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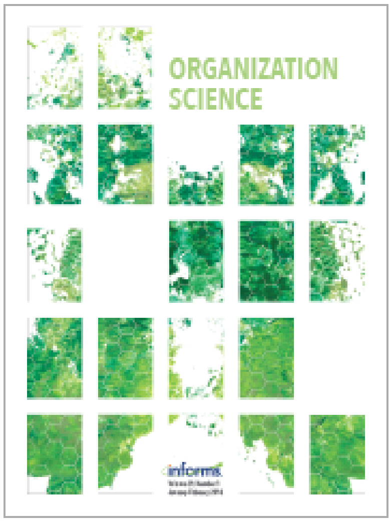

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Learning from Technologically Successful Peers: The Convergence of Asian Laggards to the Technology Frontier

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Abstract. This paper investigates whether firms from developing countries that lag the global technological frontier can learn from technologically successful peers as a means of closing the technological gap with leaders from developed countries. We define *technologically successful peers* as those that hail from similar home countries, operate in the same industry, and have achieved a certain degree of success in closing the gap with the global technological frontier. We argue that technologically successful peers represent an important reference group for lagging firms and, as such, offer opportunities for lagging firms from developing countries to hasten technological development. We find that lagging firms from developing countries that build upon the knowledge of technologically successful peers achieve higher rates of technological improvement. Moreover, learning from technologically proximal successful peers helps even further with technological improvement. However, there are limits to such learning, with diminishing marginal returns to lagging firms that over rely on successful peers.

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Keywords: technological convergence • laggards • reference group • patent • innovation

Introduction

In recent years, emerging companies from Asian countries (e.g., Hyundai-Kia Motors, LG, and Samsung from Korea; Acer, Hon Hai (Foxconn), and HTC from Taiwan; Haier, Huawei, and Lenovo from China) have rapidly developed technological capabilities and closed the technological gap with incumbent leaders in advanced, industrialized countries (Cho et al. 1998, Fan 2006, Khanna et al. 2011). Recognizing the importance of these national champions to the economic development of emerging economies, scholars have devoted increasing attention to these firms. Various studies document the ways in which Asian companies have been able to effectively close the technological gap with developed country competitors (e.g., Cho et al. 1998, Mathews and Cho 1999, Lee and Lim 2001, Song et al. 2001, Fan 2006). Those studies highlight how firms from developing countries that lag the global frontier can upgrade their technological capabilities by learning from developed country firms.

We have learned a great deal from studies that examine how technologically lagging firms from developing countries can learn from, and close the technological gap with, leading firms in developed countries. However, we understand less than we should about whether technologically lagging firms from developing countries might be able to upgrade their capabilities by learning from other developing country firms. To our knowledge, no study has examined whether technologically lagging firms from developing countries learn from developing country peer firms.

To fill this gap, we investigate whether firms from developing countries that lag the global technological frontier can learn from technologically successful peers (those that share similar environmental traits, that operate in the same industry, and that have achieved some measure of technological success). We draw from the organizational learning and technology literatures to identify technologically successful peers as an important reference group. We discuss how learning from technologically successful peers can represent an important means to upgrade technological capabilities. We argue that such learning can hasten technological development, yielding technological advances that can propel laggards from developing countries closer to the global technological frontier.

We study this phenomenon using a large sample of firms from three Asian economies—China, Korea, and Taiwan. We focus our attention on these three countries because each has national champions that have been successful in achieving some degree of convergence to the global technological frontier. Companies from Korea and Taiwan have been relatively successful in closing technological gaps with developed country firms (Guillén 2001). China, by contrast, though a bit further behind in its development path, is quickly emerging (Kroeber 2016). We therefore believe that studying companies from these three countries affords insight into the technological convergence process.

We focus our study on the period from 1977 through 2004. This is a particularly relevant window because it covers a period in which Korean, Taiwanese, and Chinese firms, at first, trailed developed country leaders in innovative capabilities and innovative output (Porter and Stern 2001, Lee and Kim 2009, Lee and Mathews 2013). The observational period therefore ensures that all the sample firms start as laggards. However, over that same time period, we observe a number of the sample firms achieving technological growth to become technological leaders, with others remaining laggards.

Our final sample therefore comprises an unbalanced panel of 3,401 Chinese, Korean, and Taiwanese firms that filed patents with the U.S. Patent and Trademark Office (USPTO) from 1977 through 2004. Among our sample of firms, we observe that lagging firms that cite the patents of technologically successful peers from developing countries achieve greater post-technological growth than those that do not. Similarly, lagging firms that cite technologically proximal successful peers achieve greater technological growth. These findings imply that firms from developing countries benefit from the knowledge of peers to upgrade their technological capabilities and hasten technological convergence. However, there are limits to learning from technologically successful (and even technologically proximal) peers. Past a certain threshold, citing the patents of peers dampens technological growth. This highlights an interesting growth and development tension: Learning from technologically successful and proximal peers can provide benefits to lagging firms from developing countries trying to upgrade their technological capabilities; however, at some point, over relying on those peers hinders technological development.

The study is structured as follows: We first review the background literature on technological upgrading and organizational learning. We then identify and define the reference group—technologically successful peers—and develop a set of hypotheses regarding the relationship between learning from technologically successful peers and technological convergence in a developing country context. The subsequent section describes the data, measures, and empirical tests. The next section presents results. The final section discusses the findings, their implications and limitations, and areas for future study.

Theory

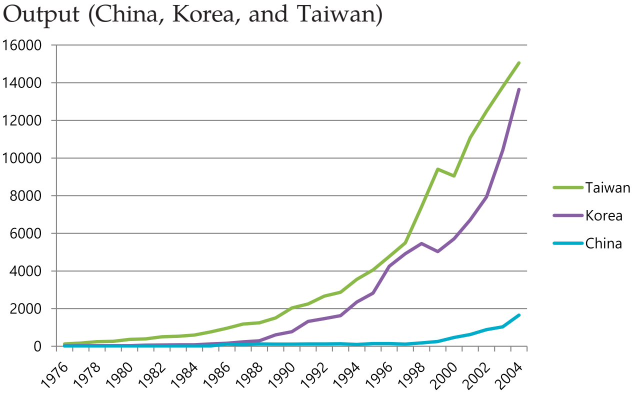
Technological Upgrading and Convergence

In recent years, scholars have documented how emerging Asian countries and their firms have been able to upgrade technologically and converge to the global technological frontier. Firms from developing Asian countries began from a disadvantaged initial position vis-à-vis their developed country counterparts; however, in recent years they have experienced dramatic economic growth. This has led some firms to converge quickly to developed country leaders, with some Asian companies in specific industries emerging as formidable global competitors.

Lee and Lim (2001), for example, detail how Korean companies in the automobile and semiconductor industries have been able to close the technological gap with developed country firms. Hu and Mathews (2005) document how Taiwanese firms have made strides in computing and optoelectronics. Guan and Yam (2015) highlight the technological advancement of Chinese firms in high-tech industries, such as telecommunications and computing. A cursory glance at patenting trends at the USPTO, the most demanding patent office in the world (Porter and Stern 2001), paints a similar picture. Korean, Taiwanese, and Chinese firms registered very few patents in the 1970s. However, the number of patents registered by firms from these countries increased exponentially in the late 1980s in the cases of Korea and Taiwan, and in the early 2000s in the case of China (see Figure 1).

Although Korean, Taiwanese, and Chinese firms have experienced some measure of success in closing the technological gap with developed countries, that convergence has been uneven, with some companies successfully closing the technological gap while others have not. The macro-level evidence corroborates the technological convergence of the aforementioned nations (e.g., Baumol 1986, Edwards 1993, Feeney 1999); however, there is still a substantial gap in patent output

Figure 1. (Color online) Cross-Country USPTO Patent Output (China, Korea, and Taiwan)



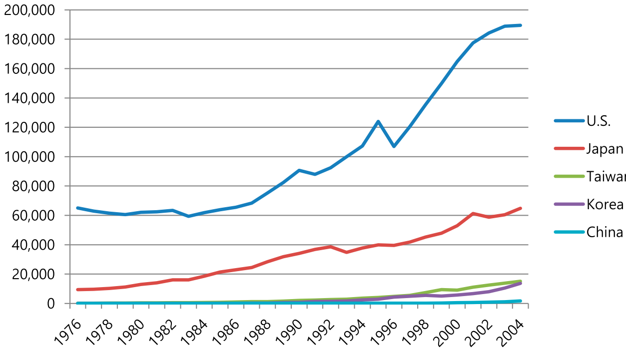
between developing nations like Korea, Taiwan, and China and developed nations like the United States and Japan (see Figure 2). That is to say, despite the technological accomplishments of Korean, Taiwanese, and Chinese firms, they continue to lag the global technological frontier.

With all that in mind, we focus on the ability of firms from technologically lagging countries—specifically, Korea, Taiwan, and China—to converge to the global technological frontier. By *convergence*, we refer to a process through which lagging firms from developing countries narrow the disparity between their own technologies and those at the global technological frontier (Chung and Alcácer 2002; Salomon and Jin 2008, 2010; Asmussen 2015). Moreover, by focusing on convergence to the global technological frontier, we adopt an approach that is consistent with the literature on technological evolution (Dosi 1982), in which firms are engaged in an ongoing and perpetual competition to develop the most advanced and sophisticated technologies in an effort to generate profits and competitive advantage (Acemoglu et al. 2006; Aghion and Howitt 2006; Salomon and Jin 2008, 2010).

We treat Korean, Taiwanese, and Chinese firms as global technological laggards in a manner consistent with the extant development literature (Mathews and Cho 1999, Mathews 2002). Firms from Korea, Taiwan, and China entered technological domains relatively late compared to technologically advanced, developed country firms. Their level of technological development has traditionally lagged that of firms from developed countries; and, on average, their technologies continue to lag those of firms in advanced countries.[1]

In the next section, we build on this base literature to focus on the mechanisms through which technologically lagging firms from developing countries (such as Taiwan, Korea, and China) have been able to close the technological gap with competitors from developed countries. Studies highlight how, aided by economic policy, technologically lagging firms from developing countries learn through trial-and-error experience, through research and development (R&D) investment, and, especially, from technologically leading firms from advanced countries.

