

CAPABILITY INTERACTIONS AND ADAPTATION TO DEMAND-SIDE CHANGE

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December 2019

Research summary. We examine how interactions among a firm's capabilities influence the extent and direction of firm adaptation under conditions of demand-side change. Our empirical context is the U.S. defense industry, within which we study firms receiving defense-related Small Business Innovation Research (SBIR) awards around September 11, 2001, an event which constituted an exogenous demand-side shock in which technology-related preferences of customers were reshuffled. We find that under demand-side change, pre-existing customer relationships have a double-edged effect: They facilitate "extension-based" adaptation when interacted with technology capabilities experiencing a decline in customer preferences, and they hinder "novelty-based" adaptation when interacted with technology capabilities experiencing an increase in such preferences. We also find that both types of technological capabilities together facilitate adaptation along the extension and novelty paths.

Managerial summary. Demand-side change, in which customer preferences for particular technologies are reshuffled, occurs in many industry settings. A deeper understanding of the factors shaping firm adaptation under this form of change can influence managers' decisions to implement strategies to plan for and react to such change. Using a sample of firms receiving defense-related Small Business Innovation Research (SBIR) awards around September 11, 2001, we show that the customer relationships a firm develops prior to demand-side change can have a double-edged effect on firm adaptation. Such relationships facilitate "extension-based" adaptation when combined with technology capabilities declining in customer preferences and hinder "novelty-based" adaptation when combined with technology capabilities increasing in customer preferences. In addition, the combination of the two technological capability types facilitates adaptation along both paths.

This is the author manuscript accepted for publication and has undergone full peer review but has not been through the copyediting, typesetting, pagination and proofreading process, which may lead to differences between this version and the Version of Record. Please cite this article as doi: [10.1002/smj.3137](https://doi.org/10.1002/smj.3137)

Keywords: Demand shock, adaptation, customer preferences, capabilities, SBIR

Running head: Capability interactions and adaptation to demand-side change

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INTRODUCTION

Why do firms differ in the extent and direction of their adaptation to external change? Change in a firm's external environment can stem from a diverse set of factors, such as new technologies, regulations, and customer preference shifts (Agarwal & Helfat, 2009; Christensen & Bower, 1996; Tripsas, 2008). Prior research gives us a deep understanding of adaptation in the context of technology-based change (Cattani, 2005; Cohen & Tripsas, 2018; Henderson & Clark, 1990; Tripsas, 1997; Tushman & Anderson, 1986). Yet demand-side change, in which customer preferences shift in the absence of immediate change in the firm's technological environment, is also an important source of external change (Di Stefano, Gambardella & Verona, 2012; Priem, Li & Carr, 2012). And while a growing stream of literature has begun to examine the salience of demand-side factors in firm strategy (Adner & Snow, 2010; Aggarwal & Wu, 2015; Ahuja, Lampert & Tandon, 2014; Rietveld & Eggers, 2018; Vergne & Depeyre, 2016; Ye, Priem & Alshwer, 2012), we have a more limited understanding of firm adaptation in demand-side change contexts.

In considering the factors that might lead to inter-firm variation in adaptation to demand-side change, it is helpful to begin by considering the extant explanations for variation in adaptation to *technology*-side change. Firm capabilities are an important class of explanations in this regard. Prior work contrasts upstream technological capabilities with downstream customer-related capabilities (Agarwal & Helfat, 2009; Helfat, 1997; Teece, 1986, 2007), showing that these two classes of capabilities independently and jointly explain variation in firm adaptation under technology-side change conditions (Danneels, 2002; Helfat & Lieberman, 2002; Nerkar & Roberts,

2004; Stieglitz & Heine, 2007; Wu, Wan & Levinthal, 2014).¹

Yet when shifting focus from technology-side to demand-side factors, a capabilities-based explanation of firm adaptation requires augmenting our conceptualization of technology capabilities. This is because demand-side change shifts the preference ordering of customers for particular technologies (Aggarwal & Wu, 2015; Priem *et al.*, 2012; Rietveld & Eggers, 2018; Tripsas, 2008; Ye *et al.*, 2012). While technology in the aggregate may remain unaffected following a demand shock, the *relative value* customers place on particular technological capabilities changes (Aggarwal & Wu, 2015; Priem *et al.*, 2012; Rietveld & Eggers, 2018; Tripsas, 2008; Ye *et al.*, 2012). Given this, we draw a conceptual distinction between what we call *preference-decreased technological capabilities*, which are those well-aligned with pre-shock demand conditions but that decline with respect to customer preferences post-shock; and *preference-increased technological capabilities*, which are those less preferred by customers before the shock but that gain with respect to customer preferences post-shock.

Armed with this conceptual bifurcation of technological capabilities, we then consider the moderating effect of downstream customer-related capabilities, as captured by the firm's propensity to engage in repeated customer relationships (Elfenbein & Zenger, 2013; Holloway & Parmigiani, 2016; Mawdsley & Somaya, 2018; Vanneste & Puranam, 2010). Customer capabilities arise from repeated interactions with "reliable and cooperative" partners that are "managed through relational governance" (Holloway & Parmigiani, 2016: 461). In our context of demand-side change, such

¹ We use the following interchangeably: upstream and technological capabilities; and downstream and customer-related capabilities.

capabilities stem from the firm's pre-shock relationships, which we argue may have different adaptation implications when considered in conjunction with the firm's technological capabilities.

Our empirical context is the U.S. defense industry, which experienced an unexpected demand-side shock as a result of the September 11, 2001 terrorist attacks (Aggarwal & Wu, 2015; Hoberg & Phillips, 2016; Tripsas, 2008; Vergne & Depeyre, 2016). The unexpected nature of the shock allows us to isolate the effects of firm capabilities on post-shock adaptation without the confounding effects that would occur if firms had prior knowledge of changes in customer preferences (Ito & Lee, 2005; Li & Tallman, 2011). We focus on the Small Business Innovation Research (SBIR) program of the U.S. Department of Defense (DoD). Unlike traditional federal R&D grants which focus on scientific discovery (e.g., the NIH and NSF), SBIR grants fulfill specific "customer needs." The DoD notes, for example, that "eligible projects must fulfill an R&D need identified by the DoD, and also have the potential to be developed into a product or service for commercial or defense markets."² SBIR grants are thus well-suited for examining the firm-level adaptation implications of changing (DoD) customer preferences.

We assemble a firm-year panel dataset of 5,226 firm-year observations on firms receiving SBIR grants between 1996 and 2006, from which we derive three core empirical results. The first two empirical results point to a double-edged effect of downstream customer capabilities. First, we find that for firms that hold preference-decreased technological capabilities, customer capabilities can be beneficial in that they *facilitate* post-demand shock adaptation occurring via an "extension-

² <http://www.acq.osd.mil/osbp/sbir/sb/program-descriptions.shtml>

based” path (i.e., a path of modifying and extending existing capabilities). Second, we find that for firms that hold preference-increased technological capabilities, these same customer capabilities *hinder* post-demand shock adaptation occurring via a “novelty-based” path (i.e., a path of pursuing completely novel products). Third, beyond these two results that highlight the double-edged effect of customer capabilities, we find that the interaction between preference-decreased and preference-increased technological capabilities facilitates post-demand shock adaptation via both the extension-based and novelty-based paths.

We conduct a series of additional analyses to deepen our insight into these patterns. First, we examine the temporal patterns of adaptation. We find that the moderating effect of customer-related capabilities is stronger in the short-run (versus the long-run) following a demand shock. At the same time, the adaptation benefits of the interaction among the two types of technological capabilities (preference-increased and preference-decreased) are stronger in the long-run. We interpret this as evidence that the adaptive effects of demand-side change may quickly dissipate as customers adapt to the new demand-side environment. Technology-driven effects, by contrast, may take longer to materialize. Second, we also examine several alternative formulations of our customer-related capabilities measure. These analyses provide evidence of the robustness of our measure, while also offering a more nuanced understanding of the link between capabilities and adaptation under demand-side change.

Taken together, our findings advance our understanding of how capabilities influence firm adaptation under conditions of demand-side change. While downstream customer capabilities have been viewed as “complementary assets” that can shape the adaptation trajectory of firms under

conditions of change (Teece, 1986, 2007), we point to their double-edged effect in shaping adaptation trajectories following a demand shock. Downstream customer capabilities help firms with preference-decreased technological capabilities adapt via extension, even though overall demand for these technological capabilities is declining; on the other hand, downstream customer capabilities hinder firms with preference-increased technological capabilities from adapting via a novelty-based path, even though overall demand for these technological capabilities is increasing.

Our findings on the interaction between preference-increased and preference-decreased technological capabilities also shed light on the divergent predictions with regard to firms holding both “old” and “new” technological capabilities. While some work suggests that hybrids (i.e., old and new together) may be beneficial (Furr & Snow, 2015; Katila & Ahuja, 2002; Nerkar, 2003) because familiarity and novelty complement one another (Rosenkopf & McGrath, 2011), other work suggests that hybrids can be detrimental because they skew firms’ trajectories in developing new technologies, thereby impeding adaptation (Tripsas & Gavetti, 2000; Wu *et al.*, 2014). Our results suggest that because there is no immediate technological change following a demand shock, the former perspective is more likely to hold in demand-side change settings.

THEORY AND HYPOTHESES

Paths of adaptation in the context of demand-side change

Firms often encounter external change as a result of customer preference shifts (Aggarwal & Wu, 2015; Priem, 2007; Priem *et al.*, 2012; Tripsas, 2008; Ye *et al.*, 2012), which create a need for firm adaptation (Adner, 2002; Adner & Zemsky, 2006; Ahuja *et al.*, 2014). Prior work suggests that

upstream (technology) and downstream (customer) capabilities can explain variation in adaptation to change more generally (Adner & Kapoor, 2010; Ethiraj *et al.*, 2005; Helfat & Lieberman, 2002; Moeen, 2017), with particular capability combinations facilitating market entry, and promoting product development and innovation (Danneels, 2002; Eggers, Grajek & Kretschmer, 2016; Moeen, 2017; Nerkar & Roberts, 2004; Stieglitz & Heine, 2007). We build on these insights to examine how the interaction between a firm’s upstream and downstream capabilities shapes the extent and direction of adaptation under demand-side change in particular. We characterize technological capabilities as preference-increased or preference-decreased (as discussed above), and we then examine how customer-related capabilities shape the link between these forms of technological capabilities and post-demand shock adaptation.

