Managing Technological Transitions by Building Bridges

Journal:	*Academy of Management Journal*
Manuscript ID	AMJ-2015-0690.R3
Manuscript Type:	Revision
Keywords:	Management of technology < Technology and Innovation Management < Topic Areas, Knowledge management < Organization and Management Theory < Topic Areas, Panel/Pooled < Research Design < Research Methods

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Susan L. Cohen
University of Georgia
susan.cohen@uga.edu

Mary Tripsas
Boston College
Chestnut Hill, MA 02467
tripsas@bc.edu

We would like to thank associate editor Marc Gruber, three anonymous reviewers, Rajshree Agarwal, Rich Bettis, Nathan Furr, Stine Grodal, Jeff Harrison, Glenn Hoetker, Candice Jones, Kate Kellogg, Mukti Khaire, Siobhan O'Mahoney, Steven Markham, Mike Roach, Christian Sandström, Henry Sauermann, Metin Sengul, Laurel Smith-Doerr, Karl Wennberg, Brian Wu and participants at the Darden Entrepreneurship and Innovation Conference, the PROS Process Research Conference, and seminar participants at UC Santa Barbara and the RATIO Institute, Stockholm for their valuable feedback on this manuscript.

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ABSTRACT

While much research has demonstrated that radical technological transitions challenge incumbents, surprisingly little empirical work has examined what factors drive variation in their ability to invent in the new domain. Through a longitudinal study of photography firms transitioning from analog to digital technology we examined a key source of heterogeneity: whether and how incumbents integrate knowledge related to both old and new technologies to bridge generations. Specifically, we explored how using three types of inter-generational knowledge bridges -- inventor bridges, technology bridges, and hybrid product bridges -- influenced inventive performance in the new generation. Consistent with theories of inertia, we found that, on average, inventor and technology bridges were associated with lower performance in the new generation. However, the strength of a firm's inventive performance in the old generation positively moderated this effect. When performance in the old technology was strong, both technology and hybrid product bridges were associated with higher inventive performance in the new generation. This finding suggests that, when combined with a strong R&D program, old-technology knowledge forms a foundation that incumbents can leverage to learn new technologies as they navigate transitions.

Keywords: Technological transition, inventive performance, hybrid technology, R&D, photography

It has been well established that incumbent firms transitioning between old and new generations of technology face significant challenges. In industries ranging from calculators, typewriters, and watches, to vacuum tubes, photolithography, disk drives, mini-computers, and cement, incumbents with strong positions in the old technology were displaced by new entrants when new technology invaded the industry (Anderson & Tushman, 1990; Christensen & Bower, 1996; Cooper & Schendel, 1976; Danneels, 2011; Glasmeier, 1991; Henderson, 1993; Henderson & Clark, 1990). Technology that is competence-destroying -- meaning that it is based on a fundamentally different set of technical disciplines that require mastery of a new knowledge base -- is particularly problematic since incumbents find it difficult to develop R&D expertise in new domains (Henderson & Clark, 1990; Tripsas, 1997; Tushman & Anderson, 1986). For instance, Henderson (1993) found that "the research efforts of incumbents attempting to develop products that incorporated major or competence-destroying innovation in photolithography were significantly less productive than those of entrants" (Henderson, 1993: 265).

While the struggles of incumbents are well-documented, we know surprisingly little about what factors influence differences in inventive performance for incumbents as they attempt to move between technological domains. Studies of industries undergoing technological transitions have either focused on comparing incumbents and entrants, neglecting heterogeneity among incumbents (e.g., Christensen & Bower, 1996; Henderson & Clark, 1990; Sosa, 2009, 2011; Tushman & Anderson, 1986; Uzunca, 2018), or have examined non-technical outcomes such as incumbent entry probability (Eggers & Kaplan, 2009; King & Tucci, 2002) or financial performance (Rothaermel & Hill, 2005), without disentangling whether some incumbents are better than others at mastering the new technology. Moreover, the large body of work that compares the inventive performance of established firms has focused on performance *within* a given technical domain, but not moving *between* domains (Ahuja & Lampert, 2001; Henderson & Cockburn, 1996; Katila & Chen, 2008; Rosenkopf & Nerkar, 2001).

In particular, we know little about how incumbents' efforts to balance the simultaneous development of old and new technologies influences their ability to successfully invent in the new. Since R&D in old and new technological generations generally overlaps for many years, even decades, during a transition (Cooper & Schendel, 1976), understanding how incumbents manage the relationship between these two efforts is important. On the one hand, the predominant view in the literature attributes the poor performance of incumbents to inertia stemming from their legacy in the old technology. Constrained by prior capabilities (Leonard-Barton, 1992; Tushman & Anderson, 1986), existing customer relationships (Christensen & Bower, 1996; Danneels, 2003), behavioral routines (Henderson & Clark, 1990; Nelson & Winter, 1982), and cognitive mindsets (Tripsas & Gavetti, 2000), established firms find it difficult to adapt. From this perspective, any effort to integrate old and new knowledge to bridge technological generations, is likely to constrain a firm's ability to develop capability in the new technology.

On the other hand, an incumbent's legacy in the old technology may provide a foundation of knowledge from which to learn the new. Such foundational knowledge has been found to be an important precursor to identifying and assimilating new knowledge (Cohen & Levinthal, 1990) and thus, rather than constraining adaptation, old-technology knowledge may provide incumbents with the absorptive capacity needed to learn about new technologies. Consistent with this idea, research has found that incumbents with higher stocks of old-technology knowledge are more likely to enter new markets (Eggers & Kaplan, 2009; King & Tucci, 2002; Mitchell, 1989). Integrating old and new may also help incumbents manage risk. During a transition, there is high uncertainty about which of many competing technologies will become dominant (Eggers, 2012, 2014) and how the ecosystem and potential technical bottlenecks will evolve (Adner & Kapoor, 2010). From this perspective, integrating knowledge from a prior generation of technology, for example, by developing hybrid products, provides an opportunity to learn about new technologies without making an irreversible commitment (Furr & Snow, 2015).

We reconcile these perspectives by exploring how incumbents leverage existing knowledge through "bridges" that span technological generations. Conceptually, we envision intergenerational knowledge bridges as a specific type of knowledge recombination (Fleming, 2001; Ghosh, Martin, Pennings, & Wezel, 2013; Gruber, Harhoff, & Hoisl, 2012; Kogut & Zander, 1992) that integrates old and new knowledge in the development of new technologies. Specifically, we examine intergenerational bridges at three levels of analysis: (a) the inventor level, where old-technology inventors work on new-technology development to form *inventor* *bridges* (b) the technology level, where new inventions build upon old-technology knowledge to form *technology bridges* and (c) the product level, where firms develop products that incorporate elements of both technological generations to form *hybrid product bridges*.

Our empirical context is photography firms transitioning from analog to digital technologies. Using a hand-collected longitudinal dataset of firm, product, and patent data for all research active photography firms from 1974 to 2010, we explored how using intergenerational bridges influenced inventive performance in the new generation, measured as the number of forward citations made to a firm's portfolio of digital imaging patents. We found that on average, inventor and technology bridges were associated with lower inventive performance in the new generation. However, when incumbents had high levels of inventive performance in the old technology, both technology and hybrid product bridges were associated with higher inventive performance in the new generation. In other words, we found evidence that stronger R&D capability in the old generation enabled firms to leverage old-technology knowledge as a foundation for learning the new technology.

By comparing the inventive performance of incumbents making a transition, we make several contributions to the management of technology literature. First, we question the prevailing wisdom that old-technology knowledge is an inertial constraint that hinders the development of the new. Instead, we find that when inventive performance in the old technology is high, old-technology knowledge has the potential to serve as a valuable resource to be leveraged through both technology and hybrid product bridges. Second, we show that R&D strength is a higher-order capability that transcends generations of technology, and is an underlying factor behind a firm's ability to adapt to radical technological changes. Overall, we move beyond comparisons of incumbents and new entrants and offer a more nuanced understanding of why some incumbents navigate technological change better than others.

THEORY AND HYPOTHESES

A well-established body of research on the management of technology has shown that established firms have difficulty navigating transitions to radically new technologies (Abernathy & Clark, 1985; Cooper & Schendel, 1976). Early work in this tradition focused on comparing incumbents and new entrants and found that incumbents underperform when new technology destroys the value of their technical competence (Henderson, 1993; Henderson & Clark, 1990; Tushman & Anderson, 1986), destroys the value of specialized complementary assets (Mitchell, 1989; Tripsas, 1997) or appeals to new customer segments with different preferences (Abernathy & Clark, 1985; Christensen & Bower, 1996). However, while this research highlights the devastating effect of technological change on incumbents as a category, it fails to address the sources of heterogeneity among incumbent firms making a transition.

