Why put all eggs in one basket: a competition-based view of how technological uncertainty affects a firm’s technological specialization

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Abstract:

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: sometimes 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 it cannot easily adapt to rivals’ technologies subsequently, specifically when rivals are more deterrent through being litigious or innovative. Using a U.S. government funding policy for fuel cell research to create a natural experiment, with stock option implied volatilities to measure expected uncertainty, we find empirical support for our propositions among firms active in R&D for the U.S. communications equipment industry. Through these findings, we demonstrate that a competition-based view of uncertainty identifies an alternate path for the firm’s resource accumulation under uncertainty, and stress that resolution of uncertainty can be something the firm attempts to influence rather than to adapt to.
In situations with competing technologies (Anderson and Tushman 1990), a firm faces a fundamental decision regarding its technological specialization, that is, it has to choose 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). 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 firms’ search for resources under uncertainty (Wernerfelt and Karnani 1987, Helfat 1994, Silverman 1999, Ahuja and Katila 2004). In early stages of a lifecycle when technological uncertainty is rife and multiple technologies compete for dominance (Suarez and Utterback 1995, Schilling 2002), the firm’s choice between focused or diffused search determines the kind of technological resources it accumulates, which may well affect its survival in 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, given competing technologies, the firm would try to advance its technology as the industry standard or prepare itself to adapt to the eventual industry standard.

Conventional wisdom suggests that technological uncertainty induces the 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, Henderson and Cool 2008). However, this underscores the competitive aspects of technological uncertainty. Behind this uncertainty are rivals pushing for their technologies’ dominance (Tushman and Anderson 1986), and they often have

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1 While 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.

2 While prior researchers have discussed uncertainty arising from competitive actions (McGrath 1997, Sutcliffe and Zaheer 1998), they typically establish such competitive uncertainty as a separate dimension without explicitly recognizing the competitive aspects underlying technological uncertainty.
compelling reasons to deter the firm from adapting to their dominant technologies (Clarkson and Toh 2010). Moreover, 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 its own technology dominating the industry. Focusing on advancing its own technology can help increase such odds (Siggelkow 2003). The broader idea, that the firm may endogenously influence resolution of technological uncertainty in its favor, is in fact aligned with existing research showing that the firm may be tolerant towards or even actively encourage imitators, so as to establish its own technology as the industry standard (Conner 1988, Khazam and Mowery 1994, Polidoro and Toh 2011).

By downplaying these competitive aspects, conventional wisdom may have over-estimated the attractiveness of technological diversification as a way to enhance adaptability (as adaptation may not be feasible due to rivals’ deterrence), and under-appreciated the merits of technological specialization under uncertainty (as it may help advance the firm’s technology against competition). Considering these competitive aspects admits the possibility of an opposite effect, 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 like digital MP3 players. These anecdotes suggest that there is an opposite force prompting a firm to instead focus on its technologies under uncertainty. Importantly, 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 and hence when we would observe a firm becoming 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 of technological uncertainty. The competition-base 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 under which this positive effect is accentuated. Specifically, we propose that when rivals are more deterrent through being more litigious or innovative, adapting to rivals’ technologies subsequently is less viable, and hence increased technological uncertainty will induce the firm to respond by becoming more technologically specialized instead.

We empirically examine our propositions among firms active in 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 due to reverse causality and omitted variables. Simply put, it is possible that specialization can in turn increase the firm’s uncertainty, or that some other firm strategy may both require the firm to specialize and subject it to high uncertainty. To circumvent these problems, we use two-stage least-square estimations. In the 1st stage, we use the U.S. government fuel cell funding policy in 2000 as a shock constituting a natural experiment to predict exogenous changes in the firm’s technological uncertainty (Berry and Waldfogel 2001, Marx et al 2009). We fine-tune this prediction with a difference-in-difference approach (Card and Krueger 1994), which captures relative changes in uncertainty from the policy shock between firms affected and firms non-affected by the shock within the industry. In the 2nd stage, we then examine our propositions by testing the effect of this predicted change in uncertainty on firms’ technological specialization. Findings strongly support our propositions.

In the empirical test, we also adopt a measure of uncertainty that is novel in the strategy literature – stock options implied volatility. This measure has the merit of being forward-looking: it captures the expected uncertainty the firm has to deal with in the upcoming period rather than historical volatility, which suits our test of how firms respond to upcoming uncertainty. The measure is also contemporaneous: it reflects current changes in uncertainty arising from new information or events that have just occurred. This attribute is necessary for our empirical design with exogenous shock. While this measure by itself incorporates the firm’s overall performance variability, we only use the portion of the
measure that is associated with technological uncertainty, as predicted by the policy shock from the 1st 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 identifies how such uncertainty can increase the firm’s technological specialization. This positive effect challenges conventional wisdom on how firms respond to uncertainty and stresses that a firm’s resource accumulation is not merely an internal process but that competition plays a pivotal role in it. This positive effect is not meant to negate conventional wisdom though. Rather, it suggests that heterogeneity does exist in firm response to uncertainty, which we address by moving beyond average firm response to identify situations where the positive effect is more salient. In other words, with an increase in technological uncertainty, whether a firm reacts by becoming more or less specialized depends on the characteristics of rivals that it faces. In short, there may be times of uncertainty where it makes sense for the firm to ‘place all eggs in one basket’ instead. The broader message we echo 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. Firms can at times be proactive, rather than reactive. We elaborate on these implications at the end of the paper.

THEORY AND HYPOTHESES

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

In the realm of 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

3 Besides 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, Loch and Dong 2009).
uncertainty refers to the variability in expected demand for the firm’s products, and is sometimes termed as demand uncertainty (Wernerfelt and Karnani 1987, Dowell and Killaly 2009). Its level depends on how customer preferences are distributed and the rate at which customer needs are satiated, and it varies with 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 for sure which product specifications to fix on during the R&D phase that will subsequently generate the greatest demand, and this problem is accentuated in dynamic environments (Krishnan and Bhattacharya 2002). Consequently, it hampers the firm’s ability to invest in the corresponding downstream design and prototyping activities.

Technological uncertainty, on the other hand, refers to the variability in the firm’s expectation of whether its technology will emerge to dominate the industry (Anderson and Tushman 2001, Oriani and Sobrero 2008). Besides fixing on product specifications, the firm often has to decide on 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), especially in the nascent or fluid phase of the industry’s lifecycle (Anderson and Tushman 1990). In these situations, the firm often 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, and whether the firm’s technology eventually becomes dominant as the lifecycle progresses depends in part on how its associated applications gain acceptability and momentum.

With technological uncertainty, firm’s ex-ante choice of technology can be onerous, as it is typically not easily reversed ex-post, unlike add-on product features. This rigidity arises because technology permeates the product or process designs and enables their performance to specifications (Krishnan and Bhattacharya 2002). Failure to pick the eventually-dominant technology to support its

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4 For instance, in the fuel cell industry, multiple sources of gaseous fuel 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, often compete for dominance within a therapeutic class.
product 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 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, Hatfield and Echols 1999).

While market uncertainty is mostly demand-driven, sources of technological uncertainty tend to relate to supply-side factors. Note that asking ‘what drives technological uncertainty’ is not the same as examining ‘what determines the winning technology or drives technological change’, but rather, is about what increases the variability in whether the firm’s technology will prevail or fail. The more obvious sources are changes in technology that may worsen technological uncertainty. Indeed, external stimuli such as scientific breakthroughs introducing new technological alternatives (Dosi 1982, Fleming and Sorenson 2004) can conceivably render the firm even less sure about whether its technology will eventually become dominant. In reality, increases in technological uncertainty are not merely due to technological changes (Fleming 2001). Policy or environmental changes can also enlarge the variability in technologies’ expect prevalence or failure. For instance, in an environment that was previously possible for multiple technologies to co-exist, 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, due to heterogeneous distribution of resources supporting these abilities (Barney 1991). Also, within an industry, firms may have different external constraints or relationships with other firms (Sutcliffe and Zaheer 1998, Beckman et al 2004), which similarly varies the impact of technological uncertainty, arising from the same external stimulus, on individual firms.