Adapting to demand-side change involves bringing the firm into closer alignment with extant demand conditions. This can occur via two distinct paths. First, a firm can develop completely novel products and technologies that are well-aligned with the new customer preferences (Adner & Snow, 2010; Ahuja *et al.*, 2014; Dosi, 1988; Rosenkopf & McGrath, 2011)—i.e., what we call a “novelty-based path.” Second, firms can modify and extend their *existing* technologies in a way that allows them to generate a better fit between their existing capabilities and the new demand environment (Adner & Snow, 2010; Ahuja *et al.*, 2014; Katila, 2002)—i.e., what we call an “extension-based path.” In both cases we conceptualize adaptation as an *outcome*, rather than as the level of effort or investment made by the firm to achieve this outcome.³

³ In our empirical specifications we do, however, control for factors that are reflective of firm investments in adaptation, such as patents and financial resources for R&D. Our central focus, however, remains on adaptation as an outcome, given our interest in

In the remainder of this section we develop a set of hypotheses regarding the determinants of firm adaptation along these two paths. For each path we first outline a baseline hypothesis with respect to technological capabilities before considering the interaction between technological and customer-related capabilities. The interaction represents our theoretical outcome of interest in each case. We also consider the interaction among the two types of technological capabilities.

Adaptation via the extension-based path

Baseline effect of preference-decreased technological capabilities

After an unexpected demand shock, firms with preference-decreased technological capabilities operate in a setting where demand for products associated with these technological capabilities is declining. Because preference-decreased capabilities fit poorly with the new demand environment, firms must ensure that their product offerings are modified so as to generate a better fit with the new demand conditions. For firms possessing preference-decreased technological capabilities, the extension-based path—modifying and extending existing technological capabilities—will be a particularly salient route for adaptation (Adner & Snow, 2010). While firms with such capabilities could feasibly pursue a novelty-based path by developing completely new products well-matched to the new demand conditions, such an approach would entail substantial risk (Schilling, 1998), high levels of investment (Dosi, 1988), and coordination costs (Ahuja *et al.*, 2014), as compared to repositioning and extending existing capabilities.⁴ Because of these challenges, firms with

observing firm-level performance.

⁴ This does not imply that these firms may not also pursue a novelty-based path in parallel; rather, we suggest that an extension-based path will be one important route for firm adaptation when holding preference-decreased capabilities. In Hypothesis 3b we examine the conditions under which such capabilities may facilitate novelty-based adaptation through their interaction with preference-increased capabilities.

preference-decreased technological capabilities would likely be inclined to pursue ongoing refinement and extension, and to engage in relatively more incremental change (Ethiraj, Ramasubbu & Krishnan, 2012).

Yet firms pursuing an extension-based path of adaptation are likely to be beset by significant challenges that arise from their preference-decreased technological capabilities. Overall demand for their products is declining, which results in a smaller overall customer base and limits the ability to access timely information on demand conditions. In addition, the need to coordinate between upstream, preference-decreased technological capabilities and the new demand environment causes frictions between “older” technologies and new demand opportunities, leading to production-level coordination challenges (Aggarwal & Wu, 2015). Additionally, firms may find it increasingly difficult to generate competence-based trust (Connelly *et al.*, 2018) as customers seek relationships with firms possessing capabilities that are better aligned with the new environment. These challenges lead to the following *baseline* hypothesis, which we will further examine below by considering the potential moderating effect of customer-related capabilities:

Hypothesis 1a (baseline). A higher level of preference-decreased technological capabilities will have a negative effect on extension-based post-demand shock adaptation.

Preference-decreased technological capabilities interacted with repeated customer proportion

A firm’s stock of customer-related capabilities is formed over time through its prior interactions with customers (Elfenbein & Zenger, 2013; Ethiraj *et al.*, 2005; Holloway & Parmigiani, 2016; Mawdsley & Somaya, 2018; Vanneste & Puranam, 2010). These prior interactions have components of breadth and depth. Deeper customer relationships are formed through repeated interactions with

the same customer, while a broader set of interactions stems from a larger overall number of distinct customers. We can capture these customer-related capabilities by measuring the firm's *repeated customer proportion*, which reflects the proportion of existing customers with which the firm has repeated relationships (prior to the shock) within the firm's overall portfolio of customers (Holloway & Parmigiani, 2016).⁵

We theorize that the relative depth of customer relationships, as captured by a higher proportion of repeated customers in the firm's customer portfolio, can mitigate the challenges of possessing preference-decreased technological capabilities when pursuing an extension-based adaptation path (as outlined in the baseline hypothesis H1a). One key challenge arises from access to timely information that can facilitate the firm's understanding of how existing technological capabilities might be extended. Effectively pursuing extension-based adaptation requires insight into how a fit between existing products and new customer preferences can be developed (Danneels, 2002; Eggers, 2012). Repeated customer relationships can provide the firm with a critical conduit for tacit information regarding customer requirements (Li & Calantone, 1998) and provide insights into the changes needed to address new market conditions (Cohen, Nelson & Walsh, 2002; Shah & Tripsas, 2007; Von Hippel, 1986).

A higher proportion of repeated customers can also enable firms to smooth the challenges of coordination and competence-based trust that arise under changing demand conditions (Holloway

⁵ In additional analyses (reported in the Supplementary Material), we deepen and unpack our understanding of the underlying mechanisms in our empirical results. We disentangle *repeated customer proportion* into its constituent components of depth and breadth, and also examine alternative formulations of depth (such as its degree), as well as whether the effects of depth stem from the overall portfolio or from its interaction with the specific customer in question.

& Parmigiani, 2016). Deeper relationships result in learning over time (Vanneste & Puranam, 2010), which can in turn engender the practical and tacit knowledge necessary to mitigate coordination and trust-based challenges. In addition, deeper relationships are likely to involve co-developed routines and relational capabilities (Dyer & Singh, 1998; Elfenbein & Zenger, 2013), as well as the dedicated personnel, equipment, and tools needed to engage in joint and coordinated action via shared problem-solving efforts (Heide & Miner, 1992; Zaheer & Venkatraman, 1995).

Taken together, the benefits of repeated customer relationships with respect to information, coordination and trust suggest that such relationships will be beneficial for firms pursuing an extension-based adaptation path. Whereas the baseline effect of preference-decreased technological capabilities may be negative, firms with a greater proportion of their customer portfolio centered on repeated relationships will likely be able to mitigate the challenges stemming from decreasing demand via greater extension-based adaptation. We thus hypothesize:

Hypothesis 1b. A higher proportion of repeated customers (i.e., deeper customer relationships) will positively moderate the effect of preference-decreased technological capabilities: the interaction will increase extension-based post-demand shock adaptation.

Adaptation via the novelty-based path

Baseline effect of preference-increased technological capabilities

After an unexpected demand shock, firms with preference-increased technological capabilities operate in a setting where demand for products associated with these technological capabilities is increasing. Expanding market demand makes it likely that firms with such technological capabilities will see adaptation-related benefits following a demand shock, as preference-increased

technological capabilities allow firms to tap into a growing customer base and to operate in an expanded combinatorial space of potential products. To realize the full potential of preference-increased technological capabilities, firm will pursue a “novelty-based path” of adaptation (e.g., Ahuja *et al.*, 2014; Rosenkopf & McGrath, 2011).⁶ Given that preference-increased technological capabilities are those that likely saw relatively limited usage and testing pre-shock, however, they would enter the post-demand shock environment with a high degree of uncertainty about the appropriate attributes of products that can employ these technologies (Katila, 2002; Rietveld & Eggers, 2018; Tripsas, 2008). In the face of such uncertainty, firms need to identify new product attributes and seek out customers with whom they can realize the full potential of their preference-increased technological capabilities. Preference-increased technological capabilities thus provide the foundational raw material upon which firms can expand into new product areas once a customer preference shift has occurred. We thus have the following *baseline* hypothesis, which we will further examine below by considering the potential moderating effect of customer-related capabilities.

Hypothesis 2a (baseline). A higher level of preference-increased technological capabilities will have a positive effect on novelty-based post-demand shock adaptation.

Preference-increased technological capabilities interacted with repeated customer proportion

The implications of having a portfolio of existing customers with a higher proportion of repeated relationships is likely to be different for firms following a novelty-based path of adaptation as

⁶ This does not imply that these firms may not also pursue an extension-based path in parallel; rather, we suggest that a novelty-based path will be one important route for firm adaptation when holding preference-increased capabilities. In Hypothesis 3a we examine the conditions under which such capabilities may facilitate extension-based adaptation through their interaction with preference-decreased capabilities.

compared to those following an extension-based path. Following a novelty-based path requires ongoing experimentation, together with the ability to obtain insights needed to enter new application areas (Danneels & Sethi, 2011; Rosenkopf & McGrath, 2011). When pursuing novelty-based adaptation by leveraging preference-increased technological capabilities, firms must identify customer needs and obtain information beyond their existing base of knowledge. When a larger proportion of their existing customer portfolio involves repeated relationships, a firm may be stymied in its ability to obtain this new knowledge and insight, hindering its ability to pursue novelty-based adaptation.

A higher proportion of repeated customers in a firm's customer portfolio could limit its ability to conduct trial-and-error experiments. This is because the focus on a well-established customer base (Christensen & Bower, 1996) often leads to local search, limiting the opportunity for the firm to fully realize the usefulness of new technologies (March, 1991; Sorenson, 2000). Moreover, many of the critical insights that arise through processes of experimentation can only be realized through interactions with customers with whom the firm is less embedded (Nerkar & Roberts, 2004), because established routines inhibit firms' willingness and ability to experiment (Li *et al.*, 2006). Repeated relationships cause firms to "ignore technically superior options since they do not want to change and make new investments" (Holloway & Parmigiani, 2016: 464), with prior investments in equipment, personnel and processes creating disincentives for change (Anderson & Jap, 2005). A greater frequency of repeated interactions would, furthermore, increase the structural embeddedness of the relationship (Elfenbein & Zenger, 2017; Uzzi, 1997), restricting access to alternative information and partners (Jones, Hesterly & Borgatti, 1997).

By contrast, firms following a novelty-based adaptation path are likely to benefit from a portfolio of prior customer relationships that is broader rather than deeper (i.e., a lower proportion of repeated customers). This is because a key precondition for effective novelty-based adaptation is the ability to experiment. A more heterogeneous customer base allows for a greater range of ongoing experimentation in a given technological domain (Nerkar & Roberts, 2004; Sorenson, 2000). With a broader customer base, the firm's overall knowledge pool is enhanced with more distinctive variation, providing the input and ideas necessary to experiment, recombine, and test new demand-related hypotheses related to more novel products (Katila & Ahuja, 2002; Leiponen & Helfat, 2010). A customer portfolio with a broader set of relationships thus allows firms to gain more substantive insights into new areas of demand, which would then aid in identifying application areas that leverage preference-increased technological capabilities in ways novel to the firm (and industry). We thus hypothesize:

Hypothesis 2b. A higher proportion of repeated customers (i.e., deeper customer relationships) will negatively moderate the effect of preference-increased technological capabilities: the interaction will decrease novelty-based post-demand shock adaptation.

Adaptation implications of interaction among upstream technological capabilities

Whereas the prior two pairs of hypotheses focused on how repeated customer relationships shape firm adaptation as a function of the interaction with preference-decreased or preference-increased technological capabilities, in a final set of hypotheses we consider the *joint* implications of preference-decreased and preference-increased technological capabilities. In particular, we seek to understand whether there are potential complementarities among these technological capabilities

with respect to the two paths of adaptation (extension-based and novelty-based).

