informs
http://pubsonline.informs.org/journal/orsc/

ORGANIZATION SCIENCE
Vol. 30, No. 4, July–August 2019, pp. 668–693
ISSN 1047-7039 (print), ISSN 1526-5455 (online)

The Dynamics of Learning and Competition in Schumpeterian Environments

Gianluigi Giustiziero,[a] Aseem Kaul,[b] Brian Wu[c]

[a] Management Department, Frankfurt School of Finance & Management, 60322 Frankfurt, Germany; [b] Carlson School of Management, University of Minnesota, Minneapolis, Minnesota 55455; [c] Ross School of Business, University of Michigan, Ann Arbor, Michigan 48109

Contact: g.giustiziero@fs.de, https://orcid.org/0000-0003-0649-6599 (GG); akaul@umn.edu, https://orcid.org/0000-0003-1455-6897 (AK); wux@umich.edu, https://orcid.org/0000-0003-4213-3808 (BW)

Received: April 16, 2013
Revised: December 13, 2015; May 14, 2017; April 29, 2018; July 13, 2018
Accepted: August 10, 2018
Published Online in Articles in Advance: May 16, 2019

https://doi.org/10.1287/orsc.2018.1264

Abstract. In this study, we examine the nature of Schumpeterian competition between entrants and incumbents. We argue that incumbents may respond to the threat of entry by either attacking the entrant or trying to learn from it, and that entrants, in turn, may react by either reciprocating the incumbent's advances or retreating from it. Putting these competitive choices together, we develop a framework of four distinct potential scenarios of Schumpeterian competition. In particular, we emphasize a scenario we term *creative divergence*, wherein incumbents try to learn from entrants and build on their technologies, but their investments to do so cause entrants to retreat, resulting in diminishing returns to learning investments by incumbents. Exploratory analyses of the U.S. cardiovascular medical device industry find patterns consistent with the creative divergence scenario, with incumbent knowledge investments helping them to learn from entrants, but these learning benefits being undermined as entrants move away from incumbents.

Funding: The authors gratefully acknowledge the University of Michigan Research Initiatives Fund and the Mack Center for Technological Innovation at the Wharton School for generous funding.
Supplemental Material: The online appendices are available at https://doi.org/10.1287/orsc.2018.1264.

Keywords: competitive dynamics • evolutionary theory • absorptive capacity • Schumpeterian environments • creative divergence • knowledge spillovers

Introduction

Schumpeterian competition—that is, the competitive interplay between incumbents and entrants—has long been a topic of interest to scholars of technology strategy (Winter 1984; Tripsas 1997). Building off the idea of "creative destruction" (Schumpeter 1934), work in this area traditionally focused on the rivalry between the two: entrants render incumbent capabilities obsolete, thus threatening incumbents' competitive advantage and (potentially) their very survival (Aghion and Howitt 1992, Agarwal and Gort 1996, Hill and Rothaermel 2003); incumbents respond by creating entry barriers and first-mover advantages to counteract or preempt entrants (Lieberman and Montgomery 1988, Lieberman 1989, Agarwal and Gort 2001, Aghion et al. 2009). More recently, however, work on "creative construction" emphasizes a more symbiotic relationship between incumbents and entrants (Agarwal et al. 2007, 2010; Agarwal and Helfat 2009). Research in this stream highlights the role of knowledge spillovers between incumbents and entrants: entrants draw on incumbent knowledge (Agarwal et al. 2004, Klepper and Sleeper 2005, Chatterji 2009, Agarwal and Shah 2014), and incumbents benefit by learning from entrants (Dushnitsky and Lenox 2005, Kotha 2010, Yang et al. 2010, Kim and Steensma 2017).

These two processes—creative destruction and creative construction—represent two ends of a continuum (Agarwal et al. 2007), the intermediate points of which remain to be fully explored. There is a need to understand "what win-lose or win-win scenarios may be created due to knowledge spillovers across organizational boundaries, particularly as they relate to entrepreneurial activity?" (Agarwal et al. 2010, p. 277). Doing so requires us to simultaneously consider the actions of both incumbents and entrants, as they seek to balance between the positive effects of spillovers that draw them closer together and the negative effects of competition that push them further apart (Agarwal et al. 2007).

The current study attempts to offer a more complete and dynamic picture of Schumpeterian competition. Focusing on competition in the technology space (rather than the product-market space), we combine work on competitive interaction with evolutionary theory to develop a framework of Schumpeterian competition that accounts for the effects of both competition and learning (Nelson and Winter 1973, 1978; Levinthal 1992) while considering the strategic responses of both incumbents and entrants (Chen and Miller 2012).[1] Specifically, we build on evolutionary theory (Nelson and Winter 1973) to argue that incumbents may compete with the emergent threat from new technologies either by aggressively pursuing rival technologies of their own (Toh and Polidoro 2013) or by seeking to build on the new technology through investments in absorptive capacity that help them learn from entrants (Cohen and Levinthal 1989, 1990). In turn, entrants may respond to incumbents' actions by reciprocating in kind or by retreating from them to less competitive spaces in an effort to avoid direct confrontation (Chen and Hambrick 1995; Katila et al. 2012; Wang and Shaver 2014, 2016). We argue that these choices influence how the knowledge investments that incumbents make in the face of an entrant threat will impact their subsequent competitive interaction—in particular, they have distinct implications for both the extent to which incumbents learn from the entrant[2] and the technological distance between incumbent and entrant.

Combining these two sets of actions, we derive four distinct scenarios of Schumpeterian competition, including the traditional creative construction and creative destruction cases, as well as the case where aggressive action by incumbents preempts further threats from entrants and drives them away (Polidoro and Toh 2011, Polidoro 2013), which we term *creative deterrence*. More novel than these, our conceptual framework highlights the possibility that even as incumbents seek to learn from entrants, the investments they make to do so cause entrants to retreat from incumbents, so that incumbents realize positive but diminishing returns to their learning investments. We term this scenario *creative divergence*, because it reflects a divergence in the two firms' technological trajectories—with incumbents trying to draw close to entrants while entrants try to move away—and because it results in an equilibrium of mutual adjustment, with both firms ending up in technological positions that are related but distinct from each other.

We demonstrate an empirical application of our framework by undertaking exploratory analyses in the cardiovascular medical device industry—a setting that combines intense Schumpeterian competition with a strong emphasis on the use of patents, making it ideal for our purpose (Chatterji 2009, Chatterji and Fabrizio 2014, Theeke et al. 2018). The goal of our analyses is exploratory, meant to produce a set of stylized findings that set the stage for future research (Moeen and Agarwal 2017). We offer no hypotheses, believing all four scenarios to be equally plausible a priori and not seeking to claim that the patterns we see in our setting will generalize to all others. Our objective is only to empirically examine which of the four scenarios plays out in our specific context, to demonstrate how our framework may be applied to an empirical setting.

Our empirical findings are generally consistent with the creative divergence scenario. Incumbent knowledge investments have a positive relation with incumbent learning from entrants, especially when the incumbent and entrant are technologically proximate, but these knowledge investments also increase the technological distance between incumbents and entrants, which negatively moderates incumbent learning. Incumbent learning from entrants thus increases at a decreasing rate with incumbent knowledge investments. Supplemental analyses show that these findings result from incumbents seeking to draw closer to entrants when threatened, but entrants responding to incumbent advances by retreating. They also show that these effects are most pronounced for entrants that enter close to incumbents.

Our study contributes to the emerging knowledge spillover-based perspective on strategic entrepreneurship (Agarwal et al. 2007). We draw together work on competitive interaction and evolutionary theory (Katila and Chen 2008) to develop a richer framework of Schumpeterian competition, which incorporates the effects of both learning and competition in such settings (Nelson and Winter 1973, 1978). We not only flesh out the scenarios that lie between the two extremes of creative destruction and creative construction (Agarwal et al. 2010) but also demonstrate how these different scenarios may be studied empirically. Moreover, we introduce the unexplored case of creative divergence. In addition, our study contributes to research on absorptive capacity (Cohen and Levinthal 1989, 1990, 1994), highlighting the possibility that investments in absorptive capacity may alter the supply of external knowledge.

A Framework of Schumpeterian Competition

To characterize the dynamics of Schumpeterian competition, we focus on the simple case of a single incumbent threatened by a single entrant, and we examine different ways the competitive interaction between them may play out. In line with the literature on competitive dynamics, we focus on the action/response dyad between the incumbent and entrant, consider the specific actions each firm may take in response to the other, and allow for asymmetric responses (Chen and Miller 2012).[3] In contrast to this literature, however, our focus is not on the likelihood, extent, or speed of competitive response (Chen and Miller 2012) but on the nature of the two firms' actions. Implicit in our framework is the assumption that both incumbents and entrants recognize and react to each other's competitive presence.

Given our interest in competitive dynamics, we focus on the case where the incumbent does not cede its position to the entrant but chooses to confront the competitive threat. Although there may certainly be situations in which the incumbent finds it prudent to surrender and retreat in the face of the threat from a new entrant (Adner and Snow 2010), a long literature on path dependence (Nelson and Winter 1982, Helfat 1994) suggests that it is more likely to stay and fight. There are several reasons for this: First, given the substantial investments incumbents make to develop both technological competence and complementary assets in an area, and the learning and experience they accrue, it may be rational for them to stick to their existing domain rather than seek out new ones where they have little advantage over others (Nelson and Winter 1982, Aghion and Tirole 1994, Helfat 1997, Tripsas 1997, Nerkar and Roberts 2004, Wu et al. 2014). In fact, incumbent firms may choose to respond to a competitive threat by trying to deepen their technological position at the cost of exploration (Toh and Polidoro 2013). Second, managers in incumbent firms may be subject to a variety of cognitive and behavioral biases that may cause them to search locally rather than look further afield (Cyert and March 1963, Levinthal and March 1993, Tripsas and Gavetti 2000, Eggers and Kaplan 2009, Chen et al. 2010). Third, even if incumbents were internally motivated to seek out new technologies and markets, such shifts in their position may invite negative scrutiny from external evaluators—such as analysts and brokerage firms—which may further constrain the incumbent's ability to pursue new technologies (Benner 2007, 2010; Theeke et al. 2018).

Incumbent Response to Entrants

Assuming that the incumbent stays to fight, how may it respond to the entrant threat? Building on evolutionary theory, we contend that the incumbent may respond in two ways: accelerate its internal efforts to develop new technologies that rival the entrants, or try to imitate and learn from the entrant in order to build on and surpass its technology (Nelson and Winter 1973, 1978). These two search processes are not mutually exclusive; on the contrary, we expect the incumbent to pursue both to some degree. Nevertheless, the incumbent may strategically choose to focus its efforts on one type of search.

Consider each approach in turn. If the incumbent's primary response to the entrant is to *attack*, it engages in a head-to-head race with the entrant, investing heavily in a technology—typically an extension of its existing knowledge—which may serve as a substitute for that of the entrant, in an effort to drive the entrant out (Nelson and Winter 1973, Chen 1996, Katila and Chen 2008, Toh and Polidoro 2013). Incumbents may also seek to bolster their position in existing areas where entrants do not compete with them, to preempt further encroachment on their turf (Polidoro and Toh 2011). Either way, the incumbent's purpose is to limit the success of the entrant's technology in favor of its own.

By contrast, if the incumbent's primary response is to *learn* from the entrant, it may embrace the entrant's innovations, seeking first to imitate and catch up with the entrant's technology (Nelson and Winter 1973, Katila and Chen 2008), and then to extend and build on it (Agarwal et al. 2007). The incumbent's purpose in doing so is to adapt to the entrant's technology (Levinthal 1991, 1992), building on this technology to rejuvenate its own position (Agarwal and Audretsch 2001, Klepper 2002, Lavie 2006, Agarwal and Helfat 2009). Such learning from the entrant may occur through various means (Capron and Mitchell 2010, Moeen and Agarwal 2017), which may complement each other (Rosenkopf and Almeida 2003, Jiang et al. 2011, Wagner and Goossen 2018): direct spillovers (Jaffe 1986, Griliches 1992, Kotha 2010, Yang et al. 2010), inventor mobility (Corredoira and Rosenkopf 2010, Singh and Agrawal 2011, Kim and Steensma 2017), alliances (Rothaermel 2001, Cozzolino and Rothaermel 2018), corporate venturing (Dushnitsky and Lenox 2005, Benson and Ziedonis 2009), and acquisitions (Ahuja and Katila 2001, Puranam et al. 2006). Whatever the means used to access the entrant's knowledge, the incumbent's core purpose is to learn from the entrant.

Such learning from entrants is likely to require substantial investments in internal knowledge development by the incumbent to enhance its absorptive capacity (Cohen and Levinthal 1989, 1990, 1994). Ongoing knowledge development will allow the firm to develop a deeper understanding of the relevant technology domain (Gavetti and Levinthal 2000, Fleming and Sorenson 2004, Jiang et al. 2011), which is likely to prove helpful when seeking to import knowledge from outside (Gatignon et al. 2002, Katila and Ahuja 2002, Zhou and Wu 2010, Zhou and Li 2012). Incumbents seeking to develop new technological capability through learning from entrants may also need to invest in additional infrastructure and personnel (Kotha 2010). Moreover, the logic of recombination (Schumpeter 1934, Ahuja and Lampert 2001, Fleming 2001) suggests that the greatest gains to the incumbent may come from combining its existing knowledge with the new knowledge gained from the entrant (Rosenkopf and Nerkar 2001, Nerkar 2003, Sosa 2011), so that incumbents seeking to appropriate value through learning from entrants may need to bolster their own technological expertise as well.[4] To the extent that "the ability to evaluate and utilize outside knowledge is largely a function of the level of prior related knowledge" (Cohen and Levinthal 1990, p. 128), incumbent learning from entrants depends on the incumbent making substantial knowledge investments in technological domains that overlap with the entrant, and such learning may require that the incumbent draw closer to the entrant.

Entrant Reaction to Incumbent Action

Next, consider how entrants react to the actions of incumbents. One possibility is that the entrant may *reciprocate* the incumbent's actions. If the incumbent's response is to attack the entrant, the entrant may choose to counterattack to defend its position (Chen 1996). Entrants confident that they possess superior resources and capabilities compared with the attacking incumbent[5] may choose to increase their investments and enter into a head-to-head race for technology with the incumbent (Katila and Chen 2008, Chen et al. 2010). In doing so, the entrant essentially bets that the selection pressures unleashed by its initial entry will act in its favor, and the incumbent will eventually be forced to exit or withdraw in defeat.

If the incumbent response is to learn from the entrant, the reciprocal response from the entrant will be to facilitate knowledge flow between the two firms. Like the incumbent, the entrant may invest in enhancing its own absorptive capacity, seeking to draw from the knowledge spillover pool jointly created by it and the incumbent (Agarwal et al. 2007, 2016; Kotha 2010). The entrant may not only seek to develop new technologies and products that complement those of the incumbent but also seek to strengthen its formal and informal ties with the incumbent by entering into alliances or buyer–supplier relationships, becoming part of the incumbent's innovation ecosystem (Adner and Kapoor 2010, Kapoor and Furr 2015).

These strategies assume the entrant will respond symmetrically to the incumbent; that is, it will reciprocate the incumbent's actions. A reciprocal response may not always be in the entrant's best interest, however, given that entrants and incumbents often differ in fundamental ways (Schumpeter 1942). By definition, entrants have less accumulated experience in the market and may lack the deep knowledge base of incumbents (Aghion and Tirole 1994, Balasubramanian and Sivadasan 2010). Entrants are also likely to lack relevant complementary assets (Klepper 1996, Tripsas 1997, Kapoor and Furr 2015), and—especially in the case of start-ups—will often have limited slack resources compared with incumbents (Chen and Hambrick 1995, Katila et al. 2012). In addition, the entrant's capacity to learn from an incumbent may be inferior to the incumbent's capacity to learn from an entrant because of the entrant's more limited knowledge base (Cohen and Levinthal 1994, Posen and Chen 2013), so that spillovers between them may be asymmetric (Knott et al. 2009). These asymmetries between incumbents and entrants are both a challenge and an opportunity: on one hand, entrants may find it challenging to directly compete with incumbents unless they have significantly superior technologies (Klepper 1996); on the other hand, entrants may be less susceptible to inertia and may find it easier to adjust their position in the market relative to more established firms (Sørensen and Stuart 2000), thus avoiding head-to-head competition.