Figure 2. (Color online) Cross-Country USPTO Patent Output (China, Korea, Taiwan, United States, and Japan)



Learning and Technological Convergence

We conceptualize learning as a process of accumulating, encoding, and leveraging insights gleaned through experience (Levitt and March 1988, Huber 1991, Argote 1999). Two forms of learning can be especially helpful in upgrading technological capabilities: experiential learning-by-doing through trial and error (for a review, see Argote 1999) and learning from the experiences of others (Argote et al. 1990, Ingram and Baum 1997).

Scholars point out that trial-and-error learning is a powerful means by which firms can increase organizational intelligence and improve their competitive position (Levinthal and March 1993). For example, firms often invest in R&D initiatives as a means of exploring new and unfamiliar technologies. However, because technological discovery and development are inherently uncertain processes, learning solely from the firm's own efforts often proves insufficient, especially for developing country firms that start from a disadvantaged position vis-à-vis the global technological frontier (Kim 1997, Cho et al. 1998, Mathews and Cho 1999, Li and Kozhikode 2008).

In order to foment learning and hasten technological development, scholars suggest that government programs—for example, targeted investment and industrial policy—can help complement internal firm efforts (Nelson 1993, Castellacci and Natera 2013). For example, public R&D spending by East Asian countries has improved national innovative capabilities and helped firms close the technological gap with developed country firms (Porter and Stern 2001, Hu and Mathews 2005). The Chinese and Korean governments have supported large state champions (i.e., state-owned companies in China and Chaebols in Korea) as a means of achieving technological development ends. Each has subsidized the R&D expenditures of those firms and enacted trade policies meant to promote exports while protecting them from foreign competition in the domestic market.

In addition to government- and firm- sponsored research programs, development research highlights how firms from developing countries learn from their counterparts in developed countries to catch up technologically (Baumol 1986, Edwards 1993, Feeney 1999). These scholars highlight the growth-enhancing role that economic exchange can play by fostering the exchange of knowledge across borders, leading to enhanced learning outcomes for emerging economies (e.g., Romer 1990; Grossman and Helpman 1990a, b). Indeed, firm-level studies suggest that laggards can acquire knowledge from developed county firms to help propel them toward the technological frontier. For instance, Kim (1997), Cho et al. (1998), and Lee and Lim (2001) describe how some Asian firms were able to improve their capabilities and move up the value chain to become technological innovators. They observed processes that were set in motion, and facilitated, by knowledge exchange with leading developed country competitors, customers, and suppliers. Due to their limited innovative capabilities, the initial phase of technological upgrading occurred through imitation. However, once developing country firms effectively replicated and internalized the shared knowledge, they shifted their focus to improving upon, and innovating, from that base (Chang et al. 2015).

Viewed as a corpus then, the extant literature has focused on several sources from which firms from technologically lagging countries can learn and upgrade their technologies. Specifically, research highlights internal firm effort (e.g., R&D), government programs (as a complement to that internal effort), and, especially, knowledge transfer from leading firms in developed countries (as a means of accessing advanced technologies). The fruits of that learning often manifest in increased patent output (an indicator of enhanced technological capabilities) on the part of firms that were once technological laggards (Song et al. 2003; Salomon and Jin 2008, 2010).

Despite all that we have learned about the mechanisms and the pathways through which firms from technologically lagging countries converge to the global technological frontier, we still understand relatively little about whether lagging firms from developing countries can learn through other means. We propose that, in addition to the sources identified above, firms from technologically lagging countries might be particularly well equipped to acquire knowledge and learn from firms with which they share similar profiles. We thereby identify technologically successful peers as an important reference group from which lagging firms might be able to fruitfully learn. In the next section, we define what we mean by *technologically successful peers* and describe why firms from technologically lagging countries might be able to lean on them as a resource to help close technological gaps and hasten development.

Learning from Technologically Successful Peers

As mentioned previously, we refer to firms from countries whose technological capabilities lag the global technological frontier as *technological laggards* (Chung and Alcácer 2002; Mathews 2002; Salomon and Jin 2008, 2010). Developing country firms can often be characterized as technological laggards because they tend to be late entrants to global industries, and are therefore at a competitive disadvantage at the outset (Cho et al. 1998, Kim 1997, Li and Kozhikode 2008, Mathews and Cho 1999). In most technological sectors, advanced country firms (notably those from the United States, Japan, and Western Europe) have established an advantage over firms from developing countries. They have had time to build technological capabilities and often have pioneered the industries in which the developing country firms wish to compete.

For technologically lagging firms looking to learn from other organizations, the reference organization is especially important. It might be tempting to focus on developed country leaders as learning targets; however, there might be other organizations to which laggards can turn. In particular, domestically oriented research highlights how firms can learn from successful firms that share similar traits and/or characteristics (Greve 1998, Baum et al. 2000).

Based on that underlying premise, we argue that technological laggards stand to learn from technologically successful peers. We define technologically successful peers as those that (1) share similar environmental, geographic, and cultural traits with the focal firm; (2) operate in the same industry as the focal firm; and (3) have achieved a certain degree of success in converging to the global technological frontier, having effectively closed the technological gap with leading firms from advanced countries prior to the focal firm.

Firms that share similar environmental, geographic, and cultural traits are especially salient to the focal firm. It is easier for the focal firm to keep tabs on their strategic moves, to monitor their progress, and observe how they have fared. When a peer is sufficiently similar in attributes and context, information about its choices is not only more readily accessible but also has greater diagnostic value (Fiegenbaum and Thomas 1995, Baum et al. 2000, Xia et al. 2008). Monitoring the behavior of peers in its reference group therefore serves as an aid to help a firm interpret ambiguous environmental information and make sense of strategic choices (Porac and Thomas 1990, Peteraf and Shanley 1997, Lee and Pennings 2002). Consistent with such a conjecture, prior studies demonstrate that organizations are more likely to imitate practices of other organizations with similar traits (Haunschild and Miner 1997, Baum and Ingram 1998).

In that respect, Korean, Taiwanese, and Chinese firms can fruitfully be considered as peers (Mathews 2002). They share similar cultural, geographical, and economic development characteristics. Korea, Taiwan, and China are geographic neighbors; their cultures are similarly steeped in Confucian ideals; and all three experienced rapid economic growth, transitioning relatively quickly from developing into more developed countries. All three adopted similar export-led, manufacturing growth policies and each concentrated its economic development efforts in similar sets of industries (Hobday 1995, Lall and Albaladejo 2004). As a result, each country can now point to notable firms that have been able to effectively close the technological gap with developed market incumbents. Hyundai-Kia Motors, LG, and Samsung from Korea; Acer, Hon Hai (Foxconn) and HTC from Taiwan; and Haier, Huawei, and Lenovo from China stand out as notable, and recognizable, examples.

Although Hyundai-Kia, LG, Samsung, Hon Hai, HTC, Haier, Huawei, and Lenovo are representative firms from Korea, Taiwan, and China that have been able to close the technological gap with incumbent leaders from developed markets, this is not to say they are the only ones. There are a number of firms from each that have made strides in closing the technological gap with developed country firms.[2] And technologically lagging firms from Korea, Taiwan, and China are likely to view those firms as peers, to look to those firms as potential learning targets, and to benchmark themselves against those firms (Mathews 2002, Lee and Yoon 2010). For example, in the early stages of its economic reform, China fashioned many of its economic development initiatives after those pursued by Korea and Taiwan (Kroeber 2016). It not only adopted similar export-led, manufacturing growth policies, but the Chinese government has regularly sent senior executives of major state-owned enterprises to visit with large Korean firms so that they can learn from, and replicate, their success.

In addition to considering peership based on environmental, geographic, and cultural characteristics, firms are likely to consider those that operate in the same industry as peers (Shaver et al. 1997, Srinivasan et al. 2007). Firms that operate in the same industry share even more in common. They compete against each other and sometimes even share suppliers and buyers. They are therefore more likely to consider each other rivals and, as such, are more likely to attend to, and benchmark against, each other.

Finally, firms are likely to focus their learning efforts on those peers that have experienced success (March and Olsen 1976, March et al. 1991, Haunschild and Miner 1997). If a peer shares not only similar environmental, geographic, cultural, and industrial characteristics, but also has a proven track record, it is likely to be viewed as a particularly apt role model. We therefore believe that lagging firms from developing countries are likely to look to successful peer firms as a model because the outcomes experienced by successful peers are thought to provide valuable clues to help laggards make sense of uncertain environments (Porac and Thomas 1990, Peteraf and Shanley 1997, Lee and Pennings 2002).

To the extent that successful peer firms possess information that the focal firm lacks, the information gleaned from them can provide tremendous value. As the organizational learning literature suggests, firms are better able to learn—that is, understand, encode, and assimilate knowledge—effectively from peer firms (March 1991, Raisch et al. 2009). The focal firm is therefore more likely to pay attention to successful peer firms, benchmark itself against them, emulate their strategies and practices in the hopes of replicating their success, reverse-engineer their products to internalize technological insights and inform future innovation, probe shared buyers and suppliers for competitive intelligence, and even attempt to hire away their employees as a means of absorbing technological knowledge (Song et al. 2003).

We believe that knowledge sourced from technologically successful peers (in our case, technologically successful Korean, Taiwanese, and Chinese firms in the same industry) is likely to help laggards improve their technological capabilities and converge to the global technological frontier. Technologically successful peers offer laggards unique learning benefits (beyond what they might gain from less-advanced peers or technologically successful nonpeers) that can help them improve their technological productivity and bridge the gap between their current technological position and the global technological frontier. We therefore expect learning from technologically successful peers to manifest as increased innovative productivity for firms from developing countries. Accordingly, we hypothesize the following.

Hypothesis 1. *Laggards from developing countries that learn from technologically successful peers are more likely to improve their technological capabilities and make progress toward converging to the global technological frontier.*

Learning from Technologically Proximal Successful Peers

Although laggards are likely to benefit from technologically successful peers in their attempt to catch up to the technological frontier, they are likely to benefit more from some peers than others. Even within the same industry, some peers are more relevant than others. Therefore, in addition to considering peership based on country characteristics and industry affiliation, we can identify technologically successful peers that share greater technological overlap.