We propose that the interaction between preference-decreased and preference-increased technological capabilities has positive benefits for extension-based adaptation. These benefits arise because holding capabilities related to new and emerging technologies can allow firms with older technologies to gain information about new demand conditions, and to identify alternative applications and markets for existing technologies (Cattani, 2005; Nerkar, 2003). Combining old and new technological capabilities has important learning benefits that facilitate firm adaptation: firms can learn about supply-side considerations such as technology and production, gain a better handle on customer preferences, and deepen their understanding of market timing (Furr & Snow, 2015; Helfat & Eisenhardt, 2004). This will smooth the ability to add new components and features to existing offerings in a way that allows firms to extend the life of products based on existing (preference-decreased) technological capabilities. Firms seeking to extend preference-decreased technological capabilities will thus be better positioned to do so when they also hold preference-increased technological capabilities. Thus, we hypothesize:

Hypothesis 3a. The interaction of preference-decreased and preference-increased technological capabilities will increase extension-based post-demand shock adaptation.

We also propose that the interaction of preference-increased and preference-decreased technological capabilities can help firms move beyond extension-based adaptation and, in addition, pursue novelty-based adaptation. Preference-decreased technological capabilities can serve as a springboard on which firms can find novel applications and customers for preference-increased technological capabilities. To identify novel application domains, firms need to engage in effective

experimentation, which can benefit from having a deeper understanding of the over-arching industry roadmap (Katila & Ahuja, 2002; Nerkar, 2003). Because preference-increased technological capabilities (by definition) have undergone relatively less market testing as compared to preference-decreased technological capabilities, they would benefit from a reliable and legitimate baseline resource through which novelty-based adaptation can occur (Furr & Snow, 2015; Katila, 2002; Rosenkopf & McGrath, 2011). Preference-decreased technological capabilities can function as such a baseline resource because even though they suffer from a demand decline they were extensively used before the demand shock and are therefore familiar to customers. In other words, preference-decreased technological capabilities can offer a stepping-stone from which firms can experiment with preference-increased technological capabilities, move beyond simple extensions, and offer novel products based on preference-increased technological capabilities.⁷ Thus, we propose:

Hypothesis 3b. The interaction of preference-decreased and preference-increased technological capabilities will increase novelty-based post-demand shock adaptation.

In Figure 1 we summarize the above discussion, illustrating our theory regarding how a firm's upstream and downstream capabilities interact to influence post-demand shock adaptation.

[Insert Figure 1 here]

⁷ As an example, growing post-demand shock interest in a technology such as unmanned aerial vehicles (UAVs) would benefit from preference-decreased technological capabilities such as optical and microwave systems by providing a valuable product that supports the further growth of UAVs into other novel applications and markets as standalone offerings or combined with other novel components. In settings such as this example, the combination of preference-decreased technological capabilities such as optical and microwave systems with preference-increased technological capabilities like UAVs would be extension-based adaptation, while the further growth of UAVs as a standalone offering or in combination with other novel components in novel applications would be novelty-based adaptation.

RESEARCH CONTEXT

The Small Business Innovation Research (SBIR) program

Our empirical context is the SBIR program in the U.S., which provides small businesses with early-stage support to engage in the development of high-risk technologies with commercial promise. DoD agencies procure new technologies and products from SBIR awardees by funding early-stage R&D projects that serve a DoD need, and that have the potential for eventual commercialization and adoption in military markets. Unlike traditional federal R&D grants that focus on purely scientific discovery (e.g., the NIH and NSF), the DoD's SBIR grants aim to fulfill specific "customer needs" by the military. There are 10 DoD agencies that award SBIR grants. These agencies can be conceptualized as customers of the focal firms in our sample (the SBIR awardees).

The SBIR program is a multi-stage process. Firms first apply for a six- to nine-month long Phase 1 award with an initial (but specific) proposal that is ultimately granted on the basis of firms' existing technological capabilities and understanding of customer needs. This phase allows firms and the DoD to "determine the scientific and technical merit and feasibility of an idea" to meet particular DoD customer needs by engaging in a set of initial product development activities. Winning a Phase 1 award thus suggests that firms hold (and will further develop over the course of the Phase 1) particular technological capabilities. Phase 2 is then conditional on product development success in Phase 1 and is aimed at continued product development in advance of commercialization. Further development beyond Phase 2 involves additional resources and other partnerships with the private sector or non-SBIR government sources.

The defense industry demand shock of September 11, 2001

The events of September 11, 2001 constituted an exogenous demand-side shock to the U.S. defense industry (Aggarwal & Wu, 2015; Ito & Lee, 2005, Li & Tallman, 2011; Tripsas, 2008; Vergne & Depeyre, 2016). September 11 caused the U.S. defense industry to move away from a Cold War mindset to one in which security and counter-terrorism concerns were much more salient. As a result, there was an aggregate increase in demand, together with a sudden shift in customer preferences such that the nature and composition of technologies demanded by customers shifted markedly (Aggarwal & Wu, 2015; Tripsas, 2008).

We illustrate the implications of the September 11 demand shock in Figure 2. Panel A shows the aggregate level of demand over the period 1986-2006 as captured by the number of SBIR awards from the DoD (together with a trendline).⁸ While the average growth rate from 1996 to 2000 was 3.7%, the growth rate from 2001 to 2002 was 30.6%, reflecting the spike in overall demand around this period. Yet, while aggregate demand growth is an important feature of the shock, a more important feature is the reshuffling of customer preferences that resulted (e.g., Tripsas, 2008).

In Panel B of Figure 2 we examine how the composition of demand changed over time in order to illustrate the reshuffling of customer preferences around the shock. We rely on demand “keywords” identified from SBIR award abstracts, as described in the section below (“Customer preference shifts”). We start with 1996, as that is the first year of our data, and we rank keywords based on whether they are in a slow-growth or a fast-growth quartile in 1996. Keeping these

⁸ Data source: <https://www.sbir.gov/analytics-dashboard>

keyword quartile definitions constant over subsequent years (in order to examine the timing of when a demand change occurs), we then plot the ratio of slow-growth 1996 keywords to fast-growth 1996 keywords over the 1996-2006 period. As the graph shows, there is a significant spike around 2001, suggesting that the most marked change in industry-wide demand composition was during that year.

[Insert Figure 2 here]

To further validate our conceptualization of September 11, 2001 as a demand shock not only for the defense industry in general, but for the SBIR program in particular, we collected data on the evolution of agency budgets and SBIR solicitations before and after September 11. We provide details of these analyses in the Supplementary Material. The analyses show that following 2001 there was a significant reshuffling among the various DoD agencies with respect to SBIR funding budgets, the number of Phase 1s awarded, and SBIR topic solicitation (i.e., technology) areas. The most significant change occurred around the time of the 2001 shock, with significant variation across agencies with respect to the magnitude of funding shifts. For example, while funding for Navy awards increased by 26%, funding for awards from the agency dealing with Chemical and Biological Defense increased by 62%.

The solicitations data we report in the Supplementary Material also shows patterns that are consistent with the demand shock effects reported in Figure 2 Panel B, as described above. Specifically, the pattern depicting the demand shift from old to new areas as illustrated in that figure is preserved when using SBIR topic solicitations (as opposed to award keywords). In addition, certain areas associated with what were clearly post-September 11 issues (such as terrorism) saw a large increase following the shock. For example, “sensors” increased by 7x, and “UAV” (i.e.,

drones) by 5x in the two years following September 11.

The SBIR program as a research context: evidence from field interviews

In order to better understand the degree to which our choice of the SBIR program as an empirical context fits with our theoretical objective of examining adaptation in the context of a demand-side change, we conducted a series of 19 in-depth field interviews with individuals involved in the SBIR program. Interviews included individuals making SBIR awards as well as SBIR awardees.⁹ The interviews were open-ended and covered a broad range of topics, with a particular emphasis on understanding two key issues: (a) the degree to which the September 11 shock may have had a significant—and near-term—effect on demand composition; and (b) the extent to which firms advance their technological capabilities over the course of a Phase 1 SBIR award.

With regard to the effects of the 2001 demand shock, our interviews suggested that the shock had an effect on demand composition, and moreover, given the leading-edge nature of SBIR solicitations, such demand-side change effects were likely to be reflected in topic solicitations relatively quickly. Interviewees pointed to the SBIR program as means for the DoD to keep abreast of new technologies and trends that may be of use in the future. This involves investing in new trends so as to be prepared for future adoption when needed. After September 11, there was, as multiple interviewees noted, a rapid shift in mindset and topical keywords used. As one interviewee pointed out, “the topics of the solicitations change three times a year, some of them once a year.”

⁹ Interviews ranged in length from around 25 minutes to 1 hour, and all were recorded and transcribed (resulting in 186 pages of transcribed notes), allowing us to clarify the issues of (a) the effects of the 2001 shock, and (b) the degree to which a firm’s stock of Phase 1 awards can serve as a proxy for its technological capabilities.

The impact of September 11 was that the DoD, as another interviewee put it, “started to see that [their] tools and tactics were ineffective” because “September 11 altered the fundamental national defense strategy.” This also led to funding getting “rerouted,” with some funding areas becoming more important than others. In sum, the interviews provided support for the idea that there was a significant (and relatively rapid) change in topic solicitations, as discussed above.

With regard to the use of Phase 1 awards as a proxy for a firm’s technological capabilities, the collective evidence from the interviews supports the idea that SBIR awardees are able to significantly advance the firm’s “performance yardsticks” as pertain to “technical fitness” (Helfat *et al.*, 2009). In other words, over the course of a Phase 1 award, SBIR awardees significantly move the needle with regard to their technological capabilities. Although Phase 1 grants are meant as a proof-of-concept, firms do make significant progress in their ability to understand and produce products that meet particular DoD customer needs. This progression in technological capability need not be “revolutionary” as one interviewee put it—rather, “it could be an evolutionary breakthrough” that involves stitching together “existing technologies in some novel way to create a new evolutionary technological application.”

