14.93	-23.43
	(30.00)	(34.42)	(31.94)
Fund source diversity	-3.405	-3.628	-3.841
	(1.945)	(2.846)	(3.018)
~~FDI spillover~~	~~1.729~~	~~0.844~~	~~-3.675~~
	~~(16.57)~~	~~(14.69)~~	~~(12.75)~~
State-owned ratio	21.81*	23.20*	-
	(6.184)	(6.817)	
Institutional development	-2.265	-1.234	-0.220

	(1.907)	(1.876)	(1.858)
Subsidy	-1.607	-0.937	-0.722
	(1.030)	(0.868)	(0.843)
Technology decomposition	-0.281	-0.0997	0.0168
	(0.204)	(0.209)	(0.266)
Technology recombination	3.062*	2.409*	2.386*
	(0.855)	(0.722)	(0.787)
Interaction items			
Technology decomposition * Technology ladder	-16.71*	-26.59**	-21.67*
	(5.201)	(6.861)	(8.667)
Technology recombination * Market ladder	6.992*	4.170*	9.332***
	(1.987)	(1.160)	(1.564)
Constant	76.67*	72.08*	62.85*
	(28.97)	(30.45)	(24.57)
Year dummies	Included	Included	Included
Fixed-effects (within) regression	$F(25,133) = 2.02^{**}$	$F(25,133) = 2.19^{**}$	$F(25,124) = 2.05^{**}$
Breusch and Pagan Lagrangian multiplier test for random effects	Chibar2(01) = 0.00	Chibar2(01) = 0.00	Chibar2(01) = 0.00
Hausman test	$\chi^2(23)= 51.51^{***}$	$\chi^2(23)= 42.55^{**}$	$\chi^2(22)= 42.97^{**}$
Wooldridge test for autocorrelation in panel data	$F(1,25)= 6.048^{*}$	$F(1,25)= 5.199^{*}$	$F(1,25)= 4.573^{*}$
Pesaran's test of cross-sectional independence	0.197	0.576	0.624
Modified Wald test for groupwise heteroskedasticity	$\chi^2(26) =3403.54^{***}$	$\chi^2(26) =7878.55^{***}$	$\chi^2(26) =11089.74^{***}$
F-value (regression model)	$F(23,6)= 10.14^{**}$	$F(23,6)= 7.45^{**}$	$F(22,6)= 6.60^{*}$
Within R^2	0.4287	0.4317	0.4339
n	182	182	182

The t-statistics based on Driscoll-Kraay standard errors in parentheses. + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. The preferred model by the test statistics: Fixed-effects regression models. For the fixed effects estimates: within R^2. Here, only ~~reports~~ the results of FE regressions are reported due to limited space. In Model 1, the technology ladder and market ladder were calculated with the data in the range [1st percentile, ~~the~~ 99th percentile]. In Model 2, the market ladder was calculated with the average of the market ladder values based on two separate subsamples (firm groups with different measurement units) in one industry. In Model 3, the state-owned ratio was deleted because of its highly correlated relationship with institutional development.