Although firms operating in the same industry are likely to share a certain amount of natural market overlap (in customers, suppliers, and competitors), underlying technological similarities between the focal firm and its peers can help us identify a subset of firms within the industry that are likely to be more technologically relevant to the focal laggard. We therefore qualify our analysis by adding a more disaggregated technological dimension and reconceptualize technologically successful peers as either technologically proximal or technologically distal to the focal firm. If our priors about technological relevance are cogent, then we should find that laggards that cite technologically successful peers that are more similar in technological profile should converge more quickly to the technological frontier.

The organizational learning literature suggests that firms learn best when the knowledge that they are trying to internalize is similar to its own (Levinthal and March 1993, Raisch et al. 2009). Knowledge that is further afield from their own area of expertise is not only more difficult for firms to understand but is also less relevant to their technological development.

Extrapolating to our context, the implication is that laggards can best learn from successful peers that are not too distant technologically. This is because laggards are likely to lack the requisite absorptive capacity to integrate distal technological knowledge effectively. Laggards are therefore likely to benefit most when there is a greater overlap in the technological domains of the source and target (Lane and Lubatkin 1998, Sampson 2007, Song and Shin 2008). That is to say, laggards will be better served when they focus their learning on technologically successful peers that are also technologically proximal. We hypothesize the following.

Hypothesis 2. *Laggards from developing countries that learn from technologically proximal successful peers are more likely to improve their technological capabilities and make progress toward converging to the global technological frontier than those that learn from technologically distal successful peers.*

The Limits to Learning from Technologically Successful Peers

Although technologically successful (and technologically proximal) peers can help developing country laggards overcome learning barriers by providing knowledge that is relevant and valuable, this is not to say that laggards can rely repeatedly and continually on those peers to close the technological gap with leaders. At some point, there are likely to be diminishing marginal returns to learning from technologically successful peers, as an overreliance on those peers can lead to learning myopia (Levinthal and March 1993).[3]

The learning literature highlights two types of myopia that have the potential to hinder convergence outcomes for lagging firms. The first is temporal myopia (Levinthal and March 1993, Souder and Bromiley 2012, Slawinski and Bansal 2015). The second is spatial myopia (Levinthal and March 1993, Miller 2002).

Temporal myopia refers to the tendency of firms to misdirect their learning effort by giving precedence to short-run progress over long-term results. It is often characterized by managerial short-termism (Marginson and McAulay 2008), a situation in which managers systematically steer their firms toward behaviors that yield immediate, incremental performance improvements in the misguided belief that continuing to exploit such behavior will also help their firms achieve long-term, stretch goals. Firms that exhibit temporal myopia tend to invest systematically in solutions to current problems rather than meaningfully investing in solutions to longer-term problems. This form of myopia can dampen investment in new technologies, yielding outcomes that, in the extreme, can hinder a firm's long-run technological development (Mueller and Reardon 1993, Zaheer et al. 2000, Souder and Bromiley 2012). Moreover, it can upset the healthy balance between short-term and long-term learning objectives that are critical to achieving sustainable growth outcomes (Slawinski and Bansal 2015).

It is possible that firms from lagging countries exhibit temporal myopia. Laggards stand to benefit from technologically successful peers because those peers possess knowledge from which the laggard can benefit more immediately. The knowledge they possess is easier for laggards to absorb and assimilate at earlier stages of development because it is more advanced than their own, yet not so advanced that it is inaccessible. The benefits laggards derive from technologically successful peers are therefore more likely to help them address temporary capability deficiencies and/or resolve current environmental uncertainty. In this sense, the effectiveness of learning from technologically successful peers is likely to be temporal and transitional. After all, catching up with technologically successful peers represents but an intermediate step in the catch-up process. The ultimate goal remains to converge to the absolute technological frontier. In order to do that, it might be better at some point for laggards from technologically lagging countries to turn their attention away from learning from technologically successful (and proximal) peers in favor of learning from technological leaders from developed countries.

Spatial myopia, by contrast, refers to the tendency of learning processes and routines to ossify, with a bias toward knowledge that is more proximal to the learner. As firms focus increasingly on proximal knowledge, they tend to overlook valuable distal knowledge. And the more firms ignore distant technological knowledge, the more they sacrifice strategic flexibility (Miller 2002). Firms that do not keep abreast of broader technological developments beyond their narrow focus risk missing environmental shifts and are less able to switch to alternative technologies when such shifts occur (Eggers 2012). Therefore, when firms engage exclusively in a local search, focusing their learning efforts on proximal knowledge (e.g., geographically local peers), they can, to their own detriment, forego opportunities to engage in a global search, unwittingly missing out on distal knowledge, thereby limiting their technological development.

Because technologically successful and technologically proximal peers share environmental, geographic, cultural, industrial, and technological similarities, they are likely to be perceived as nearer to lagging firms. For this reason, lagging firms are likely to skew their learning efforts toward those peers. This form of local search may initially serve laggards well. However, competitive dynamics do not occur in a void, and incumbent leaders do not sit idly by as laggards attempt to narrow the gap with the global technological frontier. Therefore, an unwavering focus on local search is likely to handicap lagging firms. At some point, firms from technologically lagging countries will exhaust their ability to learn from technologically successful (and proximal) peers and should turn their attention to learning from more technologically distant, developed country firms.

Although learning from technologically successful and proximal peers can help laggards catch up, an overreliance on those peers can result in learning myopia. It can lead firms from lagging countries to overlook valuable alternative sources of knowledge and miss opportunities to upgrade their technological capabilities, stunting convergence to the global technological frontier. We therefore propose that the impact of learning from technologically successful and proximal peers is likely to increase at first and then decrease as laggards increase their reliance upon those peers. We state this formally in the following hypothesis.

Hypothesis 3. *The degree to which laggards from developing countries rely on learning from technologically successful and technologically proximal peers has a curvilinear (inverted-U shaped) relationship with technological convergence.*

Data and Methodology

Sample and Data

As previously mentioned, we focus on Chinese, Korean, and Taiwanese firms as peers because firms from these countries share similar characteristics and development patterns. We investigate whether past technological success of firms from this set of countries can aid in the future technological development of other firms from this same set of countries. The sample therefore consists of all Chinese, Korean, and Taiwanese firms that registered at least one patent with the U.S. Patent and Trademark Office (USPTO) between 1977 and 2004.

Tracking firms as far back as 1977, when firms from China, Korea, and Taiwan meaningfully began to file patents at the USPTO, ensures that firms from all three countries can be reasonably considered global technological laggards, at least initially (Kim 1997, Mathews 2002). We can then track firms reliably, and dynamically, over the sample period. Indeed, between 1977 and 2004, various firms from China, Korea, and Taiwan converged successfully toward the global technological frontier. For example, the Korean company Samsung Electronics entered our data set when it filed its first patent with the USPTO in 1989. At the time, Samsung was considered a laggard relative to the global technological frontier. However, by 1996, Samsung Electronics had patented to such an extent that it achieved convergence, thereby transitioning from a laggard into a technologically successful peer. Similarly, the Taiwanese company Hon Hai (Foxconn Technology Group) filed its first patent with the USPTO in 1994, thereby entering our sample as a global technological laggard. However, by 1998, Hon Hai had achieved convergence to the global technological frontier, effectively transitioning from a technological laggard into a technologically successful peer.

In order to assess the broader technological development of Chinese, Korean, and Taiwanese firms relative to the global technological frontier, we observe their patent output. Patent data have been widely used in organizational research to study technological innovation, technological development, and technological convergence (Sørensen and Stuart 2000; Ahuja and Katila 2001; Rosenkopf and Nerkar 2001; Benner and Tushman 2002; Salomon and Jin 2008, 2010). This is because patents serve as an indicator of the knowledge stock, knowledge creation, and innovative capabilities of firms (Ahuja and Lampert 2001, Nerkar 2003, Song et al. 2003). In addition to patent output, we are interested in patent citation patterns and the information that patent citation data can impart about knowledge diffusion. As Singh (2005, p. 759) points out, patent citations provide evidence of "how an innovation potentially builds on existing knowledge." Moreover, Jaffe and Trajtenberg (2002), by comparing patent data to survey data, demonstrate that there is substantial overlap between patent citations and knowledge flows.

Although we track the patent activity of Chinese, Korean, and Taiwanese firms, we focus on the patents those firms filed with the USPTO. We do so for three reasons. First, because the United States is among the most demanding technological markets in the world, the global technological frontier is fairly well represented in patents filed with the USPTO (Song et al. 2003). According to Porter and Stern (2001, p. 7), "the use of US patents ensures a commitment to a standard of technological excellence that is at or near the global technology frontier." The USPTO has a rigorous review process, and the most technologically sophisticated firms in the world compete to patent with the USPTO. It is therefore a good market in which to evaluate whether lagging firms have introduced novel technologies that approach the global technological frontier (Salomon and Jin 2008, 2010). Second, because each patent contains detailed information on the patent assignee, the patent class, and the number of citations received by each registered patent, patents can be reliably tracked over time. As a result, scholars argue that patent citations create a cumulative body of knowledge built upon prior art. Patents can thus be traced to a lineage of related knowledge so as to gain an understanding of whether one firm learns from another (Jaffe and Trajtenberg 1993, Rosenkopf and Nerkar 2001). Third, we build on an established literature that documents how developing country firms upgrade their technological capabilities by patenting at the USPTO (Awate et al. 2015, Song and Shin 2008).

With that as background, we generated an initial list of 4,004 Chinese, Taiwanese, and Korean firms that were granted at least one patent with the USPTO between 1977 and 2004. After removing observations with missing data, the initial usable sample comprises 3,401 firms—202 Chinese firms (5.94% of the sample), 937 Korean firms (27.55% of the sample), and 2,261 Taiwanese firms (66.48% of the sample).[4] As previously mentioned, some of the firms that start out as technologically lagging firms transition to become technologically successful peers. So as not to overstate our findings (by including technologically successful peer firms citing other technologically successful peer firms), we eliminate all firm-year observations for those firms that reach the global technological frontier (starting with the year they first achieve that distinction). This results in a final usable sample of 3,885 firm-year observations.

Measures

Dependent Variable

In this study, we focus on the technological convergence achieved by the firms in our sample. Accordingly, we view convergence as a process through which firms close technological gaps with the global technological frontier. We do not view convergence as an outcome in which firms achieve absolute convergence to reach parity with the technological frontier or as an outcome in which firms surpass the global technological frontier to become a global technological leader, an outcome known as *technological leapfrogging* (Soete 1985, Lee and Lim 2001, Chatain and Zemsky 2011). We use two indicators to assess whether firms from technologically lagging developing countries close technological gaps with leading firms from developed countries. Specifically, we distinguish between two types of technological convergence: *Quantitative Convergence* and *Qualitative Convergence*.