The asymmetry in entrant and incumbent capabilities suggests that entrants may respond to the threat of incumbents catching up with them differently than incumbents do when faced with the initial threat from entrants. Whereas we argued that incumbents are unlikely to abandon their existing positions in favor of entrants, the same may not be true for entrants. Faced with the prospect of incumbents catching up with them, entrants may choose to *retreat* from the incumbent. If the entrant believes it lacks the capabilities and resources to compete head-to-head with the incumbent (Katila and Chen 2008, Chen et al. 2010), or if it fears the loss of its competitive advantage as a result of knowledge spillovers (Shaver and Flyer 2000), it may prefer to build around the incumbent's position rather than engage with the incumbent directly (Katila et al. 2012, Polidoro 2013). In such cases, the entrant may surrender its current position in favor of one more distant from the dominant incumbent (Wang and Shaver 2014) and invest in developing new technologies to occupy a competitive position that may be less visible or threatening to the incumbent (Chen and Hambrick 1995, Katila et al. 2012, Wang and Shaver 2016). New firms may thus strive to locate themselves further away from the incumbent over time (d'Aspremont et al. 1979, Salop, 1979), even if they enter close to the incumbent because of their knowledge inheritance (Agarwal et al. 2007).

A Typology of Schumpeterian Competition

The preceding discussion allows us to specify four potential scenarios of Schumpeterian competition, as shown in Figure 1. These include two extreme cases that have already received substantial attention in the literature (Agarwal et al. 2010). On the one hand, if the incumbent attacks and the entrant reciprocates, we have the classic case of *creative destruction* where both parties engage in head-to-head competition (Katila and Chen 2008), with each party trying to drive the other out of the market. In this case, selection pressures (Levinthal 1991, 1992) dominate, with the eventual outcome being a win-lose scenario where the weaker party is forced to withdraw. Given that both parties are trying to attack each other in this scenario, we would expect the technological distance between them to decrease (or, to the extent that they pursue innovation independent of each other, to stay constant). This decrease in technological distance is unlikely to be associated with increased knowledge flows between them, however; because the incumbent is trying to attack the entrant, knowledge flows may decrease with incumbent knowledge investments (at least on a proportional basis) as the incumbent pursues substitute technologies and seeks to undermine the entrant's knowledge.

On the other hand, where the incumbent learns and the entrant reciprocates, we have the *creative construction* scenario, wherein both incumbents and entrants seek to learn from and contribute to each other's technological innovations (Agarwal et al. 2007, 2010). In this case, the knowledge investments of both firms increase the flow of knowledge between them and draw them closer together in technology space. Incumbent knowledge investments not only increase knowledge flows from entrant to incumbent but do so

Figure 1. A Continuum of Schumpeterian Scenarios

	Creative Destruction	Creative Deterrence	Creative Divergence	Creative Construction
Characteristics				
Incumbent strategy	Develop rival technology	Develop rival technology	Build on entrant's knowledge	Build on entrant's knowledge
Entrant strategy	Engage in reciprocal competition	Retreat to avoid direct competition	Retreat to avoid knowledge transfer	Engage in reciprocal knowledge transfer
Competitive outcomes	Win-Lose	Weak Win-Lose	Weak Win-Win	Win-Win
Impact of incumbent knowledge investments:				
On knowledge absorption (direct effect)	(−) or (~0)	(−) or (~0)	(+)	(+)
On technological distance	(−) or (~0)	(+)	(+)	(−)
Overall effect on knowledge absorption	Negative at a decreasing rate or insignificant	Negative at an increasing rate or insignificant	Positive at a decreasing rate	Positive at an increasing rate

at an increasing rate, as the benefits of the incumbent's learning investments are amplified by the decreasing technological distance between it and the incumbent.[6] The creative construction scenario thus results in a positive and self-reinforcing cycle of mutual learning (Jovanovic and MacDonald 1994, Aghion et al. 2001) with entrants and incumbents acting as strategic complements for each other. It reflects the acceleration of adaptation in the face of increasing selection pressures (Levinthal 1991, 1992), with the eventual outcome a win for both parties.

Both the creative destruction and the creative construction scenarios assume that the incumbent and the entrant behave symmetrically; that is, the entrant reciprocates the incumbent's actions. Once we consider that the entrant may respond asymmetrically—it may retreat in the face of the incumbent's response—additional possibilities present themselves. A third scenario is that the incumbent attacks and the entrant moves away from the incumbent to avoid head-to-head competition. This scenario reflects successful adaptation by the incumbent, leading to increased selection pressure on the entrant (Levinthal 1991, 1992), which improves its likelihood of survival by retreating. Incumbent knowledge investments increase technological distance between it and the entrant while potentially reducing knowledge flows from the entrant, given that the incumbent's objective is to undermine the entrant rather than learn from it. The net effect of incumbent knowledge investments in this scenario may be to decrease knowledge flows from entrants at an increasing rate, with the negative effect of these investments on incumbent learning amplified by their positive effect on technological distance. We term this scenario *creative deterrence* because the entrant is effectively deterred from establishing itself in the technology space by the aggressiveness of the incumbent's response. This scenario is consistent with the classic models of imperfect competition in the industrial organization literature (e.g., Hotelling 1929, Salop 1979), including monopolistically competitive models (Melitz and Ottaviano 2008) and models of dominant versus fringe firms (Stackelberg 1952, Martin 1994), except that here we consider competition in the technology space rather than in the product market. The competitive outcome of creative deterrence is a win-lose in favor of the incumbent, but it is a weak win-lose because both players may survive and continue to threaten each other from afar.[7]

In the final scenario in Figure 1, which remains largely unexplored in the prior literature, the incumbent seeks to learn but the entrant retreats. In this case, the incumbent seeks to draw closer to the entrant, making knowledge investments to enhance its own absorptive capacity and enable it to imitate and learn from the entrant. The entrant, however, is threatened by the incumbent's advances, fearing the loss of its competitive advantage as a result of both diminution of its knowledge advantage through spillovers and direct competition from a more proximate incumbent. The entrant thus prefers to draw away from the incumbent rather than reciprocate its actions. As a result, the incumbent realizes diminishing returns on its investments in learning from the entrant, with its increased internal ability to learn being at least partly compromised as the entrant moves away.[8] As in the creative construction case, this scenario reflects mutual adaptation on the part of incumbents and entrants; in this case, however, the entrant adapts away from the incumbent to reduce the selection pressures in the market (Levinthal 1991, 1992).

We call this case *creative divergence* because it reflects the asymmetric choices of the incumbent and entrant—the incumbent tries to draw closer while the entrant tries to pull away—and because it results in the two firms occupying increasingly divergent positions in the technological space. Assuming both players persevere in their strategies, the end result of this process is an equilibrium where the incumbent and entrant occupy positions at a mutually acceptable distance from each other—close enough that each can still (partly) benefit from the other's knowledge but far enough that neither represents a threat to the other—that ensure their survival (Gimeno 1999, Gimeno and Woo 1999). Incumbents benefit in this case because they are able to tap into the knowledge spillovers generated by the entrants and because they are able to neutralize (or reduce) the competitive threat from the entrants. Entrants benefit because they are able to escape direct competition from the incumbents, allowing them to survive and prosper. Moreover, entrants are likely to appropriate some value from the knowledge they share with incumbents, in the form of direct payments for the use of their knowledge or through greater legitimacy and increased demand for their technology. The creative divergence scenario thus represents a weak win–win where both parties benefit from knowledge spillovers and recombination, albeit less than in the creative construction scenario.

Although Figure 1 focuses on the implications of our framework for the impact of incumbent knowledge investments on incumbent learning from entrants, it could be used to explore other outcomes. As Figure 1 shows, our framework has clear implications for the relative success of (and value appropriation by) incumbents and entrants, and it could be used to predict competitive outcomes (i.e., to lay out likely patterns of firm survival and performance). Similarly, we could use the framework to look at the effect of entrant knowledge investments, and their effect on entrant learning from incumbents. Our framework could also be extended to look at specific means of incumbent learning from entrants, such as mobility of inventors (e.g., Agarwal et al. 2016, Kim and Steensma 2017, Wagner and Goossen 2018), alliances (e.g., Rothaermel 2001, Rosenkopf and Almeida 2003, Cozzolino and Rothaermel 2018), or acquisitions (e.g., Ahuja and Katila 2001, Puranam et al. 2006, Puranam and Srikanth 2007). An implication of our framework is that these different means of incumbent learning increase or decrease in much the same way as incumbent knowledge absorption from entrants overall, especially because the success of these different means of learning from entrants will depend critically on the incumbent's absorptive capacity (Cohen and Levinthal 1990, 1994), making the firm's internal knowledge investments an important prerequisite.

Although it would be interesting to fully explore these implications of our framework, we choose to focus on the effect of incumbent knowledge investments here, in part because these effects speak directly to the key mechanisms underlying our framework and in part because they imply a distinct pattern of relationships across the four different scenarios. As Figure 1 shows, if we see empirically that incumbent knowledge investments increase knowledge flows and reduce technological distance, so that knowledge flows from entrants increase at an increasing rate with incumbent knowledge investments, that would suggest we are in a creative construction scenario. If we find instead that incumbent knowledge investments not only increase knowledge flows but also increase technological distance between the entrant and the incumbent, with the result that incumbent learning from entrants increases at a decreasing rate with incumbent knowledge investments, that would be consistent with creative divergence. A similar logic implies that incumbent learning from entrants will decrease at an increasing (or potentially insignificant) rate in the creative deterrence case and decrease at a decreasing (or potentially insignificant) rate in the creative destruction case. The patterns of incumbent learning from entrants described in Figure 1 give us a way to empirically distinguish between the four scenarios described in our framework.

Empirical Analyses

We study the implications of our theoretical framework through a series of exploratory empirical analyses. Our purpose in doing so is not to claim that any one competitive scenario is more likely than the others. On the contrary, the whole point of our framework is that all four scenarios are equally plausible a priori, and we expect to see different scenarios prevail in different contexts. That is why we have not defined a set of generalizable hypotheses from our framework, nor do we seek to test any through our empirical analyses. Our objective is only to demonstrate the empirical application of our framework. If different scenarios may prevail in different contexts, our framework is only useful if we can determine which scenario is playing out in a given setting. The following empirical analyses seek to demonstrate how that determination might be made. We first undertake a series of descriptive analyses, looking at the basic patterns we observe in our data—specifically, examining the relationship between incumbent knowledge investments, incumbent knowledge absorption, and technological distance, as laid out in Figure 1. We then confirm the validity of these observed patterns through multivariate regression analysis to try to rule out the possibility that any observed association may be spurious.

Industry Setting

Our empirical analyses use data from the cardiovascular medical device industry, which is a suitable empirical context for the current study for several reasons. First, the industry represents a dynamic Schumpeterian setting where new entrants often introduce and develop novel devices, such as angioplasty catheters, cardiac support devices, and vascular grafts (Kaplan et al. 2004; Chatterji 2009; Chatterji and Fabrizio 2012, 2014). In this setting, entrants represent both a competitive threat and a learning opportunity for incumbents. On one hand, entrants' novel devices can make the incumbents' obsolete, intensify selection pressures, and ultimately cause incumbents' displacement. On the other, entrants introduce valuable innovative ideas that incumbents may draw on to their benefit.[9] Technological dynamism in this industry is driven predominantly by Class III devices, one of the three classes—Class I, Class II, and Class III—used by the U.S. Food and Drug Administration (FDA) to categorize medical devices. Class I and Class II devices, such as plastic tubes and in vitro diagnostic devices, are low-risk and commoditized products, whose introduction to the market does not require substantial technological development (Kaplan et al. 2004). Class III devices, such as pacemakers and heart valves, however, are associated with high risk for patients and subject to the most stringent regulatory control. For these complex devices to gain FDA approval, the benefits of their technological advancements must outweigh their high risks. As a form of sophisticated technology, Class III devices delineate the type of innovation context with which the present study is concerned.[10]

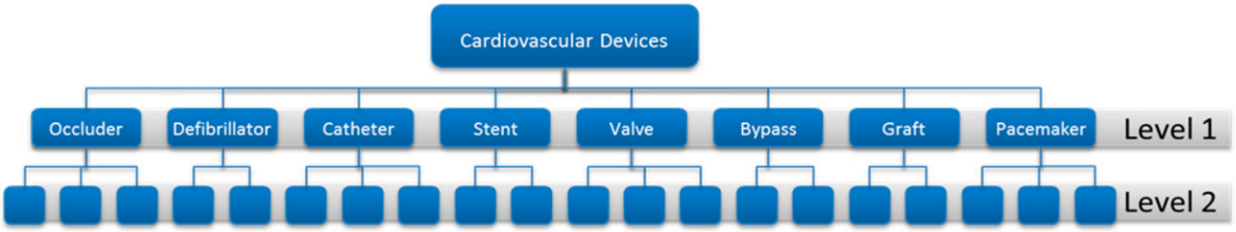
Second, the industry is patent intensive; medical device manufacturers make extensive use of patents to protect their intellectual property. In this type of setting, patent data can be used to construct meaningful proxies of the direction of firms' innovative efforts (Jaffe et al. 2000, Rosenkopf and Nerkar 2001, Hoetker and Agarwal 2007, Agarwal et al. 2009, Theeke et al. 2018). Although patents confer intellectual property rights, in practice they do not work perfectly to prevent imitation (Levin et al. 1987). In particular, patents cannot fully prevent knowledge spillovers when firms creatively recombine prior work (Schumpeter 1934, Jaffe 1986, Rosenkopf and Nerkar 2001). Because patenting firms must cite their learning sources, these citations closely mirror the knowledge flows in the industry (Jaffe et al. 2000, Hoetker and Agarwal 2007, Agarwal et al. 2009).[11]

Third, the industry consists of eight well-defined product-market categories—that is, catheters, occluders, pacemakers, heart valves, stents, defibrillators, grafts, and bypasses (level 1 in Figure 2)—established by the FDA in accordance with the therapeutic scope of devices. This FDA categorization allows us to retrieve the complete history of entry events, discern the set of incumbents and entrants competing in the same category, and infer the industry market structure. This, in combination with patent data, lets us reconstruct the technological landscape relevant to each product category by building a concordance between patent classes and product categories. To do so, we follow the approach of Silverman (1999), Alcácer and Chung (2007), and Dushnitsky and Lenox (2005). We calculate the frequency with which each patent class is used for different product categories and associate each patent class with the top five most frequent categories or with the categories that represent 90% of the total frequency, whichever contains fewer product categories.

Data

We collected data from multiple sources. Product approval data and the respective product categories from 1977 to 2002 were obtained from the Center for Devices and Radiological Health of the FDA. Patent data for the sample period were collected from the United States

Figure 2. (Color online) Product Market Classifications



Patent and Trademark Office, the National University of Singapore–Melbourne Business School patent database, and the National Bureau of Economic Research. Following the prior literature, the assignment of patents to firms is based on the application year of the patent, which reflects the actual innovation date (Rosenkopf and Nerkar 2001, Katila and Ahuja 2002). Patent litigation data were obtained from LitAlert by Derwent. Because LitAlert is known to have underreporting issues (Hall and Ziedonis 2007), we supplemented the data with information from multiple sources, including Google Scholar, Justia, the Legal Information Institute at the Cornell Law School, the Public Library of Law, WashLaw, and FindLaw. Data on downstream investments were collected from an information provider specializing in this industry, *Medical Device Register: The Official Directory of Medical Suppliers Resource*. Data on alliances, mergers, and acquisitions were collected from SDC Platinum by Thomson Reuters. We addressed ownership changes, name changes, and dissolutions by manually verifying firm information from various sources, including firms' annual reports (if publicly listed), their websites, the Thomas Register, Hoovers, CorpTech, HighBeam Research, and Informagen.

