

Why Put All Your Eggs in One Basket? A Competition-Based View of How Technological Uncertainty Affects a Firm’s Technological Specialization

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Conventional wisdom suggests that when a firm faces technological uncertainty, it responds by becoming less technologically specialized so as to remain adaptable to subsequent resolution of this uncertainty. We adopt a competition-based view of technological uncertainty to identify an opposite effect in competitive settings: the firm may instead become more specialized when faced with greater technological uncertainty so as to focus on advancing its technologies against competition and influence the resolution of uncertainty in its favor over rivals. We propose that this effect is accentuated when the firm expects that it cannot easily adapt to rivals’ technologies subsequently, specifically when rivals are a greater deterrent through being litigious or innovative. Using U.S. government funding for fuel cell research as a policy shock, with stock option-implied volatilities to measure expected uncertainty, we find empirical support for our propositions among firms active in research and development in the U.S. communications equipment industry. Through these findings, we demonstrate that a competition-based view of uncertainty identifies an alternative path for the firm’s resource accumulation under uncertainty, and we stress that the resolution of uncertainty can be something the firm attempts to influence rather than adapt to.

Key words: technological uncertainty; technological specialization; competition; innovation

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Introduction

In situations with competing technologies (Anderson and Tushman 1990), a firm faces a fundamental decision regarding its technological specialization; that is, it must determine the extent to which it focuses on its technology versus spreading its technological focus (Argyres 1996, Leiponen and Helfat 2010). This decision is non-trivial in the presence of technological uncertainty—specifically, when the firm is unsure about whether its technology will eventually become dominant in the industry (Anderson and Tushman 2001, Oriani and Sobrero 2008).¹ When faced with such technological uncertainty, does the firm respond by becoming *more* specialized to focus on advancing its technology or *less* technologically specialized so as to hedge against uncertainty?

This technological specialization decision is theoretically meaningful as it is central to a firm’s search for resources under uncertainty (Wernerfelt and Karnani 1987, Helfat 1994, Silverman 1999, Ahuja and Katila 2004). In the early stages of a life cycle, when technological uncertainty is rife and multiple technologies compete for dominance (Suarez and Utterback 1995, Schilling 2002), the firm’s choice of a focused search versus a diffused search determines the kind of technological resources it accumulates, which in turn

affects its survival of the selection process for an industry standard (Clark 1985, Suarez 2004). These contrasting firm strategies—becoming more specialized or less specialized to deal with uncertainty—reflect a fundamental dilemma of whether the firm, faced with competing technologies, would try to advance its technology as the industry standard or prepare itself to adapt to the eventual industry standard.

Conventional wisdom suggests that, in general, technological uncertainty induces a firm to become *less* technologically specialized. The basic idea is that the firm responds to uncertainty by “spreading its bets”: accumulating real options across technologies and subsequently adapting to the dominant one that emerges in the industry (McGrath 1997, Pacheco-de-Almeida et al. 2008). This idea appears to be aligned with real-life examples: Intel invested in both CISC and RISC microprocessors in the late 1980s before it was clear which would dominate the PC market. Likewise, Toshiba in the 1990s diversified from its SmartMedia technology and concurrently developed the Secure Digital technology for memory cards when it was still uncertain as to which of the two, or other competing technologies (e.g., MiniCard, CompactFlash, PC Card), would prove to be superior.

However, such conventional wisdom overlooks the competitive aspects of technological uncertainty. First, it overlooks the fact that technological uncertainty is often

driven by rivals pushing for their technologies' dominance (Tushman and Anderson 1986), and these rivals have compelling reasons to deter the firm from adapting to their dominant technologies (Clarkson and Toh 2010). Moreover, it ignores the possibility that, when faced with competition, the firm's own objective in the technology race may not always be to adapt to some technology that eventually becomes dominant but rather could be to proactively improve the odds of the firm's own technology dominating the industry. The firm may choose to focus on its own technology so as to improve such odds (Siggelkow 2003). This idea of the firm endogenously influencing the resolution of uncertainty in its favor is consistent with research showing how a firm consciously tolerates or even proactively encourages imitators so as to establish its own technology as the industry standard (Conner 1988, Khazam and Mowery 1994, Polidoro and Toh 2011).

Considering these competitive aspects, we begin to see that even a technologically diversified firm may not be able to adapt to a dominant technology, as rivals' subsequent deterrence may hinder such adaptation. We also begin to recognize that the merits of being technologically specialized under uncertainty may have perhaps been underappreciated (as specialization can help advance the firm's technology against competition). This calls into question whether, in fact, an opposite effect exists, where the firm responds to uncertainty by *increasing*, rather than decreasing, its technological specialization. This possibility is not without empirical grounds. In practice, firms do not always diversify technologically given heightened uncertainty. Marcus (2009, p. 15) provides examples of firms making focused technological bets under high uncertainty before any dominant technology emerges, such as Iridium investing \$5 billion in its satellite network. Likewise, Sony focused on its Betamax system when the VCR format war was ongoing and later on MiniDisc in the presence of competing technologies such as digital MP3 players. These anecdotes suggest that there is an opposite force prompting a firm to instead focus on its technology under uncertainty. It is important to note that this opposite force could affect firms differently depending on the circumstances that they face. A comprehensive understanding of firm reaction to uncertainty requires that we identify situations where this opposite force is likely prominent—that is, where a firm would become *more* technologically specialized in response to heightened technological uncertainty.

In this paper, we examine situations where technological uncertainty would induce a firm to *increase* its technological specialization. We adopt a competition-based view of technological uncertainty to substantiate this positive effect. The competition-based view highlights two features: that the firm's subsequent adaptation

to rivals' technology may not be viable and that specialization enhances the odds of the firm's technology dominating the competition. We then examine contingencies within a competitive setting under which this positive effect is accentuated. Specifically, we propose that when rivals are more litigious or innovative, the strategy of subsequently adapting to rivals' technologies is less viable. Hence, in these situations, increased technological uncertainty will induce the firm to become more technologically specialized instead.

We empirically examine our propositions among firms active in research and development (R&D) for the U.S. communications equipment industry from 1996 to 2006. The nature of our propositions renders empirical tests vulnerable to endogeneity issues. Simply put, it is possible that a firm's tendency toward specialization can, in turn, increase the uncertainty it faces or that some firm strategy may require the firm to specialize and subject it to high uncertainty. To circumvent these problems, we use two-stage least-square (2SLS) estimations. In the first stage, we use U.S. government fuel cell funding in 2000 as a policy shock to predict changes in the firm's technological uncertainty. We fine-tune this prediction with a difference-in-difference approach (Card and Krueger 1994, Marx et al. 2009) that captures relative changes in uncertainty from the policy shock between firms affected and firms nonaffected by the shock within the industry. In the second stage, we examine our propositions by testing the effect of this predicted change in uncertainty on firms' technological specialization. Findings support our propositions.

In the empirical test, we also adopt a measure of uncertainty that is novel in the strategy literature—stock option-implied volatility. This measure has the merit of being forward looking: it captures the uncertainty that the firm expects to deal with in the upcoming period rather than historical volatility. This suits our test of how firms respond to upcoming uncertainty. The measure is also contemporaneous in that it reflects current changes in uncertainty arising from new information or recent events. This attribute is necessary for our empirical design with exogenous shock. Although this measure by itself incorporates the firm's overall performance variability, we use only the portion of the measure that is associated with technological uncertainty, as predicted by the policy shock from the first-stage estimation, to test our propositions. We elaborate on details in a later section.

Through our findings, we demonstrate that adopting a competition-based view of technological uncertainty helps uncover a positive effect of such uncertainty on the firm's technological specialization. This positive effect challenges conventional wisdom on how firms respond to uncertainty. It stresses that a firm's resource accumulation is not merely an internal process but that

competition plays a pivotal role in it. We do not, however, mean this positive effect to negate conventional wisdom. Rather, its existence indicates heterogeneity in firm response to uncertainty, which we address by moving beyond average firm response to identify situations where the positive effect is more salient. Specifically, with an increase in technological uncertainty, whether a firm reacts by becoming more or less specialized depends on the characteristics of the rivals it faces. In short, there may be times of uncertainty where it makes sense for the firm to “place all its eggs in one basket” instead. The broader message here is that resolution of technological uncertainty can be endogenous; that is, it is a strategic variable that a firm attempts to influence in its favor, rather than an exogenous constraint that the firm adapts to. At times, firms can be proactive rather than reactive. We elaborate on these implications at the end of the paper.

Theory and Hypotheses

Technological Uncertainty

A key task of a firm is to manage uncertainty (Thompson 1967). Fundamentally, uncertainty refers to the firm not knowing precisely which state of the world it is in or moving toward (Radner 1968, Arrow 1974).² Uncertainty resides in a plethora of important dimensions, such as investment returns, technologies, partners, competitors, employees' actions, input costs, demand, and environmental conditions (McGrath 1997, Sutcliffe and Zaheer 1998, Beckman et al. 2004). The strategic action that the firm employs to deal with uncertainty depends on the dimension in question.

In R&D investments, a firm often faces uncertainty along two core dimensions—market and technological uncertainties (Abernathy and Clark 1985, Oriani and Sobrero 2008). Market uncertainty refers to the variability in demand for the firm's products (Wernerfelt and Karnani 1987, Dowell and Killaly 2009). It depends on how customer preferences are distributed and rates of need satiation, and it varies with the economic cycle or demographic or institutional changes (Adner and Levinthal 2001, Huchzermeier and Lock 2001). Market uncertainty makes it difficult for the firm to know precisely, during the R&D phase, which specifications or features to incorporate in its products, especially in dynamic environments (Krishnan and Bhattacharya 2002). Consequently, it hampers the firm's ability to invest in corresponding downstream design and prototyping activities.

Technological uncertainty, on the other hand, refers to the variability in whether the firm's technology is feasible, how it can be used, and whether it will evolve to dominate the industry (Anderson and Tushman 2001, Oriani and Sobrero 2008). Besides determining product

specifications, the firm often has to choose the technology in which to embed its products and processes (Krishnan and Bhattacharya 2002). This decision is not straightforward in situations where multiple technologies compete for industry dominance (Mitchell 1989, Polidoro and Toh 2011),³ especially in the nascent or fluid phases of an industry's life cycle (Anderson and Tushman 1990). Often in these situations, the firm has only imperfect information on how each technology can be developed or recombined and which of these developments or recombination is most feasible (Fleming 2001). Moreover, the full set of applications for each technology may be unknown. Whether the firm's technology eventually becomes dominant as the life cycle progresses depends in part on how its associated applications gain acceptability and momentum.

With technological uncertainty, a firm's ex ante choice of technology can be onerous, as it is usually not easily reversed ex post, unlike add-on product features. This rigidity is pronounced when the technology permeates the product or process designs and is a key enabler of their performance to specifications (Krishnan and Bhattacharya 2002). Failure to choose the technology that eventually becomes dominant can severely erode the firm's performance, or worse, lead to the firm's obsolescence and demise (Suarez and Utterback 1995, Tripsas 1997). Such difficulty and the potential impact of this decision under technological uncertainty exist even without market uncertainty—specifically, even if it is perfectly clear that there will be growing demand for the product (Tegarden et al. 1999).

Technological uncertainty tends to be driven by supply-side factors. Note that asking what drives technological uncertainty is not the same as asking what determines the winning technology or drives technological change. Rather, it is about what increases the variability in whether the firm's technology will prevail or fail. The more obvious sources are major changes in technology. Indeed, external stimuli such as scientific breakthroughs introducing new technological alternatives (Dosi 1982, Fleming and Sorenson 2004) can render the firm even less sure about whether its technology will eventually be dominant. In reality, increases in technological uncertainty are not merely due to technological changes (Fleming 2001). Policy or environmental changes can also increase the variability in technologies' eventual prevalence or failure. For instance, in an environment where it was previously possible for multiple technologies to coexist, an institutional change that is, in essence, set out to shrink the number of surviving technologies and weed out the rest will certainly accentuate technological uncertainty.