Faced with technological uncertainty, the firm has to decide on 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 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, given that 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 enables the firm to invest fully in the winning technology upon resolution of uncertainty (Adner and Levinthal 2004). These options’ value in fact increases with technological uncertainty (Folta 1998). Diversification also allows the firm to accumulate knowledge incrementally across multiple technological areas, which provides headway in the requisite area by the time uncertainty is resolved. Such headway is useful as knowledge accumulation requires significant 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.\(^5\)

Our main proposition is that, contrary to conventional wisdom, an opposite effect exists in some circumstances where technological uncertainty induces a firm to become more technologically specialized instead. We note that in 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. In establishing our proposition, we adopt a competition-based view of technological uncertainty which 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.

\(^5\) Note 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 be technologically non-committal meanwhile so as to be able to imitate a wider range of possible technologies subsequently. Empirically, this option-to-wait may either mean that the firm’s specialization does not change with increases in uncertainty (no observed effect), or that specialization decreases with increased uncertainty.
over technical attributes per se, to emphasize more 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 importantly, in deterring others from 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.

The competition-based view is most relevant in settings where there are competing technologies serving similar, if not the same, functions (Anderson and Tushman 1990, Polidoro and Toh 2011). A prime setting would be the early stages of a technology lifecycle, 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 acceptance and market adoption are still unclear. In extreme ‘winner-takes-all’ situations, 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 unrelated to technical superiority, which leaves room for firm strategy to influence selection (Clark 1985, Khazam and Mowery 1994). In short, in these settings, competition for technology dominance is possible and critical.

Adopting the competition-based view of technological uncertainty leads to two crucial observations. First, rivals’ potential deterrence constitutes a cost, in the firm’s strategy of ‘spreading bets’ under uncertainty to facilitate subsequent adaptation, which conventional wisdom may have missed. In other words, when uncertainty is resolved, the firm may not easily transition to the winning technology despite initial investments, as rivals championing the technology may deter the firm from using it. Indeed, these rivals often have the incentives to exclude others and enhance uniqueness so as to extract maximum

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rents (Peteraf 1993), especially when the technology constitutes the industry standard and has great rent-generation potential (Schilling 2002).\textsuperscript{6}

Rivals can deter the firm from certain technological space if they are ahead in the technology’s development. In classic deterrence theories, industry structure, or specifically rivals’ market position, constitutes a common source of deterrence (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 interests to act in a manner unprofitable for the firm should it enter the product market. However, this deterrence principle gets polluted when applied to technological space. Rivals’ signals of market saturation are noisy as technological investments do not map perfectly onto production quantities or even products, especially in early stages of the technology lifecycle. Moreover, small new entrant or follower firms may have other incentives urging them to innovate (Doraszelski 2003). Consequently, findings on the deterrence effect of industry structure within 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 bypasses industry structure which could emit deterrence signals, and instead examines the signals themselves (Clarkson and Toh 2010). Rivals can deter a firm via active exclusion or speed. Exclusion occurs when rivals control resources supporting the technologies, and such resources have ‘rival goods’ nature i.e. rivals’ use precludes others from using them. Examples of these resources include access to key scientists working on the technologies, or necessary ingredients for the technologies, or patents protecting the technologies. A common implementation of active exclusion is rivals’ engagement in patent litigation against the firm (Somaya 2003), and the firm is deterred as 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, which increase their

\textsuperscript{6} Even though prior to the establishment of industry standard, 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 retain the market share of later versions, once they became the industry standards.
abilities to engage in competitive attacks against the firm (Lieberman and Montgomery 1988). Also, rivals may have cumulatively improved upon the technology (Green and Scotchmer 1995), enhancing their generative appropriability by capturing future innovative opportunities (Ahuja 2011) and also increasing technical hurdles for the firm (Adner and Zemsky 2006). With these rivals’ deterrence, it may be costly for the firm to subsequently try to adapt to rivals’ winning technologies subsequently.

The second observation is that, given technological uncertainty, the firm’s objective may not be to adapt to the eventual winning technology, but rather to proactively increase the odds of its own technology becoming the winner. Returns to the winning technology are substantial (Farrell and Saloner 1986, Lieberman and Montgomery 1988), especially in winner-takes-all situations depicted in the standards literature (Schilling 2002) where rivals with competing technologies may be obliterated, allowing the firm to earn at least temporary monopolistic rents (Tushman and Anderson 1986, Suarez and Utterback 1995). Conversely, not having the winning technology entails the added costs of transitioning to the winning technology, which can be accentuated by internal rigidity or rivals’ potential deterrence.

Given these incentives, the firm may increase its technological specialization so as to advance its technology. Returns to specialization are well known (Siggelkow 2003). It helps the firm focus on improving its technologies’ functionalities, relative to competing ones. Also, it channels the firm’s limited resources towards obtaining intellectual property rights and gaining institutional acceptance of its technologies (Gilbert and Newberry 1982, Polidoro and Toh 2011). More generally, specialization accords first-mover advantage and lead time benefits as explained earlier. During early stages of the technology lifecycle, being on the frontier of its technologies allows the firm shape the building of installed base and customer switching costs in ways favoring the firm, such that network externalities may kick in to propel its technologies towards being the industry standard (Schilling 2002, Suarez 2004).

This tendency towards specialization can increase with technological uncertainty. Suppose the firm is in an equilibrium state prior to uncertainty increase, the question is how this firm alters its specialization to deal with the increased uncertainty. The firm becoming less sure of its eventual technological dominance suggests that the tail-end risks have increased. With greater chances of left-tail
(bad) outcomes, a possible firm reaction that is more proactive in nature is to increase specialization to resolve this problem and avoid having to face rivals’ deterrence subsequently. With greater chances of right-tail (good) outcomes, again, a proactive firm reaction may well be to convert, by being more specialized, the probability to certainty of dominance, especially in one-winner-takes-all situations. The overarching principle is that the proactive firm attempts to endogenously influence the resolution of uncertainty in its favor. This principle is echoed in other research showing that a firm may allow and in fact 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 the alternative of technological diversification in the face of uncertainty may be costly. The second observation suggests that the firm faced with technological uncertainty may attempt to endogenously influence the resolution of uncertainty in its favor. This leads to our main hypothesis.

**HYPOTHESIS 1 (H1): The greater the firm’s expected performance variability arising from technological uncertainty, the more the firm will increase its technological specialization subsequently.**

Given that H1 runs counter to conventional wisdom, the natural follow-up is to ask when H1 is likely to be salient. Technological specialization involves a tradeoff: how the firm deals with increased technological uncertainty depends on the relative net benefits of specialization versus diversification. Hence, H1 is salient either in situations where specialization is especially useful in dealing with uncertainty, or when diversification as a way to deal with uncertainty is especially costly. We focus on the latter to examine how H1 is accentuated when the likelihood of rivals’ deterrence, and hence cost of the diversification strategy, is high. We identify two contingencies based on rivals’ characteristics that vary the strength of such deterrence – rivals’ litigiousness and innovativeness.

The first contingency is rivals’ litigiousness. The corresponding deterrence principle here is rivals’ active exclusion as described in an earlier section. 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 (Lerner 1995, Clarkson and Toh 2010). One form of such cost is rivals’ litigation against the firm for patent infringement. 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 or fundamentally based on this dominant technology (Cooter and Rubinfeld 1989, Somaya 2003), rivals may file infringement suits against the firm, for the purpose of obtaining injunctions against the firm or compensation for damages or cuts of firm’s profits from infringing articles or destruction of such infringing articles (Bhagat, Brickley and Coles 1994). These suits are costly to the firm, in terms of time, monetary resources, managers’ involvement and effort, and potential reputational cost (Bhagat et al 1994, Lerner 1995). Even when firms outsource their legal activities, managers are often still actively involved, during depositions, counter-suits, etc.