For the empirical analyses, we construct an unbalanced panel in which the unit of analysis is a category-incumbent-entrant-year quadruple for the observation period 1977–2002. Categories are defined as the eight broad product categories in the cardiovascular medical device industry: catheters, occluders, pacemakers, heart valves, stents, defibrillators, grafts, and bypasses (see Figure 2). Entrants and incumbents are defined in relative terms; incumbents are firms that entered the focal product category before the entrants.

Measures

We are chiefly interested in the relations between incumbent knowledge investments and incumbent learning from entrants, as well as technological distance between incumbents and entrants. We measure *incumbent knowledge absorption* as a count of the patent citations that the incumbent makes to the entrant in a given product category in a given year (where patents are mapped to product categories based on the concordance described above). This variable is a standard proxy in the literature for knowledge flows in technology intensive industries (Jaffe et al. 2000, Rosenkopf and Nerkar 2001, Hoetker and Agarwal 2007, Agarwal et al. 2009).

We measure *technological distance* as a negative monotonic transformation of Jaffe's (1986) angular separation coefficient—a canonical measure of the overlap between two firms' patent portfolios—computed as follows:

$$\begin{aligned} \textit{Technological distance} &= 1 - \textit{Jaffe's coefficient} \\ &= 1 - \frac{E_t' U_t}{\sqrt{E_t' E_t}\sqrt{U_t' U_t}}, \end{aligned}$$

where E_t and U_t are vectors whose dimensions equal the number of patent classes associated with a given product category. Each individual element of vector E_t is the number of patents that the entrant has in a given patent class up to the observation year t;[12] U_t is computed similarly for the incumbent. *Technological distance* takes values between 0 and 1.

We measure *incumbent knowledge investments* as the discounted stock of patents that the incumbent filed in the patent classes corresponding to a given product category. This variable is computed recursively as follows:

$$\begin{aligned} &\textit{Incumbent knowledge investments}_t \\ &\quad = \textit{patents}_t + 0.7 \times \textit{incumbent knowledge investments}_{t-1}, \end{aligned}$$

where the flow variable $\textit{patents}_t$ is the number of patents filed by the incumbent in a given product category in a given year.[13] We divide *incumbent knowledge investments* by 1,000 to facilitate the interpretation of our empirical findings.

In addition to these main variables, we include a wide range of control variables to account for time-varying firm or market characteristics when undertaking our multivariate regression analyses. In the interest of brevity, and given that the regression analyses are not the focus of the paper but only a way to validate our descriptive findings, these controls are discussed in Online Appendix A, where we explain and justify the various control variables at length. Table 1 reports summary statistics and pairwise correlation matrices for our main variables and controls. Although we do see some high correlations, mostly (as expected) among variables related to incumbent size (*incumbent knowledge investments, incumbent technological scope,* and *incumbent patent count*), our variance inflation factors (VIFs) are generally within acceptable limits, with no individual VIF greater than 5.1, suggesting limited concerns with multicollinearity. In unreported analyses, we run the main regressions reported below without *incumbent patent count* and *incumbent technological scope* as controls, and we confirm that our main findings are similar even in these (potentially underspecified) models.

Findings

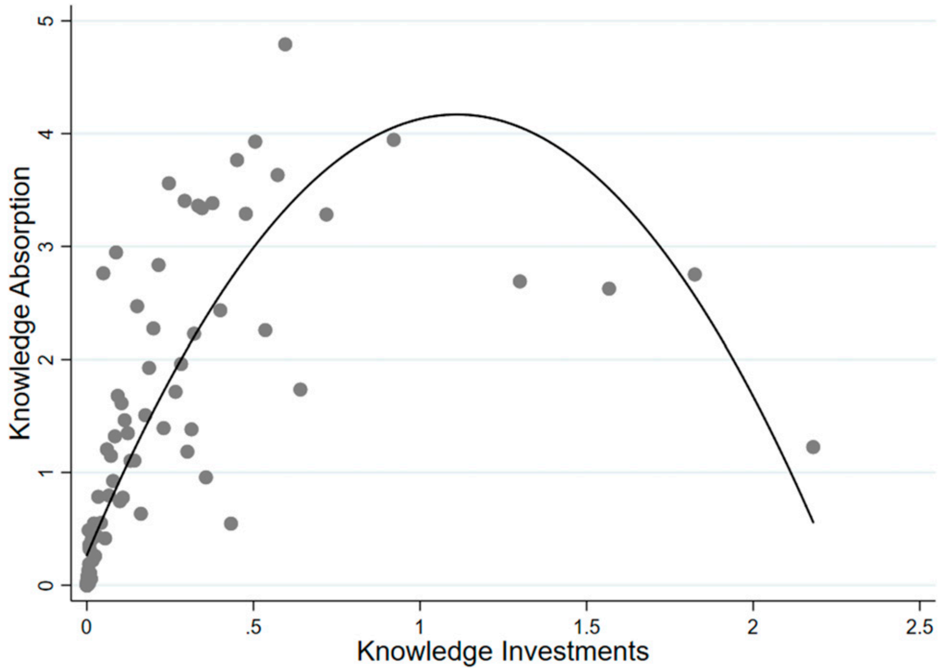
Descriptive Analyses

As discussed above, we begin our empirical analyses by examining the general patterns in our data to see how they compare with those described in our theoretical

Table 1. Summary Statistics (Main Variables)

		Avg.	SD	Min	Max	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30
1	*Incumbent knowledge absorption*	1.20	8.39	0	311	1																													
2	*Incumbent knowledge investments*	0.22	0.46	0	3.3	0.1	1																												
3	*Technological distance*	0.74	0.28	0	1	−0.2	0.1	1																											
4	*Incumbent technological scope*	67.48	73.36	0	330	0.1	0.8	0.1	1																										
5	*Incumbent patent impact*	15.63	12.38	0	116.1	0.1	0.1	−0.3	0.1	1																									
6	*External patent impact*	4.08	5.78	0	29.6	0.2	0.1	−0.3	0.2	0.7	1																								
7	*Incumbent downstream investments*	8.23	9.59	0	49.7	0.2	0.2	−0.2	0.4	0.5	0.7	1																							
8	*Incumbent litigation investments*	2.23	3.99	0	27.9	0.1	0.4	0.0	0.5	0.1	0.2	0.4	1																						
9	*Incumbent acquisition investments*	0.31	0.63	0	5.3	0.2	0.1	−0.1	0.2	0.3	0.6	0.6	0.2	1																					
10	*Incumbent alliance investments*	0.33	0.70	0	4.6	0.1	0.5	0.0	0.4	0.2	0.3	0.5	0.5	0.3	1																				
11	*Citations to incumbents*	1.34	1.76	0	7.8	0.1	0.2	−0.1	0.3	0.5	0.5	0.5	0.2	0.4	0.2	1																			
12	*Incumbent de alio*	0.58	0.49	0	1	0.1	0.2	−0.1	0.4	0.4	0.6	0.5	0.3	0.4	0.2	0.4	1																		
13	*Incumbent public firm*	0.65	0.48	0	1	0.1	0.2	−0.1	0.3	0.3	0.3	0.4	0.3	0.3	0.3	0.3	0.5	1																	
14	*Incumbent category tenure*	11.61	5.42	1	24	0.1	0.2	0.0	0.2	0.1	0.1	0.3	0.3	0.1	0.3	−0.1	0.2	0.1	1																
15	*Entrant knowledge investments*	0.13	0.37	0	3.4	0.1	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	−0.1	0.0	0.0	0.1	1															
16	*Entrant technological scope*	50.01	65.56	0	330	0.1	0.0	0.1	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.1	0.7	1														
17	*Entrant downstream investments*	6.11	8.73	0	49.8	0.2	0.1	−0.1	0.0	0.0	0.1	0.1	0.1	0.0	0.1	0.0	0.0	0.0	0.2	0.3	0.4	1													
18	*Entrant litigation investments*	1.00	2.34	0	27.9	0.2	0.0	−0.1	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.1	0.3	0.5	0.5	1												
19	*Entrant acquisition investments*	0.37	0.72	0	5.3	0.1	0.0	−0.1	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.2	0.3	0.6	0.2	1											
20	*Entrant alliance investments*	0.19	0.55	0	4.6	0.1	0.0	−0.1	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.1	0.3	0.4	0.5	0.5	0.2	1										
21	*Entrant de alio*	0.44	0.50	0	1	0.1	0.0	−0.1	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.3	0.5	0.5	0.4	0.4	0.3	1									
22	*Entrant public firm*	0.57	0.49	0	1	0.1	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.2	0.3	0.3	0.3	0.3	0.2	0.3	1								
23	*Entrant category tenure*	5.10	4.36	0	23	0.1	0.1	0.0	0.1	0.0	0.1	0.1	0.2	0.0	0.2	−0.1	0.1	0.1	0.6	0.1	0.1	0.2	0.2	−0.1	0.1	0.1	0.0	1							
24	*Market overlap*	0.29	0.45	0	1	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	−0.1	0.0	0.1	0.0	0.0	0.1	0.0	0.1	0.0	0.0	1						
25	*Competitive intensity*	0.27	0.13	0.2	1	0.1	0.1	0.0	0.0	0.0	0.1	0.0	0.0	0.0	0.0	0.0	0.0	0.0	−0.2	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.0	−0.1	0.3	1					
26	*Baseline propensity*	0.12	0.40	0	2.8	0.2	0.1	−0.2	0.1	0.3	0.3	0.3	0.1	0.2	0.2	0.4	0.2	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.2	0.1	0.1	0.0	0.1	1				
27	*Technological activity*	8.13	1.27	0.7	9.0	0.0	0.0	0.0	0.0	0.1	−0.1	−0.1	−0.2	0.0	0.0	0.3	0.0	0.0	−0.2	−0.1	0.0	−0.1	−0.1	0.0	0.0	0.0	0.0	−0.1	0.0	0.0	0.1	1			
28	*Technological maturity*	0.05	0.06	−0.1	0.2	0.1	0.1	0.0	0.1	0.0	0.1	0.2	0.2	0.1	0.2	0.0	0.0	0.1	0.5	0.1	0.1	0.2	0.0	0.0	0.1	0.0	0.1	0.3	−0.1	−0.3	0.0	−0.4	1		
29	*Firm count*	63.96	26.52	1	95	−0.1	−0.1	0.0	0.1	0.1	−0.1	0.0	0.0	0.0	0.0	0.1	0.0	−0.1	0.1	0.0	0.0	−0.1	−0.1	−0.1	−0.1	−0.2	−0.1	0.0	−0.2	−0.7	−0.1	0.0	0.4	1	
30	*IPOs*	0.68	1.19	0	6	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.1	0.0	0.0	−0.1	0.0	0.0	−0.1	0.0	0.0	0.0	0.0	0.0	0.0	−0.1	−0.2	0.0	0.1	−0.1	0.2	1
31	*Incumbent patent count*	2.25	2.10	0	7.1	0.1	0.6	0.0	0.7	0.3	0.3	0.3	0.4	0.3	0.4	0.7	0.5	0.4	0.1	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.1	0.3	0.3	−0.1	−0.1	0.0

Figure 3. Decreasing Returns to Incumbent Knowledge Investments



framework (summarized in Figure 1). We begin by looking at the overall relationship between *incumbent knowledge investments* and *incumbent knowledge absorption*, examining whether the latter increases or decreases with the former and whether it does so at an increasing or decreasing rate. Figure 3 reports a binned scatterplot (Stepner 2014) of the relationship between *knowledge absorption* and *knowledge investments*, with each data point representing the expected number of citations at a given percentile of the variable *incumbent knowledge investments*. The resulting curve shows that incumbent learning from entrants increases with *incumbent knowledge investments*, but at a decreasing rate, plateauing off at high levels of *knowledge investments* (around the 95th percentile), and even starting to decline at extremely high levels (the 99th percentile). Such a pattern of diminishing returns to *incumbent knowledge investments* is consistent with a creative divergence scenario.

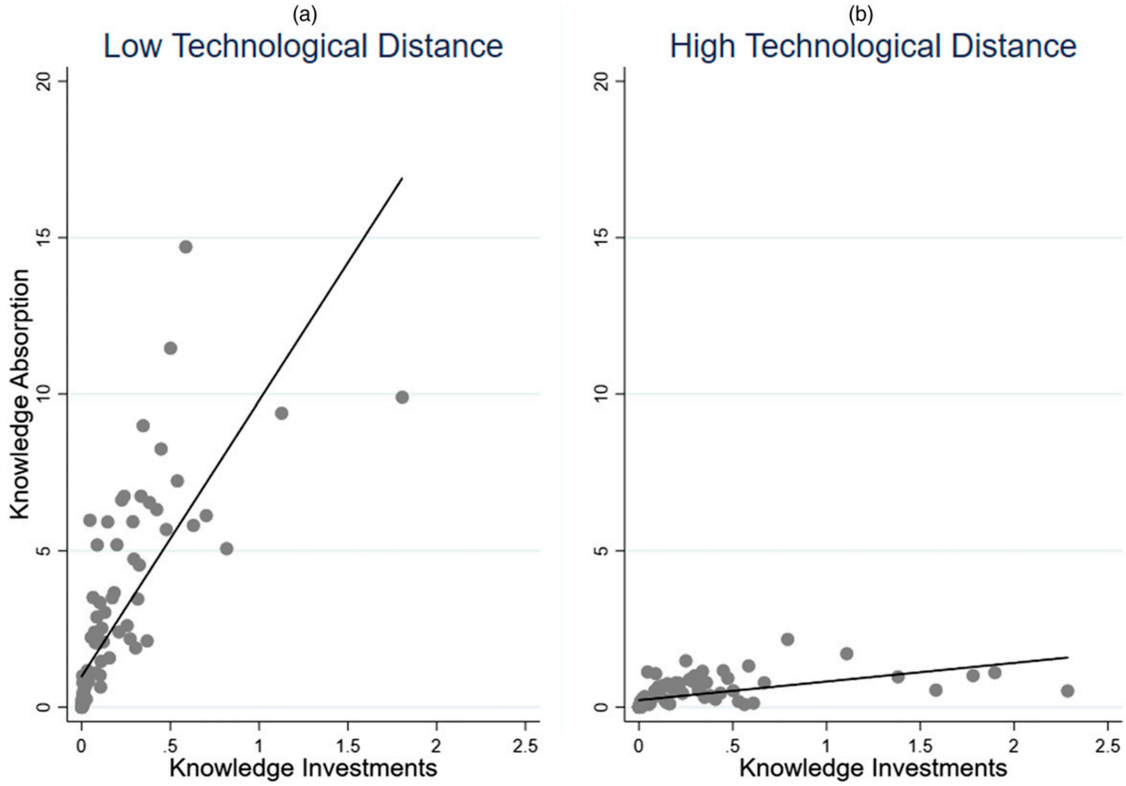
Having shown a general pattern consistent with creative divergence, we dive further into the underlying mechanisms. The logic for the positive but diminishing returns to incumbent knowledge investments in Figure 1 is that such investments directly increase knowledge absorption. They also increase technological distance between incumbent and entrant, however, which indirectly undermines incumbent

Table 2. Incumbent Knowledge Absorption and Knowledge Investments by Technological Distance

Group	*Low knowledge investments*[c]	*High knowledge investments*[d]	*t*-test: (*High knowledge investments* – *Low knowledge investments*) > 0
Low technological distance[a]	1.06***	6.40***	5.34***
	(0.06)	(0.35)	(0.36)
High technological distance[b]	0.18***	0.78***	0.60***
	(0.01)	(0.05)	(0.05)
t-test: (*Low technological distance* – *High technological distance*) > 0	0.88***	5.62***	
	(0.07)	(0.36)	

Note. Robust SEs are in parentheses.
[a]*Low technological distance* is coded as 1 if *Technological distance* < mean(*Technological distance*) and 0 otherwise.
[b]*High technological distance* is coded as 1 – *Low technological distance*.
[c]*Low knowledge investments* is coded as 1 if *Incumbent knowledge investments* < mean(*Incumbent knowledge investments*) and 0 otherwise.
[d]*High knowledge investments* is coded as 1 – *Low knowledge investments*.
***$p < 0.01$.