~~Figure 1. Interaction of technology decomposition and technology ladder.~~



~~**Figure 2. Interaction of technology recombination and market ladder.**~~

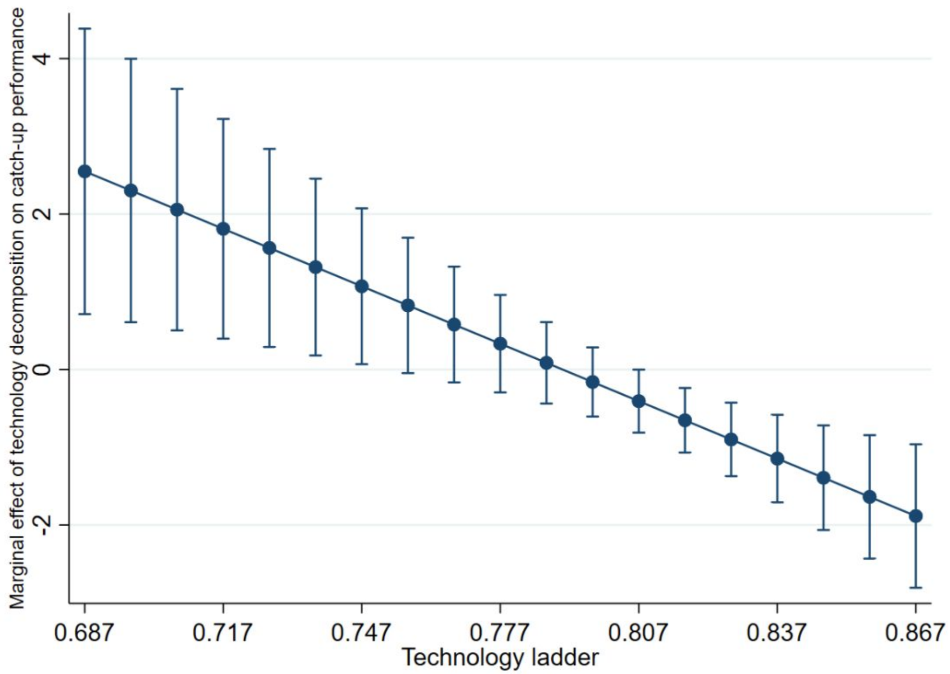


Figure 1 The marginal effect of technology decomposition on catch-up performance (technology ladder as a moderator).

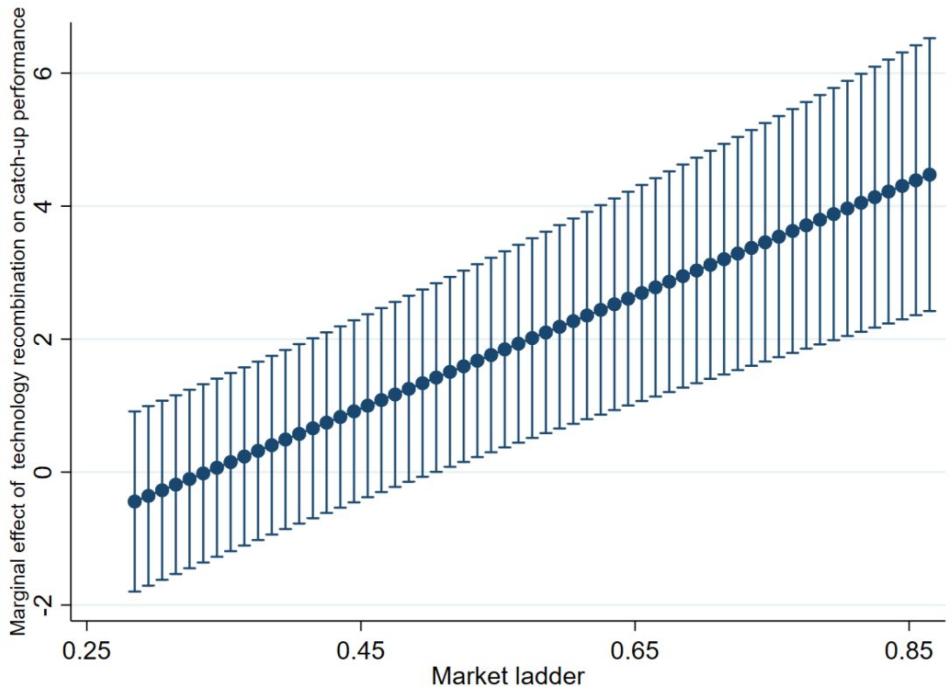


Figure 2 The marginal effect of technology recombination on catch-up performance (market ladder as a moderator).

APPENDIX I. Summary of Key Studies on Concepts Related to Technology Decomposition and Technology Recombination