Rival’s 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 greater litigation incidences. For instance, areas with greater technological complexity or interdependence between rivals’ technologies may necessitate a firm infringing on others’ technologies when developing its own. However, holding constant instances of alleged infringements, rivals differ in their propensity to litigate, depending on their 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 varying interpretation of patent laws across district courts in order to know the technological boundaries of their patents’ coverage and recognize when and where infringements can indeed be established. Long-drawn 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 considers its rivals’ abilities and inclinations towards litigation when considering infringements (Ordover 1978, Lerner 1995).

As stated earlier, when the firm faces increased technological uncertainty, it can either respond by diversifying technologically and trying to adapt to the winning technology subsequently (as per conventional wisdom), or it can respond by focusing on its current technology to advance the technology

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7 The American Intellectual Property Law Association reports that the median cost of a patent infringement lawsuit can often exceed $2mil and be up to $4mil (AIPLA 2003).
as the winning one (as per our proposition H1). When rivals are more litigious, they are more likely to
deter the firm’s subsequent attempt to adapt to their technologies. Thus, the cost of the technological
diversification strategy increases, that is, it becomes less attractive, and the firm would rather deal with
the increased technological uncertainty with the other alternative of becoming more specialized.

HYPOTHESIS 2 (H2): The greater rivals’ litigiousness, the more that firm’s expected performance
variability arising from technological uncertainty will increase the firm’s technological specialization
subsequently.

The second contingency is rivals’ innovativeness. The corresponding deterrence principle is
rivals’ speed and lead time in their technological development, as described earlier. We start by revisiting
innovations’ cumulative nature. Innovations build on common platforms and are cumulative (Anderson
and Tushman 1990, Green and Scotchmer 1995). While 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 the technologies’ key performance attributes (Wade 1995, Adner and Zemsky 2006),
with the latest versions representing state-of-the-art along that particular technological trajectory.
Accumulations, when they entail recombination with other technological components (Fleming 2001),
also exploit other opportunities of generative innovations (Ahuja 2011).

Cumulative innovations, by increasing technical hurdles and eroding generative opportunities,
affect the firm’s investment in the technological area. It is not only rivals’ potential introduction of
another latest-version technology, with its inherent risk of expropriating value of the entire chain of
sequential innovations (Ahuja 2011), that reduces the firm’s incentives to innovate (Scotchmer 1991,
O’Donoghue 1998). Rather, rivals’ existing cumulative innovations suggest to the firm that technical
hurdles for the firm itself to come up with the next improved version are likely high. Rivals having
worked on successive versions are also likely further along the learning curve and have the lead-time
advantages discussed before. Furthermore, the lead time means that rivals are likely to have already
exploited generative opportunities of these technologies and diversified into related areas.
As details of rivals’ cumulative innovations may not be observable by the firm, the firm relies on indications of their presence (Clarkson and Toh 2010). Rivals’ innovativeness serves as one such indication: the more innovative are the rivals, the more likely that they have built up substantial cumulative innovations along their technologies. While rivals’ innovativeness itself and its associated lead-time advantages may influence the firm’s technological specialization decision, we are interested in it as a contingency for technological uncertainty’s effect. We reiterate that when the firm faces increased technological uncertainty, whether it uses the specialization 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 rivals’ likely lead-time advantages that they can use to deter the firm subsequently. Hence, the firm would more likely lead towards the specialization strategy in response to the raised uncertainty.

**HYPOTHESIS 3 (H3):** The greater rivals’ innovativeness, the more that firm’s expected performance variability arising from technological uncertainty will increase the firm’s technological specialization subsequently.

**METHODS**

**Data and Sample.** We test our propositions in the setting of firms active in R&D for the U.S. communication equipment industry from 1996 to 2006, which is appropriate for the following reasons. This industry contains firms with some of the highest R&D intensities in the U.S.,⁸ and technologies represent key sources of competitive advantage for these firms. Accordingly, firms’ decision on how to allocate inventive efforts across technological areas is likely consequential. Moreover, this industry utilizes wide varieties of technology, with multiple competing ones performing similar functions,⁹ and firms have to decide whether to focus on particular technologies or to also invest in competing ones to mitigate substitution risk. Also, rapid and drastic technological changes, which are common in this

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⁸ Firms’ R&D intensities in this industry are comparable to those 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, Glaxo Smithkline, and Smithcine Beecham were 15.5%, 14.4%, and 10.8% respectively.

⁹ For example, multiple transmission media serving similar functions of data transmission compete against one another, such as light wave, wireless radio wave, power lines, satellite, etc. Within each medium, there often exist multiple competing technologies as well.
industry, render our key construct of technological uncertainty a non-trivial concern for firms, and rivalry between firms is accordingly intense. Finally, this setting supports the design of our empirical model, in that it captures firms that are involved with fuel cell technologies and potentially affected by U.S. government funding policy for fuel cell research in year 2000. We elaborate on this in a later section.

We draw data from multiple sources to construct our sample. Data on firms’ stock option implied volatilities, which we use to measure uncertainty, is obtained from the OptionMetrics database. This database contains publicly traded stock option in the U.S. from 1996 onwards, with details such as option premium, implied volatility, strike price, term (days left to maturity), and delta (extent in- or out-of-money), etc., as well as firm identifiers such as 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 U.S., with details on patent numbers, lawsuit filing dates, and USPTO-assigned technology classes of litigated patents. Information on firm identifiers (CUSIP), 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 communication equipment industry. In our sampling timeframe, some communication firms such as AT&T, Qwest and other network providers engage in little R&D themselves and instead purchase technologies from other R&D firms (Fransman 2002). For these communication firms, specialization may not be a relevant response to changes in uncertainty, since technology creation constitutes only cursory portions of their

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10 A potential concern here is that our findings may be driven by events in the communications industry over this time. From 1996 to 1999, the industry had a period of high growth during where revenue rose from $173 to $290 billion due to the 1996 Telecom Act and rapid technological advances associated with growth of the internet (Healy and Costa 1996). Subsequently, the industry declined in the early 2000s due to excess capacity in the telecommunications sector, increased competition from wire and wireless firms, and decreased demand for internet networking equipment, software, and services (Fransman 2002). This loss of momentum may raise a concern that the firm’s decision to specialize is due to a greater financial constraints and a loss in industry demand. To address this concern, in our subsequent analyses, we control for the firm’s financial constraints with Cashit-1 and Debt-Equityit-1, and other firm attributes that should vary with the industry downturn such as firm size and PPE. Furthermore, we include Environmental Uncertaintyit-1, as well as year and technology class dummies, which should largely soak up these unobserved industry downturn effects.

11 In the 1990s, network firms such as ‘Baby Bells’, AT&T, Qwest, MCI WorldCom account for some of the least R&D intensive firms across all industries, with single-digit R&D expense as percentage of sales (Fransman 2002).
operations. To capture R&D firms for which the technological specialization decision is relevant, we compile 89 USPTO-assigned technology classes which are related to communication equipment industry, namely SIC codes 366 and 367, based on the National Bureau of Economic Research (NBER) concordance files. Next, we retrieve all patents assigned to these classes throughout the sample range, and identify firms based on their assignee numbers. We then append the litigation records using the USPTO-assigned numbers of litigated patents, and match the firms’ assignee numbers to CUSIP in the stock options data, using the NBER matching file. We similarly link firms to their financials in the Compustat database. As our empirical model utilizes a policy shock as a natural experiment to compare uncertainty levels between the shock period (2001) and non-shock period (all other years), we retain firms that exist during both periods so that the comparison can be more meaningful. The unit-of-analysis is firm(i)-year(t), and the resulting sample consists of 1441 public firms.

Variables. The dependent variable, Technological Specialization, captures the extent that a firm’s inventive effort at a given time is focused on particular types of technologies. To construct this measure, we trace all patents filed by a firm in a given year that were subsequently granted, and identify the technology classes to which these patents are assigned. We then calculate the concentration ratio (Herfindahl index) of these patents across technology classes, which indicates how focused the firm is within certain classes. Using patent data involves a 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 industry across firms (Griliches 1990). Furthermore,

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12 A concern may be that this sample selection procedure captures R&D firms that are also involved in other industries, and such diversification may influence their observed technological specialization within our sample industry. To address this concern, we subsequently control for firms’ diversification in the analysis.