Figure 4. Incumbent Knowledge Investments and Knowledge Absorption

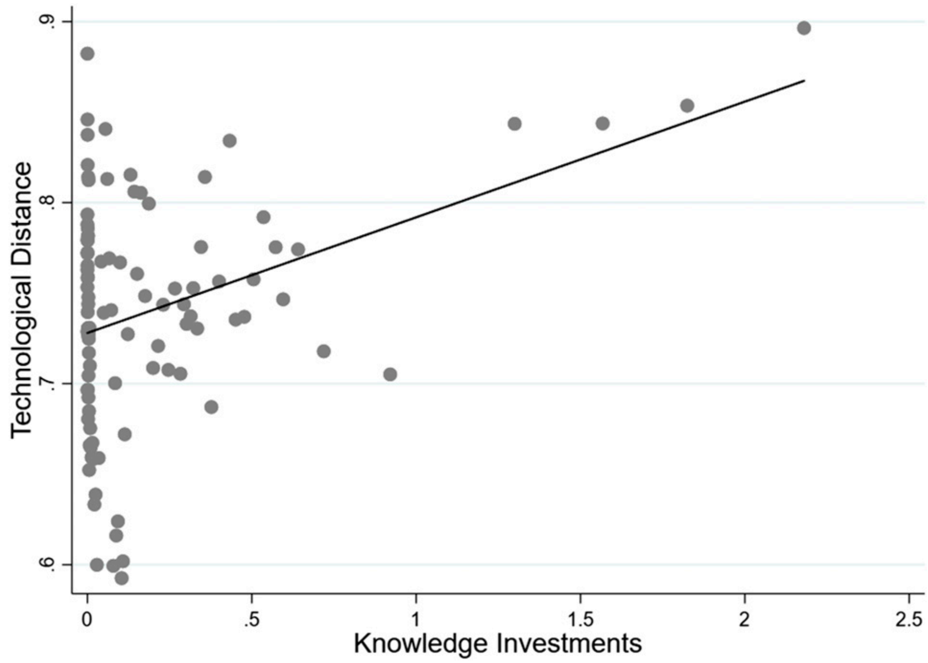


learning, because learning is negatively moderated by distance. The summary statistics in Table 1 show that *incumbent knowledge absorption* and *incumbent knowledge investments* are indeed positively correlated. This is prima facie evidence that the incumbent's primary strategy is to learn. Furthermore, if learning is facilitated by technological relatedness (Cohen and Levinthal 1990), we expect this positive correlation to be weaker when the *technological distance* between the incumbent and the entrant is high. We explore this pattern in Table 2. We compare the average *incumbent knowledge absorption* for four groups of incumbents: (i) those with *low technological distance* to entrants and *high knowledge investments*, (ii) *low technological distance* and *high knowledge investments*, (iii) *high technological distance* and *low knowledge investments*, and (iv) *high technological distance* and *high knowledge investments*.[14] The *t*-tests of the difference of means show that the incumbents with *high knowledge investments* and *low technological distance* learn significantly more from entrants. This relationship is then shown graphically in Figure 4, a binned scatterplot (Stepner 2014) of the relationship between *knowledge absorption* and *knowledge investments* for two different sub-samples: one for incumbents with low technological distance to entrants [panel (a)] and one for those with high technological distance [panel (b)]. The figure shows that the positive correlation between *incumbent knowledge investments* and *knowledge absorption* is weaker when entrants locate far from the incumbents, with a straight line fit to the data having a steeper slope in panel (a) than (b).

The summary statistics in Table 1 also show that *incumbent knowledge investments* and *technological distance* are positively related. Figure 5 is a binned scatterplot (Stepner 2014) of the relationship between *technological distance* and *knowledge investments*, showing a positive correlation between the two. Table 3 compares the average *technological distance* for the incumbents with *low knowledge investments* and those with *high knowledge investments*. On average, incumbents with *high knowledge investments* are significantly farther away from entrants.

Next, we unpack the effect of incumbent knowledge investments on technological distance to see if, in fact, entrants are retreating. An alternative explanation for a positive relationship between *incumbent knowledge investments* and *technological distance* is that incumbents themselves are moving away from entrants, seeking new technologies in which to invest, now that entrants have undermined their existing positions. Although we argued against this possibility when developing our theoretical framework, we still need to consider it

Figure 5. Incumbent Knowledge Investments and Technological Distance



empirically. To do so, we take a more granular look at the patenting behavior of incumbents and entrants. We look at two ratios—the fraction of patents filed by the incumbent in new patent classes (i.e., classes where it had no prior patents) that are in classes where the entrant has patented before and the fraction of patents filed by the entrant in new patent classes that are in classes where the incumbent has patented before—and their evolution over time. Intuitively, these two ratios measure the extent to which the incumbent and entrant are taking active steps to move closer to the other, respectively. Figure 6 shows that whereas the ratio of incumbent's patents in new classes that overlap with the entrant's increases over time, the ratio of entrant's patents in new classes that overlap with the incumbent's decreases. Consistent with the creative divergence scenario, incumbents move closer to entrants over time, but entrants move away from incumbents.

These descriptive analyses provide a general sense of the broad patterns of relationships between our variables of interest, and they suggest that our empirical setting is best characterized as a case of creative divergence. We explore these patterns further using a set of multivariate regressions. Again, our purpose here is not to test any claims or hypotheses; it is only to provide a more rigorous and robust validation of the univariate patterns we have observed thus far.

Regression Analyses

Methods. The regression equations to examine the relationships between our variables of interest are

$$I = a_0 + a_1K + a_2T + a_3KT + a_4X + \varepsilon_1, \tag{1}$$
$$T = b_0 + b_1K + b_2X + \varepsilon_2. \tag{2}$$

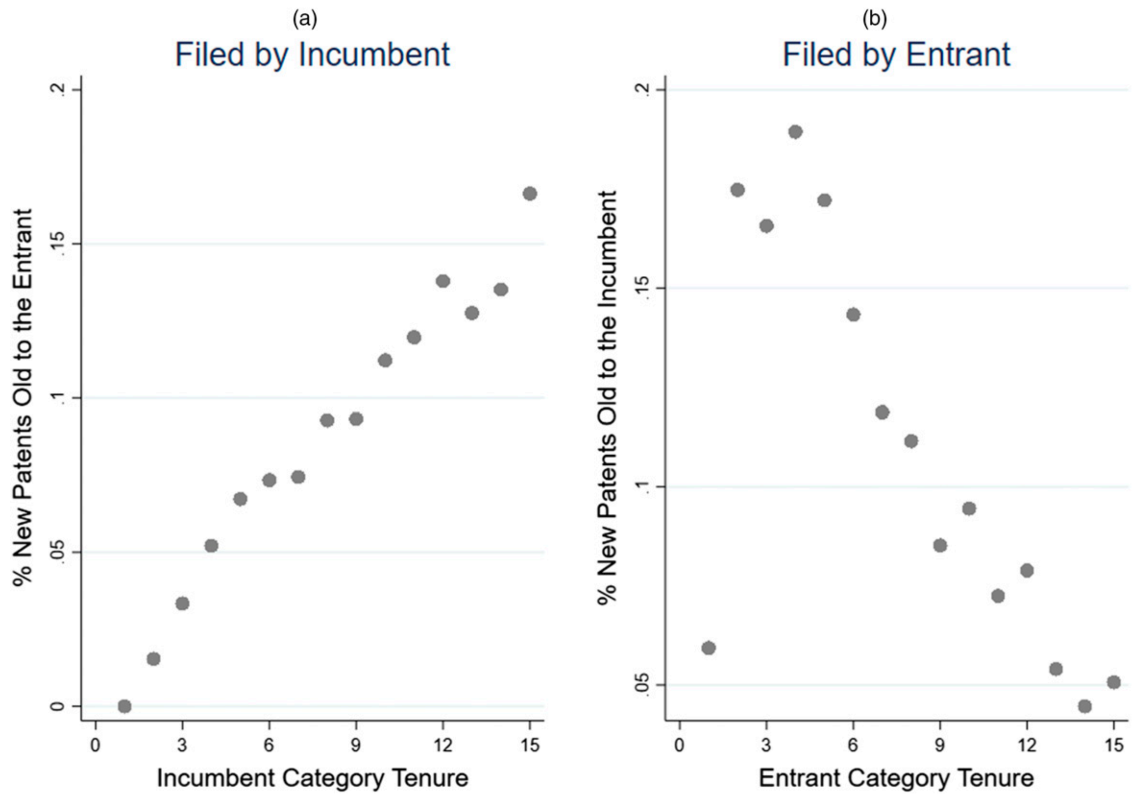
In the first regression equation, we regress *incumbent knowledge absorption I* on *incumbent knowledge investments K*,

Table 3. Technological Distance and Incumbent Knowledge Investments

Group	Mean tech. distance	Robust SE	t	[95% conf.	interval]
High knowledge investments[a]	0.77***	0.003	299.82	0.76	0.77
Low knowledge investments[b]	0.73***	0.002	418.79	0.73	0.74
t-test: (*High knowledge investments* – *Low knowledge investments*) > 0	0.04***	0.003	12.21	0.03	0.04

[a]*High knowledge investments* is coded as 1 – *Low knowledge investments*.
[b]*Low knowledge investments* is coded as 1 if *Incumbent knowledge investments* < mean(*Incumbent knowledge investments*) and 0 otherwise.
***$p < 0.01$.

Figure 6. Entrants Retreating and Incumbents Approaching



technological distance T, their interaction, the vector of controls X, and the fixed effects a_0 (ε_1 is the random disturbance). If the incumbent's primary strategy is to *learn* (i.e., to try to catch up and build on the entrant's technologies), we will observe a positive main effect of *incumbent knowledge investments* ($a_1 > 0$) that will grow weaker with *technological distance* ($a_3 < 0$). If, instead, incumbents mostly *attack* by investing in substitute technologies, we will observe an insignificant (or possibly negative) effect of knowledge investments on knowledge absorption, regardless of the distance between the incumbent and the entrant ($a_1 \leq 0$ and $a_3 \sim 0$).

In the second regression equation, we examine the entrant's response to the incumbent's investments by regressing *technological distance T* on *incumbent knowledge investments K*, the vector of controls X, and the fixed effects b_0 (ε_2 is the random disturbance). If entrants *reciprocate* incumbent actions, seeking either to learn from them or to compete head-to-head with them, we will observe a negative main effect of incumbent knowledge investments on technological distance ($b_1 \leq 0$), as entrants strive to draw closer to incumbents. However, if the entrants *retreat* to protect themselves from incumbents, we will observe a positive main effect of incumbent knowledge investments on technological distance ($b_1 > 0$).

The right-hand-side variables in (1) are lagged two years to reflect the gestation period of innovations in the industry before patent application filing (Kaplan et al. 2004), and the right-hand-side variables in (2) are not lagged because we are interested in the contemporaneous, reduced-form, effect of the interplay between incumbents' actions and entrants' reactions on the technological distance between the two types of firms.[15] Moreover, estimating Equation (2) contemporaneously allows us to compute the net effect of incumbent knowledge investments on incumbent knowledge absorption, taking into account the mediated moderating effect of technological distance (Preacher et al. 2007, Hayes 2013).[16] Our results are robust to lagging the right-hand-side variables.

We estimate these equations in two ways. First, we use linear panel regressions controlling for category-incumbent-entrant (i.e., the subject of analysis) fixed effects and calculate heteroscedasticity-robust standard errors (Stock and Watson 2008).[17] Second, because the dependent variable in Equation (1) is a nonnegative integer, we also use a nonlinear count model [Equation (2) is always estimated using a linear panel regression given the continuous nature of our *technological distance* measure[18]]. Specifically, we use a negative binomial model with a control function approach to account for selection, as developed by Wooldridge (2001, 2015). Wooldridge's approach is similar in spirit to the Durbin–Wu–Hausman test for endogeneity, a statistical equivalent to the two-stage least squares estimator where the residuals from the first-stage regression of endogenous variables on exogenous variables are included in the model of interest (Wooldridge 2001, p. 663). For our analysis, Wooldridge's approach translates into the following model specification:

$$\log(I) = \alpha_0 + \alpha_1 K + \alpha_2 T + \alpha_3 KT + \alpha_4 X + \alpha_5 \hat{u} + e_3, \quad (3)$$

where I is *incumbent knowledge absorption*; T, K, and TK are the endogenous variables; X is a vector of controls; $\hat{u}$ is a vector consisting of residuals from the first stage where the endogenous variables are regressed on a set of instruments; and e_3 is the random disturbance. Variables K, T, and KT are instrumented by Z, Y, and YZ, respectively.[19]

Main Findings. Models 4-1 and 4-2 in Table 4 report our main findings. Model 4-1 explores the effect of *incumbent knowledge investments* on *incumbent knowledge absorption*, and its moderation by *technological distance*, using a panel ordinary least squares (OLS) regression [as in Equation (1)]. It shows that the main effect

Table 4. Main Findings

	Model 4-1 (DV: *Incumbent knowledge absorption*) (OLS with FEs)		Model 4-2 (DV: *Technological distance*) (OLS with FEs)		Model 4-3 (DV: *Incumbent knowledge absorption*) (Negative binomial with instruments)	
Variable	Coefficient	Robust SE	Coefficient	Robust SE	Coefficient	Robust SE
Incumbent knowledge investments	10.499***	3.670	0.043***	0.008	11.085***	1.844
Technological distance	−2.395***	0.641			−5.331***	0.382
Inc know × Tech dist	−11.638***	3.688			−11.075***	1.821
Residual 1					−0.351	0.257
Residual 2					3.269***	0.377
Residual 3					−9.544***	1.823
Incumbent technological scope	−0.012	0.008	0.000	0.000	−0.005***	0.002
Incumbent patent impact	−0.048**	0.023	−0.004***	0.001	−0.005	0.003
External patent impact	0.847***	0.214	0.004**	0.002	−0.024***	0.008
Incumbent downstream investments	−0.160***	0.040	−0.003***	0.000	−0.012**	0.005
Incumbent litigation investments	−0.012	0.035	0.001	0.001	0.016**	0.007
Incumbent acquisition investments	0.416**	0.205	−0.001	0.003	−0.073*	0.039
Incumbent alliance investments	0.466***	0.167	0.001	0.002	−0.044	0.039
Citations to incumbents	0.502***	0.098	0.002	0.001	0.095***	0.023
Incumbent de alio	−0.712	0.529	−0.038**	0.017	0.442***	0.092
Incumbent public firm	0.180	0.872	−0.006	0.011	0.179**	0.088
Incumbent category tenure	9.676*	5.027	0.103**	0.042	−0.051***	0.009
Entrant knowledge investments	0.187	1.010	0.019	0.014	0.055	0.078
Entrant technological scope	−0.009	0.007	−0.000*	0.000	0.012***	0.001
Entrant downstream investments	0.076***	0.024	−0.001	0.000	−0.004	0.004
Entrant litigation investments	−0.225***	0.079	0.001*	0.001	0.043***	0.010
Entrant acquisition investments	−0.156	0.205	0.000	0.003	−0.064**	0.032
Entrant alliance investments	0.478**	0.221	−0.004	0.003	0.055	0.038
Entrant de alio	−0.605**	0.288	−0.039***	0.012	0.357***	0.067
Entrant public firm	−0.024	0.303	−0.035***	0.008	0.163***	0.061
Entrant category tenure	(absorbed by panel FEs)		(absorbed by panel FEs)		0.077***	0.007
Market overlap	0.011	0.328	−0.003	0.006	0.009	0.052
Competitive intensity	0.560	3.611	−0.113*	0.060	1.186	0.852
Baseline propensity	2.173***	0.214	−0.010***	0.003	2.131***	0.060
Technological activity	2.873*	1.655	0.030**	0.014	−0.482*	0.261
Technological maturity	−4.310	5.489	−0.638***	0.187	−4.518	3.193
Firm count	−0.001	0.018	0.001***	0.000	−0.003	0.004
IPOs	0.095	0.064	−0.002*	0.001	−0.027	0.029
Incumbent patent count	0.508***	0.097	0.000	0.002	0.711***	0.044
Observations	36,488		36,488		36,488	
R^2	0.523		0.869		n/a	
Size and year FEs	YES		YES		YES	
Category FEs	(absorbed by panel FEs)		(absorbed by panel FEs)		YES	

Note. DV, dependent variable; FEs, fixed effects.
***$p < 0.01$; **$p < 0.05$; *$p < 0.1$.

of *incumbent knowledge investments* is positive and statistically significant (α = 0.01), but it is negatively moderated by *technological distance*, with the interaction term being negative and statistically significant (α = 0.01). Were *technological distance* to be held constant at its mean value, the results in Model 4-1 imply that a one-standard-deviation increase in *incumbent knowledge investments* would increase *incumbent knowledge absorption* by 0.87—a 75% increase from the mean value of 1.20.[20] These results are further validated by Model 4-3, which uses a negative binomial model with control function approach (as in Equation (3)) and shows a pattern of results identical to those in Model 4-1. If anything, the average marginal effect of a standard deviation increase in *incumbent knowledge investments* in Model 4-3 is approximately 8.94 (which is slightly more than a one–standard-deviation increase in the expected number of citations), suggesting that we may be underestimating the effect of *incumbent knowledge investments* in Model 4-1. These results are consistent with the univariate patterns observed in Figure 4 and suggest that incumbents are trying to learn from entrants in order to build on their knowledge, with such efforts being more successful the closer the entrants are to the incumbent.