Quantitative Convergence focuses on a firm's rate of patent growth. Development scholars suggest that firms that exhibit convergence will often display rates of growth that are faster than that of leading, developed country firms (Dowrick and Nguyen 1989, Baumol et al. 1994, Kumar and Russell 2002, Nelson 2004). In the technological domain, Park and Lee (2006) assess convergence by comparing the technological innovation rates of firms from developing countries to those of firms from advanced countries. They measure technological catch-up as a binary variable that captures when a firm has passed a convergence hurdle. Similarly, Salomon and Jin (2008, 2010) use a binary variable to distinguish technological leaders from laggards. Building on that literature, we operationalize *Quantitative Convergence* as a binary variable, comparing the average patenting rate of the focal firm to the average of all global firms in its technological class.[5]

To calculate *Quantitative Convergence*, we define the compound annual patent growth rate (CAPGR) for firm i as$CAPGR_{iN} = (\frac{P_{tf}}{P_{ts}})^{\frac{1}{N}} - 1$, where P_{ts} is the number of patents for firm i in year *ts* (the first year in which firm i received a patent), $P_{tf}$is the total number of patents for firm i during the time period between year *ts* and year *tf* (the last year we observe the patenting behavior of firm i), and N is the total number of years (equal to *tf* − *ts+1*). We similarly calculate the CAPGR for the firm's primary technological patent class c (excluding firm i) over the same period. We measure$CAPGR_{cN} = (\frac{P_{tf}}{P_{ts}})^{\frac{1}{N}} - 1$, where P_{ts} is the total number of patents, irrespective of country of origin, in technological class c in year *ts* (in the corresponding year of the first patenting year for firm i); P_{tf} is the total number of patents, irrespective of country of origin, in technological class c during the time period between year *ts* and year *tf* (the last year we observe the patenting behavior of firm i); and N is the total number of years (equal to *tf* − *ts+1*). Following prior literature, we calculate CAPGR over three-year moving windows to assess the focal firm's technological development (Griliches 1984, Stuart and Podolny 1996, Ahuja 2000). Similar to Park and Lee (2006), we compare firm i's CAPGR to the CAPGR of its technological class and code *Quantitative Convergence* as 1 if firm i exhibits a higher average patent growth rate than that of the corresponding technological class, and 0 otherwise.[6]

Whereas *Quantitative Convergence* captures the growth rate in patent output, *Qualitative Convergence* assesses the quality and/or impact of the technology embodied by the patent. Prior research suggests that patent citations can serve as reasonable indicators of the quality and/or value of the technology embodied by the patent, with the number of forward citations to a patent correlating with higher quality/value (Trajtenberg 1990, Ahuja and Lampert 2001, Lanjouw and Schankerman 2004). We therefore use forward citations to gauge the quality and/or value of the focal firm's patents to future innovation. We consider a firm to display *Qualitative Convergence* when it develops patents that have greater technological impact (more forward citations) than the average patent in its primary technological class.

We begin by counting the number of forward citations received by each patent introduced by the focal firm (excluding self-citations) over the five-year period after the patent is issued. We then compare that number of citations to the average number (excluding the focal firm's patents) of forward citations received by all patents across all countries in the same issue year in the corresponding technological class. Given that the focal firm can have more than one patent that exceeds the technological class average, we sum the patents that the focal firm has that exceed the average of its technological class. The greater the number of patents that exceed the technological class average in forward citations, the closer the laggard becomes to the global technological frontier.

Independent Variables

In order to gauge whether the focal technological laggard learns from technologically successful peers, we turn to patent citation indicators for such evidence. Many studies have used patent citation data to track knowledge flows, and patent citations are considered reliable indicators of organizational learning (Almeida 1996, Jaffe and Trajtenberg 1993, Almeida et al. 2002, Song et al. 2003). This is because the citations contained within patents provide a trail of evidence linking the knowledge in those patents to knowledge contained in previous patents. In this way, patent citations describe how patents are connected to prior art—that is, a cumulative body of knowledge to which a particular patent relates and upon which it is based. Moreover, because patents must be deemed novel in order to be granted, they must describe how the embodied knowledge represents an advancement to prior art.

Empirical evidence suggests that learning is reflected in patent citations. For example, Jaffe and Trajtenberg (1993) demonstrate that firms pay particularly acute attention to the innovation of local actors and that learning tends to manifest in a predilection to cite the patents of geographically proximal firms. Gomes-Casseres et al. (2004) find evidence that knowledge flows between firms that collaborate; with learning reflected in an increase in the post-collaboration citation of partner firm patents. Almeida and Kogut (1999), Rosenkopf and Almeida (2003), and Song et al. (2003) all find that inventor mobility leads current employers to disproportionately cite the patents of former employers.

With all that in mind, and as an indicator of whether a firm learns from technologically successful peers, we measure the extent to which the focal firm cites—that is, builds upon and extends—the patents of technologically successful peers. This treatment is consistent with the use of patent citation data in the prevailing literature.

In order to assess the extent to which a given patent builds upon the patents of technologically successful peers (i.e., as a test of hypothesis 1), we must first identify the patents that belong to technologically successful peers. Since we consider the focal firm's technologically successful peers as those firms from Korea, Taiwan, and China that operate in the same industry and possess patents that are closer to the global technological frontier, we begin by identifying firms by home country (Korea, Taiwan, or China). We then identify the three-digit standard industrial classification (SIC) of each firm. Finally, we determine the extent of technological convergence achieved by each firm in the sample. We consider a peer firm technologically successful if it has achieved quantitative or qualitative convergence (as defined above) in the years leading up to year t.[7]

We then comb through the patent citation data of each technological laggard to determine whether the focal technological laggard cites the patents of technologically successful peers. That is, we define a dummy variable *Learning from Technologically Successful Peers* as 1 if the focal firm's patents cite patents that belong to Korean, Taiwanese, and Chinese firms that have realized convergence to the global technological frontier prior to the focal firm and that operate in the same three-digit SIC industry, and 0 otherwise.[8]

To assess whether laggards more effectively close the technological gap when they learn from technologically proximal successful peers (i.e., as a test of Hypothesis 2), we measure the technological similarity between the focal laggard and the successful peers it cites in its patents. Accordingly, we calculate the technological distance from successful peers using the Euclidean distance between the focal firm's patents and those of its technologically successful peers (Song et al. 2003). Mathematically, this relationship is defined as $\sqrt{\sum_{c=1}^{n} (p_{ic} - p_c')^2}$, where p_c is the percentage of the citing firm's (the focal laggard) patents in technological class c and p_c' is the percentage of the cited firms' (the focal firm's successful peers) patents in patent class c, and n is the total number of patent classes. Because we are interested in the technological proximity (vs. distance) between the focal laggard's patents and the patents it cites, we take the inverse of the Euclidean distance defined in the equation above. We label this measure *Learning from Technologically Proximal Successful Peers*, and increasing values indicate technologically successful peers that are more technologically similar to the focal laggard.[9]

In order to test the proposed inverted-U shape relationship from Hypothesis 3, we first convert the dichotomous *Learning from Technologically Successful*

Peers variable into a continuous variable by measuring the degree to which the focal firm relies on knowledge created by its technologically successful peers. We define *Degree of Learning from Technologically Successful Peers* as the ratio of focal firm citations to technologically successful peer patents as a percentage of its total citations. The larger the ratio, the more the focal firm relies on knowledge developed by technologically successful peers versus that of advanced country firms. We include the linear (*Degree of Learning from Technologically Successful Peers*) term and a squared (*Degree of Learning from Technologically Successful Peers Squared*) term to test for diminishing marginal returns to learning from technologically successful peers. We also include the linear (*Learning from Technologically Proximal Successful Peers*) term and a squared (*Learning from Technologically Proximal Successful Peers Squared*) term to assess diminishing marginal returns to learning from technologically proximal successful peers. Including these measures can help determine whether laggards exhibit overreliance on learning from a specific set of peers by isolating the patent output consequences of citing those peers at the highest levels in the observed citation range.

Control Variables

We control for a host of variables that stand to influence the independent and dependent variables. First, because patent growth could simply reflect the industrial policy and accompanying growth of a nation, we control for the gross domestic product (GDP) growth rate (from year t-1 to year t) of the focal firm's home country (*GDP Growth Rate*). We also control for the average number of citations (*Number of Citations*) made by each firm in each patenting year, as the more citations included in a firm's patents, the more statistically likely it is to cite one of its peers. Because technological opportunities vary across technological fields (Henderson and Cockburn 1994), we include a dummy (*Patent Intensive Industries*) that captures whether firms compete in one of the five high-tech industries that comprise 61.45% of the sample: electronics (25.37%), machinery (18.64%), professional and scientific instruments (7.02%), chemical (6.38%), and transportation (4.02%).[10] We also include random firm effects, country fixed effects, and year fixed effects to help control for systematic unobserved heterogeneity in patenting behavior across firms and countries and over time.[11] The firm, country, and year effects can control for a range of unobservables related to learning and technological development without having to precisely specify their source.

Model Specifications

In order to determine the appropriate statistical modeling technique to test our hypotheses, we must take into account the nature of the dependent variables. *Quantitative Convergence* is a binary variable; we therefore turn to a logistic regression approach for this dependent variable (Long 1997). The logistic regression estimates the probability of observing a particular binary outcome (in this case, technological convergence) as a function of explanatory variables. The logistic regression function can be expressed as$P_{it} = \frac{e^{\beta X_{it}}}{1+e^{\beta X_{it}}}$, where P_{it} is the probability of observing *Quantitative Convergence* for firm i in year t, X_{it} is the vector of exploratory variables, and$\beta$is a vector of coefficients.

By contrast, the *Qualitative Convergence* dependent variable is a count measure that can only take nonnegative integer values. A Poisson regression is generally the recommended approach in situations where the dependent variable is a count variable (Kennedy 1998, Greene 2003). However, inhered in the Poisson regression is the assumption that the dependent variable has an underlying Poisson distribution, with a mean equal to its variance (Cameron and Trivedi 1986). In our setting, the mean of the dependent variable (the number of firm patents with greater than average citations for the technological class) is 0.49 and the standard deviation is 0.89. Therefore, the distribution of the dependent variable is characterized by overdispersion. When there is overdispersion, scholars recommend a negative binomial regression (Hausman et al. 1984, Henderson and Cockburn 1996). We therefore turn to the negative binomial regression to test the hypotheses on *Qualitative Convergence*.