13 Dropping this sample restriction criterion and essentially treating observations like a cross-sectional dataset 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 robust.

14 Tracing patents at application dates rather than grant dates more accurately captures the firm’s technological specialization in its inventive efforts due to the time lag between application and grant dates.

15 Suppose a firm has four patents, two being assigned to class A, and the other two to class B. Technological Specialization = (2/4)^2 + (2/4)^2 = 0.5. Now suppose three of these patents are assigned to class A, and the remaining to class B. Technological Specialization = (3/4)^2 + (1/4)^2 = 0.625>0.5, reflecting the firm’s greater specialization.
while a firm’s patents may not capture all its inventions, they are relatively reliable indicators of its inventive effort (Hausman et al 1984, Trajtenberg 1990). Also, our objective is not to count a firm’s patents but rather to trace its specialization based on these patents. Offhand, it is not clear if specialization is systematically greater or less for patented versus non-patented inventions, since either could plausibly occur across different circumstances. For instance, while non-specialized firms may diversify into new areas where patenting of discoveries are not yet deemed worthwhile, there could also be situations where specialized firms research on new technologies that are deemed better protected by secrecy.

Our main independent variable is technological uncertainty that a firm faces. This variable is firm-specific: as firms are differentially capable of managing uncertainties (Beckman et al 2004), the extent of uncertainty they experience 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 mean to examine how the firm currently reacts to such expected uncertainty in the upcoming period rather than to how volatile the firm’s past has been. Our empirical model also requires the measure to be contemporaneous, in that it captures changes in the firm’s expectation of upcoming uncertainty due to 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 average age of past patents that the firm cites (Oriani and Sobrero 2008), or exploits the differential nature of industries in which the firm operates as indications of uncertainty (Folta 1998). Others have used survey measures to capture uncertainty the firm faces in its environment (Sutcliffe and Zaheer 1998, Luo 2007). These measures, while useful in other settings, are less appropriate here, as they are often not forward-looking and in fact seldom contemporaneous.\textsuperscript{16}

\textsuperscript{16} For example, suppose an event occurs at time t which drastically increases uncertainty the firm expects to face in the upcoming period. An uncertainty measure based on 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.
We use a new measure of uncertainty that incorporates the forward-looking and contemporaneous attributes. Before describing this measure, we first stress that while the measure by itself captures the firm’s overall uncertainty, we only retain the technological portion of variance in this measure predicted by the policy shock in our analysis, which we explain in a later section. We use the firm’s stock option implied volatility to construct the measure $Uncertainty_{it-1}$ (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 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). 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), 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 1-month-expiration European-style at-the-money call option on the first trading-day of the calendar year to measure $Uncertainty_{it-1}$. 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 1-month options are typically more sensitive to news with relevant informational contents. Note that

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17 Some 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 for us to note that implied volatility of traded stock options captures contemporaneous changes while historical volatility does not.

18 In 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 $10mil 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 $10mil = $5mil 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 $10mil = $2mil of stock at the now-lower stock price, so as to adjust the spot hedge to 30% of $10mil. When the stock price subsequently surges and the option becomes in-the-money at 70% delta, she will then sell back 40% of $10mil = $4mil 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 whichever direction 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.
implied volatility encapsulates multiple components of firm-level uncertainty. We only retain the technological portion part of it using the policy shock in the empirical model, which we explain later.

We measure \textit{Rival’s Litigiousness}_{it-1} as the number of patent infringement lawsuits initiated by rival firms within the communication equipment technology classes that firm \textit{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, while requiring infringements to have allegedly occurred, indicate how willing rivals are to proceed with litigations. Rivals who initiate more lawsuits tend to be more litigious. Likewise, for the other contingency variable – \textit{Rivals’ Innovativeness}_{it-1}, 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 potentially endogenous factors in the form of firm and environmental attributes. A highly innovative firm may innovate in diversified technological domains and accordingly face lower technological uncertainty overall. To capture such \textit{Innovativeness}_{it-1}, we add the number of patents the firm applies for in the year. Similarly, large firms may face lower uncertainty and be more diversified technologically than small firms. We control for \textit{Firm Size}_{it-1} with the natural logarithm of 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 \textit{Downstream Assets}_{it-1} with the natural logarithm of 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 \textit{Cash}_{it-1}, measuring the natural logarithm of firm’s cash and short-term investments, and \textit{Debt-Equity}_{it-1} ratio.\textsuperscript{19} Firms with diversification beyond communications equipment industry may be more inclined to become specialized within this industry when faced with increased uncertainty. We control for \textit{Diversification}_{it-1} using the well-known entropy measure (Palepu 1985) based on the firm’s weighted shares of sales across business segments.

\textsuperscript{19} We also tried adding the firm’s 1-year lagged R&D expenses to more directly get at the possibility that firms with low R&D budget may not be able to diversify technologically, despite facing with greater technological uncertainty. Sample size reduces significantly due to missing data on R&D expense, but subsequent findings remain robust.
For environmental attributes, 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 \textit{Industry Concentration}_{it-1} 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 \textit{Standards}_{it-1} 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 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 \textit{Litigation Concentration}_{it-1}, created 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 add \textit{Technological Complexity}_{it-1}. To construct this variable, we use the principle that technologies citing more prior technologies are more complex, and accordingly calculate the average, across all of firm i’s technology classes in year t, of the total citations made by all patents in each of these technology class. 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$_{t-1}$ which is calculated as the average Uncertainty$_{i,t-1}$ across all firms in the year. We lag all independent variables by a year. To capture other unobserved characteristics of technological domains and inter-temporal heterogeneity, we add technology class and year dummies.

**Empirical Model.** The nature of our propositions renders their empirical tests potentially vulnerable to two forms of endogeneity. First is reverse causality: a firm, by specializing more in a particular technology, may increase uncertainty of its performance due to reduced technological diversification. Second is omitted variable: for example, a firm with a strategy of being an imitator may experience lower uncertainty and concurrently chooses to explore widely across different technologies. Such strategy may not be adequately captured by control variables or technology class dummies, as they may be inherently unobservable and evolve over time. Both forms of endogeneity result in non-random assignments of the sample’s observations into different levels of the independent variable, creating biases in estimates (Holland 1986, Wooldridge 2002). While they do not nullify our conceptual propositions, e.g. it is possible for both effect of specialization on uncertainty and effect of uncertainty on specialization to co-exist, they do impose additional hurdles in the empirical demonstration of these propositions.

To mitigate these problems, we use two-stage least-square (2SLS) estimations, with an exogenous policy shock (Berry and Waldfogel 2001, Marx et al 2009) and a difference-in-difference approach in the 1st stage (Card and Krueger 1994). This empirical model also helps retain the technological portion of firm’s overall uncertainty. In the 1st stage, we use the U.S. Government funding policy for fuel cell in year 2000 as an exogenous shock to estimate changes in the firm’s technological uncertainty, but that likely do not otherwise affect the firm’s subsequent technological specialization or other omitted factors. In order to suppress possible confounding effects of other events that occur at 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

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20 For reverse causality, observations that are high on specialization are selected into high levels of uncertainty, and vice versa, and therefore non-random. For omitted variable bias, firms with imitator strategy, represented in the error term, are similarly selected into low levels of uncertainty in a non-random fashion. Both result in non-zero covariance between uncertainty and the error term in the estimations, which biases coefficient estimates.
(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). This policy shock essentially acts as a natural experiment, randomly assigning observations into pre- and post-shock, and into treatment and control groups. Thus, it circumvents the two endogeneity problems discussed above. Also this policy shock, by increasing volatility over the existing technologies’ success or failure, allows us to predict changes in firm’s overall uncertainty that relate to technological uncertainty. Thus, it helps narrow down on the technological portion of $Uncertainty_{it-1}$. In the 2nd stage, we then trace how this predicted change in the technological uncertainty of firm’s technologies from the 1st 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 to develop technologies for various applications. Out of this budget within the Interior Appropriation Bill, $52.7 million were allocated to stationary fuel cell R&D, which is $10 million more than requested by the Department of Energy, with the rest being allocated to transportation and buildings.