Model 4-2 estimates the relationship between technological distance and incumbent knowledge investments as in Equation (2). *Incumbent knowledge investments* have a significant positive effect on technological distance ($b_1 > 0$). In terms of magnitude, a one-standard-deviation increase in *incumbent knowledge investments* (0.46) corresponds to a 0.02 increase in *technological distance*—a 3% increase from the mean value of technological distance (0.74). This result is consistent with the entrant *retreating* from the incumbent as the incumbent invests in knowledge, consistent with the univariate pattern in Figure 5.

Figure 7 shows the overall effect *incumbent knowledge investments* has on *incumbent knowledge absorption*, based on the results in Table 4.[21] Similar to the univariate pattern we observed in Figure 3, it shows that *incumbent knowledge absorption* increases with *incumbent knowledge investment* but at a decreasing rate; the relationship eventually turns negative where the competitive effect of additional knowledge investments in driving entrants away comes to overwhelm their learning benefits.[22] The decreasing slope of the curve in Figure 7 results from the increasing technological distance between incumbent and entrant, which makes the incumbent's attempts to learn from the entrant less and less effective. As before, this pattern is consistent with the creative divergence scenario. We further confirm the robustness of the univariate patterns we observe in our data, as well as in our main multivariate analyses, through a series of robustness checks reported in Online Appendix C.

Supplemental Analyses. We undertake two sets of supplemental analyses. First, we deconstruct the effect of incumbent (and entrant) knowledge investments on the technological distance between incumbents and entrants, similar to the analyses in Figure 6. Specifically, we create two new dependent variables, *filed by incumbent: old to entrant,* which is a count of the incumbent's patents assigned to at least one patent class in which the entrant had at least one patent at time $t-2$; and *filed by entrant: new to the incumbent,* which is a count of the entrant's patents assigned to at least one patent class in which the incumbent had no patents at time $t-2$. The first variable measures attempts by the incumbent to draw closer to the entrant, and the second variable measures attempts by the entrant to retreat from the incumbent.

Models 5-1 and 5-2 in Table 5 explore the relationship between these variables and *technological distance* using a negative binomial model with a control function approach similar to that used in Model 4-3.[23] As before, we see a divergence in the two firms actions: Model 5-1 shows that incumbents become more likely to invest in entrants' knowledge areas as the technological distance between them decreases (i.e., they draw closer together); Model 5-2, by contrast, shows that entrants become more likely to invest in knowledge areas that are nonoverlapping with incumbents when that happens. These findings are broadly consistent with the univariate pattern in Figure 6, with incumbents pursuing entrants and entrants retreating from incumbents, and further indicate that we are in a creative divergence scenario.

We further deconstruct the action/response between incumbents and entrants in Models 5-3 and 5-4; we use the same dependent variables as in Models 5-1 and 5-2, respectively, but now regress incumbent patents on patents filed by entrants (Model 5-3) and entrant patents on patents filed by incumbents (Model 5-4). We divide our predictors into four groups: (i) new to the incumbent/new to the entrant, (ii) new to the incumbent/old to the entrant, (iii) old to the incumbent/new to the entrant, and (iv) old to the incumbent/old to the entrant. A patent is counted in *new to the incumbent/new to the entrant* if it is assigned to at least one patent class in which both the incumbent and the entrant had no patents at time $t-2$. Other groupings are constructed analogously. We focus specifically on the effect of patents *filed by entrant: old to the incumbent/new to the entrant* and *filed by incumbent: new to the incumbent/old to the entrant*, because these unambiguously represent moves by the entrant to get closer to the incumbent and by the incumbent to get closer to the entrant, respectively.

Model 5-3 shows a positive and significant coefficient of *filed by entrant: old to the incumbent/new to the entrant* when predicting *filed by incumbent: old to the* *entrant*, implying that, consistent with our arguments and our interpretation of Model 5-1, incumbents respond to attempts by entrants to draw closer to them by drawing closer to the entrants in turn. At the same time, Model 5-4 shows a positive and significant coefficient of *filed by incumbent: new to the incumbent/old to the entrant* when predicting *filed by entrant: new to the incumbent*, implying that, as in Model 5-2, entrants respond to incursions by incumbents into their knowledge areas by trying to move away from incumbents. These results provide further support for creative divergence: when entrants come after incumbents, incumbents move closer to entrants; however, when incumbents come after entrants, entrants tend to move away.

Our second set of supplemental analyses examines how the dynamics between incumbents and entrants are moderated by the distance at which the entrant originally enters the market. On one hand, the process of creative divergence may be more pronounced for entrants that start farther from incumbents. They may be less inclined to engage with incumbents (hence their decision to enter farther from them in the first place) and may be quick to retreat from incumbent knowledge investments. By contrast, entrants that enter quite close to incumbents—such as entrepreneurial spinouts from the incumbents (Agarwal et al. 2007, 2010)—may be more willing to reciprocate incumbent advances. In this case, creative divergence (as reflected in the results in Table 4) would be amplified by the original distance between entrants and incumbents, with entry close to incumbents more likely to result in creative construction (or destruction). On the other hand, it may be that creative divergence grows weaker as entrants start farther from incumbents, because the entrant's technologies represent less of a direct threat to the incumbent (Toh and Polidoro 2013). As a result, incumbents may respond less aggressively to more distant entrants, and entrants may feel less threatened by the responses of more distant incumbents. In this case, the effects in Table 4 would become weaker as the original distance between entrants and incumbents increases.

To examine these possibilities, we rerun Models 4-1 and 4-2 estimating the coefficient of interest for different subgroups of entrants according to how distant they are from incumbents at the time of entry.[24] These subgroups are defined as follows: First, we create a variable that measures *technological distance* for the year in which the new entrant starts commercializing a device in the focal category, *original distance*. Second, we subdivide the sample into the four quartiles of the distribution of *original distance*. The entrants in the first quartile represent the 25% of entrants that position the closest to incumbents at the time of entry; entrants in the second quartile represent the 25% of entrants in the contiguous portion of the distribution, and so on. Our models report the actual values of the coefficients of interests for each subgroup.[25]

The results of this analysis are shown in Table 6. Model 6-1 corresponds to Model 4-1 in Table 4, and Model 6-2 corresponds to Model 4-2. Across both models we see a general pattern of strong results for entrants that enter close to incumbents (Q1), becoming weaker as *original distance* increases, till they become insignificant for the entrants that enter farthest from

Figure 7. Overall Effect of Incumbent Knowledge Investments

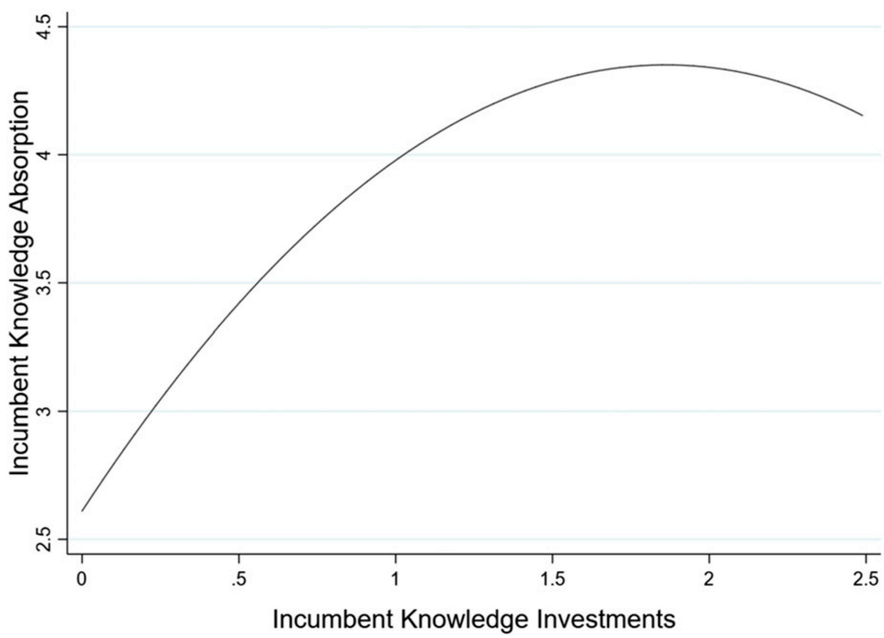


Table 5. Supplemental Analysis: Incumbent and Entrant Response to Distance

	Model 5-1 (DV: *Filed by inc: Old to ent*)		Model 5-2 (DV: *Filed by ent: New to inc*)		Model 5-3 (DV: *Filed by inc: Old to ent*)		Model 5-4 (DV: *Filed by ent: New to inc*)	
Variable	Coefficient	Robust SE	Coefficient	Robust SE	Coefficient	Robust SE	Coefficient	Robust SE
Technological distance	−10.025***	0.212	−3.006***	0.180				
Filed by ent: Old inc/new ent					0.014***	0.002		
Filed by inc: New inc/old ent							0.011***	0.004
Filed by ent: New inc/new ent					−0.011***	0.002		
Filed by ent: New inc/old ent					−0.002***	0.000		
Filed by ent: Old inc/old ent					0.014***	0.002		
Filed by inc: New inc/new ent							−0.015***	0.004
Filed by inc: Old inc/new ent							0.002***	0.000
Filed by inc: Old inc/old ent							−0.002***	0.000
Residual	8.970***	0.211	4.084***	0.177				
Incumbent technological scope	0.005***	0.000	−0.006***	0.000	−0.004***	0.000	−0.007***	0.000
Incumbent patent impact	−0.024***	0.001	−0.016***	0.001	0.007***	0.001	−0.003***	0.001
External patent impact	0.001	0.002	0.001	0.002	−0.002	0.002	0.008***	0.002
Incumbent downstream investments	−0.043***	0.001	−0.020***	0.001	0.013***	0.001	−0.001	0.001
Incumbent litigation investments	0.010***	0.002	−0.006**	0.003	0.008***	0.002	−0.003	0.004
Incumbent acquisition investments	0.078***	0.009	0.058***	0.012	−0.095***	0.010	0.004	0.015
Incumbent alliance investments	−0.051***	0.008	−0.115***	0.013	−0.027***	0.010	−0.108***	0.017
Citations to incumbents	0.038***	0.005	−0.001	0.004	−0.001	0.005	−0.009*	0.005
Incumbent de alio	−0.027	0.019	−0.106***	0.012	0.021	0.021	−0.070***	0.014
Incumbent public firm	−0.099***	0.021	−0.014	0.008	0.019	0.021	0.026***	0.010
Incumbent category tenure	−0.006***	0.002	0.000	0.001	−0.009***	0.002	0.004***	0.001
Entrant knowledge investments	−0.711***	0.022	−0.349***	0.013	−0.180*	0.092	−0.209***	0.012
Entrant technological scope	0.012***	0.000	0.007***	0.000	0.006***	0.000	0.004***	0.000
Entrant downstream investments	−0.039***	0.001	−0.026***	0.001	−0.001	0.001	−0.017***	0.001
Entrant litigation investments	−0.024***	0.003	−0.010***	0.002	0.008***	0.003	0.005**	0.002
Entrant acquisition investments	0.094***	0.008	0.038***	0.006	0.054***	0.009	0.047***	0.006
Entrant alliance investments	−0.130***	0.011	−0.048***	0.007	−0.023**	0.010	0.006	0.008
Entrant de alio	−0.309***	0.018	−0.146***	0.013	0.228***	0.020	−0.008	0.012
Entrant public firm	−0.091***	0.014	−0.037***	0.010	−0.053***	0.016	−0.040***	0.011
Entrant category tenure	0.035***	0.002	0.017***	0.001	0.006***	0.002	0.005***	0.001
Market overlap	−0.185***	0.013	−0.097***	0.009	0.079***	0.013	−0.043***	0.009
Competitive intensity	−0.966***	0.233	−0.313***	0.118	−0.241	0.218	0.159	0.148
Baseline propensity	−0.629***	0.019	−0.426***	0.020	0.153***	0.013	−0.199***	0.019
Technological activity	−0.031	0.072	0.080	0.068	0.093	0.081	0.017	0.078
Technological maturity	−6.545***	0.888	−2.403***	0.474	−2.161**	0.897	−2.091***	0.544
Firm count	−0.004***	0.001	−0.003***	0.001	−0.004***	0.001	−0.002***	0.001
IPOs	−0.034***	0.007	−0.007	0.005	−0.015*	0.008	0.002	0.006
Incumbent patent count	(restricted to 1)				(restricted to 1)			
Entrant patent count			(restricted to 1)				(restricted to 1)	
Constant	8.371***	0.374	1.670***	0.318	−1.048***	0.350	−0.649**	0.305
Observations	36,488		36,488		36,488		36,488	
Size, category, year FEs	YES		YES		YES		YES	

Notes. Negative binomial models (5-1 and 5-2 with instrument *random distance*). DV, dependent variable; FEs, fixed effects; inc, incumbent; ent, entrant.