We specify a negative binomial as follows:$\Pr(Y = y_j) = \frac{e^{-\lambda_j}\lambda_j^{Y_j}}{Y_j!}$, where $\lambda_j = \exp(\sqrt{\beta X_{ij}} e^{\mu j})$. In the aforementioned equation, λ_j represents the number of focal firm patents for which the forward citations exceed the average forward citations in the technological class, X_{it} is a vector of explanatory variables,$\beta$is a vector of coefficients, and$e^{\mu j}$ is an error with an expected distribution that approximates a gamma distribution.

Results

Findings of Quantitative and Qualitative Convergence

Tables 1 and 2 provide descriptive statistics separated by dependent variable. We note that our usable sample varies by dependent variable. The *Quantitative Convergence* sample includes 3,401 firms and 3,885 firm-year observations. However, because we use a five-year window to compute forward citations, we are forced to drop observations from 2000 to 2004 when we calculate *Qualitative Convergence* to avoid right-censoring in forward citations. Therefore, the usable sample for the *Qualitative Convergence* models reduces to 1,901 firms and 2,165 firm-year observations.[12]

There are 366 cases (firm-year observations) of *Quantitative Convergence* in our sample, about 9% of

Table 1. Descriptive Statistics and Correlations (*Quantitative Convergence*)

Variables	N	Mean	Std. dev.	Min	Max	1	2	3	4	5	6
1 *Quantitative Convergence*	3,885	0.09	0.29	0.00	1.00	1					
2 *Learning from Technologically Successful Peers*	3,885	0.06	0.23	0.00	1.00	0.19*	1				
3 *Degree of Learning from Technologically Proximal Successful Peers*	211	0.37	0.22	0.00	1.53	0.41*	—	1			
4 *Number of Citations*	3,885	4.36	5.19	1.00	158. 75	0.09*	0.13*	−0.03	1		
5 *Patent Intensive industries*	3,885	0.62	0.49	0.00	1.00	0.03*	0.20*	—	0.06*	1	
6 *GDP Growth Rate*	3,885	1,922.86	1,358.55	−0.10	3,399.73	0.07*	0.10*	0.08	−0.06*	0.06*	1

Notes. N, number of observations; Std. dev., standard deviation; —, no data.
$^{*}p < 0.05$.

the sample firms achieving patent growth rates that are on par with, or greater than, the average for all firms in their technological class. We observe 827 cases of *Qualitative Convergence*. About 43% of the sample firms in which *Qualitative Convergence* serves as the dependent variable developed at least one patent that received more forward citations than the average number of citations received by patents in their respective technology class.

As can be seen in Tables 1 and 2, the correlations are moderate in magnitude and in the expected direction.[13] There is a positive relationship between our learning measures and each of the dependent variables. Although the correlations are generally as expected, they do not control for intervening factors that have the potential to influence both the dependent and independent variables. We therefore turn to the multivariate results.

Table 3 presents multivariate regression results meant to test our hypotheses. Models 1 and 7 present baseline specifications including only the control variables. Models 2 and 8 present our test of Hypothesis 1, which suggested that technological laggards that learn from technologically successful peers would achieve better outcomes when it comes to closing technological gaps than laggards that exclusively cite the patents of developed country firms. Consistent with that hypothesis, models 2 and 8 indicate that there is a positive and significant relationship ($p < 0.01$) between learning from technologically successful peers and achieving both quantitative and qualitative convergence. Specifically, Korean, Taiwanese, and Chinese laggards that cite the patents of technologically successful Korean, Taiwanese, and Chinese firms experience higher-than-average levels of patent output. Likewise, Korean, Taiwanese, and Chinese laggards that cite the patents of technologically successful Korean, Taiwanese, and Chinese firms to a greater extent introduce patents that have a higher-than-average impact, as measured by forward citations. The marginal effect of *Learning from Technologically Successful Peers* is 1.74 (z-score = 7.06, $p < 0.01$) in the case of *Quantitative Convergence* and 1.38 (z-score=11.10, $p < 0.01$) in the case of *Qualitative Convergence*. Citing the patents of technologically successful peers increases the focal firm's chances of achieving *Quantitative Convergence* by a factor of 1.74. Because the *Qualitative Convergence* dependent variable is a count variable, the interpretation of the marginal effects is slightly different. Specifically, citing the patents of technologically successful peers increases the number of impactful patents (as measured by citations) by 1.38 patents.

Models 3 and 9 present our test of Hypothesis 2, in which we imply that laggards that learn from technologically proximal successful peers would achieve better technological outcomes. Consistent with that hypothesis, findings indicate a positive and significant relationship ($p < 0.01$) between learning from technologically proximal successful peers and quantitative convergence, but not qualitative convergence. This provides only partial support for Hypothesis 2. The marginal effect of *Learning from Technologically*

Table 2. Descriptive Statistics and Correlations (*Qualitative Convergence*)

Variables	N	Mean	Std. dev.	Min	Max	1	2	3	4	5	6
1 *Qualitative Convergence*	2,165	0.49	0.89	0.00	14.00	1					
2 *Learning from Technologically Successful Peers*	2,165	0.42	0.20	0.00	1.00	0.26*	1				
3 *Degree of Learning from Technologically Proximal Successful Peers*	89	0.45	0.24	0.00	1.13	0.20	−0.28*	1			
4 *Number of Citations*	2,165	3.88	3.20	1.00	41.00	0.09*	0.20*	−0.19	1		
5 *Patent Intensive Industries*	2,165	0.60	0.49	0.00	1.00	−0.03	0.17*	—	0.09*	1	
6 *GDP Growth Rate*	2,165	1,727.46	1,271.59	−0.10	2,990.10	0.06*	0.07*	−0.05	−0.10*	−0.11*	1

Notes. N, number of observations; Std. dev., standard deviation; —, no data.
$^{*}p < 0.05$.

Table 3. Results for Technological Convergence of Laggards

	Qualitative Convergence						*Qualitative Convergence*					
Variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10	Model 11	Model 12
Learning from Technologically Successful Peers		1.742***						1.368***				
		[7.055]						[11.10]				
Degree of Learning from Technologically Proximal Successful Peers			8.595***	11.31**					1.046	2.993		
			[2.385]	[1.731]					[1.270]	[1.017]		
Degree of Learning from Technologically Proximal Successful Peers Squared				−3.829						−2.175		
				[−0.957]						[−0.678]		
Degree of Learning from Technologically Successful Peers					1.210*	34.27***					3.853***	13.46***
					[1.367]	[5.592]					[5.001]	[6.136]
Degree of Learning from Technologically Successful Peers Squared						−134.3***						−24.42***
						[−4.635]						[−3.495]
Number of Citations	0.0482***	0.0352**	0.116	0.0798	0.0483***	0.0404***	0.0582***	0.0414***	−0.00637	−0.00430	0.0585***	0.0561***
	[3.291]	[2.311]	[0.875]	[0.893]	[3.189]	[2.658]	[6.576]	[4.452]	[−0.170]	[−0.114]	[6.509]	[6.127]
Patent Intensive Industries	0.226**	−0.0374	—	—	0.207**	0.0859	−0.0820	−0.220***	—	—	0.110*	0.141*
	[1.901]	[−0.283]			[1.721]	[0.667]	[−1.160]	[−3.054]			[−1.538]	[−1.971]
GDP Growth Rate	0.000806***	0.000764***	−0.00559	0.00147	0.000803***	0.000791***	9.48e-05	6.19e-05	0.000211	0.000391	8.75e-05	7.88e-05
	[2.568]	[2.333]	[−1.054]	[0.514]	[2.547]	[2.415]	[0.800]	[0.525]	[0.119]	[0.219]	[0.737]	[0.663]
Country Effects	Included	Included	Included	Included	Included	Included	Included	Included	Included	Included	Included	Included
Year Effects	Included	Included	Included	Included	Included	Included	Included	Included	Included	Included	Included	Included
Constant	−3.566***	−3.171***	13.09	−9.655	−3.545***	−3.354***	0.351	2.011***	−1.481	−2.276	0.530	1.035**
	[−3.046]	[−2.589]	[0.810]	[−0.996]	[−3.020]	[−2.735]	[0.838]	[2.037]	[−0.280]	[−0.422]	[1.186]	[1.810]
Observations	3,885	3,885	211	211	3,885	3,885	2,165	2,165	89	89	2,165	2,165
Number of Firms	3,401	3,401	170	170	3,401	3,401	1,901	1,901	74	74	1,901	1,901

Notes. z-statistics in brackets. Models 3, 4, 9, and 10 do not include the *Patent Intensive Industry* variable in the proximal peer regressions because there are too few industries in the smaller subsample for the models to converge. —, no data.

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$ at one-tailed test.

Proximal Successful Peers is 11.31 (z-score = 1.73, $p < 0.1$). Citing the patents of technologically proximal successful peers by an additional standard deviation (0.24) relative to the mean increases the likelihood of *Quantitative Convergence* by a factor of 11.31.

In Hypothesis 3, we argued that there would be an inverted U-shaped relationship between the extent to which laggards rely on learning from technologically successful (and proximal) peers and technological convergence. Again, in order to assess Hypothesis 3, we converted our *Learning from Technologically Successful Peers* independent variable into a continuous variable that we label *Degree of Learning from Technologically Successful Peers*. Because *Degree of Learning from Technologically Successful Peers* is a ratio variable, it includes the number of citations to technologically successful peers in the numerator and the number of citations to firms other than technologically successful peers (e.g., developed country firms) in the denominator. As such, the measure helps capture for the extent of learning from technologically successful peers versus other firms, while controlling for the effect of learning from developed country firms.