To explain this bill’s impact on our sample firms, it is helpful to highlight 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). Importantly, different fuel cell types have characteristics that render them more suitable for different applications.  

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 communication equipments, potential applications include fuel cells for cellular phones, laptop computers and other portable

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21 For instance, low operating temperature required for Direct Methanol Fuel Cell makes it suitable for mid-size applications, such as cell phones and other consumer products. In contrast, Molten Carbonate Fuel Cell requires 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. Alkaline Fuel Cell, while among the most efficient at generating electricity, is sensitive to CO$_2$ poisoning and hence unsuitable for automobile applications.
electronics, radio and other cell towers, and backup power for switch nodes. Communication equipment firms using these technologies are not constrained to telecommunications uses, but can potentially expand into other applications such as consumer electronics,\textsuperscript{22} generators for commercial or military uses, electric cars, space flights, water-water treatment plants, etc., depending on the fuel cell types they work with.

The government funding round in 2000 likely increases technological uncertainty for communication equipment firms operating with fuel-cell technologies, based on the following reasons. A majority of the budget is allocated to stationary fuel cell, which is directly relevant to communication equipment technologies and applications. The ‘surprise’ component of $10 million adds to the exogeneity of the shock. Prior to 2000, fuel cells have traditionally been passed over in appropriation bills and have received relatively small shares of federal energy research budget, which render this funding round more significant for firms. The government’s explicit objective through this sizeable funding was to support research that will advance fuel cell technologies and reduce production costs, thereby speeding up their commercialization.\textsuperscript{23} This funding presents a real opportunity for a firm awarded the funds that its fuel cell technologies will become commercialized, which significantly increases the chances that its technologies will become dominant in the industry. Concurrently, this funding also poses a viable threat that some rivals will be awarded the funds instead, and their fuel cell technologies may leap-frog, making obsolete the firm’s technologies. Similarly, particular fuel cell applications may gain substantial grounds when the supporting technologies become commercialized, further accentuating the ambiguity over whether the firm’s technologies will thrive or falter, depending on what applications it was focusing on before. Moreover, before the 21st century, few fuel cells have been successfully commercialized, and the fuel cell industry is essentially still in its nascent stage without any clear dominant design or standards. This funding may increase the threat of entry by more rivals with competing fuel cell technologies fighting to become the industry standard, and this could hurt or help propel the firm’s technologies,

\textsuperscript{22} Examples of consumer electronics powered by fuel cells include video recorders, portable power tools, hearing aids, smoke detectors, burglar alarms, and meter readers.

\textsuperscript{23} We quote the executive director for Breakthrough Technologies Institute/Fuel Cell, Robert Rose, in 2000: “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 (CNN 2000).”
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 round increases technological uncertainty, specifically, the variability over whether the firm’s fuel cells technologies and/or associated applications will emerge to dominate the industry or become obsolete.

We use the variable *Policy Shock*\textsubscript{it} to capture all firm-years in our data occurring one year after the funding policy enactment, i.e. *Policy Shock*\textsubscript{it} is 1 for observations in year 2001 and 0 otherwise.\textsuperscript{24} To define treatment and control groups for the difference-in-difference approach, we use the variable *Fuel Cell*\textsubscript{it} to capture firms that are active in generating technologies related to fuel cells. Fuel cell technologies are patented under USPTO-assigned class 429. As technologies’ usage is often not constrained to fit these classification schemes exactly, we choose to be more conservative with a broader definition of the treatment group that includes technologies similar to fuel cell ones in nature and usage. *Fuel Cell*\textsubscript{it} is 1 for firms who filed for at least one patent in year 2001 under the NBER-assigned technological subcategory 45 which encompasses technology class 429, and 0 otherwise.\textsuperscript{25} We then multiply these two variables. The resulting interaction term is the key variable in the 1\textsuperscript{st} 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 1\textsuperscript{st} stage, we estimate changes in the technological portion of *Uncertainty*\textsubscript{it} using:

\textsuperscript{24}To check if the policy shock may have longer-term effect, or if firms take longer to react to the shock, we alternatively define *Policy Shock*\textsubscript{it} as observations occurring up to two years (2001-2002), and three years (2001-2003) post enactment. Findings for all subsequent analyses remain fully robust under the two-year specification. For the three-year specification, all subsequent findings are robust except for the full-sample model in the 2nd stage regression (Model 1 of Table 4), where *Predicted(Uncertainty)\textsubscript{it-1}* remains positive but loses its significance.

\textsuperscript{25}Firms working on fuel-cell-related technologies may not have filed for fuel cell (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 *Fuel Cell*\textsubscript{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 reduced the sample size for the treatment group. Findings for 1\textsuperscript{st} stage estimations in Table 2 remain unchanged except for model 3 with robust error, where the policy shock loses its significance. Findings for 2\textsuperscript{nd} stage estimations in Table 3, which tests our propositions, are robust except for the full-sample model 1, where *Predicted(Uncertainty)\textsubscript{it} is only significant at 10% level.*
\[ \text{Uncertainty}_n = \beta_0 + \beta_1 \text{Policy Shock}_n + \beta_2 \text{Fuel Cell}_n + \beta_3 \text{Policy Shock}_n \times \text{Fuel Cell}_n + \beta_h \text{Controls} + \varepsilon_{ijt} \]

The main variable of interest is \( \text{Policy Shock}_n \times \text{Fuel Cell}_n \). The predicted change in Uncertainty from this 1st stage estimation is then lagged by one year and used to estimate technological specialization in the 2nd stage. Note that changes in Uncertainty arise from Policy Shock, which is a time dummy. This necessitates Uncertainty to change contemporaneously with the shock. Hence, measures based on past firm volatility or on prior firm behavior are not suitable here. Also, while the overall Uncertainty may vary with other non-technology aspects of the firm’s activities, Predicted(Uncertainty) used in the 2nd stage to examine our propositions includes only the technology-based portion of Uncertainty that arises from the policy shock. The main model in the 2nd stage estimation is as follows:

\[ \text{Technological Specialization}_n = \delta_0 + \delta_1 \text{Predicted(Uncertainty)} + \delta_h \text{Controls} + \varepsilon_{ijt} \]

\( \delta_1 \) tests H1, and is a consistent and also efficient estimator, as the 2SLS model converts its variance to that for the estimator of Uncertainty (Wooldridge 2002). To test contingency effects in H2 and H3, the conventional approach is to interact Uncertainty with Rival’s Litigiousness and Rival’s Innovativeness respectively and test the significance of their coefficients. However, this creates complications in the variance adjustments for coefficients of these interaction terms in the 2nd stage. We circumvent these complications with split-sample analyses. Specifically, to test H2, we split the sample by the mean of Rival’s Litigiousness into ‘low’ and ‘high’ subsamples, and obtain \( \delta_1^L \) and \( \delta_1^H \) respectively for each subsample. We then perform a t-test for the difference in these coefficients, essentially examining if the effect of Uncertainty on Technological Specialization differs across different (high versus low) levels of Rival’s Litigiousness. The test of H3 follows a similar procedure.

**FINDINGS**

Table 2 contains descriptive statistics and correlations. Mean of Uncertainty suggests that over the sample period, the market expects average stock price of firms to fluctuate with a standard deviation of 39%. Pairwise correlations are high between Rival’s Litigiousness and Innovativeness (0.75) and likewise between Firm Size and Downstream Assets. To ensure that our findings are not tainted by multicollinearity problems, we separately drop Innovativeness and Downstream Assets.
from the analyses. Subsequent findings remain unchanged. For the exogenous shock technique to work, our empirical model requires that Uncertainty$_t$ 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 (Fuel Cell$_t=1$ or 0), and for each group, plot the Technological Specialization$_t$ separately for observations affected and non-affected by the shock (Policy Shock$_t=1$ or 0) in Figure 1. While both groups exhibit an increase in Uncertainty$_t$ over the shock, likely due to 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$_t$.