Subsequent work has examined differences in how incumbents respond when faced with a technological transition, but for the most part has not included inventive performance as an outcome. For instance, Kaplan (2008) examined differences in the level of fiber optic technology investment made by communications firms with a history in copper-based technologies, but did not examine potential differences in their ability to turn investment into important inventions. Other research has explored performance differences using a range of non-technical outcomes including: the timing of incumbent commercial entry into new technologies (Anand et al., 2010; Eggers & Kaplan, 2009; Kapoor & Klueter, 2015; King & Tucci, 2002; Mitchell, 1989), new technology market share (Bergek, Berggren, Magnusson, & Hobday, 2013; Henderson, 1993), the number of new products commercialized (Rothaermel, 2001), financial performance (Rothaermel, 2001, Rothaermel & Hill, 2005), and survival rates (Bayus & Agarwal, 2007;

Christensen & Bower, 1996; Christensen, Suárez, & Utterback, 1998). While this body of work has contributed to our understanding of why incumbents differ in their overall ability to respond to technological change, it does not disentangle differences in incumbents' inventive performance in the new technology, an important part of making a transition.

Finally, an extensive stream of research on R&D capabilities at established firms has compared the performance of firms' R&D programs within a given technical domain, as reflected in the size and impact of their patent portfolios (i.e. inventive performance). The general consensus of this stream of work is that to develop radical, high impact inventions, firms need to move beyond local search and incorporate distant, new knowledge that spans technological, organizational, industry, or geographic boundaries. Specifically, the more a firm acquires and builds upon novel technical knowledge that it has not previously utilized, or combines knowledge in novel ways, the more likely it is to create technical breakthroughs (Ahuja & Lampert, 2001; Fleming, 2001). In addition, integrating knowledge that spans not only technological boundaries, but also organizational boundaries results in inventions with the broadest overall impact (Rosenkopf and Nerkar, 2001). More generally, inventions that incorporate knowledge from technologically distant alliance partners (Jiang, Tan, & Thursby, 2011; Rosenkopf & Almeida, 2003), public science (Fleming & Sorenson, 2004; Henderson & Cockburn, 1994; Sorenson & Fleming, 2004), and other divisions within an organization (Miller, Fern, & Cardinal, 2007), have higher impact.

While these studies contribute to our understanding of how firms improve their inventive performance within a given generation of technology, they provide little insight into how an incumbent improves its performance when transitioning to a completely new technological domain. Moreover, because they focus exclusively on the new technology, the few studies that are set in the context of a technological transition ignore the potential effect of old-technology knowledge on the development of new expertise (Eggers, 2012, 2014; Jiang et al., 2011; Rothaermel, 2001; Rothaermel & Hess, 2007). For example, Rothaermel and Hess's (2007) study of 81 pharmaceutical incumbents transitioning to biotech found that the total number of scientists at a firm was positively related to the number of biotech patents it filed. Yet, the study did not take into account the prior disciplinary expertise of the firm's scientists – i.e. whether they had experience in traditional pharmaceutical research, biotech research, or both domains. Similarly, Rosenkopf and Nerkar (2001) examined firms' inventive performance in new generations of optical disk technologies, but did not consider whether an organization's ongoing development of older generations of storage technology, such as magnetic disks, had any effect on its performance in newer optical disk generations.

Overall, understanding how incumbents balance old and new technologies is important since, rather than being a discrete decision—an instantaneous flip of the proverbial switch—the change from one technological regime to another is, in most cases, a gradual transition that spans several years. For example, it took 11 years for sales of transistors to exceed those of vacuum tubes and 14 years for sales of diesel-electric locomotives to exceed those of steam locomotives (Cooper & Schendel, 1976). In fact, all 22 incumbent firms across the seven transitions examined by Cooper and Schendel (1976) continued to make substantial investments in the old technology, even after sales of the old products were in decline. Related research has found that some firms invest considerable amounts in revitalizing the old technology, in a "last gasp" attempt to extend its life (Adner & Snow, 2010; Gilfillan, 1935; Tripsas, 2008; Utterback, 1994). However, while research has found that knowledge flows back and forth between technological generations during periods of transition (Taylor, 2010), and that linkages between old and new complementary assets can contribute to commercial success (Taylor & Helfat, 2009), with the exception of Furr and Snow (2015), research has not considered how linkages between the old and new technologies should be managed throughout a transition. We address this gap by examining the effect of intergenerational knowledge bridges on inventive performance in a new technological domain.

Intergenerational Knowledge Bridges

A long tradition has conceived of knowledge creation as resulting from "new combinations" of existing knowledge (Nelson & Winter, 1982; Schumpeter, 1934). From this perspective, invention is a recombinant search process aimed at identifying and integrating knowledge components (Fleming, 2001; Fleming & Sorenson, 2001; Ghosh et al., 2013; Gruber et al., 2012; Kogut & Zander, 1992; Nerkar, 2003; Sorenson & Fleming, 2004). Consistent with this work, we conceptualize intergenerational knowledge bridges as special cases of recombination that are formed when firms build upon and integrate knowledge related the old generation of technology to develop knowledge related to the new technology. We distinguish among intergenerational knowledge bridges at three levels of analysis – the individual inventor, the technology, and the product.

Recombination can occur within the mind of an individual when the same person's work spans technologies. Since tacit knowledge and much explicit knowledge resides within individuals in organizations (Grant, 1996), when inventors with experience in the old technology participate in new-technology development efforts, they are engaging in such recombination. We label these individuals inventor bridges. Bridging inventors bring their understanding of the old technology to development teams, and their potential influence persists while the inventor remains at the firm.

Recombination also occurs at the technology level when specific knowledge is invoked and combined in the creation of an invention. The majority of extant empirical research on recombination is at this level. Organizations build upon and integrate previously acquired knowledge when creating inventions, and the nature of that knowledge has a tremendous impact on the importance of inventions (Cattani, 2005; Ghosh et al., 2013; Gruber et al., 2012; Jaffe, Trajtenberg, & Henderson, 1993; Katila & Ahuja, 2002; Miller et al., 2007; Nerkar, 2003; Rosenkopf & Nerkar, 2001; Sorenson & Fleming, 2004; Srivastava & Gnyawali, 2011). In the context of an industry undergoing a technological transition, one specific type of knowledge that organizations can utilize in the creation of new-technology inventions is old-technology knowledge. When new-technology developments build upon elements of old-technology knowledge, they form what we term a *technology bridge.* Technology bridges are the result of organization-level processes in which specific old-technology knowledge is invoked in the creation of an invention.

Finally, when firms combine old- and new-technology knowledge in a single product, they form what we call a hybrid product bridge. For example, in managing the transition from internal combustion engines to electric vehicles, Toyota introduced a hybrid vehicle, the Prius, which combined elements of both, and in the shift from voice-centric 2G networks to voice and data centric 3G networks, some providers developed hybrid 2.5G mobile networks that incorporated 3G packet switching data transmission technology into existing 2G networks (Ansari & Garud, 2009; Furr & Snow, 2015).

All three types of bridges involve the combination of old and new knowledge, but they are conceptually distinct. For instance, a firm can develop hybrid products that combine old- and new-technology building blocks, without including any technology bridges. Similarly, when an analog inventor invents in a digital domain, that digital invention may not explicitly invoke analog knowledge (i.e. would not constitute a technology bridge), but it would still reflect the inventor's prior experience with the old technology. And while technology and hybrid product bridges may result from the development efforts of bridging inventors, this is not necessarily the case. Since organizational knowledge is codified in organizational memory that persists beyond the efforts of any one individual (Cook & Yanow, 1993), old-technology inventors need not be directly involved when old knowledge is invoked. Technology and hybrid product bridges thus capture the result of broader organizational processes that invoke knowledge to generate an invention or product, while inventor bridges capture the influence of having specific individuals with knowledge that spans technological generations present in the organization.

The Impact of Intergenerational Knowledge Bridges on Incumbent Inventive Performance

We next theorize about the relationship between intergenerational knowledge bridges and an incumbent's inventive performance in the new generation.

Inventor bridges. Human capital is an important source of new organizational knowledge (Almeida & Kogut, 1999; Argote & Ingram, 2000; Rosenkopf & Almeida, 2003), thus it is not surprising that hiring inventors with expertise in the new technology is considered an important element of a making a successful transition (Danneels, 2011). However, research also suggests that inventors often span technological boundaries (Gruber et al., 2012), and when a firm is moving between generations, old-technology inventors are frequently redeployed and asked to contribute to inventions in the new domain (Tripsas & Gavetti, 2000), creating inventor bridges.

Theory suggests that, due to the accumulated legacy of capabilities, behaviors, and beliefs associated with the old technology, having old-technology inventors involved in new developments will hurt inventive performance. First, given their higher level of expertise in the old technology, inventors who bridge technologies are more likely to fall into "competency traps" (Leonard-Barton, 1992; Levitt & March, 1988), developing inventions that are close to their existing capabilities, but inappropriate in the context of a transition. For instance, Tripsas (1997) found that when incumbents utilized old-technology engineers to develop a new generation of typesetters, it resulted in awkward machines that replicated the architecture of the old generation and significantly underperformed the faster, more reliable machines made by new entrants. Second, bridging inventors may also be constrained by behavioral routines that become embedded in their communication patterns and information filters. Collaboration among scientists and engineers in research environments is common, and over time organizations develop socially complex and path dependent transactive memory systems (Argote & Ren, 2012; Wegner, 1987) that coordinate the flow of knowledge by storing meta-information about "who knows what." As individuals develop reputations for expertise in a particular technical domain, more specialized assignments and inquiries are routed to them, reinforcing their expertise, reputation, and the organization's trust in them. The understanding of "who knows what" can evolve into routinized heuristics, whereby individuals become accustomed to asking particular individuals for help on specific issues. In a stable technological environment, embedded routines and transactive memory systems increase organizational efficiency. However, during a transition, they may need to be updated or inefficient and inappropriate behaviors may persist. For instance, Henderson and Clark's (1990) study of photolithography incumbents found that architectural innovation was problematic for established firms since inventors' embedded communication patterns reflected the old product architecture, and did not adapt to the need for new interfaces.