***$p < 0.01$; **$p < 0.05$; *$p < 0.1$.

incumbents (Q4). These results support the idea that the dynamics underlying the creative divergence scenario are amplified the closer the entrant is to the incumbent when it enters. Where entrants enter very close to the incumbents, incumbents act aggressively to learn from them, and the imminent threat posed by such aggressive incumbent action makes entrants more likely to retreat. Conversely, where entrants enter far from the incumbents, neither firm sees the other as a threat, and both maintain their (distant) positions. Figure 8 shows this graphically, plotting the net relationship between incumbent knowledge investments and knowledge absorption (as in Figure 7) for each subgroup. We see that the curved shape of the relationship is most pronounced for Q1 entrants, with knowledge absorption rising sharply

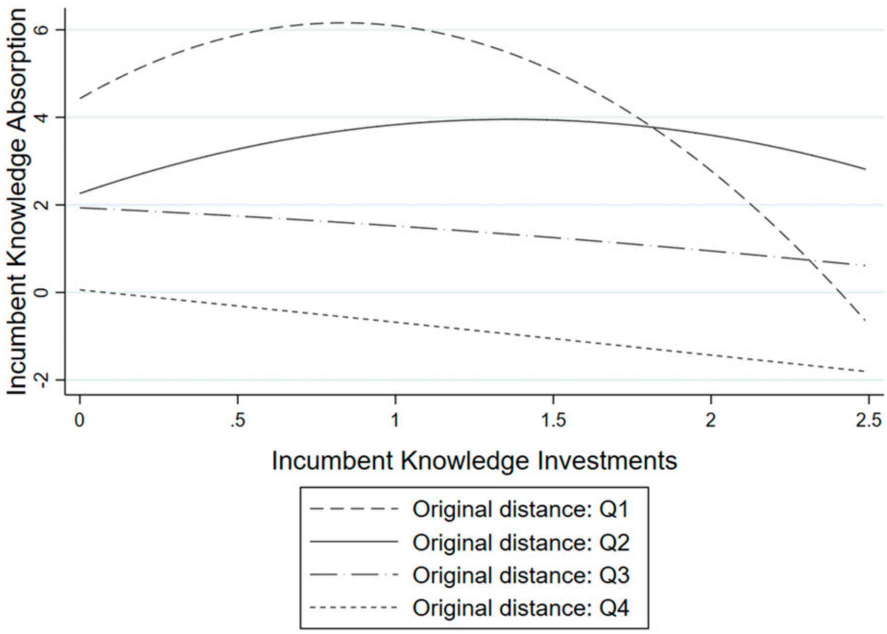
Table 6. Supplemental Analysis: Moderating Role of Original Distance

	Model 6-1 (DV: *Incumbent knowledge absorption*)		Model 6-2 (DV: *Technological distance*)	
Variable	Coefficient	Robust SE	Coefficient	Robust SE
Incumbent knowledge investments				
Original distance: Q1	11.820***	3.475	0.138***	0.015
Original distance: Q2	14.445***	4.517	0.057***	0.005
Original distance: Q3	2.752	2.237	0.023***	0.005
Original distance: Q4	0.618	1.482	0.004	0.008
Technological distance				
Original distance: Q1	−3.772***	0.707		
Original distance: Q2	−2.057**	0.907		
Original distance: Q3	−1.599***	0.579		
Original distance: Q4	0.136	0.173		
Inc know × Tech dist				
Original distance: Q1	−17.971***	4.811		
Original distance: Q2	−15.786***	4.865		
Original distance: Q3	−3.396	2.248		
Original distance: Q4	−1.545	1.429		
Incumbent technological scope	−0.011**	0.005	−0.000	0.000
Incumbent patent impact	−0.048***	0.016	−0.004***	0.000
External patent impact	0.852***	0.095	0.004***	0.001
Incumbent downstream investments	−0.152***	0.020	−0.003***	0.000
Incumbent litigation investments	−0.013	0.020	0.001***	0.000
Incumbent acquisition investments	0.426***	0.162	−0.002	0.002
Incumbent alliance investments	0.463***	0.133	0.000	0.002
Citations to incumbents	0.495***	0.057	0.002*	0.001
Incumbent de alio	−0.623**	0.286	−0.036***	0.008
Incumbent public firm	0.181	0.523	−0.006	0.006
Incumbent category tenure	9.417***	3.578	0.106***	0.030
Entrant knowledge investments	0.117	0.561	0.017**	0.006
Entrant technological scope	−0.008*	0.004	−0.000***	0.000
Entrant downstream investments	0.076***	0.015	−0.001***	0.000
Entrant litigation investments	−0.230***	0.048	0.002***	0.000
Entrant acquisition investments	−0.127	0.127	0.001	0.002
Entrant alliance investments	0.446***	0.151	−0.004*	0.002
Entrant de alio	−0.579***	0.162	−0.039***	0.006
Entrant public firm	−0.024	0.203	−0.035***	0.005
Entrant category tenure	(absorbed by panel FEs)		(absorbed by panel FEs)	
Market overlap	0.013	0.272	−0.003	0.004
Competitive intensity	0.392	2.619	−0.110***	0.034
Baseline propensity	2.182***	0.146	−0.010***	0.002
Technological activity	2.783**	1.176	0.031***	0.010
Technological maturity	−7.017	4.971	−0.604***	0.103
Firm count	−0.001	0.008	0.001***	0.000
IPOs	0.095*	0.053	−0.002**	0.001
Incumbent patent count	0.514***	0.060	0.000	0.001
Observations	36,488		36,488	
R^2	0.523		0.869	
Size and year FEs	YES		YES	

Note. OLS models with fixed effects (FEs). DV, dependent variable.
$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

with incumbents' initial knowledge investments, but reaching an inflection point much earlier (at incumbent knowledge investments of 0.90, corresponding to the 96th percentile in the subgroup). By contrast, the relation between incumbent knowledge absorption and knowledge investments is essentially flat for firms entering far from incumbents (Q3 and Q4). If anything, these curves show a slight negative slope, which may be the result of increased exploitation by the incumbents, which draw less on the knowledge of (distant) entrants as they increase knowledge investments in their core areas.

Figure 8. Overall Effect of Incumbent Knowledge Investments per Original Distance Quartile



Summary

Across both descriptive and regression analyses, the patterns we observe are strongly consistent with the creative divergence scenario. Specifically, we find that incumbent knowledge investments in our setting have a positive direct effect on incumbent learning from entrants, but these investments also increase the technological distance between entrants and incumbents, which has a negative moderating effect on the relation between knowledge investments and learning from entrants. As a result, incumbent learning from entrants increases at a decreasing rate with incumbent knowledge investments; the direct increase in learning as a result of these investments is (partially) undermined by the increasing distance between incumbents and entrants. Supplemental analyses confirm this increase in technological distance in response to incumbent knowledge investments is driven by the tendency of entrants to move away from incumbents over time, even as the incumbents move toward them. Supplemental analyses also show that both the direct and indirect effects of incumbent knowledge investments on incumbent learning are more pronounced the closer the entrant's original position to the incumbent.

Of course, support for the creative divergence scenario in the cardiovascular medical device industry does not imply that this will be the case in all other settings. On the contrary, we would expect to see different scenarios play out in different contexts. Perhaps we see creative divergence in our empirical context because it is an industry setting marked by moderate patent appropriability, well-established incumbents with valuable complementary assets, and products with a relatively limited range of complementary products. Where incumbents are less well established—for example, in newer, less mature markets—entrants may be more prone to counterattack than retreat, making creative destruction more likely in such settings (Agarwal and Gort 1996, Chen et al. 2010). Similarly, creative construction may be more likely in settings where several complementary positions in the value chain are available to entrants (Agarwal et al. 2007), making it easier for them to establish a symbiotic relationship with incumbents by contributing complementary technology components within a shared standard or ecosystem (Kapoor and Furr 2015, Toh and Miller 2017). Appropriability regimes may also have an important role to play in determining the nature of Schumpeterian competition (Teece 1986), with weak appropriability making it more attractive for firms to attack each other. Thus, creative destruction may be more likely where complementary assets provide limited protection to incumbents, and creative deterrence where weak intellectual property protection makes it easier for incumbents to drive out entrants. Given that the current study is limited to a single empirical context, we can only speculate about the possibility of other scenarios in different settings. Our empirical analyses provide an example of how our theoretical framework may be applied to a real-world setting—an example we hope future work will follow, to examine the dynamics of Schumpeterian competition in other contexts.

Discussion

Contributions

Our framework and findings contribute conceptually and empirically to the study of competitive dynamics in Schumpeterian environments (Winter 1984, Levinthal 1992). Conceptually, we complement and extend recent work on the knowledge spillover-based perspective (Agarwal et al. 2007, Agarwal et al. 2016) by defining a set of intermediate scenarios that lie between the creative construction case and the opposite extreme of creative destruction (Agarwal et al. 2010), as well as the specific strategies pursued by both incumbents and entrants that lead to these distinct scenarios. In doing so, our framework incorporates the potential for incumbent learning from entrants (Nelson and Winter 1973, 1978; Cohen and Levinthal 1990), extending prior work that has sought to examine the dynamics of technology competition in a Schumpeterian context (Chen et al. 2010, Parker 2010, Katila et al. 2012).

From an empirical perspective, our study advances beyond this prior work to directly examine the competitive dynamics between incumbents and entrants in a real-world setting. Our supplemental analyses show that these dynamics are moderated by the entrant's initial position, with incumbents responding more aggressively to entrants who start off very close to them. These findings have potential implications for work on entrepreneurial spinouts (Agarwal et al. 2004, Klepper and Sleeper 2005), suggesting that by entering close to the (spawning) incumbents, such spinouts may fundamentally alter the nature of competition and the rate of technological change in the markets they enter (Agarwal et al. 2007).

Our framework also highlights the case of creative divergence: the possibility that even as incumbents try to learn from entrants, entrants may seek to escape from them. Incumbent knowledge investments may thus realize diminishing returns in terms of learning, and the eventual outcome of Schumpeterian competition may be an equilibrium of mutual adjustment. This case is interesting because, to the best of our knowledge, it has never been discussed in the prior literature and because it reflects asymmetric behavior on the part of incumbents and entrants, with incumbents trying to draw closer to entrants even as entrants try to move away. Our study not only recognizes the theoretical possibility of this scenario; it empirically documents such a scenario through exploratory analyses.

Finally, our study also contributes to research on absorptive capacity (Cohen and Levinthal 1990, 1994). Whereas Cohen and Levinthal's (1989) seminal work saw knowledge investments as enhancing both a firm's competitive strength and its ability to learn from others, subsequent work in this tradition generally emphasizes the learning benefits of such knowledge investments, implicitly assuming that the supply of external knowledge remains fixed. We link the absorptive capacity literature to work on technology competition (Chen et al. 2010, Polidoro and Toh 2011), which highlights the possibility that investments in learning from others may impact the actions of those others, complementing prior work that examines how the capture of spillovers may be compromised by competitive concerns (Shaver and Flyer 2000, Dushnitsky and Shaver 2009). More generally, by simultaneously considering the competitive and learning implications of incumbent knowledge investments, our study brings work on absorptive capacity back to its origins (Cohen and Levinthal 1989, 1990). It allows for the joint operation of both selection and adaptation (Levinthal 1991, 1992), and it emphasizes the twin forces of learning and market power that lie at the heart of the evolutionary tradition (Nelson and Winter 1973, 1978).

Future Directions and Limitations

The framework developed in our study also suggests several potential avenues of future research. First, it suggests the need to look beyond firm-level studies of learning and innovation to consider how a firm and its competitors coevolve, with competition driving not only the overall level of firm innovation but also the nature and direction of firm search (Toh and Polidoro 2013). In particular, our framework has important implications for the overall rate of technological change under different Schumpeterian scenarios. So, for instance, whereas both creative construction and creative divergence result in win–win outcomes for the incumbent and the entrant, the former is likely to be associated with more rapid technological advance than the latter. Because the creative divergence case results in growing distance between the incumbent and the entrant, with diminishing returns to incumbent investments in learning, it is a case where firms sacrifice some potential for technological advance in the interests of mutual forbearance and survival. Similarly, whereas the creative destruction case results in a win-lose outcome, its implications for technological progress are ambiguous (Agarwal et al. 2007); the acceleration of innovation resulting from competitive pressure (Schumpeter 1934) is potentially offset by the erosion of incentives resulting from fragmentation, instability, and duplication of effort (Ferguson 1988, Aghion and Howitt 1992). These problems may be even more severe in the creative deterrence case; the successful forestalling of the entrant may block potentially valuable inventions and reduce the innovation incentives of future entrants. Although the entrant threat may force the incumbent to raise its game even in the creative deterrence case, the extent of this increased innovation is likely to be lower than in the creative destruction case. The creative deterrence case may therefore see the most modest gains in terms of technological advancement relative to all three other scenarios. Future work could further explore these implications.

Second, future work could move past our focus on technology space to study the implications of our framework in product markets. It could examine the role of complementary assets (Teece 1986, Tripsas 1997, Wu et al. 2014) in driving both the prevailing competitive scenario and the intensity of incumbent learning from entrants. Relatedly, future work could consider the potential for competition or cooperation between incumbents and entrants, with entrants having the choice of launching products that either compete with those of incumbents or complement them (Marx et al. 2014). Future work could also examine the implications of our framework for firm scope choices, studying how firms enter and exit product markets in response to rival innovation (Kaul 2012).

Third, future research could look beyond the overall effect of incumbent knowledge investments on incumbent learning from entrants in different competitive scenarios to consider the mode of such learning and the balance between internal and external knowledge investments. It could examine how the likelihood of an incumbent acquiring or forming alliances with entrants as a means of learning (Ahuja and Katila 2001, Rothaermel 2001) varies with the prevailing competitive scenario, or how mobility between incumbents and entrants (Singh and Agrawal 2011, Kim and Steensma 2017) varies across scenarios. Similarly, future research could extend our supplemental findings on the moderating role of original distance between incumbent and entrant to examine how the role of entrepreneurial spinouts (Agarwal et al. 2004, 2007; Klepper and Sleeper 2005) varies across different scenarios. As these suggestions illustrate, we believe the conceptual framework we introduce in this study has rich and wide-ranging implications for research on both entrepreneurship and industry evolution—implications that go far beyond what may be developed in a single paper and that set the stage for future work.

Of course, our work also has limitations. From a conceptual perspective, our framework considers a single action/response dyad between the incumbent and entrant. Although this is consistent with work in the competitive dynamics tradition (Chen and Miller 1994, 2012), future research could examine more complex patterns of ongoing competitive interaction between the two firms. From an empirical perspective, the analyses we undertake are exploratory, meant simply to demonstrate an application of our theoretical framework to an empirical setting. They are limited to a single industry and not meant to generalize across contexts. Moreover, although the results of our multivariate regression are robust across a variety of specifications (as reported in Online Appendix C)—including fixed effects panel models, control function approaches, three-stage least squares systems of equations, hierarchical linear models, and Tobit models—our ability to draw a causal inference from these results is limited in so far as we use observational data to study a complex phenomenon, and our instruments are necessarily imperfect. In keeping with the exploratory intent of our analyses, our empirical findings are best thought of as documenting an association between our variables of interest, rather than a causal relationship.

Conclusion

Our study offers fresh insight into the interplay between incumbents and entrants in Schumpeterian environments, combining work on competitive dynamics with evolutionary theory to develop a framework of Schumpeterian competition that incorporates both the competitive and learning effects of incumbent knowledge investments (Nelson and Winter 1973, 1978; Cohen and Levinthal 1990; Levinthal 1992). We define four distinct scenarios of competition between incumbents and entrants, and we discuss the patterns of incumbent learning we expect to see in each scenario. Exploratory empirical analysis in the cardiovascular medical device industry finds patterns that are consistent with a creative divergence scenario in this context: incumbents seek to learn from entrants, but entrants draw away from incumbents, with the result that incumbents realize positive but diminishing returns to their knowledge investments in terms of learning from entrants. Our study thus highlights a relatively unexplored scenario between the extremes of creative construction and creative destruction, and it advances our understanding of the role of knowledge spillovers in Schumpeterian competition more broadly (Agarwal et al. 2007, 2010).

Acknowledgments

The authors thank Senior Editor Rajshree Agarwal, two anonymous reviewers, Gautam Ahuja, Francesco Castellaneta, Bruno Cirillo, Jane Dutton, Sendil Ethiraj, Tobias Kretschmer, Dan Levinthal, Hart Posen, Henry Sauermann, PK Toh, Giovanni Valentini, Filippo Carlo Wezel, and Minyuan Zhao, as well as participants at the Academy of Management; Atlanta Competitive Advantage Conference; DRUID; Midwest Strategy conferences; Strategy, Entrepreneurship, and Innovation Faculty Workshop; and University of Maryland Smith Entrepreneurship Research Conference. The authors also thank seminar participants at ESMT Berlin; IE Business School; Institute for Strategy, Technology and Organization at the Ludwig Maximilian University Munich; Purdue University; State University of New York at Buffalo; and University of California at Riverside for valuable comments. The authors contributed equally and are listed in alphabetical order.

Endnotes

[1] Whereas some recent studies have sought to examine incumbent-entrant competitive dynamics (Chen et al. 2010, Parker 2010, Katila et al. 2012), these studies do not consider incumbents learning from entrants.