Even though these sources are often external and common to firms, it is helpful to perceive technological uncertainty from an individual firm's perspective (Beckman et al. 2004). Firms have different abilities to

manage uncertainty, in terms of surviving technological changes or enhancing success rates in the technology race, because they have different resources supporting these abilities (Barney 1991). Within an industry, firms may also have different external constraints or relationships with other firms (Sutcliffe and Zaheer 1998, Beckman et al. 2004), which similarly varies the level of technological uncertainty faced by each firm even when the external stimulus is common.

The Impact of Technological Uncertainty on Specialization

Faced with technological uncertainty, the firm has to determine its technological specialization—that is, the extent to which it specializes in particular technologies versus spreading its focus across multiple technologies. For the latter, the firm may diversify across core competing technologies that are potential substitutes. For instance, within fuel cell technologies, the firm with molten carbonate fuel cells may diversify into direct methanol fuel cells. Alternatively, the firm may diversify across peripheral technologies related to the application of these core competing technologies. For example, the firm with molten carbonate fuel cells, which mostly provide power for stationary sources, may diversify into supporting technologies related to cell phones, which are mostly powered by direct methanol fuel cells.

Conventional wisdom suggests that, in general settings, technological uncertainty induces a firm to become *less* technologically specialized. The intuitive idea here is that the firm “spreads its technological bets” to diversify risk because it is not sure if its technology will become dominant. Diversification allows the firm to gather real options in the form of initial investments with partial commitment across various technologies (McGrath 1997), which subsequently enable the firm to invest fully in the winning technology upon resolution of uncertainty (Adner and Levinthal 2004). The value of these options, in fact, increases with technological uncertainty (Folta 1998). Diversification also allows the firm to accumulate knowledge incrementally across multiple technological areas, providing headway in the requisite area by the time uncertainty is resolved. Such headway is useful as knowledge accumulation takes substantial time (Dierickx and Cool 1989, Pacheco-de-Almeida et al. 2008), and it may be too late to start accumulating the requisite knowledge only after the winning technology is identified.⁴

Our main proposition is that, contrary to conventional wisdom, an opposite effect exists in some settings where technological uncertainty induces a firm to become *more* technologically specialized. Under the conventional wisdom, the firm's specialization decision does not take into account its rivals' actions, and its objective is constrained to be adaptation to the winning technology

when uncertainty is resolved. Departing from conventional wisdom, we adopt a competition-based view of technological uncertainty that explicitly considers rivals' actions and allows the firm's objective to be to advance its own technology to become the winning one. This competition-based view goes beyond uncertainty over technical attributes per se, to put more emphasis on the competition underlying such uncertainty. Technological competition is not merely between technologies but also between rivals championing these technologies. Beyond technical functionality (Wade 1995, Adner and Zemsky 2006), rivals also compete in garnering institutional support for their technologies (Garud and Rappa 1994) and, more important, in preventing others from entering their technological space (Clarkson and Toh 2010). The firm's uncertainty in its technology's eventual dominance, besides stemming from ambiguity over functional superiority, also arises from ambiguity over how rivals would push for their technologies' dominance.

Our proposition based on this competition-based view is naturally more salient in competitive settings where multiple technologies serve similar, if not the same, functions (Anderson and Tushman 1990, Polidoro and Toh 2011). A prime example would be the early stages of a technology life cycle, or following a shock, where the industry is in flux and multiple technologies are competing for dominance (Dosi 1982, Suarez 2004). Typically, technologies' scientific principles, applicative boundaries, and feasibility are not yet fully known, and their potential institutional acceptances and market adoptions are still unclear. In an extreme “winner-takes-all” situation, a dominant design will eventually be selected from the competing technologies as the industry standard, locking out other technologies (Suarez and Utterback 1995, Schilling 2002). This selection process is often path dependent, based on idiosyncratic events early on that are unrelated to technical superiority. This leaves room for firm strategy to influence selection (Clark 1985, Khazam and Mowery 1994). In short, in these settings, competition for technological dominance is possible and critical.

The competition-based view of technological uncertainty leads to two crucial observations. First, in technologically competitive settings, rivals' potential deterrence reduces the firm's expected returns from technological diversification. It constitutes a cost for “spreading bets” under uncertainty that conventional wisdom overlooked. When uncertainty is resolved, the firm may not easily transition to the winning technology, despite initial investments, if rivals championing the technology prevent the firm from using it (Clarkson and Toh 2010). Indeed, these rivals often have incentive to exclude others and enhance uniqueness of their technologies so as to extract maximum rents (Peteraf 1993), especially when these technologies become the industry standard and generate high rents (Schilling 2002).⁵

Second, the prospect of winning the technology race against rivals increases the firm's expected returns to technological specialization. Faced with technological uncertainty, the firm's objective may not be to adapt to the eventual winning technology. Rather, it can be to proactively increase the odds of the firm's own technology becoming the winner. Returns for the winning technology are substantial (Farrell and Saloner 1986, Lieberman and Montgomery 1988). In winner-takes-all situations depicted in the standards literature (Schilling 2002), the winning firm earns temporary if not prolonged monopolistic rents when rivals with competing technologies are obliterated (Tushman and Anderson 1986, Suarez and Utterback 1995). Conversely, not having the winning technology means the firm must transition to the winning technology, which can be costly given internal rigidity or rivals' deterrence.

This potential of earning substantial returns induces the firm to specialize technologically so as to improve its odds of having the winning technology. Returns from specialization are well established (Siggelkow 2003). Specialization helps the firm advance its technology by improving its functionalities relative to competing technologies. Also, it channels the firm's limited resources toward obtaining intellectual property rights and gaining institutional acceptance of its technology (Gilbert and Newberry 1982, Polidoro and Toh 2011). More generally, specialization accords first-mover advantage and lead-time benefits (Lieberman and Montgomery 1988). During the early stages of the technology life cycle, being on the technological frontier allows the firm to shape the installed base and customer switching costs in ways favorable to the firm, such that network externalities may kick in to propel its technology toward becoming the industry standard (Schilling 2002, Suarez 2004).

The two observations above underlie our proposed positive effect of technological uncertainty on the firm's specialization in technologically competitive settings. Imagine a firm in an equilibrium state. An increase in uncertainty induces this firm to respond by altering its specialization. The firm being less sure of its eventual technological dominance means that the tail-end risks have increased. With greater chances of left-tail (bad) outcomes, a more proactive firm reaction is to increase specialization to resolve this problem and avoid having to face subsequent deterrence from rivals. With greater chances of right-tail (good) outcomes, again, a proactive firm reacts by becoming more specialized so as to convert the probability to certainty of dominance, especially in winner-takes-all situations. The overarching principle is that the proactive firm attempts to endogenously influence the resolution of uncertainty in its favor. In other words, the firm specializes under uncertainty not to adapt to the uncertainty but rather to induce such uncertainty to resolve in a way that picks the firm's technology over its rivals' as the dominant one in the industry. This principle is echoed in other research showing

that a firm may allow, and even encourage, imitators so as to establish its technology as the industry standard (Conner 1988, Khazam and Mowery 1994, Polidoro and Toh 2011). In sum, the first observation from the competition-based view suggests that, in technologically competitive settings, the alternative of technological diversification under uncertainty may be costly. The second observation suggests that the strategy of technological specialization under uncertainty may be beneficial to the firm. This leads to our main hypothesis.

HYPOTHESIS 1 (H1). *In technologically competitive settings, the greater the technological uncertainty faced by the firm, the more the firm will subsequently increase its technological specialization.*

Hypothesis 1 does not imply that conventional wisdom is uniformly untrue. Rather, (H1) makes the case that an opposite effect can exist in competitive settings. As (H1) runs counter to conventional wisdom, it follows naturally to question when (H1) is likely to be salient. Technological specialization involves a trade-off: how the firm deals with increased technological uncertainty depends on the relative costs and benefits of diversification versus specialization. Hence, (H1) is salient either in situations where diversification as a way to deal with uncertainty is especially costly (as in the first observation) or when specialization is especially useful in dealing with uncertainty (in line with the second observation). To stress the element of "rivals" under the competition-based view, we focus on the former: how (H1) is accentuated when the likelihood of rivals' deterrence, and hence the cost of diversification, is high.

Rivals can deter a firm from certain technological space if they are ahead in the technology's development. In product markets, classic deterrence theories suggest that industry structure or rivals' market position can be a possible deterrence tool (Demsetz 1973). The principle is that rivals signal their commitment in products or production capacity (Schmalensee 1978, Dixit 1980), indicating to the firm that it is in their best interest to act in a manner unprofitable for the firm should it enter the product market. However, this product market deterrence principle is not easily applied to technological space. Rivals' signals (to suggest market saturation) are noisy, as technological investments do not map perfectly onto production quantities or even products, especially in the early stages of the technology life cycle. Moreover, small new entrant or follower firms may have competing incentives urging them to innovate (Doraszelski 2003). Consequently, findings on the industry structure's deterrence effect in technological space have been mixed (Dasgupta and Stiglitz 1980, Gilbert and Newberry 1982, Reinganum 1985, Lerner 1997).

To examine deterrence within technological space, recent research (e.g., Clarkson and Toh 2010) has moved away from studying industry structure as a signal and

instead examined the signalers' (rivals') characteristics. Rivals can deter a firm via active exclusion or speed. Exclusion occurs when rivals control resources supporting the technologies, and such resources have a "rival goods" nature; i.e., the rivals' use precludes others from using them. Examples of these resources include access to key scientists working on the technologies, the necessary ingredients for the technologies, or patents protecting the technologies. Accordingly, the firm is deterred because it would have to incur prohibitive cost to use the technologies. Deterrence via speed occurs when rivals gain lead time in the technologies' development. With lead time, rivals may progress further along the learning curve and operate at lower costs. This increases their abilities to engage in competitive attacks against the firm (Lieberman and Montgomery 1988). Also, rivals may have cumulatively improved on the technology (Green and Scotchmer 1995). This enhances their generative appropriability by capturing future innovative opportunities (Ahuja et al. 2013) and also increases technical hurdles for the firm (Adner and Zemsky 2006). With deterrence via exclusion or speed, it is costly for the firm to subsequently try to adapt to rivals' winning technologies.

Based on these principles of exclusion and speed, we identify two corresponding contingencies—rivals' litigiousness and innovativeness—that increase the likelihood of deterrence and accordingly accentuate (H1). The first contingency is rivals' litigiousness, with the corresponding deterrence principle being rivals' active exclusion. Upon resolution of uncertainty, when the firm attempts to adapt to the winning technology, rivals championing this technology may impose prohibitive cost on the firm by suing the firm for patent infringement (Lerner 1995, Somaya 2003, Clarkson and Toh 2010). Being ahead of the firm, rivals typically have obtained patents protecting core parts of the technology. When the firm builds new products, processes, or technologies that are substantively similar to this dominant technology (Cooter and Rubinfeld 1989, Somaya 2003), rivals may file infringement suits against the firm to obtain injunctions against the firm or compensation for damages or part of the firm's profits from infringing articles or destruction of such infringing articles (Bhagat et al. 1994). These suits are costly to the firm in terms of time, monetary resources,⁶ managers' involvement and effort, and potential reputational cost (Bhagat et al. 1994, Lerner 1995). Even when the firm outsources its legal activities, its managers are often still actively involved in depositions, countersuits, etc.

Rivals' litigiousness largely reflects a characteristic of rivals, rather than of their technological environments. It is conceivable that some industry segments or technological areas may experience a greater number of litigation incidences. For instance, areas with greater technological complexity or interdependence between rivals' technologies may require a firm to infringe on others'

technologies when developing its own. However, holding constant instances of alleged infringements, rivals differ in their propensities to litigate. Litigation propensities depend on rivals' abilities to manage the litigation process (Siegelman and Waldfogel 1999, Lanjouw and Schankerman 2004). These abilities include infringement detection. Rivals need to be familiar with different interpretations of patent laws across district courts to know the technological boundaries of their patents' coverage and to recognize when and where infringements can indeed be established. Long-drawn-out debates over doctrines of equivalents, typical in infringement suits, require that rivals have knowledge and experience in navigating the litigation process and managing settlement procedures. It is well established that the firm does consider its rivals' abilities and inclinations toward litigation before deciding to infringe on their patents (Ordovery 1978, Lerner 1995).