Finally, just as top management has been found to apply outdated cognitive frames when faced with technological change (Tripsas & Gavetti, 2000), old-technology inventors may also apply outdated cognitive frames. Henderson and Clark (1990) concluded that "experience with the previous generation blinded the incumbent firms to critical aspects of the new technology" (1990: 24). Similarly, Starbuck (1996) found that technical experts in the Swedish Navy misinterpreted technical, acoustical, and visual evidence to mean that five foreign submarines were operating on Swedish territory when, in fact, re-examination of the data revealed that it was animals, not submarines. He concluded that "technical experts may be among the most resistant to new ideas and to evidence that contradicts their current beliefs and methods" (Starbuck, 1996: 727).

When combined, the existing capabilities, behaviors, and cognitive frames of old-technology inventors are likely to create inertia and diminish performance if they are involved in developing the new generation. We therefore hypothesize:

H1: The greater the presence of inventor bridges, the lower a firm's inventive performance in the new generation.

Theory provides compelling, alternative views about the potential effect of technology bridges and hybrid product bridges on incumbents' inventive performance in the new technology. We thus develop competing hypotheses. We first explain why developing technology and hybrid product bridges may reduce the inventive performance in the new technology, and then explain why they may improve performance.

Research has consistently found that development efforts that incorporate more familiar knowledge result in lower-impact, incremental inventions (Fleming, 2001; Rosenkopf & Nerkar, 2001). Specifically, the more a firm builds upon technical knowledge that it has previously utilized, the lower its overall levels of product innovation (Katila & Ahuja, 2002) and the less likely it is to create technical breakthroughs (Ahuja & Lampert, 2001). Therefore, during a technological transition, when firms apply familiar, old-technology knowledge in the context of a new generation, it is likely to constrain adaptation, resulting in a more incremental instantiation of the new technology. For example, Gilbert (2005) found that when moving online, the lowest performing newspapers were those that re-used knowledge about lay-out design from their print publication when creating the look and feel of their online products, instead of reconceptualizing layout based on the opportunities presented by the new technology. Thus, the more firms redeploy old-technology knowledge in the context of the new, the less innovative they are likely to be.

In addition, scholars have argued that unlearning the old is a precursor to mastering new technology (Bettis & Prahalad, 1995; Hedberg, 1981). For instance, Imai and coauthors' (1984: 361) study of product development practices reported that to move beyond the highly successful Civic car model, "Honda had to unlearn the lessons from the past to develop a totally new concept of cars." When incumbents invoke old-technology knowledge, even when it is integrated with the new, that knowledge becomes more deeply embedded in organizational memory, (Argote, Beckman, & Epple, 1990) making unlearning difficult. Therefore, technology bridges, which reinforce old-technology knowledge, may restrict an organization's ability to master new things or develop new logics.

Overall, by utilizing technology bridges, firms risk inappropriately using old technology which can constrain exploration into the new and reinforce old-technology knowledge, making it more difficult to transition. Thus we propose:

H2a: The greater a firm's use of technology bridges, the lower the firm's inventive performance in the new generation.

Theory also suggests that hybrid product bridges are likely to hurt inventive performance. Like technology bridges, they reinforce old-technology knowledge in the organization making it more difficult to master the new. They also have the potential to hurt inventive performance in three additional ways. First, the development of hybrid products involves creating an architecture with interfaces between old- and new-technology components. For instance, the battery in the hybrid Toyota Prius was recharged by the internal combustion engine. However, as they create interfaces between the new and the old, firms are developing architectural knowledge based on that configuration, which may become difficult to change when the firm fully transitions to the new (Henderson & Clark, 1990). Second, by focusing on new-technology components that are constrained to work with the old, the firm may forgo the development of more innovative components. Unless designs are highly modular (Baldwin & Clark, 2000), the firm's technological trajectory in the new domain will optimize on interfacing with the old, likely resulting in less impactful developments. Third, the firm may not feel the need to attempt more radical new development since they are already making an investment in a hybrid, and its performance may seem satisfactory (Ansari & Garud, 2009). In other words, firms are willing to "settle" as opposed to swinging for the fences (Suarez et al., 2018: 54). For instance, Hasselblad initially developed a modular studio camera that could work with its own conventional analog film 'back' and also worked with digital camera 'backs' developed by others. The product underperformed, and by the time Hasselblad committed to developing a fully digital system, they had been surpassed by competitors (Sandström, Magnusson, & Jörnmark, 2009). Firms that innovate more vigorously in hybrid products may therefore ultimately sacrifice success in the new technology.

H3a: The greater a firm's use of hybrid product bridges, the lower the firm's inventive performance in the new generation.

Theory also suggests reasons why both technology and hybrid product bridges may help organizations overcome challenges they face when attempting to acquire new-technology knowledge. Firms attempting to master distant knowledge face a paradox: On the one hand, for organizations to identify and absorb knowledge, it needs to be close to their existing knowledge base (Cohen & Levinthal, 1990). On the other hand, by its very nature, knowledge related to a new technological generation is distant, making it difficult for incumbents to absorb. Technology bridges may help resolve this paradox. By building upon some aspects of familiar old-technology knowledge when developing novel inventions, incumbents in essence shorten the distance to the new technology, and thus make the new knowledge more accessible. For instance, Mealey and his coauthors (2017) found that when attempting to expand to new technical areas, prior experience with a common underlying component technology increased firms' ability to absorb distant knowledge. Specifically, "component-centric knowledge can help the firm better absorb knowledge from an unfamiliar category …even when that knowledge category is unrelated to the organization's prior knowledge" (Mealey et al., 2017: 4–5). Thus, rather than serving as a constraint, prior knowledge has the potential to serve as a valuable resource to be leveraged when transitioning. Firms might therefore be able to utilize prior old-technology knowledge as a familiar foundation from which to learn new technologies.

H2b: The greater a firm's use of technology bridges, the higher the firm's inventive performance in the new generation.

As with technology bridges, hybrid products may improve inventive performance by providing a familiar foundation of absorptive capacity from which incumbents can learn a new technology. For instance, Furr and Snow's (2015) study of the transition from carburetors to electronic fuel injection (EFI) systems in the automobile industry found that incumbents with higher performing intergenerational hybrid products also developed higher performing new-technology EFI systems. In addition, hybrid product bridges may contribute to new-technology inventive performance via two further mechanisms. First, given the high uncertainty incumbents face in the early stages of a discontinuity, when technological variants compete with each other (Eggers, 2012, 2014), developing hybrid products can be an effective way to experiment with the new technology, while retaining capability in the old. As such, hybrid products can be considered real options (McGrath, 1997) in that they help the firm learn about the new technology, but with staged commitments. If the new technology fails to take off, the firm can terminate the option, stop making hybrid products, and still have a position in the old technology. If the new technology does well, the firm can then make further investments, having gained additional knowledge. Such learning and experimentation is valuable to incumbents, who *ex anti* do not know which technological variant will prevail or the rate at which new technology will overcome the old (Ansari & Garud, 2009). Second, in addition to technical knowledge, hybrid product bridges provide a window into application-specific market knowledge, which has been found to be an important contributor to R&D performance (Roy & Cohen, 2017; Sosa, 2009). Thus, just as Eggers (2014) found that firms learned about the market from commercializing the 'losing' technology, incumbents that commercialize hybrid products can learn about customer preferences in the new domain, which could improve inventive performance, regardless of whether their hybrid products are adopted broadly. In summary, hybrid products can be stepping-stones that help firms transition to a new technology over time. More formally:

H3b: The greater a firm's use of hybrid product bridges, the higher the firm's inventive performance in the new generation.