[2] Throughout this paper, we focus on incumbent learning from entrants rather than the specific means by which such learning comes about—inventor mobility, alliances, corporate venturing, or acquisitions—because we are interested in whether and to what extent the incumbent learns from the entrant, not how it does so.

[3] Although one could consider moves and countermoves between the two players ad infinitum, we limit ourselves to considering the incumbent's action when faced with the entrant threat, and the entrant's response to that action, in line with prior work that focuses on a single action/response dyad (Chen and Miller 2012). We also limit our conceptual analysis to exclude strategic errors; that is, we rule out responses that are obviously unsustainable for either party.

[4] Internal knowledge investments to develop absorptive capacity are important even if the incumbent seeks to learn through alliances (Lane and Lubatkin 1998, Mowery et al. 1998, Cassiman and Veugelers 2002, Kale et al. 2002, Steensma et al. 2012) or acquisitions (Puranam et al. 2006, Schildt and Laamanen 2006, Zaheer et al. 2010, Kaul and Wu 2016) and may thus represent an important precursor of such external sourcing mechanisms.

[5] This confidence may or may not be justified (Lowe and Ziedonis 2006, Klepper and Thompson 2010).

[6] This moderating effect of technological distance follows from the literature on absorptive capacity, which argues that interfirm learning is more effective the greater the overlap between the two firms (Cohen and Levinthal 1990, Steensma et al. 2012). Mathematically, if the knowledge flow from entrant to incumbent (I) is jointly determined by incumbent knowledge investments (K) and the distance between incumbent and entrant (T), then $dI/dK = (\partial I/\partial K)+(\partial I/\partial T)(\partial T/\partial K)$. Assuming that incumbent learning decreases with distance (i.e., $\partial I/\partial T < 0$), the second term is positive if incumbent investments decrease distance ($\partial T/\partial K < 0$) but negative if incumbent investments increase distance ($\partial T/\partial K > 0$).

[7] This is compared with the creative destruction case, where one player emerges as the unambiguous winner and the other does not survive.

[8] The incumbent realizes diminishing returns only in terms of learning; to the extent that its knowledge investments help secure the incumbent's competitive position by driving the entrant away, they may still benefit incumbent survival and performance.

[9] One example is the introduction of programmable, microprocessor-based pacemakers in the 1970s. This innovation, launched by an entrant firm, Intermedics, had an advantage over existing products in that it stimulated the heart only when the heart rate fell below the desired programmed pacing, allowing for the customization of each pacemaker to its recipient. To stay competitive, established companies such as Medtronic and Cordis were forced to learn from the entrant and adopt the programmable technology (Jeffrey 2001).

[10] To address the potential bias resulting from the possibility that some product classes changed from Class III to Class II as they became less risky over time, we also include any Class II classes that contain FDA premarket approvals (which are required for novel innovations) at any point in time.

[11] We acknowledge that examiner-added citations raise concerns regarding the use of patent citations as a measure of knowledge flows. Unfortunately, our data do not permit us to perform a meaningful robustness check by excluding examiner-added citations, because information on examiner-added citations is available only after 2001. We therefore adopt two alternative procedures. First, we consult the literature to gain confidence in our measurement. The existing literature confirms that patent citations are an accurate, although noisy, proxy for actual knowledge flows (Jaffe et al. 2000, Hoetker and Agarwal 2007, Agarwal et al. 2009). Whereas Alcácer and Gittelman (2006) and Lampe (2010) point to the noise introduced by examiner-added citations, both studies indicate that this source of noise is less pronounced in high-tech industries such as those focused on semiconductors or medical devices, and it may even help correct for strategic omission of citations by firms (Lampe 2010). Second, to the extent that examiner-added citations may cause measurement errors, we use the instrumental variable approach in the robustness checks to alleviate potential bias. That said, we acknowledge that our study is limited by data availability.

[12] We discount all stock variables at a rate of 0.7 as in Dushnitsky and Lenox (2005). Results are robust to other rates.

[13] We acknowledge that patents measure innovation outputs and are therefore an imperfect measure of knowledge investments. Given that we have no way to directly measure or compare investments in specific technologies, however, as well as the high correlation between patent output and research and development expense (Jaffe 1989), we use patents to measure knowledge investments (or search behavior) of incumbents, in line with prior work (Katila and Ahuja 2002, Ahuja and Katila 2004, Eggers 2012, Ghosh et al. 2014, Eggers and Kaul 2018).

[14] In this section, "high" and "low" indicate that the variable of interest is above and below the sample mean, respectively.

[15] In both equations, the controls *baseline propensity*, *technological activity*, and *technological maturity* (see Online Appendix A) are measured the same year as *incumbent knowledge absorption*. This is because we are interested in demonstrating that the impact of *knowledge investments* on *knowledge absorption* is above and beyond what we expect given the average technological trends of the year in which we measure the dependent variable.

[16] To estimate the overall effect of *incumbent knowledge investm*ent on *knowledge absorption* we insert Equation (2) into (1), as discussed later. This can be done only if *incumbent knowledge investments* and *technological distance* are treated as simultaneous.

[17] As shown by Arellano (2003), calculating heteroscedasticity-robust standard errors is equivalent to clustering at the panel level. Although our panel is unbalanced and does not satisfy the conditions for clustering at higher levels (Esarey and Menger 2019), our results are robust to (potentially misspecified) models clustering at more aggregate levels.

[18] Unreported robustness checks confirm that our results are robust to estimating Equation (2) as a Tobit regression.

[19] In the first stage, the endogenous variables K, T, and KT are instrumented simultaneously by all the exogenous instruments Z, Y, and YZ (Angrist and Pischke 2009). Following standard practice (Amemiya 1974), the interaction of the two instruments YZ serves as an instrument for the interaction of the two endogenous variables KT. We use *external knowledge investment* (i.e., incumbent knowledge investments in other product categories) as an instrument for *incumbent knowledge investments* and *random distance* (a measure of the random chance that two patent portfolios overlap) as an instrument for *technological distance*, as discussed in more detail in Online Appendix B.

[20] The baseline citation rate is low because we consider all possible category-incumbent-entrant-year combinations. Out of the entire population, the chance of a given incumbent citing a given entrant in a given year is small.

[21] To estimate the overall effect of *incumbent knowledge investm*ent on *knowledge absorption*, we insert Equation (2) into (1) and have $I = a_0 + a_2 b_0 + (a_1 + a_2 b_1 + a_3 b_0 + a_3 b_2 X)K + a_3 b_1 K^2 + a_4 X$. We set the controls at their mean and use the point estimates from Models 4-1 and 4-2 to trace the curve in Figure 7.

[22] This inflection point lies in the extreme right tail of the distribution at a knowledge investment of 1.98, corresponding to the 98th percentile of incumbent knowledge investments: the net effect of knowledge

investments on knowledge absorption is generally positive but grows weaker the more the incumbent invests.

[23] For Model 5-1, we use the specification $\log(C) = \alpha_0 + \alpha_1 T + \alpha_2 \hat{u} + \alpha_3 X + \log(P) + e_3$, where C is *filed by incumbent: old to entrant*; T is *technological distance*, the endogenous variables; $\hat{u}$ is a residual from the first stage where the endogenous variable is regressed on the instrument Z (as in Model 4-3); X is a vector of controls; P is the patent count; and e_3 is the random disturbance. Note that including $\log(P)$ in the regression means that our dependent variables may be interpreted as ratios. The specification for other models in Table 5 is analogous.

[24] We opted for a subgroup rather than a subsample analysis because it allows us to compare coefficients across different subgroups (Venkatraman and Camillus 1984, Ginsberg and Venkatraman 1985, Venkatraman 1989), and because it does not result in a loss of statistical power as a result of the smaller size of each subgroup.

[25] Because the main effect of the variable original distance is captured by the fixed effects, these estimates are equivalent to those obtained by interacting the variables of interest with a subgroup dummy and then adding the coefficient for the baseline group to that estimate.

References

Adner R, Kapoor R (2010) Value creation in innovation ecosystems: How the structure of technological interdependence affects firm performance in new technology generations. *Strategic Management J.* 31(3):306–333.

Adner R, Snow D (2010) Old technology responses to new technology threats: Demand heterogeneity and technology retreats. *Indust. Corporate Change* 19(5):1655–1675.

Agarwal R, Audretsch DB (2001) Does entry size matter? The impact of the life cycle and technology on firm survival. *J. Indust. Econom.* 49(1):21–43.

Agarwal R, Gort M (1996) The evolution of markets and entry, exit and survival of firms. *Rev. Econom. Statist.* 78(3):489–498.

Agarwal R, Gort M (2001) First-mover advantage and the speed of competitive entry, 1887–1986. *J. Law Econom.* 44(1):161–177.

Agarwal R, Helfat CE (2009) Strategic renewal of organizations. *Organ. Sci.* 20(2):281–293.

Agarwal R, Shah SK (2014) Knowledge sources of entrepreneurship: Firm formation by academic, user and employee innovators. *Res. Policy* 43(7):1109–1133.

Agarwal R, Audretsch DB, Sarkar MB (2007) The process of creative construction: Knowledge spillovers, entrepreneurship, and economic growth. *Strategic Entrepreneurship J.* 1(2):263–286.

Agarwal R, Ganco M, Ziedonis RH (2009) Reputations for toughness in patent enforcement: implications for knowledge spillovers via inventor mobility. *Strategic Management J.* 30(13):1349–1374.

Agarwal R, Audretsch DB, Sarkar MB (2010) Knowledge spillovers and strategic entrepreneurship. *Strategic Entrepreneurship J.* 4(4):271–283.

Agarwal R, Campbell BA, Franco AM, Ganco M (2016) What do I take with me? The mediating effect of spin-out team size and tenure on the founder–firm performance relationship. *Acad. Management J.* 59(3):1060–1087.

Agarwal R, Echambadi R, Franco AM, Sarkar MB (2004) Knowledge transfer through inheritance: Spin-out generation, development and performance. *Acad. Management J.* 47(4):501–522.

Aghion P, Howitt P (1992) A model of growth through creative destruction. *Econometrica* 60(2):323–351.

Aghion P, Tirole J (1994) The management of innovation. *Quart. J. Econom.* 109(4):1185–1209.

Aghion P, Harris C, Howitt P, Vickers J (2001) Competition, imitation and growth with step-by-step innovation. *Rev. Econom. Stud.* 68(3):467–492.

Aghion P, Blundell R, Griffith R, Howitt P, Prantl S (2009) The effects of entry on incumbent innovation and productivity. *Rev. Econom. Statist.* 91(1):20–32.

Ahuja G, Katila R (2001) Technological acquisitions and the innovation performance of acquiring firms: A longitudinal study. *Strategic Management J.* 22(3):197–220.

Ahuja G, Katila R (2004) Where do resources come from? The role of idiosyncratic situations. *Strategic Management J.* 25(8–9):887–907.

Ahuja G, Lampert C (2001) Entrepreneurship in the large corporation: A longitudinal study of how established firms create breakthrough inventions. *Strategic Management J.* 22(6–7):521–543.

Alcácer J, Chung W (2007) Location strategies and knowledge spillovers. *Management Sci.* 53(5):760–776.

Alcácer J, Gittelman M (2006) Patent citations as a measure of knowledge flows: The influence of examiner citations. *Rev. Econom. Statist.* 88(4):774–779.

Amemiya T (1974) Multivariate regression and simultaneous equation models when the dependent variables are truncated normal. *Econometrica* 42(6):999–1012.

Angrist JD, Pischke JS (2009) *Mostly Harmless Econometrics: An Empiricist's Companion* (Princeton University Press, Princeton, NJ).

Arellano M (2003) *Panel Data Econometrics* (Oxford University Press, Oxford, UK).

Balasubramanian N, Sivadasan J (2010) What happens when firms patent? New evidence from U.S. Economic Census data. *Rev. Econom. Statist.* 93(1):126–146.

Benner MJ (2007) The incumbent discount: Stock market categories and response to radical technological change. *Acad. Management Rev.* 32(3):703–720.

Benner MJ (2010) Securities analysts and incumbent response to radical technological change: Evidence from digital photography and Internet telephony. *Organ. Sci.* 21(1):42–62.

Benson D, Ziedonis RH (2009) Corporate venture capital as a window on new technologies: Implications for the performance of corporate investors when acquiring startups. *Organ. Sci.* 20(2):329–351.

Capron L, Mitchell W (2010) Finding the right path. *Harvard Bus. Rev.* 88(7–8):102–107.

Cassiman B, Veugelers R (2002) R&D cooperation and spillovers: Some empirical evidence from Belgium. *Amer. Econom. Rev.* 92(4):1169–1184.

Chatterji AK (2009) Spawned with a silver spoon? Entrepreneurial performance and innovation in the medical device industry. *Strategic Management J.* 30(2):185–206.

Chatterji AK, Fabrizio KR (2012) How do product users influence corporate invention? *Organ. Sci.* 23(4):971–987.

Chatterji AK, Fabrizio KR (2014) Using users: When does external knowledge enhance corporate product innovation? *Strategic Management J.* 35(10):1427–1445.

Chen MJ (1996) Competitor analysis and interfirm rivalry: Toward a theoretical integration. *Acad. Management Rev.* 21(1):100–134.

Chen MJ, Miller D (1994) Competitive attack, retaliation and performance: An expectancy-valence framework. *Strategic Management J.* 15(2):85–102.

Chen MJ, Miller D (2012) Competitive dynamics: Themes, trends, and a prospective research platform. *Acad. Management Ann.* 6(1):135–210.

Chen MJ, Hambrick DC (1995) Speed, stealth, and selective attack: How small firms differ from large firms in competitive behavior. *Acad. Management J.* 38(2):453–482.

Chen MJ, Lin HC, Michel JG (2010) Navigating in a hypercompetitive environment: The roles of action aggressiveness and TMT integration. *Strategic Management J.* 31(13):1410–1430.

Cohen WM, Levinthal DA (1989) Innovation and learning: The two faces of R&D. *Econom. J.* 99(397):569–596.

Cohen WM, Levinthal DA (1990) Absorptive capacity: A new perspective on learning and innovation. *Admin. Sci. Quart.* 35(1):128–152.

Cohen WM, Levinthal DA (1994) Fortune favors the prepared firm. *Management Sci.* 40(2):227–252.

Corredoira RA, Rosenkopf L (2010) Should auld acquaintance be forgot? The reverse transfer of knowledge through mobility ties. *Strategic Management J*. 31(2):159–181.

Cozzolino A, Rothaermel FT (2018) Discontinuities, competition, and cooperation: Coopetitive dynamics between incumbents and entrants. *Strategic Management J*. 39(12):3053–3085.

Cyert RM, March JG (1963) *A Behavioral Theory of the Firm* (Prentice-Hall, Englewood Cliffs, NJ).

d'Aspremont C, Gabszewicz JJ, Thisse JF (1979) On Hotelling's "Stability in competition." *Econometrica* 47(5):1145–1150.

Dushnitsky G, Lenox MJ (2005) When do incumbents learn from entrepreneurial ventures? Corporate venture capital and investing firm innovation rates. *Res. Policy* 34(5):615–639.

Dushnitsky G, Shaver JM (2009) Limitations to interorganizational knowledge acquisition: The paradox of corporate venture capital. *Strategic Management J*. 30(10):1045–1064.

Eggers JP (2012) Falling flat: Failed technologies and investment under uncertainty. *Admin. Sci. Quart.* 57(1):47–80.

Eggers JP, Kaplan S (2009) Cognition and renewal: Comparing CEO and organizational effects on incumbent adaptation to technical change. *Organ. Sci.* 20(2):461–477.

Eggers JP, Kaul A (2018) Motivation and ability? A behavioral perspective on the pursuit of radical invention in multi-technology incumbents. *Acad. Management J*. 61(1):67–93.

Esarey J, Menger A (2019) Practical and effective approaches to dealing with clustered data. *Political Sci. Res. Methods* 7(3):541–559.

Ferguson H (1988) Beyond entrepreneurialism to U.S. competitiveness: From the people who brought you voodoo economics. *Harvard Bus. Rev*. 66(3):55–62.