Earlier, we stated that with increased technological uncertainty, the firm may either respond by diversifying technologically so as to subsequently adapt to the winning technology (per conventional wisdom) or respond by focusing on its current technology to advance the technology as the winning one (per (H1)). Here, we argue that when rivals are more litigious, they are more likely to deter the firm's subsequent attempt to adapt to their technologies. The technological diversification strategy (per conventional wisdom) thus becomes more costly, and the technological specialization strategy becomes relatively more attractive to the firm. Hence, rivals' litigiousness accentuates our earlier proposition that increased technological uncertainty will induce the firm to become more specialized.

HYPOTHESIS 2 (H2). In technologically competitive settings, the greater the rivals' litigiousness, the more that the technological uncertainty faced by the firm will subsequently increase the firm's technological specialization.

The second contingency is rivals' innovativeness. The corresponding deterrence principle is rivals' speed and lead time in technological development. Innovations often build on common platforms and are cumulative (Anderson and Tushman 1990, Green and Scotchmer 1995). Whereas earlier versions may incorporate vital scientific principles, they rely on sequential improvements, each "standing on shoulders of giants," to bring to light their full potential (Scotchmer 1991, Murray and O'Mahony 2007). These accumulations reflect marginal improvements along technologies' key performance attributes (Wade 1995, Adner and Zemsky 2006), with the latest versions representing the state of the art in a particular trajectory. Accumulations, entailing recombination with other technological components (Henderson and Clark 1990), also exploit other opportunities of generative innovations (Ahuja et al. 2013).

By increasing technical hurdles and eroding generative opportunities, rivals' innovations affect the firm's investment in the technological area. It is not only the rivals' potential introduction of a latest-version technology, with its inherent risk of expropriating the value of the entire chain of sequential innovations (Ahuja et al. 2013), that reduces the firm's incentives to innovate (Scotchmer 1991, O'Donoghue 1998). Rather, rivals' existing innovations suggest to the firm that technical hurdles in developing the next improved version are likely high. Rivals who worked on successive versions are likely further along the learning curve and have the lead-time advantages discussed previously. Lead time means that rivals have likely exploited the generative opportunities of these technologies and diversified into related areas.

The firm observes rivals' existing innovations to assess the full extent of rivals' speed or lead-time advantage (Clarkson and Toh 2010). Details of rivals' technological developments or cumulative innovations may not be traceable early on, as the corresponding products are not yet available. Even when rivals obtain patents in early stages of technological development, these patents do not always provide full technical details (Cohen et al. 2000). Also, they do not always precisely indicate what the cumulative improvements are and how rivals have applied these technologies. Hence, the firm looks at rivals' existing innovativeness for indications of their speed or lead time: the more innovative the rivals, the more likely that they have built up substantial cumulative innovations along their technologies. Whereas rivals' innovativeness itself may directly affect the firm's technological specialization decision, we are interested in it as a contingency for the effect of technological uncertainty. We reiterate that with increased technological uncertainty, whether the firm uses the specialization strategy or diversification strategy to deal with such uncertainty depends on the relative net benefits of the two strategies. When rivals are more innovative, the diversification strategy is less attractive, given the rivals' likely lead-time advantages that they can subsequently use to deter the firm. Hence, the firm would more likely lean toward the specialization strategy in response to the increased uncertainty.

HYPOTHESIS 3 (H3). *In technologically competitive settings, the greater the rivals' innovativeness, the more that the technological uncertainty faced by the firm will subsequently increase the firm's technological specialization.*

Methods

Data and Sample

We test our propositions in the setting of firms active in R&D for the U.S. communications equipment industry from 1996 to 2006. This industry is appropriate because

it constitutes a competitive setting. It uses wide varieties of technology, with multiple competing technologies performing similar functions,⁷ and firms have to decide whether to focus on particular technologies or to also invest in competing ones to mitigate substitution risk. Rapid and drastic technological changes are also common in this industry, rendering our key construct of technological uncertainty a nontrivial concern. Accordingly, the rivalry is intense.⁸ Moreover, this industry contains firms with some of the highest R&D intensities in the United States,⁹ and technologies represent key sources of competitive advantage for these firms. Thus, a firm's decision on how to allocate inventive efforts across technological areas is likely consequential.

We draw data from multiple sources to construct our sample. Data on firms' stock option implied volatilities, which we use to measure uncertainty, are obtained from the OptionMetrics database. This database contains publicly traded stock options in the United States from 1996 onward, and it includes details such as option premium, implied volatility, strike price, term (days left to maturity), and delta (to what extent in-the-money or out-of-the-money), as well as firm identifiers such as Committee on Uniform Securities Identification Procedures (CUSIP) numbers. We obtain data on firms' patents and assigned technology classes from the U.S. Patent and Trademark Office (USPTO). We gather firms' litigation records from the LitAlert database, which contains text records of patent litigation cases in the United States and includes details on patent numbers, lawsuit filing dates, and USPTO-assigned technology classes of litigated patents. CUSIP firm identifier information, Standard Industrial Classification (SIC) codes, firm financials, and other information for control variables are collected from the Compustat database.

To construct the sample, we trace firms active in creating technologies within the communications equipment industry. In the sampling period, some network firms such as AT&T, Qwest, and other network providers engage in little R&D themselves and instead purchase or license technologies from other R&D firms (Fransman 2002).¹⁰ The technological specialization decision is not relevant to these firms because technology creation constitutes only cursory portions of their operations, and changes in uncertainty are likely to affect them in ways other than their degrees of specialization. To capture the relevant set of R&D firms for which the specialization decision matters, we compiled 89 USPTO-assigned technology classes related to the communications equipment industry (i.e., SIC codes 366 and 367), based on the National Bureau of Economic Research (NBER) concordance files. Next, we retrieved all patents assigned to these classes throughout the sample range and identify firms based on their assignee numbers.¹¹ We then append the litigation records using the USPTO-assigned numbers of litigated patents and matched the firms' assignee

numbers to CUSIP in the stock options data using the NBER matching file. We similarly linked firms to their financials in the Compustat database. As our empirical model utilizes a policy shock to compare uncertainty levels between the shock period (2001) and non-shock period (all other years), we retained firms that existed during both periods so that the comparison can be more meaningful.¹² The unit of analysis is firm (i)-year (t), and the resulting sample consists of 1,441 public firms.

Variables

The dependent variable, technological specialization (*Tech_Spec*), captures the extent to which a firm's inventive effort at a given time is focused on particular types of technologies. To construct this measure, we traced all patents filed by a firm in a given year that were subsequently granted¹³ and identified the technology classes to which these patents are assigned. We then calculated the concentration ratio (Herfindahl index) of these patents across technology classes, which indicates how focused the firm is within certain classes.¹⁴ Using patent data involves the potential issue that not all inventions are patented, and firms' patenting propensities differ across industries (Cohen et al. 2000). Consequently, this variable may not incorporate all of the firm's inventions. By focusing on a single industry, we minimize this problem, as propensities are likely stable within an industry across firms (Griliches 1990). Furthermore, although a firm's patents may not capture all of its inventions, they are relatively reliable indicators of its inventive effort (Hausman et al. 1984, Trajtenberg 1990). Our objective is not to count a firm's patents but rather to trace the firm's specialization in such inventive effort.

Our main independent variable is the technological uncertainty (*Tech_Uncertainty*) that a firm faces. This variable is firm specific: as firms are differentially capable of managing uncertainties (Beckman et al. 2004), the uncertainty they face can be different even when its source is external and common. For our purpose, this measure needs to be *forward looking* in that it reflects upcoming uncertainty that the firm expects to face, as we will examine how the firm currently reacts to such uncertainty in the upcoming period rather than to how volatile the firm's past has been. Our empirical model also requires that the measure be *contemporaneous* in that it captures changes in the firm's expectation of upcoming uncertainty as a result of events occurring currently. Prior research measuring firm-specific uncertainty typically uses volatility of historical firm performance, such as standard deviation of historical stock price (Beckman et al. 2004). More specific to technological uncertainty, prior research uses the average age of past patents that the firm cites (Oriani and Sobrero 2008) or exploits the differential nature of firms' industries as indications of uncertainty (Folta 1998). Others use survey measures to capture the uncertainty the firm

faces in its environment (Sutcliffe and Zaheer 1998, Luo 2007). These measures, although useful in other settings, are less appropriate here, as they are often not forward looking and, in fact, are seldom contemporaneous.¹⁵

We use a new measure of uncertainty that incorporates the forward-looking and contemporaneous attributes. Before describing this measure, we first stress that although the measure by itself captures the firm's overall uncertainty, we retain only the technological portion of variance in this measure predicted by the policy shock in our analysis, which we explain later. We use the firm's stock option-implied volatility to construct the measure *Uncertainty* (Latane and Rendleman 1976). Implied volatility is backed out from the firm's traded stock option premium (monetary price) after factoring in other parameters such as stock price, strike price, expiration date, and interest rates (Black and Scholes 1973), and it is often the basis on which options are traded in practice. Implied volatility reflects the market's current expectation of the upcoming uncertainty the firm will face and is commonly used as a forecast of the firm's future stock price volatility (Harvey and Whaley 1992, Britten-Jones and Neuberger 2000, Ni et al. 2008).¹⁶ Hence, implied volatility is forward looking. Accordingly, stock option allows an investor to trade on a view about future stock price volatility (Goyal and Saretto 2009),¹⁷ and its implied volatility captures the impact of current information releases on firm uncertainty (Ederington and Lee 1996). Hence, implied volatility is contemporaneous. We use the implied volatility of the firm's one-month-expiration, European-style, at-the-money call option on the first trading day of the calendar year to measure *Uncertainty*. Call options are appropriate for capturing changes in implied volatility of individual stock options (Bollen and Whaley 2004), and options with shorter expiration dates such as the one-month options are typically more sensitive to news with relevant informational contents. Note that implied volatility encapsulates multiple components of firm-level uncertainty. We retain only the technological portion of it using the policy shock in the empirical model, which we explain later.

We measure rivals' litigiousness (*Rival_Lit*) as the number of patent infringement lawsuits initiated by rival firms within the communications equipment technology classes that firm i patents in. This varies across firms in each year, as firms are active in different sets of technology classes and face different rivals. These lawsuits, although requiring infringements to have allegedly occurred, indicate how willing rivals are to proceed with litigations. Rivals who initiate more lawsuits are more litigious. Likewise, for the other contingency variable, rivals' innovativeness (*Rival_Innov*), we measure the number of patents filed, on average, by rivals within technology classes in which the firm is active in the year.

We control for the following firm and environmental attributes in the analyses. An innovative firm may operate in diversified technological areas within the communications equipment industry and, accordingly, face lower technological uncertainty. To capture such innovativeness, we add the number of patents the firm applies for within the communications equipment industry in the year. This also controls for instances where firms appear to become more specialized when they reduce their R&D investments within this industry. Similarly, large firms may face lower uncertainty and be more diversified technologically than small firms. We control for firm size with the natural logarithm of the number of employees. Firms with downstream assets may better manage developments of multiple technologies (low specialization) and, concurrently, better withstand technological change (low uncertainty). We control for downstream assets, or *Down_Assets*, with the natural logarithm of a firm's product, plant, and equipment (PPE). Financial liquidity may reduce risk (low uncertainty) and enable the firm to venture into multiple technological domains (low specialization). We capture liquidity with the variables *Cash*, which measures the natural logarithm of a firm's cash and short-term investments, and *DebtEquity*, its debt equity ratio.¹⁸ Firms with diversification beyond the communications equipment industry may be more inclined to become specialized within this industry when faced with increased uncertainty. We control for diversification using the well-known entropy measure (Palepu 1985) based on the firm's weighted shares of sales across business segments.