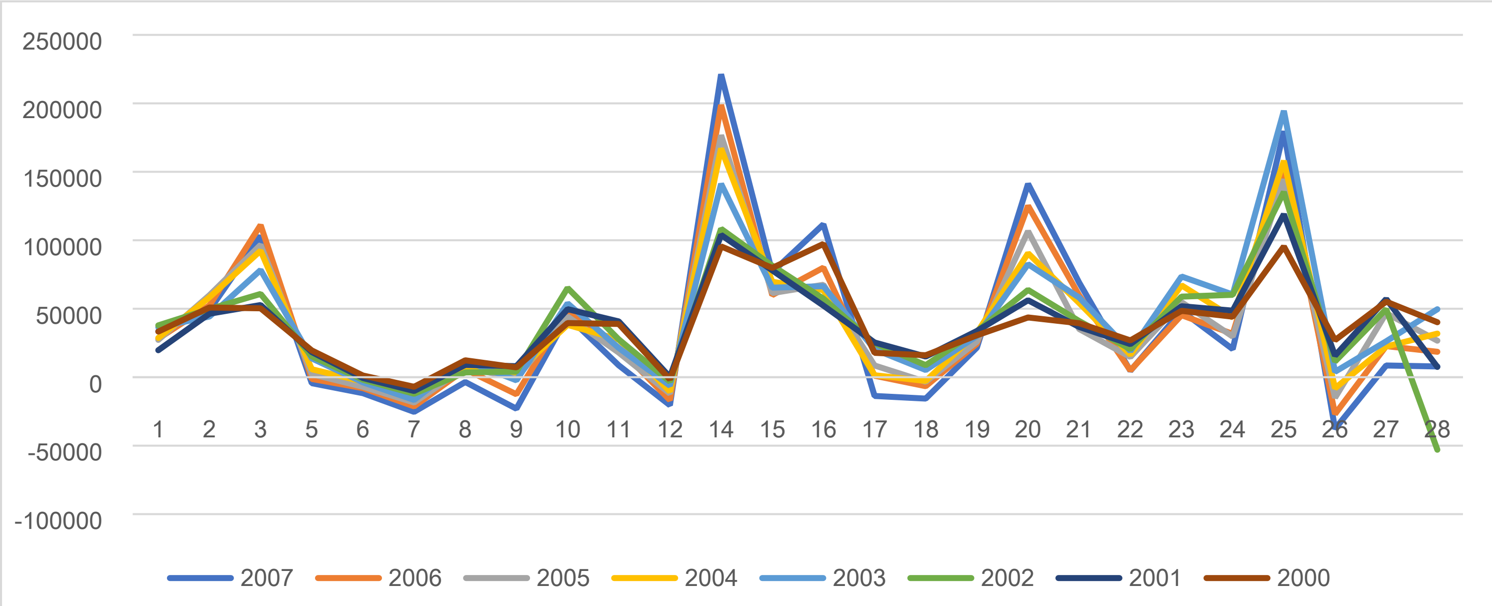
Subject	*Authors*	*Key content*	*Theoretical findings*
Concepts related to technology decomposition	Cohen and Levinthal (1990)	Propose a new perspective as absorptive capacity on learning	Absorptive capacity refers to the ability of a firm to recognize the value of external information, assimilate it, and apply it to commercial ends.
	Lee et al. (2009)	Catch-up in automobiles and mobile phone sectors in China	Early catch-up was possible because of the high modularity of production and the availability of a knowledge pool around the nation.
	Guo & Chen (2013)	Propose a learning-based model for capability building in technological catching-up	The learning process is decoupled into two complementary processes as learning by decomposition and learning by recombination. Capability building in technological catch~~ing~~-up can be conceptualized as a process in which latecomer firms purposively and strategically utilize specific learning mechanisms of technological decomposition and recombination.
	Figueiredo and Cohen (2019)	Develop a framework of learning mechanisms as proxies of dual absorptive capacity development ~~to~~ for understanding technological catch-up	External learning mechanisms include acquisition, training and nonresearch collaborations~~,~~ and research-based collaborations. Internal learning mechanisms include training and experimentation, knowledge sharing, integration, and codification.
Concepts related to technology recombination	Henderson and Clark (1990)	Develop a model of architectural innovation that helps explain how minor innovations can have great competitive consequences	Architectural innovation is defined as innovations that change the architecture of a product without changing its components, and it has the potential to offer firms the opportunity to gain a significant advantage over well-entrenched, dominant firms.
	Kogut and Zander (1992)	Develop a more dynamic view of how firms create new knowledge by recombining their current capabilities	Combinative capability reflects how firms synthesize and apply current and acquired knowledge and generate new applications from existing knowledge.
	Zahra and George (2002)	Identify key dimensions of absorptive capacity and offer a reconceptualization of this construct	Absorptive capacity is defined as a set of organizational routines and processes by which firms acquire, assimilate, transform, and exploit knowledge to produce a dynamic organizational capability. Specifically, transformation denotes a firm's capability to develop the routines that facilitate combining existing knowledge and newly acquired and assimilated knowledge, and exploitation is based on the routines that allow firms to leverage existing competencies or to create new ones by incorporating acquired and transformed knowledge into their operations.
	Arts and Veugelers (2014)	Explore the effects of recombinant novelty on the breakthrough invention	The creation of new combinations of technology components not only stimulates average usefulness but also leads to a significantly higher likelihood of breakthroughs while reducing the probability of failure.
	Guan and Yan (2016)	Develop a new measurement of recombinative innovation, first exploring its antecedents at the country-dyad level	Two countries' technological proximity takes an inverted U-shaped relationship with their recombinative innovation, and cultural distance negatively moderates the relationship between technological proximity and recombinative innovation.
	Guo and Zheng (2019)	Explore the reconfiguration mechanism as upgrading capabilities change over time for systemic catch-up	Four mechanisms based on market and technology reconfigurations are effective in promoting capability upgrading as the market-driven mechanism, the market-driving mechanism, the technological spill-back mechanism, and the technological spill-forward reconfiguration from the recombinant perspective of capability.