Table 3 documents tests of the policy shock’s effect on Uncertainty$_t$ in the 1$^{st}$ stage equation. Model 1 is the base model with main variables, model 2 includes the interaction term Policy Shock$_t$*Fuel Cell$_t$, and model 3 allows for robust standard errors. Policy Shock$_t$ is significantly positive across all models, suggesting that Uncertainty$_t$ for sample firms is higher in 2001 compared to average of other years. Importantly, Policy Shock$_t$*Fuel Cell$_t$ is significantly positive at 1% in both models 2 and 3 (t-statistics 9.423 and 4.984 respectively), showing that the fuel cell funding policy increases Uncertainty$_t$ 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$_t$. We use Model 2 as the 1$^{st}$ stage estimation to predict Predicted(Uncertainty$_{t-1}$).

Table 4 reports findings for Predicted(Uncertainty$_{t-1}$)’s effect on Technological Specialization$_t$ in the 2$^{nd}$ stage regressions. Model 1 contains the main effect of Predicted(Uncertainty$_{t-1}$) for the full sample 2SLS model. Predicted(Uncertainty$_{t-1}$) is significantly positive in model 1 (z-statistics 3.087), suggesting that when faced with greater technological uncertainty, the firm will increase its technological specialization subsequently. This supports H1. It is possible that firm’s specialization takes longer than one year to react to changes in technological uncertainty. We include 2-year and 3-year lags of predicted uncertainty in model 1, and all three lags are jointly significantly positive.

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26 Using model 3 as the 1$^{st}$ stage estimation in the 2SLS model with robust error produces fully robust results.
Models 2 and 3 represent the split-sample analysis testing H2, and contain findings for the ‘low’ and ‘high’ subsamples of Rival’s Litigiousness_{it-1} respectively. The objective in this analysis is to examine, through t-test, if the coefficient of Predicted(Uncertainty_{it-1}) is significantly larger in the ‘high’ than in the ‘low’ subsample, i.e. whether the effect of uncertainty is accentuated when rivals are more litigious. The coefficient of Predicted(Uncertainty_{it-1}) is positive (though non-significant) in both models 2 and 3, and appears larger in Model 3 (z-statistics 1.192) than in Model 2 (z-statistics 0.029). More importantly, t-test of Predicted(Uncertainty_{it-1}) across these two subsamples, reported in the next row, shows that Predicted(Uncertainty_{it-1}) is significantly larger in Model 3 when Rival’s Litigiousness_{it-1} is high than in Model 2 when Rival’s Litigiousness_{it-1} is low (t-statistics -44.16). This supports H2.

Models 4 and 5 similarly test H3, with the objective of examining through t-test if the effect of uncertainty on the firm’s technological specialization is greater when rivals are more innovative. Predicted(Uncertainty_{it-1}) is significantly positive in Model 5 for the ‘high’ subsample of Rival’s Innovativeness_{it-1} (z-statistics 2.738) but is negative and insignificant in Model 4 for the ‘low’ subsample (z-statistics -0.254). T-test shows that Predicted(Uncertainty_{it-1}) is significantly larger in Model 5 with high Rival’s Innovativeness_{it-1} than in Model 4 with low Rival’s Innovativeness_{it-1} (t-statistics -104.18). This supports H3. As in Model 1, we allow for the possibility that these contingency predictions require longer than a year to take effect. We include 2-year and 3-year 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 per in Models 2 and 3), and likewise when rivals are more innovative (as per in Models 4 and 5).

Due to reduced sample size in the split-sample analysis, we have to drop the year dummies in Models 2 and 3, and further drop the technology class dummies in models 4 and 5. A potential concern is that some technology class or year specific factors may be driving the findings for the contingency effects. However, we have controlled for various time-varying factors capturing environmental attributes in the analysis, and importantly, Environmental Uncertainty_{it-1} should have helped absorb these class- or year-specific effects. Our empirical model with the policy shock further mitigates this concern of unobserved technology class or year effects.

It 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 also further factor in focal firm’s deterrence of rivals by calculating Rival’s Innovativeness_{it-1} and Rival’s Innovativeness_{it-1} as being relative to firm i (rivals’ minus firm i’s), and repeat all analyses in Tables 3 and 4. Findings remain fully robust.

27 Due to reduced sample size in the split-sample analysis, we have to drop the year dummies in Models 2 and 3, and further drop the technology class dummies in models 4 and 5. A potential concern is that some technology class or year specific factors may be driving the findings for the contingency effects. However, we have controlled for various time-varying factors capturing environmental attributes in the analysis, and importantly, Environmental Uncertainty_{it-1} should have helped absorb these class- or year-specific effects. Our empirical model with the policy shock further mitigates this concern of unobserved technology class or year effects.

28 It 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 also further factor in focal firm’s deterrence of rivals by calculating Rival’s Innovativeness_{it-1} and Rival’s Innovativeness_{it-1} as being relative to firm i (rivals’ minus firm i’s), and repeat all analyses in Tables 3 and 4. Findings remain fully robust.
We use graphical analysis to further demonstrate these contingency effects. We first regress Technological Specialization$_{it}$ on all control variables to obtain the residual unexplained variance in specialization. We then split the sample at the mean of Rival’s Litigiousness$_{it-1}$ to obtain two subsamples with high and low rivals’ litigiousness, and plot the linear prediction of this residual of technological specialization against Predicted(Uncertainty$_{it-1}$) for the two subsamples as well as the full sample in Figure 2. The positive slope for the full-sample reflects the positive Predicted(Uncertainty$_{it-1}$) in model 1 of Table 4. The subsample with high Rival’s Litigiousness$_{it-1}$ has a positive slope, which supports H2 and is driving the overall positive slope for the full-sample. The slope for the sub-sample with low Rival’s Litigiousness$_{it-1}$ is in fact negative. Likewise, we perform a similar analysis for Rival’s Innovativeness$_{it-1}$ in Figure 3. Again, we find that the positive slope for the full-sample is driven by subsample with high Rival’s Innovativeness$_{it-1}$, which supports H3, and that when the firm does not face innovative rivals (subsample with low Rival’s Innovativeness$_{it-1}$), the effect of uncertainty on specialization is in fact negative. Overall, these graphical analyses strongly demonstrate our proposition 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.

We further examine the policy shock, given its central role in our empirical model. Specifically, we examine its appropriateness and effectiveness in three aspects: (i) if it is exogenous to firms, (ii) if it affects firms’ specialization other than through uncertainty, and (iii) if it creates a random assignment of observations to different levels of uncertainty. For (i), the concern is that some firms may try 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 (close to 25% increase from expected funding for stationary fuel cell) was unexpected by firms. This ‘surprise’ portion helps ensure exogeneity, even if the other portions of funding was a result of 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 (FCHEA). This association serves as an advocacy group focusing on commercialization of fuel cells and hydrogen energy technologies, and its members are heavily involved in securing federal funding and increasing 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 find fully robust results. Hence, we are fairly confident that firms’ potential influences on the funding policy are not driving our results.

In (ii), the policy instrument is appropriate if it changes firms’ specialization only through its effect on uncertainty. While there may be hypothetical reasons for why this may not be the case in general, the relevant concern is whether it is the case in our sample. We first regress specialization on the policy variables, and find that the effect of \( Policy\ Shock_{i,t} \times Fuel\ Cell_{i,t} \) is significantly positive (t-statistics 2.47). To examine if this effect occurs through uncertainty, we insert \( Predicted(Uncertainty_{it-1}) \) (obtained from Model 2 of Table 3) into the regression, and find that while \( Predicted(Uncertainty_{it-1}) \) is significantly positive (t-statistics 11.32) as consistent with earlier findings, \( Policy\ Shock_{i,t} \times Fuel\ Cell_{i,t} \) is now insignificant (t-statistics 1.35). Thus, we have some indications that, in our sample, there is no clear sign of the policy instrument directly affecting specialization other than through changing uncertainty.