For environmental attributes, the presence of dominant technological leaders may induce the firm to specialize in niches and also put the firm in a high-risk situation. To address this concern, we add industry concentration, or *Industry_Conc*, which indicates the extent to which particular dominant firms are responsible for large portions of new-technology creation within firm *i*'s active technological domains. To create this measure, for each technology class in which firm *i* patents in year *t*, we first calculate the concentration ratio (Herfindahl index) of patents applied for among firms. We then average this concentration ratio across all technology classes in which firm *i* is active in year *t*. We also include the variable *Standards* to address the possibility that certain technological standards may already exist in the industry, increasing obsolescence risk for some firms and pushing them to focus on these standards. Technologies constituting these standards will likely dominate citations received. To capture such standards, within each of firm *i*'s technology class in year *t*, we trace all backwards citations made by all patents in that year, calculate a concentration ratio reflecting the extent that these citations are made on particular cited patents, and then we average this concentration ratio across all of firm *i*'s technology classes in year *t*.

Observed litigiousness, instead of being rivals' characteristics, may correspond with unobserved endogenous characteristics of the firm's technological areas. To ensure that litigiousness is specific to rivals rather than to technology classes, we control for litigation concentration, or *Litigation_Conc*, by tracing all litigations in firm *i*'s technology classes in year *t* and calculating a concentration ratio for the extent that these litigations are occurring within particular technology classes. Likewise, to ensure that litigiousness is not driven by technological complexity in the firm's domains, we include the variable *Tech_Complex*. To construct *Tech_Complex*, we use the principle that technologies citing more prior technologies are more complex, and, accordingly, we calculate the average of the total citations made by all patents in each of these technology classes across all of firm *i*'s technology classes in year *t*. This variable also controls for the possibility that the firm operating with complex technology needs to specialize to advance the technology and at the same time faces higher uncertainty because of the technology's complexity. Firm-level uncertainty may be driven in part by systematic, environmental-level sources of uncertainty, and firms' specialization may be a reaction to this environmental uncertainty rather than firm-level uncertainty. We control for environmental uncertainty, which is calculated as the average uncertainty across all firms in the year. We lag all independent variables by a year. To capture other unobserved characteristics of technological domains and intertemporal heterogeneity, we add technology class and year dummies.

Empirical Model

The nature of our propositions renders their empirical tests vulnerable to endogeneity problems. Our propositions can be recast as $Tech_Spec = f(Tech_Uncertainty, Rival_Lit, Rival_Innov, Controls) + \varepsilon$, where *f* is a function and ε is the error term. From this equation, we can see that a firm's inherent tendency toward more risky specialization, either in its prior technological investments or in other aspects of operations, may increase the technological uncertainty it faces. Or, a firm with a strategy of being an imitator may experience lower uncertainty and concurrently choose to explore widely across different technologies. Such strategy may not be adequately captured by control variables or technology class dummies, because it may be inherently unobservable and evolving over time. These forms of endogeneity result in nonrandom assignments of the sample's observations into different levels of the independent variable, creating biases in estimates (Holland 1986, Wooldridge 2002).¹⁹ They do not nullify our conceptual propositions—e.g., it is possible for both the effect of specialization on uncertainty and the effect of uncertainty on specialization to coexist—but they do impose additional hurdles in the empirical demonstration of these propositions.

To mitigate these problems, we use 2SLS estimations with an exogenous policy shock (Berry and Waldfogel 2001) and a difference-in-difference approach in the first stage (Card and Krueger 1994, Marx et al. 2009). In the first stage, we use the U.S. government funding policy for fuel cells in the year 2000 as an exogenous shock to estimate changes in the firm's technological uncertainty, but which likely do not otherwise affect the firm's subsequent technological specialization or other omitted factors. To suppress possible confounding effects of other events that occur around the same time period, we fine-tune the shock with a difference-in-difference approach. In other words, we trace how this resulting change in technological uncertainty from the shock, for firms more likely subjected to the shock (treatment group), may be different from other corresponding changes in uncertainty over the same time for firms less likely affected by the shock (control group). In essence, this policy shock assigns observations randomly into pre- and post-shock groups and into treatment and control groups. Thus, it circumvents the endogeneity problems discussed above. Also, by increasing volatility over the existing technologies' success or failure, this policy shock allows us to predict changes in the firm's overall uncertainty that pertain to technological uncertainty. Thus, it helps narrow our focus on the technological portion of $Uncertainty_{it-1}$. In the second stage, we trace how this predicted change in the technological uncertainty of firm's technologies from the first stage subsequently causes the firm's specialization to vary systematically, thereby demonstrating our propositions.

U.S. Government Funding for Fuel Cells in 2000.

Before specifying the model, we first document details of the policy shock and explain how it affects technological uncertainty. In October 2000, the U.S. government gave fuel cells a boost with an infusion of \$100 million in funding to the U.S. Department of Energy for the development of fuel cell technologies. Out of this budget within the Interior Appropriation Bill, \$52.7 million was allocated to stationary fuel cell R&D, which was \$10 million more than requested by the Department of Energy (indicated in President Clinton's budget in February 2000), with the rest being allocated to transportation fuel cell research and buildings.

To explain this bill's impact on our sample firms, it is helpful to describe the basic nature of fuel cell technologies. Fuel cells are electrochemical devices that convert energy from chemical reactions into electrical energy. The typical chemical reaction is between an oxidant (e.g., oxygen from air) and gaseous fuel, and this fuel can originate from various types of fuel cell sources (see Table 1). It is important to note that different fuel cell types have characteristics that render them more suitable for different applications.²⁰ Hence, a firm operating with particular type of fuel cell technology faces competition from substitute fuel cell types and may be excluded from some types of applications. Within the communications equipment industry, potential applications include fuel cells for cellular phones, laptop computers and other portable electronics, radio and other cell towers, and backup power for switch nodes. Communications equipment firms using these technologies are not constrained to telecommunication uses but can expand into other applications such as consumer electronics,²¹ generators for commercial or military uses, electric cars, space flights, wastewater treatment plants, etc., depending on the fuel cell types they work with.

Government funding in 2000 increased technological uncertainty for communications equipment firms operating with fuel cell technologies for the following reasons. A majority of the budget was allocated to stationary fuel cells, which is directly relevant to communications equipment technologies and applications. The surprise component of an additional \$10 million added to the exogeneity of the shock. Before 2000, fuel cells were traditionally passed over in appropriation bills and received relatively small shares of the federal energy research budget. This funding, in contrast, was significant for firms. The government's explicit objective in this sizeable funding was to support research that would advance fuel cell technologies and reduce their production costs, thereby accelerating their commercialization.²² Because the bill did not specify any targeted fuel cell technology, it is unlikely to have directly caused firms to specialize in a particular fuel cell type. Rather, this funding presented a real opportunity for a firm awarded the funds that its fuel cell technologies would become commercialized and subsequently dominate the industry. Concurrently, this funding also

Table 1 Fuel Cell Types

Fuel cell type	Electrolyte used	Operating temperature (°C)	Examples of applications
Polymer electrolyte	Polymer membrane	60–140	Stationary and transportation applications
Direct methanol	Polymer membrane	30–80	Cellular phones, other consumer products, automobile power plants
Alkaline	Potassium hydroxide	150–200	Space and undersea vehicles
Phosphoric acid	Phosphoric acid	180–200	Buildings, hotels, hospitals, electric utilities, military installations
Molten carbonate	Lithium/Potassium carbonate	650	Industrial and commercial applications
Solid oxide	Yttria-stabilized zirconia	1,000	Industrial and large-scale central electricity-generating stations

Note. Other fuel cell types include proton exchange membrane fuel cells, regenerative fuel cells, and zinc–air fuel cells.

posed a viable threat that some rivals would be awarded the funds instead, and their fuel cell technologies might leapfrog, making the firm's technologies obsolete.

Similarly, particular fuel cell applications may gain substantial ground when the supporting technologies become commercialized. This further accentuates the ambiguity over whether the firm's technologies will thrive or falter, depending on what applications it was focusing on previously. Moreover, few fuel cells have been successfully commercialized through 2000, and the fuel cell industry is essentially still in its nascent stage without any clear dominant design or standards. This funding may also increase the threat of new rival entries with competing fuel cell technologies, which could hurt or help propel the firm's technologies, depending on which rivals' technologies gain dominance. These effects on technological uncertainty are pronounced for the fuel cell R&D firms, as they tend to be heavily technology-based such that variations in their technologies' fate are impactful. Hence, this funding increased technological uncertainty—specifically, the variability over whether the firm's fuel cell technologies and/or associated applications will emerge to dominate the industry or become obsolete.

We use the variable *PolicyShock* to capture all firm-years in our data occurring one year after the funding policy enactment; i.e., *PolicyShock* is 1 for observations in year 2001 and 0 otherwise.²³ To define treatment and control groups for the difference-in-difference approach, we use the variable *FuelCell* to capture firms that are active in generating technologies related to fuel cells. Fuel cell technologies are patented under USPTO-assigned class 429. As technology usage is often not constrained to fit these classification schemes exactly, we choose to be more conservative and use a broader definition of the treatment group that includes technologies similar to those for fuel cell in nature and usage. *FuelCell* is 1 for firms who filed for at least one patent in the year 2001 under the NBER-assigned technological subcategory 45, which encompasses technology class 429, and 0 otherwise.²⁴ We then multiply these two variables. The resulting interaction term is the key variable in the first-stage estimation, indicating the effect of the policy shock on technological uncertainty of firms that are exposed to the shock, relative to other changes in uncertainty that firms not exposed to the shock may experience over the same period.

Model Specification. The 2SLS model consists of the following estimations for each stage. In the first stage, changes in the technological portion of *Uncertainty_{it}* are estimated with

$$\begin{aligned} \text{Uncertainty}_{it} = & \beta_0 + \beta_1 \text{PolicyShock}_{it} + \beta_2 \text{FuelCell}_{it} \\ & + \beta_3 \text{PolicyShock}_{it} \times \text{FuelCell}_{it} \\ & + \beta_h \text{Controls} + \varepsilon_{ijt}. \end{aligned} \quad (1)$$

The main variable of interest is *PolicyShock_{it}* × *FuelCell_{it}*. The predicted change in *Uncertainty_{it}* from this first-stage estimation is then used to estimate the firm's technological specialization in the following year in the second stage. Note that changes in *Uncertainty_{it}* arise from *PolicyShock_{it}*, which is a time dummy. This necessitates *Uncertainty_{it}* to change contemporaneously with the shock. Hence, measures based on past firm volatility or on prior firm behavior are not suitable here. Also, whereas the overall *Uncertainty_{it}* may vary with other nontechnology aspects of the firm's activities, *Pred_Uncertainty_{it}* used in the second stage to examine our propositions includes only the technology-based portion of *Uncertainty_{it}* that arises from the policy shock. The main model in the second-stage estimation is as follows:

$$\begin{aligned} \text{Tech_Spec}_{it+1} = & \delta_0 + \delta_1 \text{Pred_Uncertainty}_{it} \\ & + \delta_h \text{Controls} + \xi_{ijt+1}. \end{aligned} \quad (2)$$

Here, δ_1 tests (H1). By using Stata's 2SLS command, which comes with standard variance adjustments for δ_1 in the second stage, we obtain a consistent and efficient estimator for δ_1 (Wooldridge 2002). To test contingency effects in (H2) and (H3), the conventional approach is to interact *Uncertainty_{it}* with *Rival_Lit_{it}* and *Rival_Innov_{it}*, respectively, and test the significance of their coefficients in the second stage. However, in the 2SLS model, this approach complicates the variance adjustments in the second stage, because only part of the variance of these coefficient estimates (arising from *Pred_Uncertainty_{it}*) requires adjustments. We circumvent these complications with split-sample analyses. Specifically, to test (H2), we split the sample by the mean of *Rival_Lit_{it}* into "low" and "high" subsamples and obtain δ_1^L and δ_1^H , respectively, for each subsample. We then perform a *t*-test for the difference in these coefficients, essentially examining whether the effect of *Uncertainty_{it}* on *Tech_Spec_{it+1}* differs across different (high versus low) levels of *Rival_Lit_{it}*. The test of (H3) follows a similar procedure.