The extent of progress in a firm’s technological capabilities can be crystalized quantitatively in what the DoD calls its “technology readiness level (TRL).”¹⁰ Individuals we interviewed pointed to substantial movement along the technology readiness level scale. As one interviewee noted, “SBIR funding doesn’t build a carrier, it doesn’t build a ship, but it can certainly provide a better

¹⁰ The following document describes the DoD TRL scale: <https://www.army.mil/e2/c/downloads/404585.pdf>

algorithm, a different coding, a lighter structure” which can take you up to a TRL level 4. An interviewee noted that “it was an [SBIR] Phase 1 [where] we went from a [TRL] level 1 to basically a level 8.” In sum, while the end-product of a Phase 1 award is still pre-commercialization, after a Phase 1 is complete firms have generally made significant process along the technology readiness level scale.¹¹

DATA AND METHODS

Sample construction

Our sample is the universe of all firms receiving an SBIR award from the DoD between 1996 and 2006, for which we obtain data from the U.S. Small Business Administration. Each year, the various defense agencies (i.e., customers) within the DoD issue SBIR solicitations on a variety of topics describing their product needs, inviting small businesses to submit proposals. Phase 1 awards serve as a clear and direct indicator of firm responses to customer needs based on their existing technological capabilities and customer know-how. Phase 1 awards are thus consistent with our central theoretical goal of understanding how firms adapt in the context of unexpectedly changing customer needs (versus continued commercialization in subsequent stages of the SBIR process). Our dataset contains 14,596 Phase 1 awards granted between 1996 and 2006.¹²

¹¹ To further validate the role of Phase 1 as leading to technological capabilities, we examined the patents associated with Phase 1 SBIR grants (exploiting United States Code Title 35 202(c)(6) which requires reporting links between SBIR grants and patents under shared IPR). We find that the firms in our sample produced 372 patents under shared IPR with the DoD: 173 from Phase 1 (across 106 awards) and 199 from Phase 2 (across 104 awards). Thus, the ability to “produce” patents is similar between Phase 1 and 2.

¹² Consistent with our empirical context and conceptual focus as described above, we confine our attention to Phase 1 awards. These allow us to capture a firm’s pre-shock capabilities, as Phase 1 awards result in a series of actions related to technological capability development. Phase 1 awards are consistent with our theoretical objective of understanding the immediate post-shock paths of adaptation. Award criteria of Phase 1 are mainly driven by technological capabilities, together with DoD and defense customer needs. Phase 2 on the other hand is largely a step toward commercialization in the private sector, and thus constitutes a theoretical outcome

We supplement SBIR data with patent data from the NBER patent database, matching by firm name, location and principal investigator to ensure accuracy. Patent data allows us to control for R&D activity and investments, which are generally unavailable for private firms using other metrics. We match 7,100 awards from 1,125 firms using this process.¹³ We select as our sample of firms those “incumbents” that have been awarded at least one Phase 1 award in the pre-shock period (1996 through 2000).¹⁴ We aggregate variables to the firm-year level, with the final sample containing 533 firms and 5,226 firm-year observations (between 1996 and 2006).

Customer preference shifts

We use SBIR award abstracts to capture customer preference shifts based on text analysis and topic modeling using the NVivo and Mallet software packages. We follow the standard approach to text analysis and topic modeling used in prior work in strategy, economics and management (Ansari, Garud & Kumaraswamy, 2016; Bache, Newman & Smyth, 2013; Hoberg & Phillips, 2016; Kaplan & Vakili, 2015; Ndofor, Sirmon & He, 2011; Pehlivan, Sarican & Berthon, 2011).

We begin with the 14,596 Phase 1 abstracts, dividing these into pre-shock and post-shock groups (based on award date). From the abstracts we generate two lists (a pre-shock period list and a post-shock period list) of the 1,000 most frequently mentioned keywords in each period using

of interest beyond our scope. In our empirical specifications, however, we do control for the ratio of Phase 1 awards that result in Phase 2 awards during the pre-shock period.

¹³ We use the data sample conditioned on firms with patents for the following reasons: first, doing so allows us to use various controls from the patent data to capture characteristics such as patent count and patent diversity; second, the patent data also allows us to more precisely track industry technological shifts over time by comparing the occurrence of various patent classes before and after the shock; third, the patent sample gives us a high-tech, R&D-intensive firm list, enabling a more homogenous sample. For firms that never patented in the pre-shock period, the firms may not be technology-driven, representing a qualitatively different type of firm.

¹⁴ We use 1996-2000 as the pre-shock period, and 2002-2006 as the post-shock period, excluding awards granted in 2001 to ensure cleanly identified pre- and post-shock samples.

NVivo. Occurrences of these words represent major clusters of demand in each period. To identify the candidate word list for increasing- and decreasing-demand words, we then calculate the normalized word frequency, defined as the number of instances of a word divided by the total word count in all award abstracts before and after the shock (Eggers & Kaplan, 2009). We expect that, for increasing-demand words, the normalized word frequency after the shock will be higher than before the shock (we use a 30% threshold—i.e., post-shock is 30% higher than pre-shock).¹⁵ By contrast, for decreasing-demand words, the normalized word frequency after the shock will be lower than before the shock (we also use a 30% threshold—i.e., post-shock is 30% lower than pre-shock). The end result is 115 increasing-demand words and 124 decreasing-demand words (“List A”).

To confirm that the keywords we use map to technologies used by DoD customers, we apply the Latent Dirichlet Allocation algorithm for topic modeling to award abstracts using MALLET. This algorithm infers topics from a set of documents (in our case, award abstracts) as collections of words that appear together frequently. With this approach, categories are not defined *ex ante*; rather they are allowed to emerge from the underlying text data. As Kaplan and Vakili (2015: 1441) note, this “allows the researcher to uncover automatically themes that are latent in a collection of documents and to identify which composition of themes best accounts for each document.” With this method we obtain 100 keywords across 10 topics (“List B”).¹⁶ The intersection of List A and List B results in a final list of 51 keywords: 26 words for increasing-demand and 25 words for decreasing-demand (see Supplementary Material for details).

¹⁵ We conducted sensitivity analyses using alternate threshold values of 20% and 40%, finding consistent results.

¹⁶ The 10 topics are aircraft, automation, battery, engine, health, material, network, optics, power, and radio.

Identification strategy

Our identification strategy employs fixed-effects OLS models to capture the within-firm percent change in awards before and after the 2001 demand shock.¹⁷ This approach parallels that used in Aggarwal and Wu (2015) and Li and Tallman (2011), where the authors examine the impact of pre-shock characteristics on within-firm performance change. Our specification follows the difference-in-differences estimation strategy employed for individual-level panel data as described by Imbens and Wooldridge (2007): $\ln y_{it} = \beta_0 + \beta_1 D_t x_i + f_i + \gamma_t + \theta_{it}$.¹⁸ In this specification, the outcome variable y_{it} captures the time-varying performance of a given firm across the entire sample period as captured by either *extension-based awards* or *novelty-based awards* (see the Dependent Variables section below for details). We use the natural log transformation of the outcome variable to capture the within-firm percentage change from the pre- to the post-shock period in either extension-based or novelty-based awards, in accordance with our theoretical objective of capturing post-shock adaptation performance of two different types.¹⁹

The *post-shock dummy* D_t takes on a value of 1 from 2002 to 2006, and 0 from 1996 to 2000. Because the shock occurred in 2001, we exclude this year from our sample. The interactions between the post-shock dummy, D_t , and our main independent variables as contained within the vector x_i thus constitute our core theoretical effects of interest. This approach follows Greene (2002): by log transforming the yearly number awards, we capture the within-firm percent change in awards as a

¹⁷ The Hausman test rejects the random effects model (DF=11, m-value=264, p<0.01).

¹⁸ See in particular equation 4.5 of Imbens and Wooldridge (2007: 8).

¹⁹ We conducted a robustness check using the 1996-97 window to construct our IVs, in line the methodological approach used in Duchin *et al.* (2010). Specifically, we used data from 1996-97 to construct the IV, and then compared the three-year windows before and after 2001, 1998-2000 and 2002-2004. Our results, available upon request, remain robust to this alternative construction.

function of various firm characteristics from before to after the demand shock.²⁰ Pre-shock characteristics (the vector \mathbf{x}_i) include both the main variables, as well as the control variables, and are measured by pooling awards over the pre-shock five-year period (see the Independent Variables section below.)²¹ For example, to measure pre-shock *preference-decreased technological capabilities*, we pool all award abstracts in the five-year period of 1996 to 2000 and count the number of associated words in these abstracts. This ensures that pre-shock characteristics represent a stock immediately before 2001.²² Since these pre-shock characteristics are time-invariant, their main effects will be dropped in fixed effects models. By contrast, their interaction with the post-shock dummy is time-varying and can capture the impact of heterogeneous pre-shock characteristics on post-shock adaptation (Greene, 2002; Greve & Goldeng, 2004).

Prior work supports this methodological approach of using OLS as opposed to GLM count models under certain conditions—namely, when skewness in the underlying data exceeds a certain level. Manning and Mullahy (2001) show that when skewness is above 3, the precision of estimates is better for OLS models than for count models. Such a loss of precision in count models is even more substantial when skewness is above 7 and can lead to overfitting. Thus, employing OLS on log-transformed values of the DV (e.g., per Wooldridge, 2006) reduces Type 1 errors and achieves

²⁰ We employ the semi-log specification as discussed in Greene (2002: 123): when the dependent variable $\ln(y)$ is a natural log and the independent variable x is left unlogged, the coefficient on the (unlogged) independent variable is interpreted as the semi-elasticity of that independent variable.

²¹ We use Phase 1 awards to construct our independent variable of pre-shock technological capabilities. In unreported results we examine the construction of this variable using Phase 2 awards, with the results consistent with our main findings (i.e., robust support for H1, H2, and H3). Because Phase 1 is a stronger fit with our current theoretical objectives (Phase 2 would involve two layers of selection—first a selection into Phase 1, and then another selection into Phase 2), we use Phase 1 in our main analyses.

²² This approach ensures that pre-shock characteristics do not fluctuate from year-to-year, consistent with the idea of capabilities accumulated based on “a repetitive pattern of activity” (Nelson & Winter, 1982: 97).

greater precision than models such as Poisson and negative binomial. Note that in our case, skewness=7. In line with this approach, in a recent article, Choudhury and Kim (2019) use OLS on the log-transformed values of a count variable. We follow their overall methodological strategy in this regard and, like them, also run robustness checks using a fixed effects negative binomial model. We find that the negative binomial results are consistent with the log transformed OLS approach.²³

Dependent variables

Extension-based and novelty-based awards. To capture the two different directions of adaptation in our theory, we construct two dependent variables that capture the performance change pre- to post-shock with respect to the two adaptation paths. To do so we partition the SBIR award count in each firm-year into two separate categories: extension-based awards, in which the award abstract contains at least one decreasing-demand and one increasing-demand word; and novelty-based awards, in which the award abstract contains at least one increasing-demand word but no decreasing-demand words.^{24,25} The mean of the (non-logged) *extension-based awards* variable is 0.32, with a standard deviation of 1.10 and a range of 0 to 25. The mean of the (non-logged) *novelty-based awards* variable is 0.15, with a standard deviation of 0.75 and a range of 0 to 16.

Main independent variables

²³ One additional benefit of OLS is that it allows for a direct interpretation of the interaction effects (in our case, the explanatory variable * post-shock dummy) as the percent change in the DV. This is consistent with our theoretical focus on adaptation: the pre- to post-shock percent change in the outcome variable. If using fixed effects Poisson or negative binomial, we could run into the issue of non-linear estimators not capturing the true marginal effects (Hoetker, 2007; Zelner, 2009).