The Moderating Effect of Old-Technology Inventive Performance

Even when the technical knowledge associated with the old regime becomes less relevant in the context of the new, a firm's overall ability to perform research may persist since capabilities essential to conducting R&D, such as those related to knowledge creation and integration may retain relevancy (Danneels, 2002; Helfat & Raubitschek, 2000; Helfat & Winter, 2011; Iansiti, 2000; Lavie, 2006; Winter, 2003; Zollo & Winter, 2002). For instance, Henderson and Cockburn (1994: 2) found that a higher-order "architectural competence" was associated with higher firm productivity in drug discovery across technical generations. Similarly, Cardinal (2001) found that common control mechanisms were effective in managing R&D projects within highly disparate technical settings. From this perspective, R&D capabilities are fungible, and thus firms may be able to apply research skills developed in one technical domain to a new one. Overall, this reasoning suggests that the stronger a firm's inventive performance in the old domain, the more likely it will be able to leverage intergenerational bridges when moving to the new domain. At the inventor level, the firm may have organizational structures in the R&D unit that help them to take advantage of team diversity, making them better able to leverage the knowledge of old-technology inventors. They may also have staffing expertise that enables them to better select old-technology inventors to assign as bridges on new-technology projects. At the technology level, the firm's R&D capability may make it more adept at deciding which old-technology knowledge to use in bridges. Finally, at the product level, high performing R&D organizations may have superior systems for codifying knowledge gained in the development of hybrid products and for absorbing hybrid product market feedback. Thus, when they have stronger old-technology inventive capabilities, firms are more likely to benefit from the use of bridges between generations of technology. More formally,

> *H4: A firm's inventive performance in the old technology will positively moderate the relationship between using bridges and inventive performance in the new generation of technology.*

DATA AND METHODS

Research Setting

Our research context is the photography industry during the transitional period between analog and digital technologies. We examine research-active analog photography firms (i.e.

firms that patented in analog photography technical domains) making the transition to digital photography. This setting is ideal for a number of reasons. First, the scientific and technical disciplines upon which analog photography was based are fundamentally different from those used in the design and production of digital cameras (Benner & Tripsas, 2012; Tripsas & Gavetti, 2000). Firms therefore had to develop new domain expertise to have high inventive performance in the new generation. Second, all photography firms that were active in analog R&D also became active in digital R&D, thus reducing concerns about selection bias. Third, all analog camera producers also introduced digital cameras. Since these firms had similar prior industry experience, they had access to the same analog distribution channels and suppliers, limiting concerns about differences in complementary assets influencing digital research activities (cf. Eggers, 2012; Wu, Wan, & Levinthal, 2014). Fourth, very few start-ups entered the digital camera industry. Instead, many of the major technological advances were made by established photography firms, providing a fertile context for comparing the performance of incumbents making a transition. Finally, there was an extended period during which firms simultaneously produced both types of cameras and conducted research in both technical domains. As a result, we are able to observe how these firms managed the relationship between old and new technology innovation over time.

Figure 1 shows U.S. sales of analog and digital cameras from 1991, when the first consumer digital camera was introduced, until 2010 when nearly all patenting and camera sales were in digital technologies. It was not until 2003, or 12 years after the first digital camera was introduced, that 50% of the industry's sales came from cameras based on digital technologies. Figure 2 shows the percentage of photography firm patents related to analog as opposed to digital photography from 1974 through 2010. As one might expect, increases in digital technology patent applications preceded increases in digital camera product introductions. Throughout this period, incremental improvements in analog photography were ongoing, including the single-use camera first introduced by Fujifilm in 1986 and Polaroid's Captiva instant camera and high-resolution instant film, which were introduced in 1993. Thus, while photography firms were developing proficiency in digital technology, they were simultaneously making improvements to analog technologies.

Insert Figures 1 and 2 about here

During this transition period, photography firms were also attempting to leverage their analog capabilities in the digital realm. Some expressed the belief that their prior capabilities could help them succeed in the new domain. For instance, in its 1999 Annual Report, Kodak stated, "Leveraging our core competencies in film and paper media, we will be a leader in developing digital imaging products and services." Similarly, Polaroid built what they called an "image science bridge" between generations in order 'to relate the measurable physical attributes of an image [based on expertise developed in analog imaging] to the engineering parameters of a digital photographic system,' according to one development engineer (Rosenbloom & Pruyne, 1997: 13).

At the same time, in reflecting back on early digital efforts, development team members felt that assumptions and routines that were carried over from analog developments hurt digital efforts. For instance, in developing their first digital minilab, a developer from one firm explained that applying assumptions from analog minilabs about how film should advance caused problems when applied in the context of digital, noting, "The analog minilab advanced film in blocks, not a steady feed like would be needed for a linear scan. So … in the first digital minilab we developed a special area sensor CCD the size of a negative. This CCD, however, was very expensive and distorted the image. We corrected this in the second generation of the digital minilab, which was equipped with a linear sensor."[1] Another example involved the inappropriate application of analog evaluation routines in the context of digital. When examining the quality of an analog film-based image, developers used a loupe, which is a specialized type of magnifying glass, to discern picture quality. Despite the inability of these tools to determine the quality of digitally-produced images, employees with analog film experience continued to use them when examining digital images. As a newly hired manager of digital imaging at one firm explained, "We would get into a discussion, always about image quality. Everybody would pull out from their pocket their personal loupe, and they would look at the image…they looked like jewelers looking at a piece of jewelry… They'd be down looking at the image, telling you how good it is… The problem with electronic imaging … was the loupe couldn't tell you about those electrons down there… The problem was they couldn't do the same thing with the electrons." Overall, our qualitative data suggest that incumbents sometimes inappropriately applied analog knowledge in the context of digital, but also believed they could leverage the old technology as they developed the new. We next explore the relationship between bridging and inventive performance quantitatively.

Sources and Data

Since our goal was to understand how firms manage the relationship between old- and new-technology development during a transition, our sample includes all incumbents with an active research presence in analog technology. Not all firms that produced analog cameras

[1] Quotations in this section are from field research conducted by one of the authors as part of a broader research initiative on the evolution of digital photography that has included interviews with over 50 individuals, including company CEOs, analog and digital development engineers, marketing personnel and industry analysts (see Tripsas & Gavetti, 2000; Tripsas, 2009; Benner & Tripsas, 2012).

engaged in research since there was a well-developed supply chain that provided firms with camera designs, components, and manufacturing services (Benner & Tripsas, 2012). Therefore, we examined the patent portfolio for each of the 25 photography firms that produced analog, consumer-oriented point and shoot cameras, or high-end SLR cameras to determine which ones were research active (following Eggers 2014, firms needed to have at least two patents to be considered research active). Fourteen firms had an active research presence in analog technology, and all of these firms developed digital technology and filed digital photography patents. (See Table 1 for a list.)

Insert Table 1 about here

To test our theory, we needed information about inventive performance, knowledge built upon in technology development, and inventors across multiple generations of technology. Patent data are one of the few data sources that include such information (Griliches, Pakes, & Hall, 1986). One of the benefits of patents and patent citations is that they undergo significant scrutiny. Firms are required to cite all relevant prior art or risk having their patents invalidated by the court or patent office. Moreover, citations are checked and corrected by patent examiners, technical experts who certify that all relevant prior art has been cited (Alcácer & Gittelman, 2006). While patent data have limitations (Levin et al., 1987), we made efforts to reduce these through our research design. By examining one industry only, we removed the risk that differences in intra-industry patenting norms (Cohen, Nelson, & Walsh, 2000) could influence our results. In addition, we included year fixed effects in our models to account for difference across years. We also created measures using the patent application year rather than the grant-year, since the application year is closer to the time of invention.

We retrieved general patent data from the NBER Patent Data Project (Hall, Jaffe, &

Trajtenberg, 2001) and inventor-level data from the Patent Network Dataverse (Lai, D'Amour, & Fleming, 2009). Our observation period begins with patents that were applied for in 1974, well before the first US consumer digital camera was introduced in 1991, and ends in 2010, when nearly all new cameras were based on digital technology. To identify the patents granted to our focal firms, we began with Bessen's (2009) tables, which correlate firms' Compustat keys and patent lookup codes and then entered the codes to select corresponding patents. Next we string-searched the assignee fields of the NBER and Dataverse databases by entering each of our focal firm names and verified any assignee name returned from our string search that was not clearly associated with one of our focal firms by consulting the LexisNexis Corporate Affiliations database, archival annual reports, press releases, and company websites. For example, searching "Fuji" returned "Fuji Electric Co., Ltd.", which is not associated with our focal firm, and so we excluded patents associated with it.

Since patent classes are not clearly associated with photography generations, we engaged in a systematic process to classify each patent according to its technological generation. These classifications included: analog photography (e.g., chemistry associated with manufacturing film, mechanisms used to wind film in a camera); digital photography (e.g., image sensors, flash memory); both analog and digital photography (e.g., zoom lenses); or neither (not related to photography). Our classification process involved three steps. First, we examined the U.S. Patent and Trademark Office (USPTO) and International Patent Classification (IPC) guides to identify patent classes that clearly fell into one of our categories, based upon the patent class description. For example, USPTO class 396.273 is described as "having light reflected from film or shutter or through film," and thus we assigned the patents in this class to analog photography.

Second, we created a list of specific technologies and keywords associated with each of our three categories and searched the titles of patents from the USPTO to identify the associated patent classes. For analog photography we used terms such as “film cartridge.” For digital photography we used terms such as “image sensor” and “image processing.” We identified USPTO classes associated with returned patents and added them to our categorization scheme. We next examined the international patent classes of those patents, to see if a more granular classification could be used. For instance, the IPC had a separate class for ink jet printers, so we used the IPC class to categorize those patents.