Findings

Table 2 contains descriptive statistics and correlations. The mean of *Uncertainty_{it}* suggests that over the sample period, the market expects stock price of firms to fluctuate with a standard deviation of 39%, on average. The distribution of *Tech_Spec_{it+1}* (mean = 0.1, SD = 0.26) indicates varying degrees of specialization for firms. When we restrict the sample to the treatment group (*FuelCell_{it}* = 1) for three years (2001–2003) following the shock (not reported in table), the constrained distribution (mean = 0.28, SD = 0.22) indicates that even with increased uncertainty from the shock, not all affected firms become fully specialized.

Table 2 Descriptive Statistics

Variable	No. of obs.	Mean	SD	Min	Max	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	
1 Tech_Spec _{it+1}	14,873	0.10	0.26	0	1.00	1															
2 Uncertainty _{it}	14,873	0.39	0.17	0.08	1.95	0.09	1														
3 Rival_Lit _{it} ^a	13,892	0.08	0.32	0	4.71	0.16	0.04	1													
4 Rival_Innov _{it}	13,892	6.91	1.48	3.40	9.25	0.01	-0.06	0.04	1												
5 Innovativeness _{it} ^b	13,892	0.01	0.07	0	1.88	0.04	0.04	0.75	0.02	1											
6 FirmSize _{it}	13,367	38.54	63.06	0.01	779.10	-0.08	-0.29	0.11	-0.02	0.13	1										
7 Down_Assets _{it} ^{b,c}	13,891	3.39	8.12	0	84.10	-0.08	-0.22	0.04	-0.01	0.06	0.74	1									
8 Cash _{it} ^c	13,891	1.43	6.29	0	199.23	-0.06	-0.19	0.11	0.00	0.12	0.62	0.64	1								
9 Diversification _{it}	12,699	0.82	0.61	0	2.70	-0.07	-0.31	0.03	0.00	0.02	0.43	0.31	0.25	1							
10 DebtEquity _{it}	13,888	1.21	1.91	0	42.63	0.07	0.26	0.03	0.01	0.02	-0.19	-0.15	-0.07	-0.27	1						
11 Industry_Conc _{it}	13,892	0.01	0.01	0	0.58	0.31	0.14	0.39	-0.03	0.23	-0.02	-0.04	0.01	-0.05	0.09	1					
12 Standards _{it}	13,892	0.01	0.01	0	0.07	0.12	0.01	0.18	-0.02	0.15	0.01	0.00	0.00	-0.06	0.00	0.19	1				
13 Litigation_Conc _{it}	13,892	0.10	0.27	0	1.00	0.49	0.09	0.14	0.01	0.01	-0.08	-0.08	-0.06	-0.06	0.07	0.47	0.19	1			
14 Tech_Complex _{it}	13,892	7.76	28.36	0	385.08	0.30	0.15	0.40	0.00	0.29	-0.02	-0.04	-0.02	-0.12	0.06	0.39	0.29	0.41	1		
15 Env_Uncertainty _{it}	13,892	0.37	0.08	0.26	0.53	-0.01	0.35	-0.01	-0.02	0.00	-0.01	0.00	-0.04	0.04	-0.01	-0.02	-0.06	-0.02	-0.06	1	

^aScaled by 100.

^bScaled by 1,000.

^cVariables are not in logarithm in these descriptive statistics and correlations. They are subsequently logged in the regressions analyses (see Tables 3 and 4).

Pairwise correlations are high between *Rival_Lit_{it}* and *Innovativeness_{it}* (0.75) and likewise between *FirmSize_{it}* and *Down_Assets_{it}* (0.74). To ensure that our findings are not tainted by multicollinearity problems, we separately drop *Innovativeness_{it}*, *Down_Assets_{it}*, and all control variables other than the year and technology class dummies from the analyses. Subsequent findings remain unchanged.

For the exogenous shock technique to work, our empirical model requires that *Uncertainty_{it}* of the treatment group increases over the policy shock, more so than that of the control group. As a preliminary check, we split the sample into treatment and control groups (*FuelCell_{it}* = 1 or 0), and for each group, we plot the *Tech_Spec_{it+1}* separately for observations affected and nonaffected by the shock (*PolicyShock_{it}* = 1 or 0) in Figure 1. Whereas both groups exhibit an increase in *Uncertainty_{it}* over the shock, likely as a result of other corresponding factors affecting communications equipment firms over that time period, the treatment group experienced a visibly larger increase than the control group. This lends some confidence that the fuel cell funding shock is an appropriate instrument for *Uncertainty_{it}*.

Table 3 documents tests of the policy shock's effect on *Uncertainty_{it}* in the first-stage equation. Model 1 is the base model with main variables, Model 2 includes the interaction term *PolicyShock_{it}* × *FuelCell_{it}*, and Model 3 allows for robust standard errors. *PolicyShock_{it}* is significantly positive across all models, suggesting that *Uncertainty_{it}* for sample firms is higher in 2001 compared with the average of other years. It is important to note that *PolicyShock_{it}* × *FuelCell_{it}* is significantly positive at 1% in both Models 2 and 3 (*t*-statistics of 9.423 and 4.984, respectively), showing that the fuel cell funding policy increases *Uncertainty_{it}* for firms affected by the policy, relative to other communications equipment firms that are not affected by the policy. This helps validate the policy shock's effectiveness as an instrument for *Uncertainty_{it}*. We use Model 2 as the first-stage estimation to predict *Pred_Uncertainty_{it}*.²⁵

Figure 1 Effect of Policy Shock on Firm-Level Uncertainty

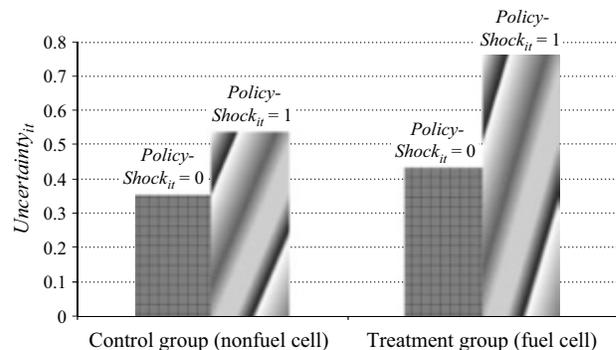


Table 3 First-Stage Regressions—Effect of Policy Shock on Firm-Level Uncertainty

Dependent variable:	<i>Uncertainty_{it}</i>		
	Model 1	Model 2	Model 3 ^a
<i>PolicyShock_{it}</i>	0.264*** (6.327)	0.264*** (6.334)	0.264*** (13.79)
<i>FuelCell_{it}</i>	0.0138* (1.947)	−0.00345 (−0.473)	−0.00345 (−0.345)
<i>PolicyShock</i> × <i>FuelCell</i>		0.152*** (9.423)	0.152*** (4.984)
<i>Rival_Lit_{it-1}</i> ^b	−0.0210*** (−2.923)	−0.0191*** (−2.665)	−0.0191*** (−2.682)
<i>Rival_Innov_{it-1}</i>	0.00188 (0.174)	0.00228 (0.212)	0.00228 (0.393)
<i>Innovativeness_{it-1}</i> ^c	0.0274 (1.195)	0.0225 (0.987)	0.0225 (1.120)
<i>FirmSize_{it-1}</i> ^d	−0.0282*** (−21.06)	−0.0282*** (−21.15)	−0.0282*** (−19.09)
<i>Down_Assets_{it-1}</i> ^{c,d}	−23.01*** (−21.97)	−22.95*** (−21.99)	−22.95*** (−21.81)
<i>Cash_{it-1}</i> ^{c,d}	13.41*** (18.28)	13.30*** (18.20)	13.30*** (16.59)
<i>Diversification_{it-1}</i>	−0.00720*** (−3.575)	−0.00708*** (−3.527)	−0.00708*** (−3.388)
<i>DebtEquity_{it-1}</i>	0.00203*** (3.246)	0.00197*** (3.163)	0.00197** (2.133)
<i>Industry_Conc_{t-1}</i>	0.613*** (5.971)	0.616*** (6.028)	0.616*** (3.590)
<i>Standards_{t-1}</i>	−1.288 (−1.302)	−0.857 (−0.868)	−0.857 (−1.068)
<i>Litigation_Conc_{t-1}</i>	−0.00330 (−0.711)	−0.00338 (−0.730)	−0.00338 (−0.683)
<i>Tech_Complex_{t-1}</i>	0.000317*** (6.894)	0.000318*** (6.929)	0.000318*** (6.777)
<i>Env_Uncertainty_{t-1}</i>	0.183 (0.334)	0.0826 (0.151)	0.0826 (0.423)
Constant	0.342* (1.708)	0.380* (1.904)	0.380*** (5.676)
Year dummies	Included	Included	Included
Technology class dummies	Included	Included	Included
Observations	11,808	11,808	11,808

Note. *t*-Statistics are in parentheses.

^aModel allows for robust errors.

^bScaled by 100.

^cScaled by 1,000.

^dVariables are in logarithm.

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

Table 4 contains findings for the effect of uncertainty on the firm's technological specialization. To have a baseline comparison with our 2SLS approach, we start with a simple ordinary least squares (OLS) examining the effect of *Uncertainty_{it}* without instruments in Model 1. The coefficient of *Uncertainty_{it}* is positive at a 10% significance level (z -statistic of 1.90), which is in line with our prediction in (H1). We note that this measure of *Uncertainty_{it}* by itself without instruments may be noisy, as it includes other nontechnological portions of uncertainty. The rest of the models contain findings for our 2SLS approach. Model 2 reports the main effect of *Pred_Uncertainty_{it}* for the full sample 2SLS model.

Pred_Uncertainty_{it} is significantly positive in Model 2 (z -statistic of 3.12), suggesting that when faced with greater technological uncertainty, the firm will subsequently increase its technological specialization. This supports (H1). It is possible that the firm's specialization takes longer than one year to react to changes in technological uncertainty. We include two-year ($t - 1$) and three-year ($t - 2$) lags of predicted uncertainty in Model 2, and all three lags are jointly significantly positive.