APPENDIX II. Summary of Key Empirical Studies on Emerging Markets Contexts[6]

Subject	*Authors*	*Empirical*	*Samples*	*Key contexts*	*Key findings*
Technology-related context	Xiao et al. (2013)	Case study	Three Chinese firms	Technological level	The technological level of the sector c~~w~~ould influence the early-stage choice between dependent and imitative strategy and when and how effectively the firm would move to a defensive strategy.
	Lee and Ki (2017)	Case study	The world steel industry	Generational changes in technologies	Generational changes in technologies could offer a window of opportunity for a long-cycle, capital-intensive sector, such as the steel industry.
	Li et al. (2019)	History-friendly simulation	Chinese firms in the mobile communications industry	Generational technological change	This combination of demand regimes (segmented markets) and technological regimes (generational technological change) facilitated the catching-up of Chinese domestic firms with respect to foreign firms. Generational technological change opened windows of opportunities for domestic firms to catch up with foreign multinationals in new product segments.
	Guo, Zhang, Dodgson, Gann, and Cai (2019)	Case study	Huawei	Windows of opportunity	Huawei utilized dual technology-building and market-seeking strategies to capitalize on those windows of opportunity and to achieve sustained catch-up.
Market-related context	Mu and Lee (2005)	Case study	The telecommunications industry in China	Market segment	The domestic Chinese firms were able to secure their competitive advantage because of the segmented nature of markets. On the one hand, in ~~its~~ the competition with foreign or local JV firms within China, the domestic firms took advantage of the segmented nature of the Chinese market. On the other hand, in their later competition in the international export market, the domestic firms took advantage of relatively cheap labor costs and numerous other resources.
	Buckley and Hashai (2014)	Secondary sources	139 firms	Domestic market size	~~That~~ The large domestic market size of emerging countries is a fundamental condition for these countries' EMNCs to become dominant players in the newly emerging global system.
	Brandt and Thun (2016)	Case study	Three large industrial sectors in China	Market segment	Each market segment is a crucial rung on the developmental ladder; industrial upgrading efforts stall when state policy inadvertently knocks out rungs on the development ladder.
	Thun (2018)	Case study	The Chinese automotive sector	Market segment	The middle segment is a crucial pathway for the development of new capabilities because it forces foreign and local firms to combine and recombine their respective resources in new ways to achieve the exact ratio of price and quality demanded by "value-for-money" customers.
	Butollo and Ten Brink (2018)	Case study	The Chinese LED industry	Domestic market size	Firms benefited from a growing domestic market on which they outcompeted foreign companies in midprice segments. The combination of state policies and expanding domestic markets accounts for the ~~peculiarly~~ unique Chinese upgrading experience.

[6] It should be noted that these empirical studies do not discuss effect size in the results section.

APPENDIX III. Productivity gap between local firms and foreign firms in China between 2000 and 2007



Notes: X-axis: industry ID; Y-axis: labor productivity gap; Unit of Measurement: Yuan per capital; Source: sample firms.