Third, we identified technologically focused firms and examined their patent portfolios to identify relevant classes. For instance, to identify the technology classes associated with removable flash memory used in a digital camera, we examined the patents of Lexar Media, a firm that narrowly focused on digital camera memory cards. Fourth, we manually examined the patent portfolios of each of our focal firms to identify patents that we could not categorize based on one of the prior steps. We examined the classes of a subset of those patents to determine if there were any relevant technology classes that had been missed.

Finally, we verified our categorization schema by making several additional comparisons. We analyzed how we categorized patents that were originally in class 354, the retired U.S. photography patent class. Since this class was eliminated in 1996, the patents assigned to that class should have been categorized primarily as analog photography or ‘both analog and digital photography’, and 96% of them were categorized as such. For LCD display technology, we cross-checked the classes we identified with prior research focused on the emergence of LCDs (Eggers, 2014). As a final verification, we cross-checked our categorization with the Silverman patent concordance (Silverman, 1999) to identify any potential inconsistencies.

After excluding patents not related to photography, we had a final sample of 84,861 patents held by the focal firms in our study between the years 1974 and 2004. We also identified 32,585 individual inventors who were named on the patents in our database using the lower bound of the disambiguation algorithm in the Patent Network Dataverse (Lai et al., 2009).

We supplemented our patent data with hand-collected data on digital and APS camera introductions from trade publications (e.g., the Future Image Report, PC Photo and Popular Photography), research reports (e.g., International Data Corporation and Forrester), company website archives, photography industry websites (primarily dpreview.com, imaging-resource.com, and dcviews.com), and press coverage of the industry throughout our sample period. Product shipment dates were cross-checked and confirmed using two or more sources. Finally, we collected firm-level sales data from Compustat.

Measures

Dependent variable. In line with prior empirical research, we use the well-established metric, forward citation counts, to measure the inventive performance of firms (Aghion, Reenen, & Zingales, 2013; Albert, Avery, Narin, & McAllister, 1991; Eggers & Kaul, 2017; Hall, Jaffe, & Trajtenberg, 2005; Harhoff, Narin, Scherer, & Vopel, 1999; Jung & Lee, 2016; Khanna, Guler, & Nerkar, 2016; Narin, Noma, & Perry, 1987; Trajtenberg, 1990)[2]. Patent citations have been found to be highly correlated with the profitability of the underlying technology, patent renewals, and overall economic value (Hall et al., 2005; Harhoff et al., 1999; Trajtenberg, 1990). Patents and citations are also highly correlated with the number of new products introduced by a firm (Comanor & Scherer, 1969), invention counts (Basberg, 1982), and nonpatentable

[2] Authors have used a range of labels to capture what a highly cited patent portfolio represents, all of which imply strong inventive performance. The various labels applied to forward citations include "innovative performance" (Galasso & Simcoe, 2011; Van de Vrande, 2013), the "impact" of the invention (Ghosh, Martin, Pennings, & Wezel, 2013; Rosenkopf & Nerkar, 2001), whether technology is "breakthrough" (Conti, Gambardella, & Mariani, 2013; Jung & Lee, 2016) the "quality" of the technology (Singh, 2008; Singh & Fleming, 2010; Sorenson & Fleming, 2004) and "quality of R&D output" (Khanna, Guler, & Nerkar, 2016).

innovations (Patel & Pavitt, 1997). Finally, the number of forward citations made to patents in the photography industry have been found to be highly correlated with technical experts' assessment of the importance of the underlying technology (Albert et al., 1991).

Specifically, we constructed our dependent variable, *digital inventive performance,* by summing the number of citations made to a firm's digital imaging patent portfolio for each application year[3]. Since patents granted later have less time to accumulate citations, they may systematically have fewer forward citations. We corrected for this bias in three ways. First, we adjusted the total citations for each patent, based on its grant year, using the truncation factor from the NBER database (Hall et al., 2001). Second, we included year fixed effects. Finally, we stopped our analysis at the end of 2004 to allow forward citations to accumulate for an additional five years (Hall et al., 2001).

Independent variables. Our measure of inventor bridges captures the presence of inventors who invent in both analog and digital technologies. It is a count, for each year, of how many inventors currently at each firm have patented in both analog and digital classes. To calculate *inventor bridges*, we tagged all inventors at the firm who had worked in both analog and digital classes. Since the inventor's research leading to the patent application would have occurred before applying for the patent, we labeled each individual as a bridge inventor 2 years before their first bridging patent. We also do not know the exact date that inventors left their firms, so, consistent with prior research, we imputed the time when the inventor departed based of the last patent filed at the firm (Agarwal, Ganco, & Ziedonis, 2009; Palomeras & Melero, 2010; Rosenkopf & Almeida, 2003; Trajtenberg & Shalem, 2009). We assumed that inventors

[3] Consistent with similar research (Aghion, Reenen, & Zingales, 2013; Conti et al., 2013; Fleming, 2001; Fleming & Sorenson, 2001; Ghosh et al., 2013; Rosenkopf & Nerkar, 2001) we include self-citations.

left a firm two years after their last patent application.[4] We then created a total, for each year, of how many inventors currently at each firm had invented in both in the old and the new technology.

While our measure of inventor bridges captures the presence of inventors, regardless of whether they filed a granted patent in a given year, our measure of *technology bridges* captures instances in which a firm invokes a combination of analog and digital knowledge in a specific invention. In line with prior research, we utilized patents cited by a focal patent (backward citations) to construct measures of the knowledge used by the firm in developing the focal patent (Almeida & Kogut, 1999; Cattani, 2005; Ghosh et al., 2013; Gruber et al., 2012; Jaffe et al., 1993; Katila & Ahuja, 2002; Katila & Chen, 2008; Miller et al., 2007; Nerkar, 2003; Rosenkopf & Nerkar, 2001; Sorenson & Fleming, 2004; Srivastava & Gnyawali, 2011). While patents do not capture the specific beliefs and actions of individuals, like Fleming (2001), we propose that patent categories "can be used to observe indirectly the process of recombinant search and learning" (p.122). We envisioned citations from a digital patent to an analog patent as representing the building of a bridge between the two technologies. To measure the strength of each firm's *technology bridges*, we calculated the percentage of each digital patent's citations that were made to analog patents. We then calculated the average percentage of analog citations for each firm's digital patents applied for each year to obtain a measure of technology bridges for each firm-year.

During the transition period, some photography companies produced intergenerational hybrid products based on the Advanced Photography System (APS), which combined digital

[4] We ran robustness checks to see if changing our assumptions about when individual inventors left the firm altered our results. In alternate specifications we assumed that the inventor joined the firm one or three years before his first patent, and left the firm one or three years after his last patent. Results were highly similar when we used these alternative measures: all coefficients retained their sign and significance, with only minor changes in magnitude.

components with analog film, cameras, and film processing. APS cameras were smaller and lighter, used film cartridges that were smaller and easier to load, and recorded digitally encoded timestamps on magnetic tracks along the edges of the filmstrip. We measured *hybrid product bridges* by summing the number of new APS cameras shipped by each firm in each year[5,6].

Like our measure of digital inventive performance, our measure of *analog inventive performance* is based on the importance of a firm's patent portfolio in analog photography. To generate a performance measure that controlled for the quantity of patenting, we calculated the average number of citations made to each of a firm's analog photography patents. Specifically, for each firm we divided the sum of citations made to the firm's analog photography patents applied for each year by the total number of analog photography patents applied for that year. To correct for the truncation problem discussed above, we adjusted the number of citations for each patent, based on the grant year, using the NBER truncation factor (Hall et al., 2001).

Control variables. To measure the relative emphasis a firm placed on each technology in each year of our study, similar to Eggers and Kaplan (2009), we calculated *percent analog patents,* the number of analog photography patents in a given year divided by the total number of photography patents in the same year. As discussed above, large body of prior research has found that innovations that build on distant, exploratory knowledge are more important (e.g., Rosenkopf & Almeida, 2003; Rosenkopf & Nerkar, 2001). We therefore controlled for the amount of *digital exploration.* Similar to prior work, we measured digital exploration as the

[5] We used two alternative measures of hybrid product bridges as robustness checks: 1) a dummy variable that equaled one for the years that a firm shipped any APS cameras, and 2) the total number of APS patents applied for by each firm in each year (smoothed over the prior three years since R&D for products occurs over multiple years). Our results were highly robust to each of these alternative measures. We flagged the patents associated with APS by searching for the text string "Advanced Photo System" in the patent specification from the USPTO website. As would be expected, given that APS products were hybrids, 46 % of the APS patents were classified as analog, 32% as digital, 12% as both, and the remainder in other categories.

[6] While some individual firms developed hybrid products other than APS (most notably, Kodak developed a Photo CD system), the APS system is the only industry-wide hybrid, and as such allows for a more consistent comparison across firms. We also ran our models without Kodak, and our results are robust.

degree to which a firm's digital imaging patents in a given year built upon technological fields that the firm had not used previously (Rosenkopf & Nerkar, 2001). To construct this measure, for each firm's digital imaging patents in a given year, we calculated the average percentage of cited patent class-subclasses that the firm had not cited previously.