For (iii), the policy shock mitigates endogeneity issues by randomly assigning observations to being treated or non-treated by the shock. If randomization is effective, unobserved firm attributes should not systematically differ between treated and non-treated firms (observed differences are explicitly controlled for). Besides checking the exogeneity of shock as per above, we can apply a more stringent test for differences in observed firm attributes between treated and non-treated firms, with the principle being 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 non-treated firms (\( Policy\ Shock_{i,t} \times Fuel\ Cell_{i,t} = 1 \) and 0 respectively), and trace their observed firm attributes from earlier analysis. Table 5 documents t-tests of differences in these firm attributes. As per the intention of the shock, \( Technological\ Specialization_{it} \) and \( Predicted(Uncertainty_{it-1}) \) are both greater for the treated firms. The other firm attributes, however, are mostly not significantly different between treated and non-treated firms (other than \( Innovativeness_{it-1} \) and \( Cash_{it-1} \)), which lends some confidence in the randomized assignments of observations. Higher \( Innovativeness_{it-1} \) for treated
firms is perhaps due to these firms responding to the funding policy, and does not necessarily suggest non-random selection of more innovative firms into being treated. The marginal difference in $Cash_{it-1}$ between treated and non-treated firms, while significant, appears small. Hence, we interpret overall 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 due to serial correlation (Bertrand et al 2004). Given our relatively short time-series (11 years), this concern is likely not 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 remains as before. We then rerun all analysis as per Tables 3 and 4 on what is now essentially a cross-section dataset, and find fully robust results.

When constructing $Technological Specialization_{it}$, we focus on patents related to communications equipment industry. A potential issue is that our sample firms may be diversified across other industries, such that this variable may not reflect specialization for the entire firm. We dealt with this issue in our earlier analyses by controlling for $Diversification_{it-1}$. However, a lingering concern remains that firms in our sample appearing to become more specialized given greater uncertainty may actually be responding to uncertainty by specializing within communications equipment industry but diversifying technologically across industries. We construct an alternative variable, $Alt. Specialization_{it}$, with the same principles but based instead on the firm’s entire patent portfolio spanning all industries, and rerun the 2SLS analysis in Table 4. Findings for the full-sample Model 1 are robust, but the split-sample results in Models 2-5 are not. These findings are hard to interpret due to the increased noise in the alternative measure: increased uncertainty in fuel cell technologies are likely not relevant to all industries, and a firm may operate more as a collection of separate divisions by industry. Instead, we directly examine the core challenge – firms specializing within communications equipment industry (high $Technological Specialization_{it}$) may be systematically diversifying across industry (low $Alt. Specialization_{it}$). We find that correlation between the two measures is 0.63 (significant at 1%), suggesting little divergence between them. We regress $Alt.
Specialization, on Technological Specialization, with all our earlier control variables, and find that Technological Specialization significantly explains Alt. Specialization (t-statistics 60.59). This finding is robust when we constrain the sample to only fuel cell firms (t-statistics 13.80) or even fuel cell firms in year 2001 (t-statistics 4.07). These findings suggest that firms specializing within communications equipment industry are not diversifying technologically across other industries.

As our measure for technological uncertainty (Predicted(Uncertainty)) 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 technological 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 – 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 and our measure Predicted(Uncertainty) is 0.34 and significant at 1%, suggesting that while these two measures likely contain substantively different information, they at least consist of a common component related to technological uncertainty. We then replace Predicted(Uncertainty) with PatCite Uncertainty in Table 4, and run OLS regressions (2SLS is inappropriate since PatCite Uncertainty likely does not change contemporaneously with the policy shock). In the full-sample Model 1, PatCite Uncertainty is insignificant and has the wrong sign (t-statistic -0.13), but findings remain robust for the split-sample analysis in Models 2-5. We refrain from drawing too much conclusions here, since we lack the abilities here to resolve the endogeneity issues (reverse causality and omitted variables) which we described earlier that are likely present with PatCite Uncertainty as the regressor.

CONCLUSIONS

Conventional wisdom suggests that a firm, when faced with technological uncertainty, responds by decreasing its technological specialization so as to ‘spread its bets’ and better adapt to the dominant technology subsequently. Our central proposition is that under a competition-based view of technological uncertainty, an opposite effect exists where the firm increases its technological specialization instead.
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, and is especially salient when rivals are highly litigious or innovative. Using a U.S. government funding policy for fuel cell research in 2000 to create a natural experiment and stock option implied volatility to measure expected uncertainty, we find empirical support for our propositions in the communications equipment industry.

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, while others focus on particular ‘bets’. The former ‘diversification’ response anchors on the basic principle of risk-reduction through diversification and is intuitive. In fact, much of existing theories can and has explained its rationale. The latter ‘focused’ response, however, remains relatively puzzling. Rather than to relegate 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 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 be its effort to change the way the uncertainty is resolved.

Our propositions are meaningful to the extent that they can be generalized across settings. In the paper where we theorize these propositions, we recurrently situate discussions within more extreme settings involving early stages of lifecycle, with possible emergence of industry standards and network externalities locking in these standards, because these settings are useful in illustrating our arguments. However, our propositions are not necessarily constrained within these more extreme settings. The necessary features of settings in which our propositions can take effect are only that multiple technologies compete and that the firm experiences uncertainty regarding whether its technology will eventually turn out to be the superior one. For example, in the pharmaceutical industry within a therapeutic class, there are often multiple competing mechanisms of action that drugs can be based on (Polidoro and Toh 2011),
and they do not always exhibit a lifecycle nor converge towards some uniform standard. Hence, we believe these propositions are likely more generalized than we may have portrayed.

Our propositions also 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 itself 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 towards 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 towards 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. Considering influences of rivals’ deterrence can potentially shed more light on and enhance completeness of theories involving firm’s value-creation.
While we focus on rivals’ characteristics as contingencies, there are possibly other 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 hope of winning the technology race. We defer to future research to pursue these fruitful directions.

Inherent in our propositions is a tradeoff between a firm’s adaptability versus 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 tradeoff, as evidenced by observed heterogeneity of technological specialization across firms within a given environment. This tradeoff carries an important message: while organizational adaptability is a useful skill, as shown by 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.
REFERENCES


Figure 1: Effect of policy shock on firm-level uncertainty

Figure 2: Effect of uncertainty on specialization contingent on rivals’ litigiousness

Figure 3: Effect of uncertainty on specialization contingent on rivals’ innovativeness
### Table 1: Fuel cell types

<table>
<thead>
<tr>
<th>Fuel Cell Type</th>
<th>Electrolyte Used</th>
<th>Operating Temperature</th>
<th>Examples of Applications</th>
</tr>
</thead>
<tbody>
<tr>
<td>Polymer Electrolyte</td>
<td>Polymer Membrane</td>
<td>60-140°C</td>
<td>Stationary applications, Transportation applications</td>
</tr>
<tr>
<td>Direct Methanol</td>
<td>Polymer Membrane</td>
<td>30-80°C</td>
<td>Cellular phones, other consumer products, automobile power</td>
</tr>
<tr>
<td>Alkaline</td>
<td>Potassium Hydroxide</td>
<td>150-200°C</td>
<td>Space and undersea vehicles</td>
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<tr>
<td>Phosphoric Acid</td>
<td>Phosphoric Acid</td>
<td>180-200°C</td>
<td>Buildings, hotels, hospitals, electric utilities, military</td>
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<tr>
<td>Molten Carbonate</td>
<td>Lithium / Potassium Carbonate</td>
<td>650°C</td>
<td>Industrial and commercial applications</td>
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<tr>
<td>Solid Oxide</td>
<td>Yttria Stabilized Zirconia</td>
<td>1000°C</td>
<td>Industrial and large-scale central-electricity generating-stations</td>
</tr>
</tbody>
</table>

Other fuel cell types include: proton exchange membrane fuel cell, regenerative fuel cell, zinc-air fuel cell