²⁴ This conceptualization is in line with previous literature on incremental (both old and new) vs. radical (completely new) innovation (Dewar & Dutton, 1986; Eggers & Kaul, 2018; Nagarajan & Mitchell, 1998). We ran robustness checks on alternative threshold ratios for constructing extension-based award count (e.g., both decreasing-demand words and increasing-demand words ≥ 2) and novelty-based award count (e.g., number of increasing-demand words ≥ 2), obtaining consistent results.

²⁵ As discussed above (see the Identification Strategy section), to measure adaptation (whether extension-based or novelty-based), we take the natural log of one plus the raw number of each count, which allows us to estimate the effect on the percentage change in SBIR award count of each of the two adaptation types for the same firm before and after the shock.

Our main independent variables concern the degree to which a firm's pre-shock technological capabilities align (or not) with post-shock demand conditions.²⁶ In contrast with the dependent variables, which capture the "flow," or change in adaptation in response to an unexpected demand change, the main independent variables capture a firm's capability "stock" *prior* to the demand shock, consistent with the idea of a firm's cumulative experience serving as evidence of capability development (Dierickx & Cool, 1989; Helfat, 1997; Winter, 1987). The main independent variables, *preference-decreased technological capabilities*, and *preference-increased technological capabilities* pool award abstracts over the five-year pre-shock period (1996-2000). *Preference-decreased technological capabilities* is constructed by using pre-shock decreasing-demand word count for each firm, normalized by the total number of words within abstracts for the same firm (Eggers & Kaplan, 2009; Helfat, 1997); and *preference-increased technological capabilities* is constructed analogously, using pre-shock increasing-demand word count instead.

Moderating variable

The moderating variable, *repeated customer proportion*, captures the relative depth of relationships with all existing customers. It is measured at the portfolio level across all DoD agencies (i.e., customers) granting SBIR awards. This measure parsimoniously captures the number of agencies that have granted more than one award to the focal firm, divided by the total number of agencies

²⁶Our measure of preference-increased and preference-decreased technological capabilities relates to those characteristics of a firm's technological capabilities that are affected by the demand-side shock, consistent with our identification strategy. These capabilities are naturally more product-focused given that they are associated with pre-shock DoD awards, which are focused on the initial stages of product development. In our empirical specifications we aim to control for other aspects of a firm's technological capabilities that may lie even further upstream (e.g., the firm's patent-based inventive capabilities, which we capture through a variety of controls) as well as capabilities that may influence its commercialization potential (e.g., the ability to convert Phase 1 awards into Phase 2 awards).

that have granted awards to the focal firm (Holloway & Parmigiani, 2016). In essence, the numerator reflects the depth of repeated relationships with existing customers, while the denominator captures the breadth of relationships with all existing customers who have at least one tie with the firm. Thus, the value of this repeated customer proportion variable ranges from 0 to 1.²⁷ For example, if a firm received awards from 5 different agencies during the pre-shock period, and 2 of the 5 agencies awarded the firm more than once, the repeated customer count would be 2, and the total customer count would be 5. Thus, the repeated customer proportion would be $2/5=0.4$. This operationalization is well-suited for our empirical context because the tradeoff between the pros (e.g., trust) and cons (e.g., lack of flexibility) of repeated relationships may be influenced by both the breadth and depth of the firm's portfolio of customer relationships.²⁸

Control variables

We construct a set of control variables at the award and firm levels. A first set of variables deals with characteristics of the firm's pre-shock awards. *Pre-shock total financial amount* captures the total dollar amount of all pre-shock SBIR awards (in \$100,000), thus serving as a proxy for the firm's pre-shock financial resources for R&D. *Pre-shock last award year before shock* captures the number of years elapsed between the last year a firm received an SBIR award before the shock, and the shock year of 2001, thus accounting for the recency of the firm's customer capabilities. *Pre-*

²⁷ In analyses reported in the Supplementary Material, we separate these two measures and re-run the model, obtaining consistent results.

²⁸ Our measure of repeated customer proportion has a mean value of 0.27. To understand this variable better, we can unpack summary statistics of its components. Within a firm's pre-shock customer portfolio, conditional on having repeated customers, the average number of ties with repeated customers is 6 (minimum of 2, maximum of 87). The average number of unique repeated customers is 0.7 (minimum of 0, maximum of 7), and the average number of unique total customers is 1.9 (minimum of 1, maximum of 8). These values suggest that deep and repeated interactions with particular customers are likely to occur in our sample, allowing for the development of customer-related capabilities.

shock last year awards captures the total number of awards in the last award year before the shock (we use the natural log transformation, similar to the way in which we construct the dependent variable). And *pre-shock customer count* captures the total number of unique customers of the focal firm in the pre-shock period.

We also control for various characteristics of the firm's pre-shock patents. *Pre-shock patent count* captures the total number of patents before the shock, thus serving as a proxy for a firm's inventive ability (Jaffe & Trajtenberg, 2002). *Pre-shock hot patent ratio* captures the percent of patents in the pre-shock period that are in patent classes that increased by over 30% following the shock. *Pre-shock cold patent ratio* captures the percent of patents in the pre-shock period that are in patent classes that decreased by over 30% following the shock. *Pre-shock patent diversity* captures the diversity of patent classes of the firm's patent portfolio in the pre-shock period based on the 1-Herfindahl index.²⁹ And *pre-shock patent co-assignee count* captures the number of unique patent co-assignees in the pre-shock period.

Finally, we also include controls for alliance characteristics and the firm's Phase 2 awards. *Pre-shock alliance count*, sourced from SDC Platinum, captures the number of unique alliances in which the firm has engaged in the pre-shock period. Both the co-assignee count and the alliance count are used to control for a firm's technological capabilities sourced from external partners, outside of its internal technological capabilities. And *pre-shock successful Phase 1 award ratio* captures the proportion of Phase 1 awards that result in Phase 2 award success in the pre-shock

²⁹ It is important to note that patent count and patent diversity control for firm-level technological capabilities, whereas the hot and cold patent ratios reflect the industry's overall technological trends with respect to patent classes.

period, thus accounting for variation in a firm’s commercialization capabilities. In addition, we include *firm and year dummies* in all specifications to capture firm and year fixed effects (Choudhury & Kim, 2019).

EMPIRICAL RESULTS

Descriptive statistics

We report descriptive statistics in Table 1. The maximum VIF value in all models is 2.81, suggesting that multicollinearity is not a concern.

[Insert Table 1 here]

As noted previously, we employ fixed effects OLS models to test our hypotheses regarding the two directions of adaptation (extension-based and novelty-based). All pre-shock characteristics are interacted with the post-shock dummy to identify their effects in the post-shock period.³⁰ An F-test shows that all specifications are significant overall ($p = 0.000$). As noted previously, our dependent variable and model specification together allow us to estimate the adaptation measures (of the two different types, extension and novelty) as the within-firm percent change in the respective award count pre- to post-shock.

Extension-based adaptation

To test the extension-based mechanisms (H1a, H1b, and H3a), we rely on logged extension-based

³⁰ For a more concise discussion of our results, because the post-shock dummy is interacted with *all* right-hand side variables (per our identification strategy above), when referring to a particular coefficient we simply name the main variable(s) of interest, omitting mention of the post-shock dummy, as it is understood that each of the right-hand side variables is interacted with this dummy. As an example, when we say, “the coefficient on the interaction between preference-decreased technological capabilities and repeated customers,” we are referring to the coefficient on the interaction between preference-decreased technological capabilities, repeated customers, *and* the post-shock dummy.

awards as the dependent variable from Model 2-1 through Model 2-4 in Table 2. The results are consistent across the various specifications through 2-4. In Model 2-1, we find support for H1a, which suggests that firms possessing preference-decreased technological capabilities will have lower post-shock extension-based adaptation ($\beta = -0.667, p=0.000$).³¹

Turning to our test of H1b on extension-based adaptation, the key variable of interest is the interaction between preference-decreased technological capabilities and repeated customer proportion. Because the results are consistent between the partial models and fully specified model (2-4), we confine our discussion of the results to Model 2-4. H1b suggests that a firm's repeated customer proportion will facilitate extension-based adaptation for firms possessing preference-decreased technological capabilities. In Model 2-4, we find a significant and positive interaction effect between preference-decreased technological capabilities and repeated customer proportion ($\beta = 1.552, p=0.003$), strongly supporting H1b. H3a states that the interaction between preference-decreased and preference-increased technological capabilities will facilitate extension-based adaptation post-demand shock. In Model 2-4, we find a significant and positive interaction effect on this interaction ($\beta = 1.613, p = 0.000$), strongly supporting H3a.

[Insert Table 2 here]

Novelty-based adaptation

To test the novelty-based mechanisms and hypotheses (H2a, H2b, and H3b), we rely on logged novelty-based awards as the dependent variable in Models 3-1 through 3-4 in Table 3. The layout

³¹ We find consistent results using as our DV the share of extension-based awards relative to total awards.

of these models is analogous to Models 2-1 through Model 2-4 in Table 2. In Model 3-1, we see that firms possessing preference-increased technological capabilities have higher post-shock novelty-based adaptation ($\beta = 0.403$, $p=0.013$), supporting H2a. H2b states that repeated customer relationships will impede post-shock novelty-based adaptation for firms possessing preference-increased technological capabilities. In Model 3-4, we find a significant and negative interaction effect between preference-increased technological capabilities and repeated customer proportion ($\beta = -1.362$, $p=0.005$), strongly supporting H2b. H3b states that the interaction between preference-decreased and preference-increased technological capabilities will facilitate novelty-based adaptation. In Model 3-4, we find a significant and positive interaction effect on this interaction ($\beta = 1.720$, $p=0.000$), strongly supporting H3b.

[Insert Table 3 here]

Magnitude of effects

To gain further insight into H1b and H2b, in Figure 3 we plot the implications of variation in the level of a firm's preference-decreased and preference-increased technological capabilities over the range of their values (with their mean values as noted in Table 1). Our dependent variable and model specification together allow us to capture the percent change in award count pre- to post-shock (our measure of adaptation). The y-axes of the graphs in Figure 3 are accordingly labeled "within-firm performance change from pre- to post-shock," as discussed in our Identification Strategy section above. In plotting these graphs, we set all non-focal variables to their mean levels. The moderator, repeated customer proportion (which ranges from 0 to 1) is plotted at its mean (0.27), minimum

(0=no repeated customers), and maximum (1=all customers are repeated) values.

Panel A of Figure 3, which is based on Model 2-2 and focused on the magnitude of the extension-based adaptation effects, shows that while preference-decreased technological capabilities hinder post-shock extension-based adaptation, a high proportion of repeated customer relationships can mitigate this decline (H1b). On the other hand, Panel B of Figure 3, which is based on Model 3-2, shows that while preference-increased technological capabilities can facilitate novelty-based adaptation, high proportions of repeated customer relationships can hurt such adaptation (H2b).