Models 3 and 4 represent the split-sample analysis testing (H2) and contain findings for the low and high subsamples of *Rival_Lit_{it}*, respectively. The objective in

Table 4 Second-Stage Regressions—Effect of Uncertainty on Technological Specialization

Dependent variable:	<i>Tech_Spec_{it+1}</i>					
	OLS	Base model	Low rivals' litigiousness	High rivals' litigiousness	Low rivals' innovativeness	High rivals' innovativeness
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
<i>Uncertainty_{it}</i>	0.0365* (1.90)					
<i>Pred_Uncertainty_{it}^a</i>		0.686*** (3.12)	0.192 (0.65)	0.796 (1.47)	−2.030* (−1.72)	0.377** (2.07)
<i>t</i> -Statistics of difference				−40.73***		−119.92***
Across models ^b						
<i>Rival_Lit_{it}^c</i>	−0.0258* (−1.71)	−0.0120 (−0.72)	1.472*** (4.66)	−0.0768** (−2.21)	−0.0169 (−0.45)	0.0493*** (3.06)
<i>Rival_Innov_{it}</i>	−0.0179 (−0.81)	−0.0141 (−0.61)	−0.0200 (−0.80)	−0.0439 (−0.95)	−0.167 (−1.56)	−0.411** (−2.01)
<i>Innovativeness_{it}^d</i>	−0.183*** (−3.87)	−0.207*** (−4.11)	−2.948*** (−5.80)	0.126 (1.46)	−0.0263 (−0.14)	−0.294*** (−5.77)
<i>FirmSize_{it}^e</i>	−0.00252 (−0.89)	0.0155** (2.31)	0.00375 (0.49)	0.0315 (0.91)	−0.0613* (−1.83)	0.00833 (1.35)
<i>Down_Assets_{it}^{d,e}</i>	−1.925 (−0.86)	13.62** (2.36)	0.572 (0.079)	26.26 (1.40)	−51.69* (−1.79)	8.987* (1.69)
<i>Cash_{it}^{d,e}</i>	−0.173 (−0.11)	−9.343*** (−2.69)	−1.845 (−0.48)	−27.37* (−1.82)	35.49* (1.75)	−7.318** (−2.29)
<i>Diversification_{it}</i>	−0.00408 (−0.98)	0.000731 (0.15)	−0.00223 (−0.48)	−0.00550 (−0.31)	−0.0159 (−1.36)	−0.00243 (−0.44)
<i>DebtEquity_{it}</i>	0.000793 (0.61)	−0.000536 (−0.37)	−0.000956 (−0.61)	0.00343 (0.76)	0.00412 (0.95)	0.000347 (0.20)
<i>Industry_Conc_{it}</i>	0.809*** (3.81)	0.404 (1.55)	0.204 (0.87)	−0.755 (−0.76)	1.266* (1.87)	1.637*** (4.03)
<i>Standards_{it}</i>	−0.954 (−0.49)	0.0901 (0.044)	−1.953 (−0.95)	1.440 (0.24)	−1.712 (−0.45)	0.927 (0.26)
<i>Litigation_Conc_{it}</i>	0.344*** (35.9)	0.345*** (34.2)	0.215*** (12.1)	−0.0527 (−1.09)	0.384*** (16.4)	0.352*** (29.2)
<i>Tech_Complex_{it}</i>	0.000207** (2.23)	0.0000370 (0.33)	−0.000321* (−1.90)	−0.000467* (−1.65)	0.000469* (1.84)	0.000277* (1.91)
<i>Env_Uncertainty_{it}</i>	−0.811 (−0.75)	−1.684 (−1.47)	0.000 (0.00)	−1.120 (−0.67)	0.000 (0.00)	1.628 (0.82)
Constant	0.687** (2.06)	0.695** (1.97)	0.0217 (0.11)	0.632 (0.94)	1.778** (2.53)	3.287** (2.34)
Year dummies	Included	Included	Included	Included	Included	Included
Technology class dummies	Included	Included	Included	Included	Included ^g	Included ^g
Observations	10,553	10,552 ^f	9,147	1,405	3,496	7,056

Note. *z*-Statistics are in parentheses.

^a*Pred_Uncertainty_{it}* is the predicted uncertainty from the first stage (see Table 3, Model 2).

^bThe *t*-test compares the coefficients of *Pred_Uncertainty_{it}* across the pairs of subsamples.

^cScaled by 100.

^dScaled by 1,000.

^eVariables are in logarithm.

^fObservations are reduced from first-stage regressions because of the leading of *Tech_Spec_{it+1}*.

^gSome technology class dummies were dropped because of reduced sample size.

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

this analysis is to examine, through a *t*-test, whether the coefficient of *Pred_Uncertainty_{it}* is significantly larger in the high subsample than it is the low one, i.e., whether the effect of uncertainty is accentuated when rivals are more litigious. The coefficient of *Pred_Uncertainty_{it}* is positive, albeit nonsignificant, in both Models 3 and 4. Although the lack of statistical significance does not allow us to interpret support for (H2) too

liberally, the coefficient does appear larger in Model 4 (*z*-statistic of 1.47) than in Model 3 (*z*-statistic of 0.65). More importantly, the *t*-test of *Pred_Uncertainty_{it}* across these two subsamples, reported in Table 4, shows that *Pred_Uncertainty_{it}* is clearly significantly larger in Model 4 when *Rival_Lit_{it}* is high than in Model 3 when *Rival_Lit_{it}* is low (*t*-statistic of −40.73). This *t*-test constitutes evidence in line with (H2).

Models 5 and 6 similarly test (H3), with the objective of examining through a t -test whether the effect of uncertainty on the firm's technological specialization is greater when rivals are more innovative. $Pred_Uncertainty_{it}$ is significantly positive in Model 6 for the high subsample of $Rival_Innov_{it}$ (z -statistics of 2.07) but is negative and insignificant in Model 5 for the low subsample (z -statistic of -1.72). Our t -test shows that $Pred_Uncertainty_{it}$ is significantly larger in Model 6 with high $Rival_Innov_{it}$ than in Model 5 with low $Rival_Innov_{it}$ (t -statistic of -119.92). This supports (H3). As in Model 2, we allow for the possibility that these contingency predictions require longer than a year to take effect. We include two-year ($t - 1$) and three-year ($t - 2$) lags of predicted uncertainty and repeat all split-sample analyses above. Results are fully robust in that we find the joint effect of the three lags of predicted uncertainty to be significantly more positive when rivals are more litigious (as in Models 3 and 4) and, likewise, when rivals are more innovative (as in Models 5 and 6).^{26, 27}

We use graphical analysis to further demonstrate these contingency effects. We first regress $Tech_Spec_{it+1}$ on all control variables to obtain the residual unexplained variance in specialization. We then split the sample at the mean of $Rival_Lit_{it}$ to obtain two subsamples with high and low rivals' litigiousness, and we plot the linear prediction of this residual of technological specialization against $Pred_Uncertainty_{it}$ for the two subsamples as well as for the full sample in Figure 2. The positive slope for the full sample reflects the positive $Pred_Uncertainty_{it}$ in Model 2 of Table 4. The subsample with high $Rival_Lit_{it}$ has a positive slope, which supports (H2) and is driving the overall positive slope for the full sample. The slope for the subsample with low $Rival_Lit_{it}$ is negative, per conventional wisdom, suggesting that there is heterogeneity in firm response to uncertainty even within this competitive setting. We use a similar analysis for $Rival_Innov_{it}$ in Figure 3. Again, we find that the positive slope for the full sample is driven by the subsample with high $Rival_Innov_{it}$, which

Figure 2 Effect of Uncertainty on Specialization Contingent on Rivals' Litigiousness

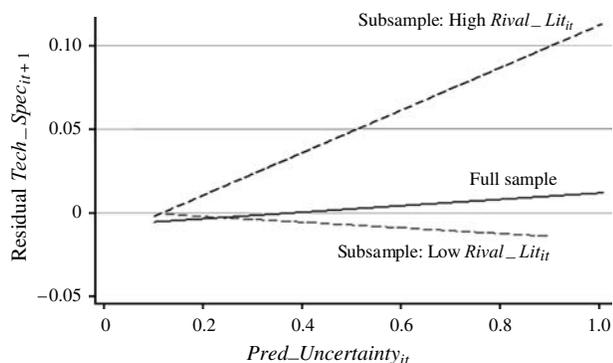
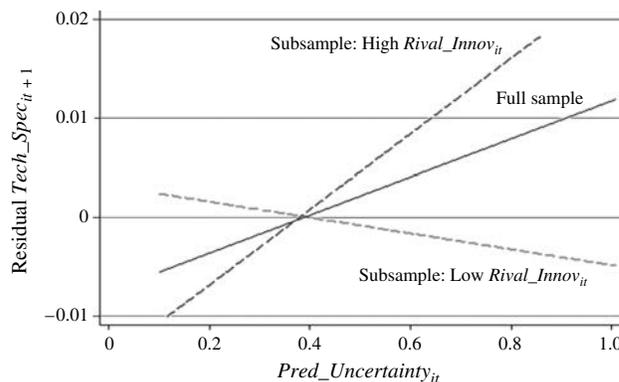


Figure 3 Effect of Uncertainty on Specialization Contingent on Rivals' Innovativeness



supports (H3), and that when the firm does not face innovative rivals (subsample with low $Rival_Innov_{it}$), the effect of uncertainty on specialization is negative, per conventional wisdom. Overall, these graphical analyses strongly demonstrate that there exists a positive effect of technological uncertainty on a firm's technological specialization, and this positive effect is especially salient when the focal firm faces highly litigious or innovative rivals.

Additional Analyses

Given the policy shock's central role in our empirical model, we examine its appropriateness and effectiveness further in two aspects: (a) if it is exogenous to firms and (b) if it creates a random assignment of observations to different levels of uncertainty. For (a), the concern is that some firms may have tried to influence policy makers in making funding available, which would erode the exogeneity of the policy instrument for these firms. This concern is partially mitigated by the fact that the additional \$10 million in the funding (an increase of close to 25% from expected funding for stationary fuel cells) was unexpected by firms. This unexpected portion ensures exogeneity, even if other portions of funding resulted from these firms' lobbying. We further address this concern by dropping lobbying firms for whom the funding may not be exogenous. We identify 15 lobbying firms from the membership list of the Fuel Cell and Hydrogen Energy Association. This association serves as an advocacy group focusing on the commercialization of fuel cells and hydrogen energy technologies, and its members are heavily involved in securing federal funding and raising government awareness of the role of fuel cells in clean energy efforts. We rerun all analyses in Tables 3 and 4 without these firms, and we find fully robust results. Hence, we are fairly confident that firms' potential influences on the funding policy are not driving our results.

For (b), the policy shock mitigates endogeneity issues by randomly assigning observations to being treated or

nontreated by the shock. If randomization is effective, unobserved firm attributes should not differ systematically between treated and nontreated firms (observed differences are explicitly controlled for). Besides ensuring the exogeneity of the shock, we can apply a more stringent test for differences in observed firm attributes between treated and nontreated firms, with the principle that firms that do not differ in observed attributes likely do not differ in unobserved ones as well. We split the sample into treated and nontreated firms ($PolicyShock_{it} \times FuelCell_{it} = 1$ and 0, respectively) and trace the observed firm attributes. Table 5 documents the *t*-tests of differences in these firm attributes. Per the intention of the shock, *Tech_Spec* and *Pred_Uncertainty* are both greater for the treated firms. However, the other firm attributes (with the exception of *Innovativeness* and *Cash*) are not significantly different between treated and nontreated firms, which lends some confidence in the randomized assignments of observations. Higher *Innovativeness* for treated firms is perhaps due to these firms responding to the funding policy and does not necessarily suggest nonrandom selection of more innovative firms into being treated. The marginal difference in *Cash* between treated and nontreated firms, although significant, appears small and could well be due to the increased funding. Overall, our results show that there is no strong sign of the shock failing in its randomization of observations.

Another empirical concern is that the standard error of the difference-in-difference estimator may be inconsistent as a result of serial correlation (Bertrand et al. 2004). Given our relatively short time series (11 years), this concern is unlikely to be salient here. Nonetheless, we address the concern by collapsing our data into cross sections for shock and non-shock periods. Specifically, for the non-shock period (all years other than 2001), for each variable, we calculate and retain the firm average across years. The shock period (2001) data remain as before. We then rerun all analysis per Tables 3 and 4 on

what is now essentially a cross-section data set, and we find fully robust results.

Tech_Spec is constructed from patents in the communications equipment industry. It does not reflect specialization for the entire firm if the firm is diversified across other industries. Despite controlling for *Diversification* earlier, a lingering concern remains that firms appearing to become more specialized with greater uncertainty within the communications equipment industry may actually be diversifying technologically across industries. The time lag between technological investments and product sales could prevent *Diversification* from fully capturing such cross-industry technological diversification. We address this concern in three ways. First, we further demonstrate that cross-industry technological diversification does not affect our earlier findings. We control for such diversification with the count of the firm's patents outside the communications equipment industry and the number of technology classes unrelated to communications equipment to which these patents are assigned. Findings in Table 4 remain fully robust, suggesting that specialization within the communications equipment industry is not driven by technological diversification in other industries.