Since our dependent variable is the annual total number of forward citations to digital patents, we controlled for the *number of digital patents* to account for differences in the quantity of output (Trajtenberg, 1990). Prior literature has also suggested a relationship between firm size and patenting behavior, thus we controlled for *firm size*, using a firm's prior year total revenues. Ideally, we would like to control for each firm's level of R&D investment in digital imaging, but these data are not available. To proxy for the level of effort in digital imaging, we include the *number of digital cameras introduced*[7] by each firm in the prior year and the *number of new digital inventors* who join the firm each year. As with our other inventor measures, we assume that new digital inventors join a firm two years before their first patent at the firm. We smoothed this variable over the prior three years. We logged several of control variables to correct for skewness (number of digital patents, firm size, number of digital cameras, and number of new digital inventors). Finally, we used firm-fixed effects to control for unobserved firm-level differences, such as varying initial stocks of knowledge.

Methods

Our econometric models examine the relationship between a count-based measure (forward citations) of inventive performance in the new, digital generation and measures of bridging via technology, inventors, and hybrid products. We model the conditional expectation of digital inventive performance as

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[7] The data used to create this measure were also used to create the control variable, "firm [digital] models on the market" used in Benner & Tripsas, 2012.

$$E[Y_{it}] = \exp(\alpha A_{it} + \beta x_{it} + \gamma_i + \lambda_t) \quad (1)$$

where x_{it} is a vector of controls, γ_i is a firm-specific effect that controls for unobserved heterogeneity across firms and λ_t is a vector of time-period effects (annual). Since our dependent variable is a non-negative count-based measure, ordinary least squares estimations may be mis-specified, and negative binomial or quasi-Poisson specifications are therefore more appropriate (Hausman, Hall, & Griliches, 1984; King, 1988; Long, 1997). Negative binomial and Poisson quasi-maximum likelihood specifications both allow for over-dispersion, but may estimate different standard errors due to differences in weighting. Specifically, quasi-Poisson weights are directly proportional to the mean, but negative binomial weights are concave to the mean, thus giving firms with less patenting more weight (Ver Hoef & Boveng, 2007). Since we hypothesize about the patenting behavior of firms, we do not want smaller firms to be over-represented in our results. We therefore use conditional fixed effects Poisson quasi-maximum likelihood estimation with Huber–White robust standard errors to account for overdispersion and residual heteroscedasticity across panels (Simcoe, 2007; Wooldridge, 1999).

RESULTS

Insert Table 2 about here

Table 2 presents descriptive statistics, bivariate zero-order correlations, and bivariate within correlations for the variables in our models. Though most correlations between our independent variables are small to moderate, we checked for multicollinearity two ways. First, we calculated variation inflation factors (VIFs) based on the full model, and each was well below the threshold of 10, with an average of 1.65 (O'Brien, 2007). Next, we calculated the condition number on the specification, which was 4.57, well below the threshold of 15 (Belsley, Kuh, & Welsch, 2005). The calculated VIFs and condition number indicate that our results are not biased by multicollinearity. Nonetheless, since correlated variables may inflate standard errors, even if multicollinearity was an issue, it would be more – not less -- difficult to reject the null hypothesis (Darlington, 1990).

Results of QMLE Poisson regressions with digital inventive performance as the dependent variable are reported in Table 3. Model 1 includes only control variables, including firm and year dummies, which are not reported. Models 2-4 add all three of our bridging variables. Models 5-7 examine the interactions between our three bridge variables and analog inventive capability. Finally, Model 8 is the full model.

We first discuss results of the baseline model. Though prior research has suggested that shifting attention and resources away from the old technology should improve performance in the new (Lavie, 2006), this was not the case in our study. The coefficient of *percent analog patents,* though negative, was insignificant. In addition, the coefficients of the *number of digital cameras introduced* and *number of new digital inventors,* though positive in most models, were also not significant. These results suggest that switching from one generation of technology to the next is more complicated than simply redirecting attention and resources. Consistent with prior research, the more firms incorporated new, exploratory knowledge, the more successful they were in the new technology: *digital exploration* had a positive and significant coefficient ($p<.05$). It is interesting to note that the coefficient on *firm size* was negative and significant. Prior research has found that firm size has a positive effect on the importance of patents (Sørensen & Stuart, 2000), however in the context of a technological transition, firm size appears to instead have a negative effect. As expected, the coefficient of *number of digital patents* was positive and highly significant.

Insert Table 3 about here

Models 2-4 explore the main effects of *inventor bridges, technology bridges*, *and hybrid product bridges* respectively. Our theory proposed that the greater the number of inventors who bridge technologies at a firm, the lower the firms' inventive performance in the new technology (H1). Consistent with H1, in Model 2, the coefficient for inventor bridges is negative and highly significant ($p<.001$). The effect of increasing the number of bridging inventors by one standard deviation would be to reduce forward citations by 11%. For a firm receiving a mean number of forward citations, this would equal 316 additional citations per year. According to Hall and her coauthors (2005) an average increase of one forward citation per patent corresponds to a 3% increase in a firm's market value. Thus, on average, avoiding inventor bridges could have an economically significant effect for incumbents transitioning between technological generations.

Since theory provides alternative views about the potential effect of technology and hybrid product bridges on incumbents' performance in the new technology, we developed competing hypotheses. H2a and H3a argued that developing technology and hybrid product bridges would activate and extend knowledge related to an old technology, and thus restrict incumbents' performance in the new technology, while H2b and H3b argued that technology and hybrid product bridges could provide a foundation for learning new technologies and thus help a firm transition. We find some support for H2a, that the more firms use technology bridges, the lower their inventive performance; the coefficient for technology bridges in Model 3 is negative and marginally significant ($p<.10$). The coefficient for *hybrid product bridges* is negative in Model 4, but is not significant, leaving H3a and H3b unresolved.

The next set of models (Models 5 - 7) report the interactions between our three bridge variables and analog inventive performance. Given difficulty interpreting interaction effects in nonlinear models (Zelner, 2009), we graphed each interaction to facilitate interpretation[8] (see Figures 3, 4 and 5). We hypothesized that when firms have stronger analog inventive performance, they possess second order R&D capabilities that allow them to better leverage intergenerational bridges when moving to the new domain (H4). The interaction between inventor bridges and analog inventive performance in Model 5 was insignificant, though it was positive. Figure 3 shows that the marginal effect of additional bridging inventors was negative regardless of the firms' level of analog inventive performance. However, the positive and significant coefficients for the interactions between analog inventive performance and both technology bridges (Model 6, $p<.01$), and hybrid product bridges (Model 7, $p<.05$) provide support for H4 and suggest that as an incumbent's analog inventive performance increases, it is able to mitigate the negative effects of bridges. In fact, Figures 4 and 5 show that when analog inventive performance is high, the effect of additional technology and hybrid product bridges becomes positive and is associated with higher digital inventive performance. These findings help resolve the competing logics provided for H2a/H3a and H2b/H3b. They suggests that H2a and H3a hold when firms have low analog inventive performance, but H2b and H3b are supported when analog inventive performance is high; when analog inventive performance is stronger, firms seem to be able to use technology bridges and hybrid products to help them transition to new technologies. We included all of our variables in Model 8, and obtained consistent results. Overall, our statistical analyses provide some support for our theory that stronger R&D capabilities enable firms to leverage old-technology knowledge when transitioning between technological generations.

[8] We used the margins command in Stata to graph interactions.

Insert figures 3, 4 and 5 about here

Additional Analyses

Like similar research that lacks suitable instruments to address endogeneity concerns (Chatterji & Fabrizio, 2012; Rosenkopf & Nerkar, 2001), we relied on control variables and conditional fixed effects (Hausman et al., 1984) with Huber–White robust standard errors to address firm level differences. As an additional robustness check, we also re-ran our analyses using the "mean scaling estimator" method suggested by Blundell and coauthors (1999). This method controls for pre-sample firm heterogeneity, thus relaxing the assumption that the x_i are strictly endogenous (Galasso & Simcoe, 2011). We cumulated seven years of pre-sample data to account for initial conditions and then replaced firm-level dummies with this pre-sample measure of our dependent variables in our models. The main effects of all three bridges were negative and became highly significant ($p<.001$), and instead of two, all three interaction effects were positive and highly significant, lending stronger support for H4. Nevertheless, our results should be interpreted as indicating correlation and not necessarily causation.

We also examined whether systematic differences in the quality of inventors who bridge versus those who do not might be driving the negative effect of inventor bridges. Using a t-test, we compared the average number of patents per year for bridging inventors and non-bridging inventors and were unable to reject the null hypothesis that they were the same, leading us to conclude that it is unlikely that differences in inventor quality are driving our results. In addition, since inventors who bridge may develop technology bridge patents or hybrid products, we also ran post-hoc analyses to explore whether the relationship between inventor bridges and inventive performance was mediated by either technology or hybrid product bridges. Tests of mediation failed, indicating that inventor bridges has a direct relationship to inventive performance.