Fleming L (2001) Recombinant uncertainty in technological search. *Management Sci*. 47(1):117–132.

Fleming L, Sorenson O (2004) Science as a map in technological search. *Strategic Management J*. 25(8-9):909–928.

Gatignon H, Tushman ML, Smith W, Anderson P (2002) A structural approach to assessing innovation: Construct development of innovation locus, type, and characteristics. *Management Sci*. 48(9): 1103–1122.

Gavetti G, Levinthal DA (2000) Looking forward and looking backward: Cognitive and experiential search. *Admin. Sci. Quart*. 45(1):113–137.

Ghosh A, Martin X, Pennings JM, Wezel FC (2014) Ambition is nothing without focus: Compensating for negative transfer of experience in R&D. *Organ. Sci*. 25(2):572–590.

Gimeno J (1999) Reciprocal threats in multimarket rivalry: Staking out "spheres of influence" in the U.S. airline industry. *Strategic Management J*. 20(2):101–128.

Gimeno J, Woo CY (1999) Multimarket contact, economies of scope, and firm performance. *Acad. Management J*. 42(3):239–259.

Ginsberg A, Venkatraman N (1985) Contingency perspectives of organizational strategy: A critical review of the empirical research. *Acad. Management Rev*. 10(3):421–434.

Griliches Z (1992) The search for R&D spillovers. *Scandinavian J. Econom*. 94(Supplement):S29–S47.

Hall BH, Ziedonis RH (2007) An empirical analysis of patent litigation in the semiconductor industry. Working paper, University of California, Berkeley, Berkeley.

Hayes AF (2013) *Introduction to Mediation, Moderation, and Conditional Process Analysis: A Regression-Based Approach* (Guilford Press, New York).

Helfat CE (1994) Evolutionary trajectories in petroleum firm R&D. *Management Sci*. 40(12):1720–1747.

Helfat CE (1997) Know-how and asset complementarity and dynamic capability accumulation: The case of R&D. *Strategic Management J.* 18(5):339–360.

Hill CW, Rothaermel FT (2003) The performance of incumbent firms in the face of radical technological innovation. *Acad. Management Rev*. 28(2):257–274.

Hoetker G, Agarwal R (2007) Death hurts, but it isn't fatal: The postexit diffusion of knowledge created by innovative companies. *Acad. Management J*. 50(2):446–467.

Hotelling H (1929) Stability in competition. *Econom. J*. 39(153):41–57.

Jaffe AB (1986) Technological opportunity and spillovers of R&D: Evidence from firms' patents, profits, and market value. *Amer. Econom. Rev* 76(5):984–1001.

Jaffe AB (1989) Real effects of academic research. *Amer. Econom. Rev.* 79(5):957–970.

Jaffe AB, Trajtenberg M, Fogarty MS (2000) Knowledge spillovers and patent citations: Evidence from a survey of inventors. *Amer. Econom. Rev*. 90(2):215–218.

Jeffrey K (2001) *Machines in Our Hearts: The Cardiac Pacemaker, the Implantable Defibrillator, and American Healthcare* (Johns Hopkins University Press, Baltimore).

Jiang L, Tan J, Thursby M (2011) Incumbent firm invention in emerging fields: Evidence from the semiconductor industry. *Strategic Management J*. 32(1):55–75.

Jovanovic B, MacDonald GM (1994) The life cycle of a competitive industry. *J. Political Econom*. 102(2):322–347.

Kale P, Dyer JH, Singh H (2002) Alliance capability, stock market response, and long-term alliance success: The role of the alliance function. *Strategic Management J*. 23(8):747–767.

Kaplan AV, Baim DS, Smith JJ, Feigal DA, Simons M, Jefferys D, Fogerty TJ, Kuntz RE, Leon MB (2004) Medical device development: From prototype to regulatory approval. *Circulation* 109(25):3068–3072.

Kapoor R, Furr NR (2015) Complementarities and competition: Unpacking the drivers of entrants' technology choices in the solar photovoltaic industry. *Strategic Management J*. 36(3):416–436.

Katila R, Ahuja G (2002) Something old, something new: A longitudinal study of search behavior and new product introduction. *Acad. Management J*. 45(6):1183–1194.

Katila R, Chen EL (2008) Effects of search timing on innovation: The value of not being in sync with rivals. *Admin. Sci. Quart.* 53(4): 593–625.

Katila R, Chen EL, Piezunka H (2012) All the right moves: How entrepreneurial firms compete effectively. *Strategic Entrepreneurship J*. 6(2):116–132.

Kaul A (2012) Technology and corporate scope: Firm and rival innovation as antecedents of corporate transactions. *Strategic Management J.* 33:347–367.

Kaul A, Wu B (2016) A capabilities-based perspective on target selection in acquisitions. *Strategic Management J*. 37(7):1220–1239.

Kim JYR, Steensma HK (2017) Employee mobility, spin-outs, and knowledge spill-in: How incumbent firms can learn from new ventures. *Strategic Management J*. 38(8):1626–1645.

Klepper S (1996) Entry, exit, growth, and innovation over the product life cycle. *Amer. Econom. Rev*. 86(3):562–583.

Klepper S (2002) The capabilities of new firms and the evolution of the US automobile industry. *Indust. Corporate Change* 11(4):645–666.

Klepper S, Sleeper S (2005) Entry by spinoffs. *Management Sci*. 51(8): 1291–1306.

Klepper S, Thompson P (2010) Disagreements and intra-industry spinoffs. *Internat. J. Indust. Organ*. 28(5):526–538.

Knott AM, Posen HE, Wu B (2009) Spillover asymmetry and why it matters. *Management Sci*. 55(3):373–388.

Kotha S (2010) Spillovers, spill-ins, and strategic entrepreneurship: America's first commercial jet airplane and Boeing's ascendancy in commercial aviation. *Strategic Entrepreneurship J*. 4(4):284–306.

Lampe R (2010) Strategic citation. *Rev. Econom. Statist*. 94(1):320–333.

Lane PJ, Lubatkin M (1998) Relative absorptive capacity and interorganizational learning. *Strategic Management J.* 19(5):461–477.

Lavie D (2006) The competitive advantage of interconnected firms: An extension of the resource-based view. *Acad. Management Rev.* 31(3):638–658.
Levin RC, Klevorick AK, Nelson RR, Winter SG (1987) Appropriating the returns from industrial research and development. *Brookings Papers Econom. Activity* 18(3):783–833.
Levinthal DA (1991) Organizational adaptation and environmental selection-interrelated processes of change. *Organ. Sci.* 2(1): 140–145.
Levinthal DA (1992) Surviving Schumpeterian environments: An evolutionary perspective. *Indust. Corporate Change* 1(3):427–443.
Levinthal DA, March JG (1993) The myopia of learning. *Strategic Management J.* 14(Special issue):95–112.
Lieberman MB (1989) The learning curve, technology barriers to entry, and competitive survival in the chemical processing industries. *Strategic Management J.* 10(5):431–447.
Lieberman MB, Montgomery DB (1988) First-mover advantages. *Strategic Management J.* 9(Special issue):41–58.
Lowe LA, Ziedonis A (2006) Overoptimism and the performance of entrepreneurial firms. *Management Sci.* 52(2):173–186.
Martin S (1994) *Industrial Economics: Economic Analysis and Public Policy* (Prentice Hall, New York).
Marx M, Gans JS, Hsu DH (2014) Dynamic commercialization strategies for disruptive technologies: Evidence from the speech recognition industry. *Management Sci.* 60(12):3103–3123.
Melitz MJ, Ottaviano GI (2008) Market size, trade, and productivity. *Rev. Econom. Stud.* 75(1):295–316.
Moeen M, Agarwal R (2017) Incubation of an industry: Heterogeneous knowledge bases and modes of value capture. *Strategic Management J.* 38(3):566–587.
Mowery DC, Oxley JE, Silverman BS (1998) Technological overlap and interfirm cooperation: implications for the resource-based view of the firm. *Res. Policy* 27(5):507–523.
Nelson RR, Winter SG (1973) Toward an evolutionary theory of economic capabilities. *Amer. Econom. Rev.* 63(2):440–449.
Nelson RR, Winter SG (1978) Forces generating and limiting concentration under Schumpeterian competition. *Bell J. Econom.* 9(2): 524–548.
Nelson R, Winter S (1982) *An Evolutionary Theory of Economic Change* (Belknap Press, Cambridge, MA).
Nerkar A (2003) Old is gold? The value of temporal exploration in the creation of new knowledge. *Management Sci.* 49(2):211–229.
Nerkar A, Roberts PW (2004) Technological and product-market experience and the success of new product introductions in the pharmaceutical industry. *Strategic Management J.* 25(8–9):779–799.
Parker SC (2010) A predator–prey model of knowledge spillovers and entrepreneurship. *Strategic Entrepreneurship J.* 4(4):307–322.
Polidoro F (2013) The competitive implications of certifications: The effects of scientific and regulatory certifications on entries into new technical fields. *Acad. Management J.* 56(2):597–627.
Polidoro F, Toh PK (2011) Letting rivals come close or warding them off? The effects of substitution threat on imitation deterrence. *Acad. Management J.* 54(2):369–392.
Posen HE, Chen JS (2013) An advantage of newness: Vicarious learning despite limited absorptive capacity. *Organ. Sci.* 24(6): 1701–1716.
Preacher KJ, Rucker DD, Hayes AF (2007) Addressing moderated mediation hypotheses: Theory, methods, and prescriptions. *Multivariate Behav. Res.* 42(1):185–227.
Puranam P, Srikanth K (2007) What they know vs. what they do: How acquirers leverage technology acquisitions. *Strategic Management J.* 28(8):805–825.
Puranam P, Singh H, Zollo M (2006) Organizing for innovation: Managing the coordination-autonomy dilemma in technology acquisitions. *Acad. Management J.* 49(2):263–280.
Rosenkopf L, Almeida P (2003) Overcoming local search through alliances and mobility. *Management Sci.* 49(6):751–766.
Rosenkopf L, Nerkar A (2001) Beyond local search: Boundary-spanning, exploration, and impact in the optical disk industry. *Strategic Management J.* 22(4):287–306.
Rothaermel FT (2001) Incumbent's advantage through exploiting complementary assets via interfirm cooperation. *Strategic Management J.* 22(6–7):687–699.
Salop SC (1979) Monopolistic competition with outside goods. *Bell J. Econom.* 10(1):141–156.
Schildt HA, Laamanen T (2006) Who buys whom: Information environments and organizational boundary spanning through acquisitions. *Strategic Organ.* 4(2):111–133.
Schumpeter JA (1934) *The Theory of Economic Development: An Inquiry into Profits, Capital, Credit, Interest, and the Business Cycle* (Harvard University Press, Cambridge, MA).
Schumpeter JA (1942) *Capitalism, Socialism and Democracy* (Harper & Brothers, New York).
Shaver JM, Flyer F (2000) Agglomeration economies, firm heterogeneity, and foreign direct investment in the United States. *Strategic Management J.* 21(12):1175–1193.
Silverman BS (1999) Technological resources and the direction of corporate diversification: Toward an integration of the resource-based view and transaction cost economics. *Management Sci.* 45(8):1109–1124.
Singh J, Agrawal A (2011) Recruiting for ideas: How firms exploit the prior inventions of new hires. *Management Sci.* 57(1):129–150.
Sørensen JB, Stuart TE (2000) Aging, obsolescence, and organizational innovation. *Admin. Sci. Quart.* 45(1):81–112.
Sosa ML (2011) From old competence destruction to new competence access: Evidence from the comparison of two discontinuities in anticancer drug discovery. *Organ. Sci.* 22(6):1500–1516.
Stackelberg H (1952) *The Theory of The Market Economy* (Oxford University Press, Oxford, UK).
Steensma HK, Howard M, Lyles M, Dhanaraj C (2012) The compensatory relationship between technological relatedness, social interaction, and knowledge flow between firms. *Strategic Entrepreneurship J.* 6(4):291–306.
Stepner M (2014) Binscatter: binned scatterplots in Stata. Accessed December 9, 2018, https://michaelstepner.com/binscatter/binscatter-StataConference2014.pdf.
Stock JH, Watson MW (2008) Heteroskedasticity-robust standard errors for fixed effects panel data regression. *Econometrica* 76(1): 155–174.
Teece DJ (1986) Profiting from technological innovation: Implications for integration, collaboration, licensing and public policy. *Res. Policy* 15(6):285–305.
Theeke M, Polidoro F Jr, Fredrickson JW (2018) Path-dependent routines in the evaluation of novelty: The effects of innovators' new knowledge use on brokerage firms' coverage. *Admin. Sci. Quart.* 63(4):910–942.
Toh PK, Miller CD (2017) Pawn to save a chariot, or drawbridge into the fort? Firms' disclosure during standard setting and complementary technologies within ecosystems. *Strategic Management J.* 38(11):2213–2236.
Toh PK, Polidoro F (2013) A competition-based explanation of collaborative invention within the firm. *Strategic Management J.* 34(10):1186–1208.
Tripsas M (1997) Unraveling the process of creative destruction: Complementary assets and incumbent survival in the typesetter industry. *Strategic Management J.* 18(Summer special issue): 119–142.
Tripsas M, Gavetti G (2000) Capabilities, cognition, and inertia: Evidence from digital imaging. *Strategic Management J.* 21(10–11):1147–1161.
Venkatraman N (1989) The concept of fit in strategy research: Toward verbal and statistical correspondence. *Acad. Management Rev.* 14(3):423–444.
Venkatraman N, Camillus JC (1984) Exploring the concept of "fit" in strategic management. *Acad. Management Rev.* 9(3):513–525.

Wagner S, Goossen MC (2018) Knowing me, knowing you: Inventor mobility and the formation of technology-oriented alliances. *Acad. Management J.* 61(6):2026–2052.

Wang RD, Shaver JM (2014) Competition-driven repositioning. *Strategic Management J.* 35(11):1585–1604.

Wang RD, Shaver JM (2016) The multifaceted nature of competitive response: Repositioning and new product launch as joint response to competition. *Strategy Sci.* 1(3):148–162.

Winter SG (1984) Schumpeterian competition in alternative technological regimes. *J. Econom. Behav. Organ*. 5(3–4):287–320.

Wooldridge JM (2001) *Econometric Analysis of Cross Section and Panel Data* (MIT Press, Cambridge, MA).

Wooldridge JM (2015) Control function methods in applied econometrics. *J. Human Resources* 50(2):420–445.

Wu B, Wan Z, Levinthal DA (2014) Complementary assets as pipes and prisms: Innovation incentives and trajectory choices. *Strategic Management J.* 35(9):1257–1278.

Yang H, Phelps C, Steensma HK (2010) Learning from what others have learned from you: The effects of knowledge spillovers on originating firms. *Acad. Management J.* 53(2):371–389.

Zaheer A, Hernandez E, Banerjee S (2010) Prior alliances with targets and acquisition performance in knowledge-intensive industries. *Organ. Sci.* 21(5):1072–1091.

Zhou KZ, Li CB (2012) How knowledge affects radical innovation: Knowledge base, market knowledge acquisition, and internal knowledge sharing. *Strategic Management J.* 33(9):1090–1102.

Zhou KZ, Wu F (2010) Technological capability, strategic flexibility, and product innovation. *Strategic Management J.* 31(5): 547–561.

Gianluigi Giustiziero is an assistant professor of strategy at the Frankfurt School of Finance & Management. He received his PhD in strategy at the University of Michigan. His research examines how market forces and strategic interactions shape the competition–cooperation interplay for firms and individuals.

Aseem Kaul is an associate professor of strategic management and entrepreneurship at the Carlson School of Management, University of Minnesota. He received his PhD in management from the Wharton School. His research focuses on questions of organizational scope and governance, especially the relationship between scope choices and organizational innovation.

Brian Wu is an associate professor of strategy at the University of Michigan's Ross School of Business. He received his PhD from the Wharton School at the University of Pennsylvania. His research examines the role of firm capabilities in influencing the dynamics of corporate scope and the evolution of industries.