Second, we examine whether uncertainty in the communications equipment industry is inducing the firm to diversify technologically outside this industry. This conjecture is plausible because the firm, while achieving the benefits of specialization within this industry as we propose, may concurrently seek to diversify its risk across industries. We construct an alternative dependent variable, *Alt_Spec*, of similar principles, but based on all of the firm's patents not captured by *Tech_Spec*. This variable thus reflects the firm's specialization outside the communications equipment industry. Rerunning the analyses in Table 4 with this variable, we find that *Pred_Uncertainty_{it}* in the full-sample model (Model 2) becomes insignificant, though it still has the same positive sign per (H1) (*z*-statistic of 0.029).

Table 5 Differences in Firm Attributes Between Treated and Nontreated Firms

Firm attributes	Nontreated firms ^a		Treated firms ^a		<i>t</i> -Statistics ^b
	Mean	SD	Mean	SD	
<i>Tech_Spec_{it+1}</i>	0.09	0.25	0.28	0.21	-6.29
<i>Uncertainty_{it}</i>	0.37	0.16	0.76	0.29	-10.13
<i>Innovativeness_{it}</i> ^c	0.01	0.07	0.16	0.32	-3.58
<i>FirmSize_{it}</i> ^d	2.54	1.77	2.88	1.63	-1.57
<i>Down_Assets_{it}</i> ^{c,d}	0.01	0.00	0.01	0.00	-1.37
<i>Cash_{it}</i> ^{c,d}	0.01	0.00	0.01	0.00	-4.44
<i>Diversification_{it}</i>	0.84	0.61	0.87	0.67	-0.31
<i>DebtEquity_{it}</i>	1.19	1.81	2.14	4.51	-1.57

^aTreated firms are observations that are active in the fuel cell industry in 2001 ($PolicyShock_{it} \times FuelCell_{it} = 1$), and nontreated firms are all other observations.

^bCompares difference in firm attributes between nontreated and treated firms.

^cScaled by 1,000.

^dVariables are not in logarithm.

In the split sample, $Pred_Uncertainty_{it}$ is positive when $Rival_Lit_{it}$ is high (Model 4; z -statistic of 1.32) and negative when $Rival_Lit_{it}$ is low (Model 3; z -statistic of -0.47), with a t -test showing a significant difference between them (t -statistic of -40.7), per (H2). Similarly, $Pred_Uncertainty_{it}$ is less negative when $Rival_Innov_{it}$ is high (Model 6; z -statistic of -0.92) than when it is low (Model 5; z -statistic of -3.82), with a significant difference between them (t -statistic of -78.4), per (H3). These findings show that uncertainty in this industry has a similar, albeit weaker, effect of increasing the firm's specialization across other industries. The findings do not support the notion that observed firm specializations within the communications equipment industry are really just instances of firms diversifying beyond this industry. Thus, the conjecture that the firm may concurrently diversify across industries and specialize technologically within one industry, although plausible, is not supported empirically.

Third, we directly show that firms specializing within the communications equipment industry (high $Tech_Spec$) as a result of the fuel cell shock are not systematically diversifying across industries (low Alt_Spec). We find that the two measures have a low correlation of -0.04 , which casts doubt that they are meaningfully related. Focusing on the treatment group ($FuelCell_{it} = 1$), i.e., sample firms that face exogenous increase in uncertainty, we regress Alt_Spec on $Tech_Spec$ and account for possible confounding factors with our earlier control variables. We find that $Tech_Spec$, in fact, positively explains Alt_Spec (t -statistic of 3.23). In other words, for a firm that responds to increased uncertainty by specializing within the communications equipment industry, its response in other industries, if any, is also to be more specialized, not diversified.

A related concern is that with increased uncertainty, firms that appear to become more specialized within the communications equipment industry may have simply reduced their R&D efforts in this industry.²⁸ This could occur when these firms switch to other external means of innovation (e.g., licensing) as a way to maintain their overall technological diversification. We have attempted to address this concern by controlling for $Innovativeness_{it}$ (count of the firm's patents in this industry) in our earlier analyses. Here, we further demonstrate that firms that became more specialized in response to heightened uncertainty are indeed increasing, rather than decreasing, their inventive effort in the specialized areas within the communications equipment industry. We focus on the treatment group ($FuelCell_{it} = 1$; i.e., firms in our sample that faced exogenous increase in uncertainty) and trace $Innovativeness_{it}$ of the firms that became more specialized after the shock. To parse out noise that may affect $Innovativeness_{it}$ over time, we restrict the examination to the year before and year after the shock (1999 and 2001). We then conduct a t -test for the difference in $Innovativeness_{it}$ over the two years, and we

find that these firms' patents in this industry significantly increased (t -statistic of 5.07), rather than decreased, after the shock.

Because our measure for technological uncertainty ($Pred_Uncertainty_{it}$) is new, we compare it to a more familiar measure based on patent citations (Oriani and Sobrero 2008). The principle of this alternative measure is that uncertainty is likely higher when patents are citing newer patents. For each technology class that firm i patents in year t , we calculate the mean age (number of years) of all cited patents in that class in year t . We then construct a measure— $PatCite_Uncertainty_{it}$ —by taking the average across all technology classes that firm i patents in year t and calculating its inverse (so that the higher the value, the greater the technological uncertainty). The correlation between $PatCite_Uncertainty_{it}$ and our measure $Pred_Uncertainty_{it}$ is 0.34 and significant at 1%, suggesting that although these two measures likely contain different information, they at least consist of a common component related to technological uncertainty. We then replace $Pred_Uncertainty_{it}$ with $PatCite_Uncertainty_{it}$ in Table 4 and run OLS regressions (2SLS is inappropriate because $PatCite_Uncertainty_{it}$ likely does not change contemporaneously with the policy shock). In the full-sample model (Model 2), $PatCite_Uncertainty_{it}$ is insignificant and has the wrong sign (t -statistic of -0.12), but findings remain robust for the split-sample analyses. Specifically, $PatCite_Uncertainty_{it}$ is significantly more positive in Model 4 (coefficient = 0.0252), where $Rival_Lit_{it}$ is high, than in Model 3 (coefficient = -0.167), where it is low, with a t -test confirming such significance (t -statistic of -37.9). Likewise, $PatCite_Uncertainty_{it}$ is significantly more positive in Model 6 (coefficient 0.0236) with high $Rival_Innov_{it}$ than in Model 5 (coefficient -0.0408) with low $Rival_Innov_{it}$, and a t -test confirms that significance (t -statistic of -27). We refrain from drawing strong conclusions here because we lack the abilities to resolve the above-mentioned endogeneity issues that are likely present with $PatCite_Uncertainty_{it}$ as the regressor.

Limitations. The single-industry focus in the empirical design constitutes a limitation of our study. We select this competitive setting of the U.S. communications equipment industry because it is effective in illustrating the counterintuitive positive effect of technological uncertainty. Rivals' litigiousness and innovativeness are critical concerns within this setting. However, the fact that our proposed positive effect exists in this selected setting does not mean that the negative effect, per conventional wisdom, cannot be true in other settings. This raises the question of the generalizability of our propositions and findings. Put differently, an interesting follow-up question is whether, in less competitive settings, a firm facing deterrent rivals would also respond to technological uncertainty by becoming more specialized.

Do our propositions only exist in settings involving the early stages of life cycles, with a possible emergence of industry standards, or do they also exist in more mature settings as long as there are multiple technologies in competition? We are unable to address this question with our single-industry study, and instead, we leave this as a potential direction for future studies.

Another limitation of this study is that we have focused on technological specialization as a reaction to uncertainty for firms active in creating new technologies, and thus we are unable to observe whether firms react to the same uncertainty through external means of innovation, such as licensing or other collaborative arrangements. This is a shortcoming, as the proposed mechanisms underlying the effect of uncertainty (concerns of competition and deterrence) could conceivably transfer to these other reactions, and the observed firm reaction in technological specialization could be driven by the external means of innovation the firm is engaging in or that are available to it. We have tried to mitigate this shortcoming by restricting our sample selection to firms active in generating their own technologies and by showing that firms that become more specialized under uncertainty are not merely reducing their own innovative effort while switching to external means of innovation. Yet even if our findings are not confounded per se, it remains important to examine firms' reactions through these other means to have a comprehensive understanding of how firms manage their entire technological portfolios to deal with the technological uncertainties that they face. We encourage future research to pursue this extension.

Conclusions

Conventional wisdom suggests that a firm, when faced with technological uncertainty, responds by *decreasing* its technological specialization in general so as to spread its bets and better subsequently adapt to the dominant technology. Our central proposition is that under a competition-based view of technological uncertainty, an opposite effect exists in competitive settings where the firm *increases* its technological specialization instead. We propose that this effect exists because rivals' potential deterrence against the firm's subsequent adaptation induces the firm to instead specialize so as to increase its odds of winning the technology race. This is especially salient when rivals are highly litigious or innovative. To identify this opposite effect in our empirical study, we focus on a competitive setting—the U.S. communications equipment industry from 1996 to 2006. We use U.S. government funding for fuel cell research in 2000 as a policy shock and stock option-implied volatility to measure expected uncertainty, and we find support for our propositions.

Through our propositions, we aim to push the theoretical frontier in the study of firm response to uncertainty.

In reality, a singular source of uncertainty can solicit a heterogeneous span of responses across firms. Some firms diversify their investments so as to hedge their risk, whereas others focus on particular “bets.” The former “diversification” response rests on the basic principle of risk reduction through diversification and is intuitive. In fact, many existing theories can and have explained this rationale. The latter “focused” response, however, remains relatively puzzling. Rather than relegating these observed responses to random off-average variances and possibly erroneous firm decisions, we provide a systematic rationale for them, essentially by identifying situations that challenge the expected benefits of the diversification response and that magnify the merits of the focused response. Embedded in our rationale is a key point that a firm's response does not necessarily represent its effort to live with the given uncertainty, but rather can sometimes indicate its effort to change the way the uncertainty is resolved.

Our propositions stress the role of competition in a firm's resource accumulation process. The mix of resources that a firm eventually accumulates depends on its current decision on technological specialization, and we demonstrate that this strategic decision is influenced by how the firm expects its rivals would react. Our assertion is that the firm's response to uncertainty involves more than managing ambiguity over which set of resources will prove to be most valuable. Such ambiguity comes with rivals who are working with these resources, and the firm's response must include its anticipation of what these rivals may do to deter the firm from developing these resources. This insight is potentially meaningful to research on resource-based view (RBV). Early RBV scholars, when examining performance differences across firms, shift their attention from product market competition toward individual firm's upstream resources accumulation (Barney 1991, Peteraf 1993). Since then, research has focused mainly on the firm's internal process of searching for resources (Ahuja and Katila 2004) with little explicit recognition that this seemingly internal process of firm search is ultimately not decoupled from external competition. Our paper constitutes a modest step toward reinstating the role of competition.

This core message—that a firm's resource accumulation does not occur in isolation from its rivals—is potentially applicable to other research areas as well. For instance, in real options theory (McGrath 1997, Folta 1998), valuations of initial investments under uncertainty seldom consider rivals' reactions to focal firm's investments. Yet there are conceivably situations where rivals' reactions can erode the inherent optionality in these initial investments, such that even if these initial investments turn out to be accurate bets, rivals' subsequent reactions may render the firm's further investments suboptimal. Likewise, studies of knowledge management

typically focus on internal value creation of knowledge-based resources and compare it to external contracting of such resources (Grant 1996, Szulanski 1996). Yet how much value these internal resources create for the firm must surely depend on what rivals do in related resource space. Examining the influences of rivals' deterrence could shed more light on and enhance completeness of theories involving firm's value creation.

We focus on rivals' characteristics as contingencies, but there are other possible contingencies that can further inform research on when the firm will increase versus decrease specialization in response to uncertainty. We examine rivals' litigiousness and innovativeness so as to substantiate our message about the influence of competition. However, the focal firm's own attributes are also possible contingencies, and it may be interesting to know what types of firms will more likely avoid facing rivals' deterrence or be more inclined to focus on championing their own technologies under uncertainty in the hope of winning the technology race. We defer to future research to pursue these fruitful directions.