Mono-method bias can also be a concern when patents and patent citations are used to calculate both dependent and independent variables, though much prior work uses such a structure (e.g., Fleming & Sorenson, 2001; Hsu & Lim, 2013; Kotha, Zheng, & George, 2011; Rosenkopf & Nerkar, 2001; Sorenson & Fleming, 2004). To address this concern we repeated our analysis using *number of digital cameras introduced* as the dependent variable. While some studies suggest that the number of new products associated with a technology might be an alternative measure of firm innovativeness (Katila & Ahuja, 2002), others emphasize the key differences between inventive performance and commercialization performance, since the latter requires not only inventive capabilities but also the additional ability to turn technology into commercializable products. Thus, as a dependent variable, *number of digital cameras introduced* extends beyond our interest in a firm's inventive performance since it obfuscates invention and commercialization. Nonetheless, some results (not reported) remain robust. The coefficient of inventor bridges remains negative and significant ($p<.05$), the coefficient of technology bridges loses significance, and the coefficient of hybrid product bridges remains insignificant. Interestingly, the interaction between hybrid product bridges and analog inventive performance is significant, but becomes negative, suggesting that when inventive performance in analog is stronger, introducing more hybrid products makes firms even less likely to introduce pure digital products. These firms may believe that their analog strength allows them to develop better hybrid products, and they therefore introduce hybrids instead of digital models.

DISCUSSION

When transitioning between technological generations, firms often attempt to leverage old-technology knowledge when inventing in the new domain. While much prior research has viewed such activity as evidence of organizational pathologies that inhibit effective development of new technology, we find that using old knowledge to bridge between old and new generations can have a positive impact on inventive performance. Using data on photography firms transitioning from analog to digital technologies, we explore the effect of three types of intergenerational knowledge bridges on inventive performance in the new domain – inventor bridges in which analog inventors are redeployed on digital inventions, technology bridges in which digital patents build upon analog knowledge, and hybrid-product bridges in which products include both analog and digital components. Consistent with theories of inertia, we find that on average, the more that incumbents used inventor and technology bridges, the lower their inventive performance in the new domain. However, technology and hybrid product bridges were associated with higher inventive performance when incumbents had higher levels of analog inventive capabilities. Higher-order R&D capabilities appear to have enabled firms to identify and leverage the right old-technology knowledge when developing digital inventions, and to learn from the experience of developing hybrid products. We thus propose a more nuanced theoretical explanation of the relationship between old and new-technology efforts by suggesting limits to theories of inertia (Argote et al., 1990; Bettis & Prahalad, 1995; Hedberg, 1981; Henderson & Clark, 1990; Leonard-Barton, 1992).

Our work extends research on technological transitions in three ways. First, while prior work highlights the many challenges incumbents face as they transition from one generation to the next, the emphasis has been either on comparing incumbents and new entrants or on identifying differences in incumbents' ultimate commercial performance without disentangling the role of inventive performance. By identifying intergenerational knowledge bridges as an important driver of incumbent inventive performance in the new domain, we advance our understanding of why incumbents perform differently. Second, we bring into question the notion that a competence-destroying innovation, by definition, makes all old-technology knowledge obsolete. Even if the old technology is no longer directly useful, and thus “obsolete,” in that it no longer forms the basis for new-technology products, our findings imply that it can serve as a stepping stone to help organizations move between generations. So while the old-knowledge ultimately becomes obsolete, it serves a temporary role of providing a bridge to the new technology. Third, while prior research suggests that adding new-technology resources should help in a transition, in our study, simply adding digital inventors was not a significant predictor of inventive performance in digital. Similarly, the percent of patents in analog technologies, an indicator of how quickly the firm is shifting directions, was also not a significant predictor of inventive performance. Our findings thus suggest that that navigating technological transitions is more subtle and more complicated than simply shifting attention and resources from one generation to the next.

Our study also extends research that applies a real options lens to R&D investments. Since technology investments involve significant uncertainty, real options reasoning helps to explain the nature of firm R&D commitments (McGrath, 1997). In particular, early investments into new technological areas can be characterized as a real options, in that they allow the firm to experiment and learn before deciding whether to further invest or exit the area. While existing empirical work has focused on understanding a firm’s overall level of R&D or the amount of R&D in new areas (e.g., McGrath & Nerkar, 2004; Ross, Fisch, & Varga, 2017), we show that a real options logic can also explain technology investments in hybrid products. However, the benefits of engaging in such options are not uniform: only when incumbents had superior R&D capabilities were they able to leverage learning from hybrid product bridges in their digital innovation programs. When analog performance was lower, hybrid product bridges actually hurt inventive performance, indicating that, in this context, there is potentially an additional cost to creating real options.

Limitations and Future Research

Our study has several limitations. Primarily, patent data do not directly measure inventors' beliefs or behaviors. Our study is also limited to one technological domain where the new technology ultimately overcame the old. Research in an industry where there is a competition between multiple possible new technologies or where the new technology does not completely displace the old could refine our theory.

More research is also needed to understand the boundary conditions around when and for how long bridges are useful. For example, bridges may not be as useful when the old technology is replaced quickly, when the old technology survives the disruption, or when consumer preferences change substantially. In addition, intergenerational knowledge bridges are not meant to be an endpoint in and of themselves, so we need a better understanding of at what point a firm should finish "crossing the bridge" and disengage from bridging activities.

We have focused on a context in which, when faced with a technological transition, all of the firms that were research active in the old technology were also research active in the new technology – in other words, they attempted to develop new-technology expertise. An alternative strategic response to competence-destroying technology invading a firm's core market would be to leverage their old technical expertise in a different market. For instance, in addition to their efforts to develop digital imaging technology for their core imaging market, Fujifilm, also parlayed its specialty chemical expertise from analog photography into a number of new markets ranging from flat panel displays to cosmetics (Gavetti, Tripsas, & Aoshima, 2007). Understanding how and when firms facing a transition redeploy their existing expertise in new markets, and to what effect, is an important question for future research.

Our findings also raise important questions about the optimal organization design for new-technology developments. While prior research has suggested that new-technology development be organizationally separated from the old (Danneels, Verona, & Provera, 2018; Gilbert, 2005; O'Reilly III & Tushman, 2008), our findings imply that if the new unit is staffed with old-technology inventors, it will not perform well. At the same time, if an organization has strong R&D capability in the old technology, separation may not be optimal since it might preclude access to organizational knowledge that could be used effectively in technology or hybrid product bridges. While we were not able to directly test the effect of organizational design choices in this study, we welcome future research that examines how the internal structure and staffing of separate development units affects inventive performance.

In sum, building upon old-technology knowledge does not always reduce inventive performance during a transition. Rather, our results suggest that when firms have stronger R&D capabilities, they can enhance their inventive performance in the new technology by creating knowledge bridges between the old and new.

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Table 1
Patent and Camera Counts by Firm

Firm	Analog Photo Patents	Digital Photo Patents	Number of APS Cameras	Number of New Digital Cameras
Agfa	1,457	529	5	16
Canon	1,706	17,729	19	77
Concord	23	2	0	30
Fujifilm	7,032	4,581	48	83
Kodak	6,484	4,626	43	95
Konica	1,674	811	5	23
Kyocera	96	275	8	22
Minolta	326	1,845	20	30
Nikon	357	1,324	18	47
Olympus	239	1,956	14	73
Pentax	201	845	3	34
Polaroid	677	238	0	18
Ricoh	694	4,193	0	23
Rollei	7	5	0	3
Total	20,973	38,959	183	574

Table 2
Descriptive Statistics, Bivariate Zero-order Correlations (Lower Triangle), and Bivariate within Correlations (Upper Triangle)

	Mean	Std. Dev.	Min	Max	1	2	3	4	5	6	7	8	9	10	11
1. Inventive performance – Digital	2885	5930	0	38663	1.00	0.28	-0.06	0.84	0.27	-0.27	-0.49	0.69	0.46	0.37	0.63
2. Inventor bridges	121	160	0	749	0.23	1.00	0.05	0.47	0.10	-0.03	-0.33	0.33	0.18	0.50	0.25
3. Technology bridges	0.03	0.04	0	.24	0.03	0.12	1.00	0.13	-0.09	0.41	-0.04	-0.03	0.23	0.15	-0.09
4. Product bridges	2.04	8.27	0	10	0.47	0.43	0.15	1.00	0.28	-0.17	-0.63	0.79	0.55	0.56	0.70
5. Analog inventive performance	12.82	8.58	0	96.06	0.06	0.07	-0.02	0.17	1.00	-0.13	-0.30	0.40	0.24	0.23	0.43
6. Percent analog patents	0.40	0.30	0	1	-0.15	-0.21	-0.15	-0.37	0.04	1.00	0.33	-0.37	0.21	-0.20	-0.31
7. Digital exploration	0.35	0.24	0	1	-0.27	-0.29	-0.17	-0.55	-0.18	0.46	1.00	-0.81	-0.31	-0.54	-0.68
8. Number of digital patents	125	233	0	1519	0.29	0.33	0.13	0.62	0.32	-0.44	-0.73	1.00	0.49	0.44	0.89
9. Firm size	783	771	2	3493	0.27	0.17	0.04	0.47	0.31	-0.30	-0.59	0.64	1.00	0.29	0.51
10. Number of digital camera models	1.85	3.57	0	17	0.28	0.46	0.16	0.68	0.20	-0.41	-0.56	0.52	0.43	1.00	0.28
11. Number of new digital inventors	50	61	0	343	0.20	0.04	0.42	0.20	0.35	-0.23	-0.56	0.67	0.55	0.24	1.00