[Insert Figure 3 here]

These figures also allow us to discuss the overall magnitude of our effects. In Figure 3 Panel A, we see that when preference-decreased technological capabilities and repeated customer proportion are set to their mean levels, there is a 5% decline in extension-based awards pre- to post-shock. When repeated customer proportion is at its minimum level (no repeated customers), however, there is a 7% decline in extension-based awards pre- to post-shock. Finally, when repeated customer proportion is at its maximum level (all customers are repeated), there is only a 0.5% decline in extension-based awards pre- to post-shock.

Similarly, in Figure 3 Panel B, we see that when preference-increased technological capabilities and repeated customer proportion are set to their mean levels, there is a 14% increase in novelty-based awards pre- to post-shock. When repeated customer proportion is at its minimum level (no repeated customers), there is an 16% increase in novelty-based awards pre- to post-shock. When repeated customer proportion is at its maximum level (all customers are repeated), however,

there is only an 8% increase in novelty-based awards pre- to post-shock.

Temporal patterns

In an additional set of analyses, we examine temporal variation in our results to further corroborate our main analyses and also explore additional nuance in the empirical patterns we uncover. In Table 4 we examine whether our results may be sensitive to shorter versus longer-run post-shock windows. We re-run the full specifications (2-4 and 3-4) using a short-run time window where the pre-shock time period is 1996-2000, but the post-shock time period is reported separately for the short-run, 2002-2004, as well as for the long-run, 2005-2006.

As the Table 4 results suggest, the interactions between technological capabilities (of either of the two different forms) and repeated customer proportion—in other words, the tests of H1b and H2b—are relatively stronger immediately after the shock (2002-2004) as compared to the longer-run after the shock (2005-2006). For example, for H1b, the interaction between preference-decreased technological capabilities and repeated customer proportion is stronger for the 2002-2004 post-shock period ($\beta = 2.267$, $p=0.000$) as compared to the 2005-2006 post-shock period where the coefficient is insignificant ($\beta = 0.479$, $p=0.492$). Likewise, for H2b, the interaction between preference-increased technological capabilities and repeated customer proportion is stronger for the 2002-2004 post-shock period ($\beta = -1.606$, $p=0.003$) as compared to the 2005-2006 post-shock period where the coefficient is insignificant ($\beta = -0.981$, $p=0.104$). In contrast with these results, the hybrid effects in which we interact preference-decreased and preference-increased technological capabilities (i.e., the tests of H3a and H3b) are stronger in the longer-term: e.g., in the case of H3a we have ($\beta = 1.359$, $p=0.001$) for 2002-2004 and ($\beta = 1.996$, $p=0.000$) for 2005-2006, and for the

case of H3b we have ($\beta = 1.424$, $p=0.000$) for 2002-2004 and ($\beta = 2.168$, $p=0.000$) for 2005-2006.

These results are consistent with our theoretical development and main findings. In the longer-run, firms have likely evolved their customer portfolio toward the new demand conditions, making the benefits and downsides of the stock of repeated (pre-shock) customers less salient for post-shock adaptation. On the other hand, in the case of the interaction among the two types of technological capabilities, there is a stronger effect. This suggests that customer-related capabilities may elicit more immediate effects from demand-side change as compared to technological capabilities, as the latter may require a longer timeframe in order for the benefits to be fully realized due to the need for technological developments and knowledge recombination to materialize.

[Insert Table 4 here]

In addition to the analyses reported above, which vary the time windows used in our analyses, we also conducted several other robustness checks that vary the windows used. We report these in the Supplementary Material. These analyses include a 3-year balanced window and a 2-year balanced window (in addition to short- and long-term effects). Taken together, these various robustness tests across a range of observation windows add support to our core findings.

Robustness of customer-related capabilities measure

In the Supplementary Material, we also report and discuss several sets of analyses in which we examine alternative formulations for customer-related capabilities: disentangling the depth and breadth components of repeated customer proportion; restructuring our data at the firm-customer-year level (in contrast with the firm-year level of analysis in the main tables) to disaggregate customers and examine the implications of depth with respect to a given focal customer; and

categorizing the number of customer ties into zero-tie, single-tie and repeated-tie categories. Our results are broadly robust to these alternative formulations. These analyses also offer additional nuance to our main results. For example, we find that breadth and depth of customer relationships have opposing implications for the double-edged effect of customer relationships; in addition, we find that the customer relationship effect occurs both at the level of the portfolio of all customers, as well as at the level of the individual customer.

DISCUSSION AND CONCLUSION

In this paper we examine how interactions among a firm's capabilities shape the extent and direction of firm adaptation to demand-side change. While firms often face situations of demand-side change, we know relatively little about firm adaptation in such settings. Our central insight is that repeated customer relationships can be a double-edged sword under demand-side change: when interacted with preference-decreased technological capabilities, repeated customer relationships can facilitate extension-based adaptation; when interacted with preference-increased technological capabilities, however, repeated customer relationships can hinder novelty-based adaptation. Beyond these main findings, we find that the interaction among technological capabilities (preference-decreased and preference-increased) facilitates adaptation along both paths, and also that customer effects may dissipate more quickly than technology effects.

Limitations

Before turning to the implications of our study, we briefly note some of its limitations, which might set the stage for future research. First, we focus on a single industry setting to make use of an

exogenous industry-wide shock. Future research may seek to replicate our results in other contexts. Second, we focus on private firms, where there is little information on financial performance. Future work may look beyond investment and technology-related factors to firms' actual financial performance in the context of a demand shock. Third, while we control for overall alliance activity, more could be done in future studies to understand how the link between capabilities and adaptation is shaped by activities outside firm boundaries. Fourth, we focus on Phase 1 SBIR awards as these represent the immediate outcome of a firm's technological capabilities and customer needs right after the shock. While this approach is well-aligned with our theoretical objectives, future research could examine the implications of pre-shock capabilities for the firm's ongoing technology development and longer-term commercialization success in Phase 2 and beyond.

Implications for theory

Our results have a number of implications for the strategy literature. One set of implications relates to our understanding of how customer-related capabilities shape firms' trajectories of adaptation under conditions of change (Helfat, 1997; Teece, 1986, 2007). The dual effects of extending the old and hindering the new point to an important underlying mechanism for path dependence in firms' post-shock adaptation trajectories. These insights, moreover, help expand on Teece's (2007: 1138) notion of co-specialization, which suggests that complementary assets can be value-enhancing as a function of "their use in conjunction with other particular assets." Our results suggest that repeated customer relationships, as a form of downstream customer-related capabilities, can either enhance or diminish the value of a firm's technological capabilities with respect to its adaptation performance in a changing demand-side environment. These results thus expand our understanding of the value

of customer relationships. While prior work suggests that customer-related capabilities can have both negative and positive effects with respect to firm-level outcomes (Christensen & Bower, 1996; Ethiraj *et al.*, 2005; Holloway & Parmigiani, 2016), by showing that customer-related effects are contingent on a firm's upstream capabilities, we deepen our understanding of the link between capabilities and performance under conditions of external change.

Another set of implications for the strategy literature stems from our insights regarding the interaction between preference-decreased and preference-increased technological capabilities. Our results demonstrate that the interaction among these upstream capabilities serves to benefit both extension and novelty-based adaptation. These results stand in contrast with prior work in the context of technological change arguing that such hybrid situations can impede adaptation (Tripsas & Gavetti, 2000; Wu *et al.*, 2014). In a demand shock context, the complementarity between familiarity and novelty seems to be the more salient mechanism (Furr & Snow, 2015; Katila & Ahuja, 2002; Nerkar, 2003; Rosenkopf & McGrath, 2011). This has implications for how we think about the role of ambidexterity in the context of external change. Scholars have suggested that managing the dual challenges of exploration and exploitation (March, 1991) can be facilitated by isolating sub-units within the organization (Tushman & O'Reilly, 1996), ensuring organizational agility (Gibson & Birkinshaw, 2004), and balancing among internal and external modes of development (Capron & Mitchell, 2009; Parmigiani & Mitchell, 2009; Stettner & Lavie, 2014; Zollo & Reuer, 2010). The issue of how internal and external design choices may interact with and potentially complement a firm's capabilities in the context of a demand-side change points to an opportunity for future research to expand our understanding of the nexus between work on

capabilities, corporate strategy and organization design.

Our results also have implications for the longstanding debate as to whether innovation and industry evolution are ultimately driven by technological innovation (i.e., “technology-push”) or by demand (i.e., “demand-pull”). At the heart of this debate is the question of whether the trajectory of technologies within industries is driven by the allocation of inventive effort toward pre-existing demand-side considerations, or whether it is in fact ongoing technological developments that serve as the catalyst for changes in consumer preferences (Adner & Levinthal, 2001; Di Stefano *et al.*, 2012; Schmookler, 1966; Mowery & Rosenberg, 1979; Rosenberg, 1982; Von Hippel, 1976). Disentangling these factors is difficult as the two are likely to be reciprocally co-determined. Our empirical approach of focusing on a demand-side shock allows us to hold one side (technology) constant, while unpacking the mechanisms that occur when the other side (demand) changes. By elaborating on the mechanisms that shape adaptation to demand-side change in this study, we contribute to this broader debate with a more fine-grained understanding of the ways in which firm capabilities might serve as the critical glue between the technology and demand-side drivers of ongoing firm and industry-level change (Priem *et al.*, 2012; Rietveld & Eggers, 2018; Vergne & Depeyre, 2016; Ye *et al.*, 2012).

Implications for practice

Our study also has implications for practice. At the most basic level we offer insight into the types of strategies managers can follow in the context of demand-side change. Whereas prior work on external change has addressed issues of how firms can modify their existing capabilities in order to initiate, catch-up, and lead in dynamic technological environments (Cattani, 2005; Christensen &

Bower, 1996; Karim & Mitchell, 2000; Tripsas, 1997; Tushman & Anderson, 1986), our study points to implications for adapting to situations of evolving customer preferences. In particular, when selecting among strategies to react to external change (e.g., racing or repositioning per Adner and Snow [2010]), managers should be attentive to the constraints imposed by their pre-demand shock capabilities. A deeper understanding of the mechanisms through which capabilities shape success along particular pathways can facilitate the decision to invest in particular adaptation strategies; and knowledge of the factors that impede particular pathways can be useful in constructing organizational solutions to counter these effects.

Finally, understanding the implications of demand-side change can be an invaluable complement to the managerial cognitive capabilities that underpin a firm's dynamic capabilities (Helfat & Peteraf, 2015). For example, as Helfat and Peteraf (2015) discuss, a key cognitive building block of dynamic capabilities is managers' ability to sense—such as in the context of recognizing patterns of change in the external environment. Managers that are able to recognize that they are operating under conditions in which there is likely to be change due to shifts in customer preferences may select strategies that reconfigure their upstream and downstream capabilities so as to more effectively seize opportunities that arise in the context of such change.

Conclusion

To conclude, our paper advances our understanding of firm adaptation in the context of demand-side change. We highlight the double-edged sword of repeated customer relationships, together with the complementary relationship between preference-increased and preference-decreased technological capabilities. In so doing we advance our understanding of the link between capabilities

and adaptation in the face of external change.