Turning to the results meant to test Hypothesis 3, models 5, 6, 11, and 12 present the linear and quadratic effects for *Degree of Learning from Technologically Successful Peers* and *Learning from Technologically Proximal Successful Peers*. Consistent with Hypothesis 3, results indicate that there are diminishing marginal returns to relying on technologically successful and proximal peers. Firms that over rely on the knowledge of technologically successful peers and technologically proximal successful peers fail to achieve desired convergence outcomes, ultimately hindering technological progress. Figures 3 and 4 graph the curvilinear relationship of learning from technologically successful peers and technological convergence for the *Learning from Technologically Successful Peers*

Figure 3. (Color online) The Curvilinear Effect of *Learning from Technologically Successful Peers* on *Quantitative Convergence*

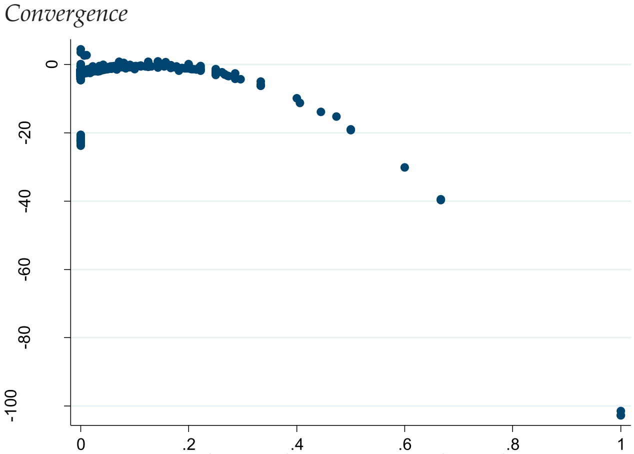
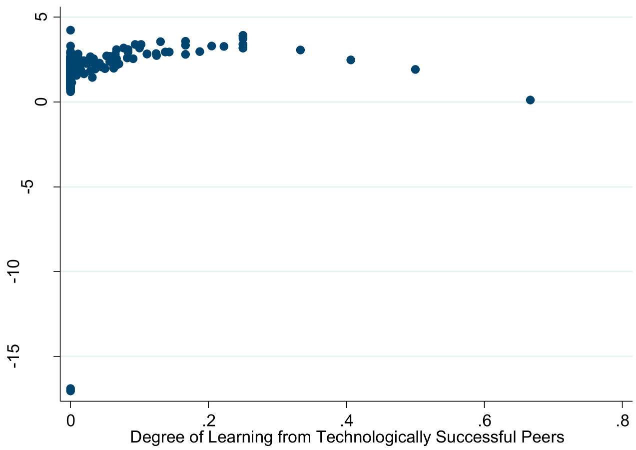


Figure 4. (Color online) The Curvilinear Effect of *Learning from Technologically Successful Peers* on *Qualitative Convergence*



variable. They demonstrate that laggards are best served relying only moderately on the knowledge of technologically successful peers. With respect to quantitative convergence, the inflection point is at about 0.18 (Figure 3), suggesting that when citations to technologically successful peer patents make up more than 18% of all their citations, laggards begin to suffer declining likelihoods of quantitative convergence. Insofar as qualitative convergence is concerned, the inflection point is about 0.25 (Figure 4), suggesting that when citations to technologically successful peer patents make up more than 25% of all their citations, laggards begin to suffer declining likelihoods of quantitative convergence.

Sensitivity and Robustness

To assess the sensitivity and robustness of our findings, we tested variants of the results presented herein.

First, to the extent that our theory is cogent and provides support for our notion that Korean, Taiwanese, and Chinese firms are peers, we should be able to replicate our findings in subsamples consisting only of Korean firms, Taiwanese firms, and Chinese firms. Although we could not run such a robustness check using the Chinese subsample because the sample was too small, we did replicate our analyses using the Korean and Taiwanese subsamples. These results appear in Tables 4 and 5, respectively. Although there are slight variations across subsamples, the patterns of results are largely consistent with those from Table 3.

Second, although we include country, firm, and year effects to control for unobserved heterogeneity, there is a concern that unobserved firm- or government-specific factors that are correlated with learning from technologically successful peers could be driving our findings. Because the overwhelming majority of firms in this sample are small, privately owned companies,

Table 4. Results for Technological Convergence of Laggards (Korean Firms)

Qualitative Convergence							*Qualitative Convergence*					
Variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10	Model 11	Model 12
Learning from Technologically Successful Peers		2.035***						0.794***				
		[4.774]						[2.703]				
Degree of Learning from Technologically Successful Peers Squared			186.1	294.9					5.388*	−1.362		
			[0.946]	[0.613]					[1.592]	[−0.0477]		
Degree of Learning from Technologically Proximal Successful Peers Squared				−244.0						15.72		
				[−0.454]						[0.238]		
Degree of Learning from Technologically Successful Peers					2.274	30.22**					2.585	3.128
					[0.697]	[1.857]					[1.199]	[0.416]
Degree of Learning from Technologically Successful Peers Squared						−136.5						−2.995
						[−1.437]						[−0.134]
Number of Citations	0.0888***	0.0706***	5.087	4.527	0.0829***	0.0803***	0.0625***	0.0452***	−0.00301	−0.00453	0.0604***	0.0635***
	[3.339]	[2.483]	[0.957]	[0.716]	[3.206]	[2.936]	[4.022]	[2.691]	[−0.0592]	[−0.0874]	[3.860]	[3.880]
Patent Intensive Industries	0.0524	−0.139	—	—	0.0508	0.0194	0.261**	0.326***	—	—	−0.273**	−0.269**
	[0.204]	[−0.524]			[0.199]	[0.0747]	[−1.826]	[−2.241]			[−1.901]	[−1.878]
GDP Growth Rate	−25,060	2,790	−8.044e+06	−6.373e+06	277,338**	−392,742	275,784***	270,951***	730,374	690,396	277,312***	239,914***
	[−0.0716]	[0.00793]	[−0.908]	[−0.684]	[2.370]	[−1.030]	[4.153]	[4.081]	[1.289]	[1.166]	[4.175]	[3.457]
Country Effects	Included	Included	Included	Included	Included	Included	Included	Included	Included	Included	Included	Included
Year Effects	Included	Included	Included	Included	Included	Included	Included	Included	Included	Included	Included	Included
Constant	10.01	−3.831	3,935	3,093	−141.8***	195.0	−136.2***	−132.8***	−364.8	−344.1	−136.9***	−117.9***
	[0.0569]	[−0.0217]	[0.905]	[0.682]	[−2.419]	[1.018]	[−4.066]	[−3.922]	[−1.291]	[−1.161]	[−4.086]	[−3.358]
Observations	1,040	1,040	32	32	1,040	1,040	574	574	22	22	574	574
Number of Firms	937	937	29	29	937	937	486	486	16	16	486	486

Notes. z-statistics in brackets. Models 3, 4, 9, and 10 do not include the *Patent Intensive Industry* variable in the proximal peer regressions because there are too few industries in the smaller subsample for the models to converge. —, no data.

*** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$ at one-tailed test.

Table 5. Results for Technological Convergence of Laggards (Taiwanese Firms)

	Qualitative Convergence						*Qualitative Convergence*					
Variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10	Model 11	Model 12
Learning from Technologically Successful Peers		1.849***						1.448***				
		[5.563]						[10.17]				
Degree of Learning from Technologically Proximal Successful Peers			8.825***	12.84*					0.906	2.913		
			[2.486]	[1.626]					[1.099]	[0.863]		
Degree of Learning from Technologically Proximal Successful Peers Squared				−3.519						−1.852		
				[−0.632]						[−0.609]		
Degree of Learning from Technologically Successful Peers					1.201	40.54***					3.908***	14.09***
					[1.149]	[4.850]					[4.420]	[6.058]
Degree of Learning from Technologically Successful Peers Squared						−154.9***						−24.62***
						[−4.251]						[−3.536]
Number of Citations	0.0348**	0.0187	0.0500	0.0469	0.0352**	0.0279*	0.0492***	0.0374***	−0.0371	−0.0353	0.0505***	0.0499***
	[1.954]	[1.004]	[0.813]	[0.782]	[1.957]	[1.511]	[4.372]	[3.181]	[−0.555]	[−0.521]	[4.414]	[4.288]
Patent Intensive Industries	0.328***	0.0361	—	—	0.307**	0.154	−0.0524	−0.209***	—	—	−0.0839	−0.122*
	[2.170]	[0.216]			[2.007]	[0.912]	[−0.637]	[−2.484]			[−1.010]	[−1.465]
GDP Growth Rate	0.00357**	0.00473***	0.000500	0.000872	0.00367**	0.00467**	−0.000772	−0.000994*	−0.00119	−0.000975	−0.000947*	−0.000953*
	[1.645]	[2.050]	[0.0262]	[0.0466]	[1.682]	[1.953]	[−1.120]	[−1.526]	[−0.553]	[−0.449]	[−1.382]	[−1.416]
Country Effects	Included	Included	Included	Included	Included	Included	Included	Included	Included	Included	Included	Included
Year Effects	Included	Included	Included	Included	Included	Included	Included	Included	Included	Included	Included	Included
Constant	−12.80**	−16.46***	−6.128	−8.100	−13.16**	−16.36**	2.760*	4.928***	2.533	1.551	3.439**	3.944**
	[−1.866]	[−2.258]	[−0.105]	[−0.141]	[−1.903]	[−2.163]	[1.384]	[2.333]	[0.407]	[0.242]	[1.724]	[2.001]
Observations	2,632	2,632	176	176	2,632	2,632	1,487	1,487	67	67	1,487	1,487
Number of Firms	2,262	2,262	138	138	2,262	2,262	1,313	1,313	58	58	1,313	1,313

Notes. z-statistics in brackets. Models 3, 4, 9, and 10 do not include the *Patent Intensive Industry* variable in the proximal peer regressions because there are too few industries in the smaller subsample for the models to converge. —, no data

***$p < 0.01$; **$p < 0.05$; *$p < 0.1$ at one-tailed test.

we were unable to collect firm-specific data for all of them. However, we were able to collect firm-specific size, age, and R&D data for a subset of the firms from the KISLINE, KISVALUE, and Compustat Global databases. We then use those data to impute missing firm-specific data for the remainder of the sample using the multiple imputation method (Allison 2001, Little and Rubin 2002, Enders 2010). In addition, we were able to collect data on government R&D spending programs from the Organisation for Economic Co-operation and Development (OECD). We report results including these additional variables in Table 6. The results are consistent with those from Table 3, providing additional support for our hypotheses.