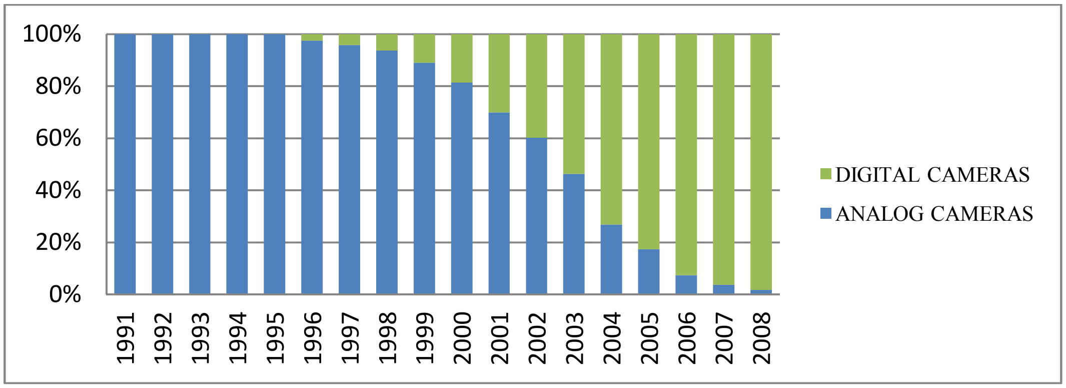
(Descriptive statistics are for non-transformed variables; correlations are calculated using transformed variables)

Table 3
The Effect of Bridges on Digital Inventive Performance

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Inventor bridges		-0.000685***			-0.00120*	-0.000684***	-0.000739***	-0.00119*
		(0.000177)			(0.000628)	(0.000211)	(0.000214)	(0.000614)
Technology bridges			-1.171*		-0.593	-9.230***	-0.822	-9.315***
			(0.611)		(0.697)	(3.287)	(0.651)	(3.003)
Hybrid product bridges				-0.00894	-0.000232	-0.00519	-0.0943**	-0.0939*
				(0.00966)	(0.00818)	(0.00729)	(0.0472)	(0.0515)
Analog inventive performance					0.0129	-0.0316	0.00215	-0.0794**
					(0.0366)	(0.0264)	(0.0335)	(0.0384)
Inventor bridge x Analog Inventive performance					0.000177			0.000122
					(0.000180)			(0.000181)
Technology bridge x Analog Inventive performance						3.702***		3.775***
						(1.408)		(1.320)
Hybrid product bridge x Analog Inventive performance							0.0358**	0.0354**
							(0.0166)	(0.0178)
Percent analog patents	-0.0719	-0.00983	-0.0259	-0.107	-0.0349	-0.0263	0.0144	-0.0156
	(0.191)	(0.202)	(0.196)	(0.183)	(0.215)	(0.218)	(0.208)	(0.233)
Number of digital camera models	-0.0141	0.0165	-0.0160	-0.0126	0.0144	0.0253	0.0196	0.0323
	(0.0385)	(0.0398)	(0.0360)	(0.0380)	(0.0366)	(0.0368)	(0.0371)	(0.0344)
Number of new digital inventors	0.0152	0.0332	0.0239	0.0230	0.0270	-0.00495	0.0411	0.00774
	(0.0583)	(0.0618)	(0.0652)	(0.0602)	(0.0688)	(0.0675)	(0.0686)	(0.0673)
Digital exploration	0.397**	0.638***	0.346**	0.434**	0.569***	0.598***	0.581***	0.565***
	(0.193)	(0.132)	(0.170)	(0.171)	(0.107)	(0.111)	(0.115)	(0.111)
Firm size	-0.108**	-0.126***	-0.131**	-0.121**	-0.157**	-0.133**	-0.159**	-0.137**
	(0.0481)	(0.0483)	(0.0633)	(0.0517)	(0.0664)	(0.0601)	(0.0665)	(0.0619)
Number of digital patents	0.787***	0.838***	0.785***	0.786***	0.842***	0.842***	0.837***	0.847***
	(0.0632)	(0.0573)	(0.0634)	(0.0613)	(0.0572)	(0.0556)	(0.0588)	(0.0557)
Observations	293	293	293	293	293	293	293	293
Number of fid	14	14	14	14	14	14	14	14
ll	-12304	-11680	-12172	-12245	-11543	-11298	-11438	-11129

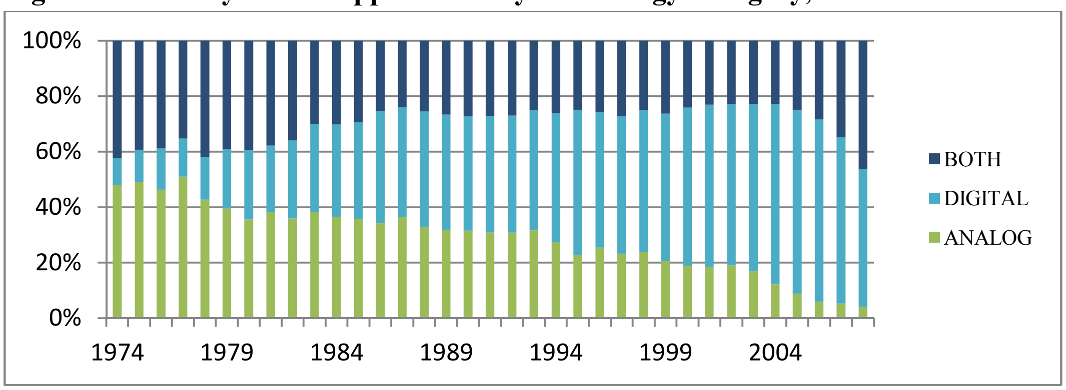
Note: Robust standard errors in parentheses
* p<0.1
** p<0.05
*** p<0.01

Figure 1: US New Camera Sales by Technology, 1991-2008



Source: Photo Marketing Association

Figure 2: Industry Patent Applications by Technology Category, 1974-2010



Source: NBER Patent Data Project, Patent Network Dataverse

Figure 3: Inventor Bridge x Analog Inventive Performance

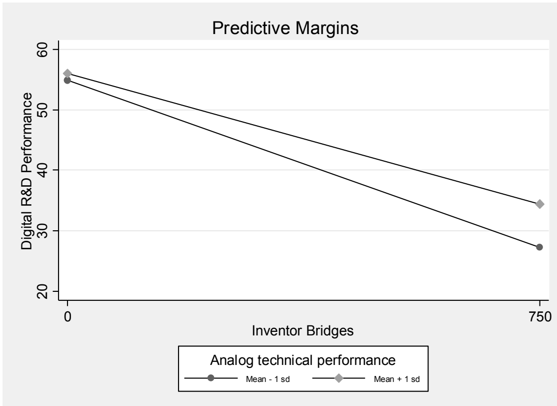


Figure 4: Technology Bridge x Analog Inventive Performance

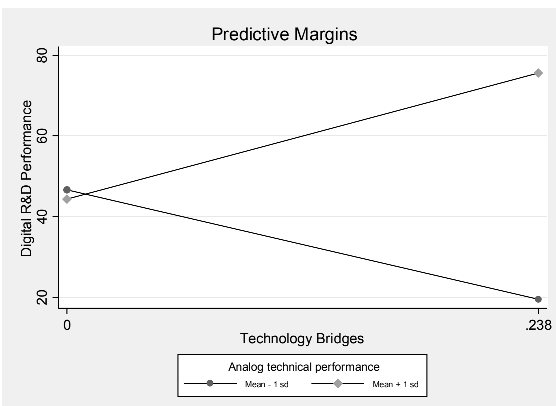
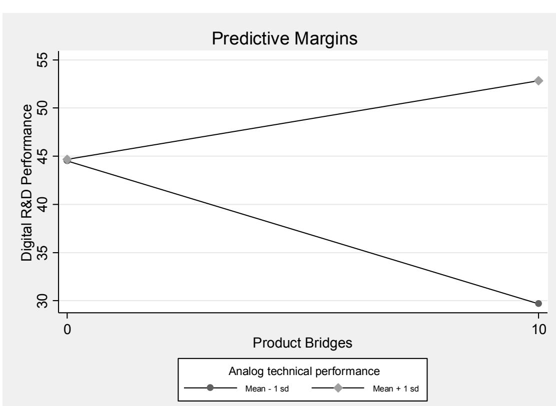


Figure 5: Hybrid Product Bridge x Analog Inventive Performance



Susan Cohen (susan.cohen@uga.edu) is an Assistant Professor in the Department of Management at the University of Georgia's Terry College of Business. She received her PhD from the Kenan-Flagler Business School at the University of North Carolina at Chapel Hill. Her research interests rest at the intersection of organizational learning, entrepreneurship and innovation.

Mary Tripsas (tripsas@bc.edu) is an associate professor of management and organizations at Boston College. She received her Ph.D from the MIT Sloan School of Management. Her research interests include technological innovation, nascent industries, entrepreneurship, and managerial cognition.