Inherent in our propositions is a trade-off between a firm's adaptability and its potential leadership in a particular area. By becoming less specialized, the firm potentially enhances its adaptability to different technologies, at the expense of not significantly advancing any one particular technology. By being technologically specialized, the firm champions that technology to potentially gain leadership while sacrificing adaptability to other technologies. When faced with uncertainty, firms may choose either side of the trade-off, as evidenced by observed heterogeneity of technological specialization across firms within a given environment. This trade-off carries an important message: although organizational adaptability is a useful skill, as shown by the massive research on this topic, sometimes it is not the firm's intention to be reactive and adaptive. Rather, the firm can at times be proactive, strategizing not with the purpose of adapting to outcomes of uncertainty resolution but with the objective of endogenously influencing the resolution of uncertainty in a way that is favorable to itself. The study of firm behavior has much to gain by shifting its focus from characterizations of a reactive firm toward theories of a proactive firm.

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Endnotes

¹Whereas uncertainty manifests across multiple dimensions (Thompson 1967, McGrath 1997, Sutcliffe and Zaheer 1998), our focus here is on the variability of firm's subsequent performance arising from technological uncertainty.

²Besides facing a probability distribution across states, the firm sometimes even lacks clarity on what all possible states are and their associated likelihood of occurrence (Knight 1921, Sommer et al. 2009).

³For example, in the fuel cell industry, gaseous fuels such as direct methanol, alkaline, and phosphoric acid compete to be the primary source of alternative fuel. Likewise, in the pharmaceutical industry, different mechanisms of action underlying drugs, which achieve similar therapeutic effects, compete for dominance within a therapeutic class.

⁴Note that even if the firm chooses to avoid first-mover disadvantages by waiting for uncertainty to be resolved and then imitating later, it typically does not halt its R&D activities completely. Rather, it would likely remain technologically noncommittal so as to be able to subsequently imitate a wider range of possible technologies. Empirically, this option to wait may mean either that the firm's specialization does not change with increases in uncertainty (no observed effect) or that specialization decreases with increased uncertainty.

⁵Even though rivals may sometimes allow and encourage the firm to use their technologies so as to increase the odds of becoming the industry standard (Khazam and Mowery 1994, Polidoro and Toh 2011), they often attempt to be exclusive after their technologies become the industry standard. For instance, Intel actively licensed its earlier versions of CISC chips cheaply to competitors to establish them as industry standards but drastically retained the market share of later versions, once they became the industry standards.

⁶The American Intellectual Property Law Association reports that the median cost of a patent infringement lawsuit can often exceed \$2 million and be up to \$4 million (AIPLA 2003).

⁷For example, multiple data-transmission media compete against one another, such as light waves, wireless radio waves, power lines, and satellites. Within each medium, there exist multiple competing technologies as well.

⁸A potential concern is that our findings may be driven by events in the communications industry over this time. From 1996 to 1999, the industry experienced rapid technological advances and high growth as a result of the rise of the Internet and the 1996 Telecom Act, with revenue growing from \$173 billion to \$290 billion. Subsequently, in the early 2000s, the industry declined as a result of excess capacity in telecommunications; increased competition from wire and wireless firms; and decreased demand for Internet networking equipment, software, and services (Fransman 2002). This decline raises a concern that observed firm specialization after 2000 may be due to greater financial constraints and loss in demand. To address this concern, in our analyses, we control for the firm's financial constraints with *Cash*, *DebtEquity*, and other firm attributes that vary with the industry downturn, such as firm size and PPE. Furthermore, we include *Env_Uncertainty*, as well as year and technology class dummies, which should largely soak up these unobserved industry downturn effects.

⁹Firms' R&D intensities in this industry are comparable to that of pharmaceutical firms (Fransman 2002). In 1999, R&D expenses for Cisco, Ericsson, and Nortel were 18.7%,

14.5%, and 13.9% of sales, respectively. Equivalent figures for Roche, GlaxoSmithKline, and SmithKline Beecham were 15.5%, 14.4%, and 10.8%, respectively.

¹⁰In the 1990s, network firms such as “Baby Bells,” AT&T, Qwest, and MCI WorldCom accounted for some of the least R&D-intensive firms across all industries, with single-digit R&D expense as a percentage of sales (Fransman 2002).

¹¹Potential concerns with this sample selection procedure are that it captures (i) R&D firms that are diversified across industries and (ii) R&D firms that concurrently pursue innovation strategy through external means. For (i), observed specialization within our sample industry may reflect these firms further diversifying across industries. For (ii), observed specialization may mean that these firms are reducing their own innovative effort and switching to other external means of accessing innovations, such as licensing or other collaborative arrangements. We subsequently address these two concerns by controlling for firm's diversification and innovative effort within this industry, respectively. We also further examine each concern separately in the Additional Analyses section.

¹²Dropping this sample restriction criterion and essentially treating observations like a cross-sectional data set does not change subsequent findings. Alternatively, we apply a more stringent criterion of a balanced panel, i.e., retain only firms that exist throughout the entire sample range. All subsequent findings remain fully robust (going forward, “fully robust” implies similar levels of significance and substantive interpretations).

¹³Tracing patents at application dates rather than grant dates more accurately captures the firm's technological specialization in its inventive efforts because of the time lag between application and grant dates.

¹⁴Suppose a firm has four patents, two assigned to class A and the other two to class B. Thus $Tech_Spec = (2/4)^2 + (2/4)^2 = 0.5$. Now suppose three of these patents are assigned to class A and the remaining patents to class B. Then $Tech_Spec = (3/4)^2 + (1/4)^2 = 0.625 > 0.5$, reflecting the firm's greater specialization.

¹⁵For example, suppose an event occurs at time t that drastically increases the uncertainty a firm expects to face in the upcoming period. An uncertainty measure based on the volatility of historical stock price prior and leading up to t does not adequately capture this increased uncertainty at time t , even if the measure incorporates price at time t , because the volatility of historical stock price prior to t does not change.

¹⁶Some researchers go further to assert that stock option-implied volatility is more effective than historical stock price volatility at predicting future stock return variance (Chiras and Manaster 1978, Christensen and Prabhala 1998, Szakmary et al. 2003). We do not require this assertion to hold true for our purpose. Rather, it suffices to note that the implied volatility of traded stock options captures contemporaneous changes while historical volatility does not.

¹⁷In practice, implied volatility is traded, especially in short-term options. This constitutes a strong inducement for option traders to align implied volatility with their expectations of future stock price volatility. For example, when a trader buys \$10 million of an at-the-money (50% delta) call option and hence goes long on implied volatility, she typically puts on a spot hedge by shorting 50% of \$10 million, or \$5 million, of underlying stock. When the stock price subsequently dips and

the option becomes out-of-the-money at 30% delta (i.e., 30% chance of being in-the-money at expiration), she rebalances the spot hedge by buying back 20% of \$10 million, or \$2 million, of stock at the now-lower stock price so as to adjust the spot hedge to 30% of \$10 million. When the stock price subsequently surges and the option becomes in-the-money at 70% delta, she will then sell back 40% of \$10 million, or \$4 million, of stock at the now-higher stock price. This example of gamma trading illustrates that the trader owning the option makes money on the spot-hedge rebalancing regardless of the direction in which the stock price fluctuates. Thus, she will price this option, and be willing to pay its premium, at a level of implied volatility that corresponds with the expected volatility of stock price.

¹⁸We also tried adding the firm's one-year lagged R&D expenses to more directly focus on the possibility that firms with low R&D budgets may not be able to diversify technologically, despite being faced with greater technological uncertainty. Sample size reduces significantly because of missing data on R&D expenses, but subsequent findings remain robust.

¹⁹For instance, observations (firms) that are highly (lowly) specialized may be selected into high (low) levels of uncertainty and therefore be nonrandom. Likewise, firms with an imitator strategy, represented in the error term, are similarly selected into low levels of uncertainty in a nonrandom fashion. Both result in nonzero covariance between uncertainty and the error term in the estimations, which biases coefficient estimates.

²⁰For instance, the low operating temperature required for direct methanol fuel cell makes it suitable for midsize applications, such as cell phones and other consumer products. In contrast, molten carbonate fuel cell requires a high temperature, which takes significant time to reach operating conditions and responds slowly to changing power demands, rendering it more suitable for constant power applications. An alkaline fuel cell, although among the most efficient at generating electricity, is sensitive to CO₂ poisoning and hence unsuitable for automobile applications.

²¹Examples of consumer electronics powered by fuel cells include video recorders, portable power tools, hearing aids, smoke detectors, burglar alarms, and meter readers.

²²According to the executive director for Breakthrough Technologies Institute/Fuel Cells 2000, Robert Rose, “The chief aim of the government's support is to fuel research that will advance technology and reduce the cost of fuel cells, making them a more viable energy option” (Environmental News Network 2000).

²³Short windows are appropriate for capturing the spike in option volatility resulting from the shock, as volatility would subsequently ease off as more information emerges about funding candidates and the viability of particular fuel cell technologies. To determine whether the policy shock may have a longer-term effect, or if firms take longer to react to the shock, we separately define $PolicyShock_{it}$ as observations occurring up to two years (2001–2002) and three years (2001–2003) after enactment. Subsequent findings remain fully robust under the two-year specification. In the three-year specification, subsequent findings are robust except for the full-sample model in the second stage (Model 2 of Table 4), where $Pred_Uncertainty_{it}$ remains positive but loses its significance. Alternatively, to avoid assuming a temporal length of effect,

we define $PolicyShock_{it}$ as all observations beyond 2000. Findings remain robust.

²⁴Firms working on fuel-cell-related technologies may not have filed for fuel cell patents (class 429) or related patents (technology subcategory 45) in 2001. To define our treatment group more broadly as all firms potentially working on these technologies, we alternatively define $FuelCell_{it} = 1$ for firms who have filed at least one fuel-cell-related patent throughout the sample range (1996–2006) and 0 otherwise. Findings for all subsequent analyses are fully robust. Conversely, we constrain the treatment group to include only firms patenting in class 429 in 2001, which drastically reduces the sample size for the treatment group. Findings for first-stage estimations in Table 3 remain unchanged except for Model 3, where the policy shock loses its significance. Findings for second-stage estimations in Table 4, which tests our propositions, are robust except for Model 2, where $Pred_Uncertainty_{it}$ is only significant at the 10% level.

²⁵Using Model 3 as the first-stage estimation in the 2SLS model with robust error produces fully robust results. We also tried clustering the error by firm, and results for both stages remain robust.

²⁶We repeat all analyses in Table 4 using firm fixed-effect models instead. This approach is likely stringent, as the empirical models in Table 4 already use the policy shock to circumvent potentially omitted firm attributes that could cause endogeneity problems. Moreover, the difference-in-difference estimator ($FuelCell$, capturing whether the firm operates in fuel cell technologies) further constrains the variance needed to examine within-firm effects. Consequently, the year dummies were dropped in Models 3 and 4, and the technology class dummies were dropped as well in Models 5 and 6. The results, however, remain fully robust with these fixed-effect models.

²⁷It is also possible that if the focal firm is itself highly deterrent, specifically litigious or innovative, it may choose to innovate and patent widely under uncertainty so as to actively deter its rivals. We note that this would work against our propositions and make it harder for us to find results. We further factor in the focal firm's deterrence of rivals by calculating $Rival_Lit_{it}$ and $Rivals_Innov_{it}$ as being relative to firm i (rivals' minus firm i 's) and repeat all analyses in Tables 3 and 4. Findings remain fully robust.

²⁸For example, suppose that before the uncertainty increase, a firm has 10 patents—5 in class A and 5 in class B. $Tech_Spec$ is thus 0.5. After the uncertainty increase, the firm has three patents in class A and none in class B (while shifting the remaining R&D effort to other industries). $Tech_Spec$ is now 1, an increase from 0.5, even though the firm probably has not channeled more R&D effort into class A.

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