Third, although we drop firm-year observations for those firms that become successful based on global technological standards, it is possible that our sample still includes firms that are relatively sophisticated local firms. In order to ensure that our results are not biased to the inclusion of such locally leading firms, we ran an additional set of results that removes the older firms from the sample. This is because the older firms in the sample tend to evolve into more technologically sophisticated firms. Younger firms—that is, those firms founded during the latter part of the sample period—can more reasonably be considered laggards that have yet to achieve convergence. For this reason, we split the sample by age and reran results including only those firms younger than the median firm age. These results appear in Table 7. They are largely consistent with those from Table 3.

Discussion and Conclusion

Contributions and Implications

For developing countries, upgrading the technological capabilities of their firms is an important goal and provides a means through which they can hasten development, improve their competitive standing, and close income gaps with developed countries. Research suggests that lagging firms from developing economies can close the gap with global technological leaders in a variety of ways. However, we still understand less than we should about the technological upgrading process and about whether lagging firms from developing countries can learn from one another to upgrade their technological capabilities.

In this study, we attempt to fill the aforementioned research gap by documenting a specific means (learning from technologically successful peers and learning from technologically proximal successful peers) through which laggards from developing economies can improve their technological standing and close the technological gap with global technological leaders. We identify technologically successful peers as those that share environmental, geographic, cultural, and industrial characteristics and that have been successful in the past. We define technologically proximal successful peers as technologically successful peers that are closer in technological proximity to the focal firm. In contrast with prior learning studies that focus on incumbent leaders from developed countries (whether customers, suppliers, and/or competitors) as sources for learning, we identify, and highlight, a slightly different learning source. We argue that technologically successful (and technologically proximal) peers are a set of firms from which lagging firms from developing countries can learn effectively. We then investigate the role of learning from those peers on the technological convergence outcomes of laggards.

Our findings demonstrate that learning from technologically successful and proximal peers affords laggards the opportunity to hasten their pace of technological convergence. It helps them meet short- and medium- term technological objectives, upgrading their absorptive capacity in increments, without having to make a giant leap straight to the global technological frontier. As such, learning from technologically successful (and proximal) peers can serve as a bridge between the laggard's current position and its ultimate goal—that of achieving parity with the global technological frontier. Moreover, we find that learning from those peers provides important incremental, exploitative gains that are critical to laggards early on.

For managers of upstart, lagging firms from developing countries, this suggests that, rather than trying to imitate and/or learn from incumbent leaders from developed countries, their firms might be better served focusing their learning efforts on peer firms, at least initially. Technologically successful and proximal peers are likely to possess knowledge that is relatively easier for lagging firms to absorb. Moreover, the experiences of technologically successful peers are more relevant for laggards. All this makes it not only easier for lagging firms to learn from technologically successful peers but also to succeed in those endeavors.

The findings also indicate that managers ought to proceed with caution when it comes to learning from peers. Although technologically successful and proximal peers can play an important role as a bridge to the global technological frontier, laggards from developing countries should not become overreliant on learning from them. Relying too much on those peers can result in laggards ultimately falling into a learning/myopia trap (Levinthal and March 1993). Indeed, our findings suggest that firms benefit most when relying on technologically successful and proximal peers to a moderate degree. This provides nuance to the findings and reveals important boundary conditions associated with learning.

For policymakers from developing countries, our findings highlight the critical role that national champions can play to technological development and

Table 6. Results Including Firm-Level Variables and Government Data

	Quantitative Convergence						*Quantitative Convergence*					
Variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10	Model 11	Model 12
Learning from Technologically Successful Peers		1.915***						1.320***				
		[7.043]						[10.73]				
Degree of Learning from Technologically Proximal Successful Peers			9.389***	14.08**					0.621	4.220*		
			[2.562]	[1.753]					[0.657]	[1.125]		
Degree of Learning from Technologically Proximal Successful Peers Squared				−4.260						−3.889		
				[−0.742]						[−0.971]		
Degree of Learning from Technologically Successful Peers					1.506*	38.42***					3.888***	14.11***
					[1.555]	[5.706]					[4.971]	[6.374]
Degree of Learning from Technologically Successful Peers Squared						−147.8***						−25.98***
						[−4.744]						[−3.625]
Number of Citations	0.0334***	0.0231**	0.131	0.130	0.0335	0.0268**	0.0479***	0.0361***	−0.0272	−0.0248	0.0479***	0.0437***
	[2.431]	[1.863]	[0.811]	[0.798]	[2.438]	[2.155]	[4.808]	[3.541]	[−0.577]	[−0.524]	[4.756]	[4.281]
Patent Intensive Industries	0.251***	−0.0173	—	—	0.228**	0.103	−0.0950	−0.227***			−0.122**	−0.157**
	[1.963]	[−0.122]			[1.764]	[0.741]	[−1.346]	[−3.154]			[−1.722]	[−2.197]
GDP Growth Rate	−4.98e-05	2.66e-05	−0.0568	−0.0552	−4.03e-05	−8.07e-06	−0.000961**	−0.000822**	−0.0182	0.00199*	−0.000918**	−0.000951**
	[−0.0644]	[0.0329]	[−1.086]	[−1.063]	[−0.0520]	[−0.00995]	[−1.961]	[−1.685]	[−0.644]	[0.699]	[−1.866]	[−1.936]

Table 6. (Continued)

	Quantitative Convergence						*Quantitative Convergence*					
Variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10	Model 11	Model 12
Government R&D	−0.000151	−0.000153*	−0.000119	−0.000197	−0.000151*	−0.000156*	−0.000233***	−0.000189**	0.000374	1.66e-05	−0.000218***	−0.000227***
	[−1.409]	[−1.372]	[−0.0639]	[−0.106]	[−1.408]	[−1.381]	[−2.711]	[−2.212]	[0.529]	[0.0359]	[−2.523]	[−2.650]
Population	9.81e-08**	9.38e-08*	−4.24e-06	−4.06e-06	9.72e-08*	1.05e-07**	−7.71e-09	−6.18e-09	−1.24e-05	−3.73e-06	−7.38e-09	−7.44e-09
	[1.663]	[1.579]	[−0.242]	[−0.233]	[1.656]	[1.678]	[−1.229]	[−0.991]	[−1.063]	[−1.490]	[−1.173]	[−1.180]
Import	2.21e-08	2.54e-08	−6.56e-07	−6.28e-07	2.09e-08	1.85e-08	−6.73e-08	−3.27e-08	−1.99e-06	−6.49e-07***	−5.99e-08	−7.99e-08
	[0.184]	[0.195]	[−0.215]	[−0.207]	[0.173]	[0.144]	[−1.065]	[−0.524]	[−1.024]	[−2.178]	[−0.947]	[−1.268]
Export	−1.94e-07*	−0.000000179*	−4.73e-06	−4.61e-06	−1.90e-07*	−1.84e-07*	−1.67e-07**	−1.67e-07**	2.90e-06*	1.83e-06**	−1.63e-07**	−1.49e-07**
	[−1.476]	[−1.282]	[−1.218]	[−1.187]	[−1.445]	[−1.330]	[−1.985]	[−2.005]	[1.540]	[1.539]	[−1.933]	[−1.770]
Firm Age	0.00929***	0.0124***	−0.0128	−0.0148	0.00960***	0.0114***	0.000569	0.000602	0.0120*	0.0140*	0.000836	0.00105
	[2.862]	[3.539]	[−0.243]	[−0.283]	[2.932]	[3.247]	[0.321]	[0.347]	[1.307]	[1.072]	[0.470]	[0.592]
Firm Size	1.10e-05***	1.32e-05***	−3.70e-06	−5.90e-06	1.11e-05***	1.39e-05***	6.49e-06**	3.99e-06	1.53e-06	4.51e-07	6.78e-06***	7.80e-06***
	[2.423]	[2.721]	[−0.111]	[−0.178]	[2.435]	[2.897]	[2.274]	[1.424]	[0.198]	[0.0539]	[2.368]	[2.752]
R&D Expenditures	7.06e-09***	6.72e-09***	5.57e-09	5.16e-09	7.13e-09***	7.23e-09***	1.90e-09**	1.70e-09**	2.17e-09	1.68e-09	2.00e-09**	2.09e-09***
	[4.255]	[3.769]	[1.019]	[0.944]	[4.273]	[4.100]	[2.135]	[1.923]	[0.637]	[0.483]	[2.250]	[2.373]
Country Effects	Included	Included	Included	Included	Included	Included	Included	Included	Included	Included	Included	Included
Year Effects	Included	Included	Included	Included	Included	Included	Included	Included	Included	Included	Included	Included
Constant	−2.345	−2.381	270.7	261.2	−2.357	−2.569	4.558***	5.358***	321.7	72.99**	4.549**	5.240***
	[−0.747]	[−0.727]	[0.514]	[0.499]	[−0.749]	[−0.778]	[2.569]	[2.837]	[0.966]	[1.602]	[2.546]	[2.874]
Observations	3,885	3,885	211	211	3,885	3,885	2,165	2,165	89	89	2,165	2,165
Number of Firms	3,401	3,401	170	170	3,401	3,401	1,901	1,901	74	74	1,901	1,901

Notes. z-statistics in brackets. Models 3, 4, 9, and 10 do not include the *Patent Intensive Industry* variable in the proximal peer regressions because there are too few industries in the smaller subsample for the models to converge. —, no data.

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$ at one-tailed test.