ACKNOWLEDGEMENTS

The authors thank the Editor, Connie Helfat, and two anonymous reviewers, for their thoughtful feedback throughout the review process. The authors also thank seminar participants at IESE and Southern Denmark University, and participants at the Academy of Management and Strategic Management Society conferences, for valuable comments. Maja Ivkovic provided excellent research assistance. Funding from the INSEAD Alumni Fund is gratefully acknowledged.

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Figure 1. Theoretical predictions

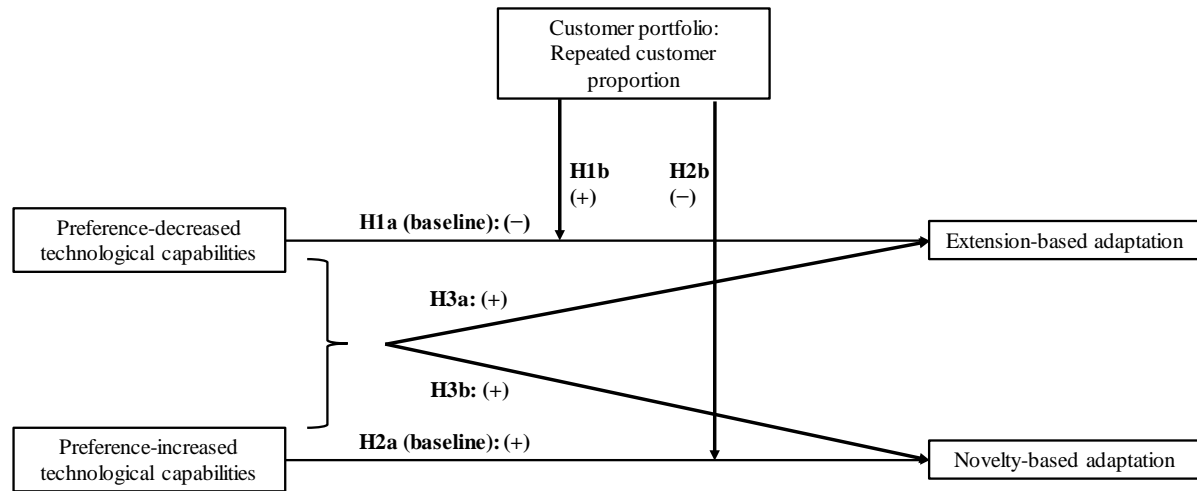
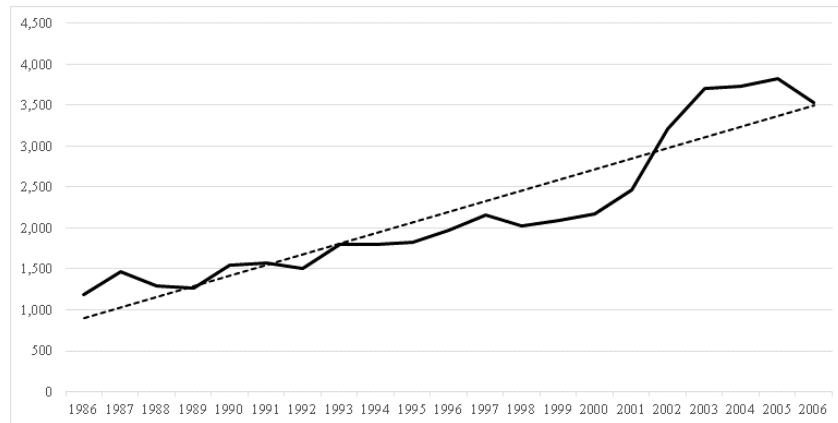
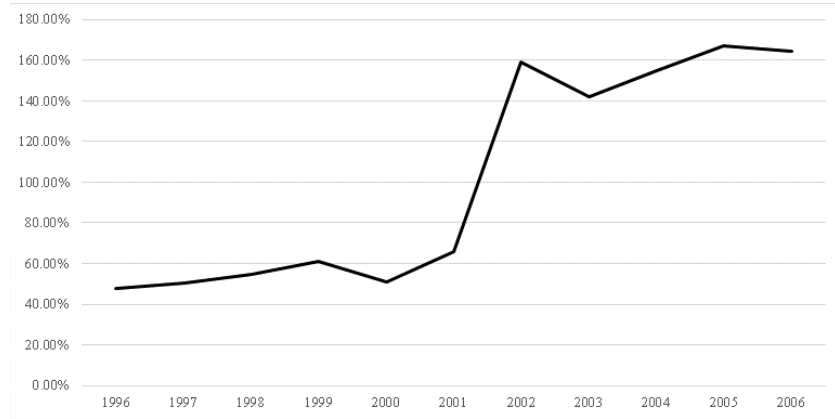


Figure 2. Demand-shock around 2001

Panel A: Overall increase in demand



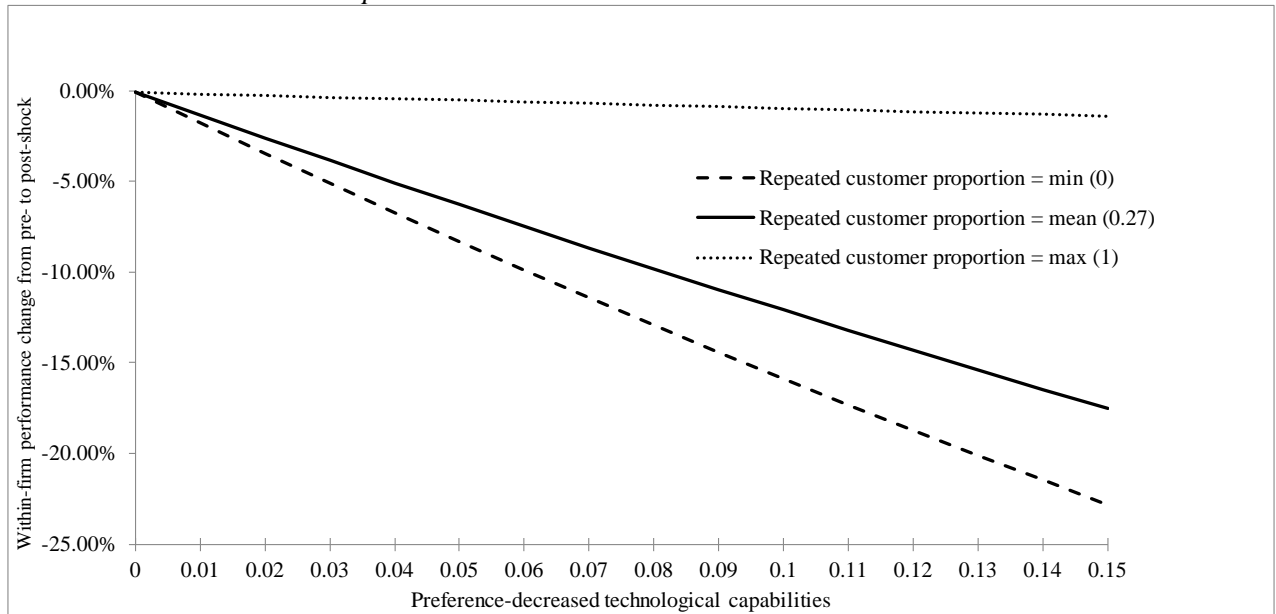
Panel B: Shift in demand conditions (slow-growth 1996 keywords / fast-growth 1996 keywords)



Note: Panel A depicts the total number of SBIR awards from the DoD over time. Panel B depicts the composition of demand as captured by the ratio of slow-growth 1996 keywords to fast-growth 1996 keywords (see text).