Table 7. Results Using Subsamples of Younger Firms

	Quantitative Convergence				*Quantitative Convergence*					
Variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10
Learning from Technologically Successful Peers		2.167**					1.308***			
		[2.341]					[8.304]			
Degree of Learning from Technologically Proximal Successful Peers			12.35**	25.16				3.220*	9.713	
			[1.971]	[0.820]				[1.809]	[1.454]	
Degree of Learning from Technologically Proximal Successful Peers Squared				−11.30					−7.336	
				[−0.491]					[−0.964]	
Degree of Learning from Technologically Successful Peers					37.59***					11.93***
					[2.748]					[6.065]
Degree of Learning from Technologically Successful Peers Squared					−136.6***					−20.21***
					[−2.586]					[−3.562]
Number of Citations	0.0973**	0.0666	0.0802	0.0432	0.0663	0.0782***	0.0470**	−0.0437	−0.0436	0.0603***
	[2.278]	[1.176]	[0.178]	[0.0986]	[1.312]	[4.171]	[2.398]	[−0.561]	[−0.508]	[3.183]
Patent Intensive Industries	0.0369	−0.328	—	—	−0.161	−0.116	−0.297***	—	—	−0.225**
	[0.188]	[−1.160]			[−0.670]	[−1.209]	[−2.998]			[−2.325]
GDP Growth Rate	0.000787	0.000839	0.00773	0.00928	0.000910	−0.000365	−0.000221	0.00109	0.000250	−0.000359
	[0.572]	[0.489]	[0.835]	[0.721]	[0.570]	[−0.517]	[−0.317]	[0.401]	[0.0971]	[−0.515]
Government R&D	−0.000230	−0.000215	−0.00193	−0.00200	−0.000225	−3.17e-05	1.39e-05	−8.38e-05	0.000172	−6.69e-06
	[−0.614]	[−0.475]	[−0.548]	[−0.464]	[−0.526]	[−0.231]	[0.103]	[−0.0903]	[0.194]	[−0.0495]
Population	4.21e-07	4.43e-07	−5.41e-06	−5.93e-06	4.81e-07	−7.86e-09	−5.86e-09	−3.02e-09	4.21e-08	−7.64e-09
	[0.933]	[0.798]	[−0.885]	[−0.737]	[0.919]	[−0.903]	[−0.679]	[−0.00311]	[0.0404]	[−0.882]
Import	1.35e-07	2.06e-07	3.64e-06	4.55e-06	1.70e-07	9.95e-08	1.39e-07	−6.04e-07	−5.28e-07	1.01e-07
	[0.695]	[0.817]	[0.709]	[0.784]	[0.738]	[1.093]	[1.542]	[−0.947]	[−0.764]	[1.121]
Export	−3.03e-07	−3.89e-07	−3.67e-06	−4.87e-06	−3.51e-07	−2.24e-07*	−2.18e-07*	7.69e-07	4.00e-07	−2.16e-07*
	[−1.443]	[−1.355]	[−0.452]	[−0.565]	[−1.395]	[−1.899]	[−1.865]	[0.403]	[0.197]	[−1.849]
Firm Age	0.0279*	0.0140	−0.174	−0.182	0.0121	0.00932	0.00832	0.0650	0.0876	0.000190
	[1.678]	[0.662]	[−0.979]	[−0.891]	[0.605]	[1.136]	[1.049]	[1.034]	[1.589]	[0.0230]
Firm Size	3.39e-05**	5.13e-05**	−0.000209	−0.000205	4.73e-05**	8.37e-06	1.02e-05*	−5.79e-05	−5.39e-05	1.05e-05*
	[2.310]	[2.094]	[−0.882]	[−0.820]	[2.470]	[1.461]	[1.793]	[−0.730]	[−0.647]	[1.859]
R&D Expenditures	8.14e-09*	1.10e-08*	8.76e-09	2.47e-10	1.07e-08**	3.64e-10	6.30e-10	−1.97e-08	−1.68e-08	8.91e-10
	[1.913]	[1.669]	[0.311]	[0.00688]	[1.970]	[0.232]	[0.406]	[−0.312]	[−0.327]	[0.572]
Country Effects	Included	Included	Included	Included	Included	Included	Included	Included	Included	
Year Effects	Included	Included	Included	Included	Included	Included	Included	Included	Included	
Constant	−11.16	−11.30	95.05	100.1	−12.44	2.378	2.752	−3.461	10.11	3.025
	[−0.983]	[−0.806]	[0.769]	[0.635]	[−0.941]	[0.930]	[1.061]	[−0.138]	[0.00692]	[1.177]
Observations	2,101	2,101	105	105	2,101	1,263	1,263	44	44	1,263
Number of Firms	1,998	1,998	94	94	1,998	1,149	1,149	39	39	1,149

Notes. z-statistics in brackets. Models 3, 4, 9, and 10 do not include the *Patent Intensive Industry* variable in the proximal peer regressions because there are too few industries in the smaller subsample for the models to converge. —, no data.

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$ at one-tailed test.

economic growth. National champions (i.e., technologically successful peers in our setting) are not only important economic actors in their own right, contributing to economic growth in the domestic economy, they also help spur technological development amongst lagging firms. These firms can therefore help developing countries meet broader development goals.

Limitations and Future Research

This research advances our understanding of the technological convergence of firms from developing countries to the global technological frontier and highlights the importance of technologically successful peers in that process. Despite its theoretical, empirical, and managerial contributions, we acknowledge several limitations.

First, this study relies on patent citations as an indicator of learning. Given that patent examiners add citations to patents (Alcacer and Gittelman 2006), it is possible that the focal firms in our study are unaware of some of the knowledge contained in the patents they cite. Although we take some comfort in recent studies that confirm that patent citations can still serve as a valuable means of assessing technological learning (e.g., Grimple and Hussinger 2014, Kaplan and Vakili 2014, Vasudeva et al. 2015), we would encourage future studies examining technological development to incorporate alternative indicators of learning.

Second, this study focuses on firms from three Asian countries (China, Taiwan, and Korea). Country-specific macroeconomic policies might influence convergence differently across countries, and future research might examine the influence of macro-institutional factors more closely. Similarly, given our focus on Korea, Taiwan, and China, we cannot be sure if our findings generalize outside the context of these three countries. Future research would be well served to examine convergence dynamics in other developing country settings.

Third, in this study, we make a distinction between citations to technologically successful peers and citations to other nonpeer firms. Unfortunately, our data do not allow us to distinguish among those nonpeer firms—for example, developed country firms or other developing country firms and technologically successful or lagging nonpeer firms. For this reason, although we control for the effect of citations to nonpeer firms, we cannot compare explicitly the efficacy of citations to technologically successful peers versus other nonpeer firms. That notwithstanding, we do believe it is important to compare the relative benefits of learning from technologically successful peers to learning from other firms, and we hope that future research will extend our contributions to make that comparison.

Finally, consistent with similar studies that use patent citation data, we acknowledge that we do not get to observe the precise mechanisms through which the firms in our sample learn from technologically successful peers. Rather, we draw inferences from citation patterns combined with insights from previous research that details the avenues through which knowledge spills over and diffuses from technologically advanced to technologically lagging firms. We encourage future studies to add more flesh to the structural bones laid out in this study by exploring detailed knowledge transfer mechanisms using more grounded data.

The aforementioned limitations notwithstanding, we take an important first step toward understanding a complex phenomenon—that is, the role of peer firms in the technological development of lagging firms from developing countries. We encourage future research in this area, especially into the mechanisms that underpin such learning and the boundary conditions that govern the relationships between learning and technological convergence. We sincerely hope that others will help advance our understanding of this phenomenon and extend the work herein in new and interesting directions.

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Endnotes

[1] This is not to say that all Korean, Taiwanese, and Chinese firms systematically lag the global technological frontier. We recognize that there are some firms in our data that are closer to the technological frontier than others. There are even some, like Samsung, LG, Acer, Lenovo, and Huawei, that have achieved near parity with the global technological frontier during the latter stages of our sample period. Our empirical approach allows for such dynamics, whereby firms from the sample start out as laggard but then successfully converge to become technological leaders.

[2] Other examples in our data include Hynix (from Korea), Taiwan Semiconductor Manufacturing and United Microelectronic Corporation (from Taiwan), and China Petroleum and Chemical Corporation and the Jiang Goodbaby Group (from China).

[3] We note that firms might also exhibit learning hypermetropia, which would be characterized in this context as an overreliance on developed country leaders. As scholars note, however, firms are more likely to display myopia. We therefore focus on myopia, instead of hypermetropia, in this study.

[4] We note that the Taiwanese firms in the sample are more numerous because they tend to be small- to medium-sized enterprises (SMEs), whereas the Korean sample of firms are larger, typically chaebols. The Chinese sample, by contrast, is the smallest of the three, as more Chinese firms entered the sample in later years.

[5] Given the rigor of the USPTO patent regime, exhibiting a patenting rate greater than the average of all other global firms patenting with the USPTO is an especially high hurdle. We therefore believe that the measure of *Quantitative Convergence* is likely to reflect a conservative estimate of the phenomenon.

[6] In results not reported herein, we explored models using a continuous measure of *Quantitative Convergence* in lieu of a binary measure. Results did not change.

[7] We note that we operationalize technologically successful peers slightly differently depending upon whether the dependent variable is *Quantitative Convergence* or *Qualitative Convergence*. In models with *Quantitative Convergence* as the dependent variable, we consider technologically successful peers to be those that had previously achieved quantitative convergence. Similarly, in models where the dependent variable is *Qualitative Convergence*, we consider peer firms technologically successful if they had previously achieved qualitative convergence. In models not reported, we found similar results if we limit the set of technologically successful peers to those peer firms that previously achieved both qualitative and quantitative convergence.

[8] Firms from Korea, Taiwan, and China that do not cite technologically successful peers (i.e., those that receive a value of 0 for *Learning from Technologically Successful Peers*) typically cite the patents of advanced country firms (such as U.S., European, and Japanese firms). Those that do cite technologically successful peers (i.e., those that receive a value of 1 for *Learning from Technologically Successful Peers*) typically cite firms from developed and developing countries.

[9] Given the computational challenges of calculating the technological similarity between the focal firm patents and each of the patents it cites, we note that we were only able to calculate *Learning from Technologically Proximal Successful Peers* for a subset of the data.

[10] We note that the *Number of Citations* and *GDP Growth Rate* control variables are time varying. The *Patent Intensive Industries* dummy is time-invariant.

[11] We explored models with firm fixed effects as an alternative to the random firm effects. Results of the Hausman test ($p < 0.01$) suggested that the firm fixed effects specification is preferable to the random effects specification for our sample. Unfortunately, we could not specify full firm fixed effects models because we are forced to drop time-invariant covariates and observations that exhibit no within-firm variance in the dependent variable. Doing so eliminates nearly 90% of the sample observations, and, therefore, firm fixed effects do not converge in Stata. We therefore opted for the random firm effects models, which the Breusch–Pagan LM test ($p < 0.01$) suggests are better than pooled models without firm effects.

[12] In order to ensure that our results were not biased due to differences across subsamples, we reran both sets of regression results across the harmonized subsample of observations. The findings did not change.

[13] Influence tests do not suggest any multicollinearity concerns. Indeed, the highest variance inflation factor (VIF) in any of the regressions was 6.82, well below the suggested threshold of 10 (Kleinbaum et al. 1988).

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