Figure 3. Moderating effects of repeated customer proportion

Panel A: Extension-based adaptation



Panel B: Novelty-based adaptation

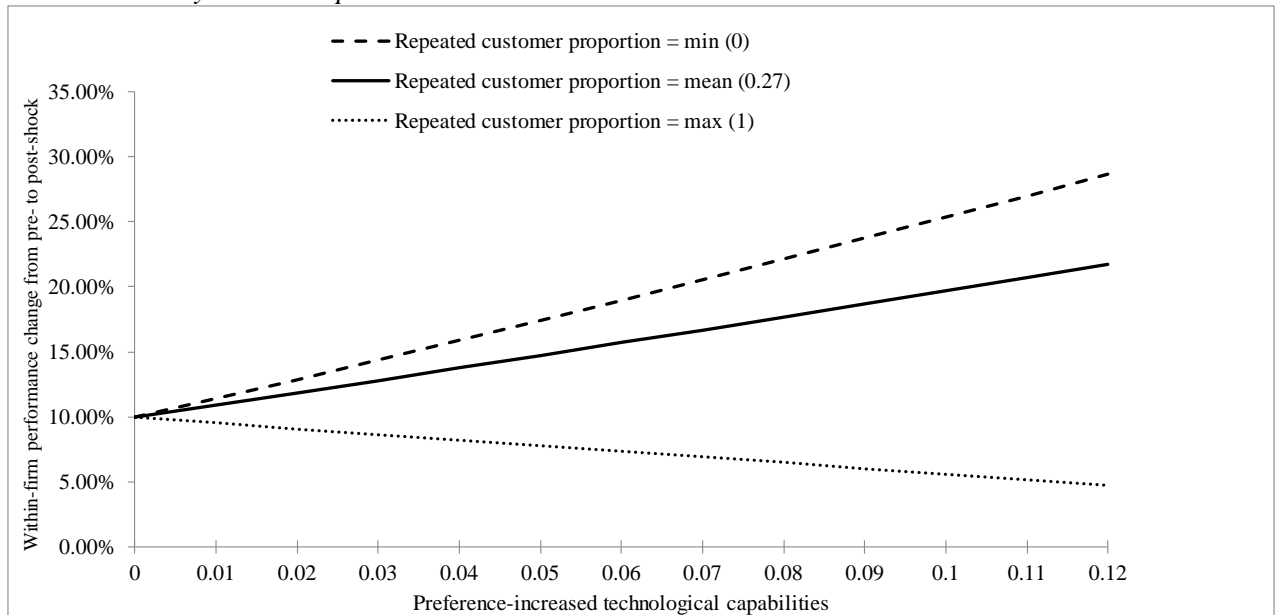


Table 1. Summary statistics and correlations

Variable	Mean	SD	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
1. Extension-based awards	0.16	0.39	1																
2. Novelty-based awards	0.08	0.28	0.33	1															
3. Pref-decreased tech	0.04	0.11	0.44	0.18	1														
4. Pref-increased tech	0.04	0.08	0.42	0.44	-0.25	1													
5. Rep. customer proportion	0.27	0.37	0.23	0.15	0.28	0.32	1												
6. Post-shock dummy	0.51	0.50	0.01	0.10	-0.01	-0.01	-0.01	1											
7. Total financial amount	3.06	5.24	0.45	0.38	0.57	0.56	0.39	-0.01	1										
8. Last award year before shock	3.28	0.93	-0.24	-0.21	-0.20	-0.31	-0.29	-0.02	-0.33	1									
9. Last year awards	0.23	0.45	0.29	0.23	0.51	0.49	0.39	-0.01	0.58	-0.08	1								
10. Customer count	1.93	1.38	0.42	0.34	0.59	0.51	0.32	-0.01	0.57	-0.40	0.59	1							
11. Patent count	9.61	86.54	0.00	0.00	0.03	0.00	0.10	0.00	0.02	-0.02	0.01	0.00	1						
12. Hot patent ratio	0.05	0.16	0.02	0.02	0.03	0.04	0.00	0.00	0.06	-0.03	0.02	0.09	0.00	1					
13. Cold patent ratio	0.16	0.30	-0.03	0.02	-0.08	-0.04	-0.07	0.00	-0.04	0.10	-0.05	-0.09	-0.02	-0.11	1				
14. Patent diversity	0.32	0.21	-0.08	-0.05	-0.13	-0.12	-0.04	0.00	-0.16	0.08	-0.10	-0.19	-0.08	-0.07	0.00	1			
15. Patent co-assignee count	0.17	0.95	0.04	-0.01	0.17	0.03	0.06	0.00	0.13	-0.02	0.12	0.06	0.66	0.02	-0.01	-0.11	1		
16. Alliance count	0.58	2.20	-0.02	-0.01	0.02	-0.02	0.11	0.00	-0.01	0.03	0.02	-0.01	0.44	0.06	-0.02	-0.12	0.32	1	
17. Successful	0.10	0.17	0.02	0.01	0.01	0.03	0.10	0.00	0.06	-0.13	0.03	0.03	0.06	0.06	-0.09	0.01	0.01	-0.01	1

phase 1 award

Note: 5,226 firm-year observations from 1996 to 2006 with 2001 excluded. 533 firms. All pre-shock variables are measured by pooling over the five-years pre-shock (1996-2000). Natural log transformation is applied to award counts.

Table 2. Extension direction of adaptation

Fixed effects OLS models DV: logged extension-based awards	2-1	2-2	2-3	2-4
Intercept	0.300 (0.006)	0.324 (0.003)	0.282 (0.009)	0.305 (0.005)
Pref-decreased tech * post-shock (H1a)	-0.667 (0.000)	-1.720 (0.000)	-1.178 (0.000)	-2.170 (0.000)
Pref-increased tech * post-shock	0.383 (0.087)	0.587 (0.012)	-0.058 (0.810)	0.156 (0.727)
Rep. customer proportion * post-shock	-0.011 (0.672)	-0.043 (0.133)	0.028 (0.324)	-0.003 (0.921)
Pref-decreased tech * Rep. customer proportion * post-shock (H1b)		1.632 (0.002)		1.552 (0.003)
Pref-increased tech * Rep. customer proportion * post-shock				-0.021 (0.976)
Pref-decreased tech * Pref-increased tech * post-shock (H3a)			1.646 (0.000)	1.613 (0.000)
Total financial amount * post-shock	0.011 (0.013)	0.001 (0.827)	0.004 (0.430)	-0.005 (0.386)
Last award year before shock * post-shock	-0.055 (0.000)	-0.057 (0.000)	-0.056 (0.000)	-0.058 (0.000)
Last year awards * post-shock	0.033 (0.218)	0.041 (0.119)	0.038 (0.148)	0.047 (0.080)
Customer count * post-shock	-0.024 (0.029)	-0.006 (0.653)	0.006 (0.639)	0.022 (0.122)
Patent count * post-shock	0.000 (0.113)	0.000 (0.204)	0.000 (0.165)	0.000 (0.274)
Hot patent ratio * post-shock	0.004 (0.937)	0.010 (0.852)	0.000 (0.993)	0.006 (0.911)
Cold patent ratio * post-shock	0.058 (0.048)	0.050 (0.088)	0.052 (0.079)	0.044 (0.134)
Patent diversity * post-shock	0.020 (0.636)	0.024 (0.568)	0.022 (0.591)	0.026 (0.532)
Patent co-assignee count * post-shock	-0.040 (0.002)	-0.033 (0.010)	-0.034 (0.008)	-0.028 (0.032)
Alliance count * post-shock	-0.002 (0.615)	-0.002 (0.674)	-0.004 (0.321)	-0.004 (0.366)
Successful phase 1 award * post-shock	-0.037 (0.468)	-0.027 (0.599)	-0.047 (0.362)	-0.037 (0.473)
R-square	0.445	0.446	0.447	0.449
F value	6.74	6.75	6.80	6.80

Note: 5,226 firm-year observations from 1996 to 2006 with 2001 excluded. 533 firms. Firm and year fixed effects are included, and robust standard errors are used. Coefficients in bold are for hypothesis testing and p-values are in parentheses.

Table 3. Novelty direction of adaptation

Fixed effects OLS models DV: logged novelty-based awards	3-1	3-2	3-3	3-4
Intercept	0.083 (0.294)	0.071 (0.369)	0.064 (0.417)	0.049 (0.535)
Pref-decreased tech * post-shock	-0.032 (0.727)	-0.066 (0.465)	-0.583 (0.000)	-0.336 (0.211)
Pref-increased tech * post-shock (H2a)	0.403 (0.013)	1.309 (0.000)	-0.072 (0.679)	0.614 (0.057)
Rep. customer proportion * post-shock	-0.052 (0.008)	-0.025 (0.232)	-0.010 (0.629)	0.018 (0.423)
Pref-decreased tech *Rep. customer proportion * post-shock				-0.400 (0.290)
Pref-increased tech * Rep. customer proportion * post-shock (H2b)		-1.711 (0.001)		-1.362 (0.005)
Pref-decreased tech * Pref-increased tech * post-shock (H3b)			1.775 (0.000)	1.720 (0.000)
Total financial amount * post-shock	0.009 (0.005)	0.016 (0.000)	0.001 (0.765)	0.009 (0.038)
Last award year before shock * post-shock	-0.036 (0.000)	-0.035 (0.000)	-0.038 (0.000)	-0.036 (0.000)
Last year awards * post-shock	0.036 (0.057)	0.036 (0.058)	0.043 (0.026)	0.040 (0.037)
Customer count * post-shock	-0.001 (0.936)	-0.013 (0.142)	0.031 (0.001)	0.016 (0.119)
Patent count * post-shock	0.000 (0.422)	0.000 (0.379)	0.000 (0.612)	0.000 (0.497)
Hot patent ratio * post-shock	0.047 (0.239)	0.041 (0.306)	0.043 (0.280)	0.036 (0.357)
Cold patent ratio * post-shock	0.050 (0.018)	0.049 (0.021)	0.043 (0.042)	0.044 (0.038)
Patent diversity * post-shock	0.023 (0.455)	0.015 (0.619)	0.025 (0.399)	0.018 (0.544)
Patent co-assignee count * post-shock	-0.014 (0.133)	-0.016 (0.081)	-0.007 (0.422)	-0.011 (0.237)
Alliance count * post-shock	0.003 (0.285)	0.003 (0.288)	0.001 (0.737)	0.001 (0.746)
Successful phase 1 award * post-shock	0.016 (0.661)	0.004 (0.904)	0.006 (0.869)	-0.005 (0.882)
R-square	0.441	0.443	0.448	0.449
F value	6.64	6.67	6.80	6.81

Note: 5,226 firm-year observations from 1996 to 2006 with 2001 excluded. 533 firms. Firm and year fixed effects are included, and robust standard errors are used. Coefficients in bold are for hypothesis testing and p-values are in parentheses.

Table 4. Short-term vs. long-term adaptation effects during post-shock period

Fixed effects OLS models DV: logged awards	Post-shock= 2002, 2003, 2004		Post-shock= 2005, 2006	
	Extension- based awards 4-1	Novelty- based awards 4-2	Extension- based awards 4-3	Novelty- based awards 4-4
Intercept	0.378 (0.002)	0.073 (0.394)	0.235 (0.078)	0.063 (0.477)
Pref-decreased tech * post-shock	-2.560 (0.000)	-0.433 (0.152)	-1.584 (0.001)	-0.178 (0.592)
Pref-increased tech * post-shock	0.062 (0.906)	0.686 (0.059)	0.285 (0.631)	0.494 (0.214)
Rep. customer proportion * post-shock	-0.018 (0.624)	0.000 (0.985)	0.021 (0.612)	0.047 (0.092)
Pref-decreased tech * Rep. customer proportion * post-shock (H1b for 4-1, 4-3)	2.267 (0.000)	-0.353 (0.406)	0.479 (0.492)	-0.487 (0.296)
Pref-increased tech * Rep. customer proportion * post-shock (H2b for 4-2, 4-4)	-0.222 (0.780)	-1.606 (0.003)	-0.371 (0.680)	-0.981 (0.104)
Pref-decreased tech * Pref-increased tech * post-shock (H3a for 4-1, 4-3 and H3b for 4-2, 4-4)	1.359 (0.001)	1.424 (0.000)	1.996 (0.000)	2.168 (0.000)
Total financial amount * post-shock	0.000 (0.969)	0.023 (0.000)	-0.014 (0.090)	-0.012 (0.034)
Last award year before shock * post-shock	-0.065 (0.000)	-0.037 (0.000)	-0.047 (0.001)	-0.035 (0.000)
Last year awards * post-shock	0.040 (0.198)	0.043 (0.047)	0.056 (0.117)	0.035 (0.135)
Customer count * post-shock	0.023 (0.173)	-0.005 (0.690)	0.022 (0.247)	0.048 (0.000)
Patent count * post-shock	0.000 (0.436)	0.000 (0.548)	0.000 (0.314)	0.000 (0.583)
Hot patent ratio * post-shock	-0.036 (0.571)	0.054 (0.226)	0.067 (0.355)	0.010 (0.840)
Cold patent ratio * post-shock	0.039 (0.262)	0.040 (0.095)	0.052 (0.182)	0.054 (0.040)
Patent diversity * post-shock	0.045 (0.358)	0.028 (0.409)	0.002 (0.970)	0.007 (0.846)
Patent co-assignee count * post-shock	-0.025 (0.103)	-0.015 (0.146)	-0.032 (0.065)	-0.005 (0.692)
Alliance count * post-shock	-0.004 (0.402)	0.003 (0.419)	-0.003 (0.573)	-0.002 (0.650)
Successful phase 1 award * post-shock	-0.012 (0.842)	0.009 (0.832)	-0.075 (0.271)	-0.028 (0.534)
R-square	0.455	0.441	0.408	0.395
F value	5.42	5.11	3.82	3.61

Note: Firm and year fixed effects are included, and robust standard errors are used. Coefficients in bold are for hypothesis testing and p-values are in parentheses. 4,160 firm-year observations in Model 4-1/4-2 and 3,627 firm-year observations in Model 4-3/4-4.