### Table 2: Descriptive statistics

| Variable                              | Obs  | Mean  | Std Dev | Min  | Max  | i   | ii  | iii  | iv   | v    | vi   | vii  | viii | ix   | x    | xi   | xii  | xiii | xiv  | xv   |
|---------------------------------------|------|-------|---------|------|------|-----|-----|------|------|------|------|------|------|------|------|------|------|------|------|
| Technological Specialization$_{it}$   | 14873| 0.10  | 0.26    | 0.00 | 1.00 | 1   |     |      |      |      |      |      |      |      |      |      |      |      |      |
| Uncertainty$_{it-1}$                   | 14873| 0.39  | 0.17    | 0.08 | 1.95 | 0.09| 1   |      |      |      |      |      |      |      |      |      |      |      |      |
| Rival's Litigiousness$_{it-1}$         | 13892| 0.08  | 0.32    | 0.08 | 4.71 | 0.16| 0.04| 1    |      |      |      |      |      |      |      |      |      |      |      |
| Rival's Innovativeness$_{it-1}$        | 13892| 6.91  | 1.48    | 3.40 | 9.25 | 0.01| -0.06| 0.04| 1    |      |      |      |      |      |      |      |      |      |      |
| Innovativeness$_{it-1}$                | 13892| 0.01  | 0.07    | 0.00 | 1.88 | 0.04| 0.04 | 0.75| 0.02| 1    |      |      |      |      |      |      |      |      |      |
| Firm Size$_{it-1}$                     | 13367| 38.54 | 63.06   | 0.01 | 779.10 | -0.08| -0.29 | 0.11| -0.02| 0.13| 1    |      |      |      |      |      |      |      |      |      |
| Downstream Assets$_{it-1}$             | 13891| 3.39  | 8.12    | 0.00 | 84.10 | -0.08| -0.22| 0.04| -0.01| 0.06| 0.74| 1    |      |      |      |      |      |      |      |      |
| Cash$_{it-1}$                          | 13891| 1.43  | 6.29    | 0.00 | 199.23 | -0.06| -0.19| 0.11| 0.00| 0.12| 0.62| 0.64| 1    |      |      |      |      |      |      |
| Diversification$_{it-1}$               | 12699| 0.82  | 0.61    | 0.00 | 2.70 | -0.07| -0.31| 0.03| 0.00| 0.02| 0.43| 0.31| 0.25| 1    |      |      |      |      |      |
| Debt Equity$_{it-1}$                    | 13888| 1.21  | 1.91    | 0.00 | 42.63 | 0.07| 0.26| 0.03| 0.01| 0.02| -0.19| -0.15| -0.07| -0.27| 1    |      |      |      |      |
| Industry Concentration$_{it-1}$        | 13892| 0.01  | 0.01    | 0.00 | 0.58 | 0.31| 0.14| 0.39| -0.03| 0.23| -0.02| -0.04| 0.01| -0.05| 0.09| 1    |      |      |
| Standards$_{it-1}$                      | 13892| 0.01  | 0.01    | 0.00 | 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    |      |
| Litigation Concentration$_{it-1}$      | 13892| 0.10  | 0.27    | 0.00 | 1.00 | 0.49| 0.09| 0.14| 0.01| 0.01| -0.08| -0.08| -0.06| 0.07| 0.47| 0.19| 1    |      |
| Technological Complexity$_{it-1}$      | 13892| 7.76  | 28.36   | 0.00 | 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    |
| Environmental Uncertainty$_{it-1}$     | 13892| 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    |

a. Scaled by 1,000
b. Scaled by 100
c. Variables are not logged in this descriptive statistics and correlations. They are subsequently logged in the regressions analyses (Tables 3 and 4).
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<td>(1.708)</td>
<td>(1.904)</td>
<td>(5.676)</td>
</tr>
<tr>
<td>Year Dummies</td>
<td>included</td>
<td>included</td>
<td>included</td>
</tr>
<tr>
<td>Technology Class Dummies</td>
<td>included</td>
<td>included</td>
<td>included</td>
</tr>
<tr>
<td>Observations</td>
<td>11,808</td>
<td>11,808</td>
<td>11,808</td>
</tr>
</tbody>
</table>

<sup>a</sup> t statistics in parentheses (** p<0.01, * p<0.05, * p<0.1)
<sup>b</sup> a. Model allows for robust errors.
<sup>c</sup> b. Variables are logged.
<sup>d</sup> c. Scaled by 1,000
<sup>e</sup> d. Scaled by 100
Table 4: 2nd stage regressions – effect of uncertainty on technological specialization

<table>
<thead>
<tr>
<th>Dependent Variable</th>
<th>Base Model</th>
<th>Low Rival Litigiousness</th>
<th>High Rival Litigiousness</th>
<th>Low Rival Innovativeness</th>
<th>High Rival Innovativeness</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
<td>(4)</td>
<td>(5)</td>
</tr>
<tr>
<td>Predicted (Uncertainty&lt;it-1)&lt;sup&gt;a&lt;/sup&gt;</td>
<td>0.675***</td>
<td>0.0105</td>
<td>0.170</td>
<td>-0.0373</td>
<td>0.244***</td>
</tr>
<tr>
<td>T-statistics of Difference Across Models&lt;sup&gt;b&lt;/sup&gt;</td>
<td>-44.16***</td>
<td>-104.18***</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Rival's Litigiousness&lt;it-1&gt;&lt;sup&gt;f&lt;/sup&gt;</td>
<td>-0.0145</td>
<td>1.439***</td>
<td>-0.105***</td>
<td>0.0710***</td>
<td>0.0869***</td>
</tr>
<tr>
<td>Rival's Innovativeness&lt;it-1&gt;</td>
<td>-0.00578</td>
<td>-0.00379***</td>
<td>0.00939</td>
<td>-0.00224</td>
<td>0.0274**</td>
</tr>
<tr>
<td>Innovativeness&lt;it-1&gt;&lt;sup&gt;e&lt;/sup&gt;</td>
<td>-0.195***</td>
<td>-3.034***</td>
<td>0.171**</td>
<td>-0.188*</td>
<td>-0.310***</td>
</tr>
<tr>
<td>Firm Size&lt;it-1&gt;&lt;sup&gt;c&lt;/sup&gt;</td>
<td>0.0152**</td>
<td>-0.000176</td>
<td>-0.00438</td>
<td>-0.00352</td>
<td>0.00677</td>
</tr>
<tr>
<td>Downstream Assets&lt;it-1&gt;&lt;sup&gt;c,e&lt;/sup&gt;</td>
<td>13.24**</td>
<td>-4.047*</td>
<td>12.39</td>
<td>-5.443</td>
<td>5.354</td>
</tr>
<tr>
<td>Cash&lt;it-1&gt;&lt;sup&gt;c,e&lt;/sup&gt;</td>
<td>-9.080***</td>
<td>-0.0872</td>
<td>-12.22*</td>
<td>1.799</td>
<td>-6.250***</td>
</tr>
<tr>
<td>Diversification&lt;it-1&gt;</td>
<td>0.00119</td>
<td>-0.00482</td>
<td>-0.00450</td>
<td>-0.00680</td>
<td>-0.00624</td>
</tr>
<tr>
<td>Debt Equity&lt;it-1&gt;</td>
<td>-0.00619</td>
<td>-0.000308</td>
<td>0.00142</td>
<td>0.000631</td>
<td>0.000998</td>
</tr>
<tr>
<td>Industry Concentration&lt;it-1&gt;</td>
<td>0.402</td>
<td>0.270</td>
<td>0.0232</td>
<td>0.539*</td>
<td>2.088***</td>
</tr>
<tr>
<td>Standards&lt;it-1&gt;</td>
<td>0.0868</td>
<td>-1.623</td>
<td>-0.583</td>
<td>1.276</td>
<td>2.071</td>
</tr>
<tr>
<td>Litigation Concentration&lt;it-1&gt;</td>
<td>0.342***</td>
<td>0.213***</td>
<td>-0.0772*</td>
<td>0.382***</td>
<td>0.346***</td>
</tr>
<tr>
<td>Technological Complexity&lt;it-1&gt;</td>
<td>5.056e-05</td>
<td>-0.000204</td>
<td>-0.000386*</td>
<td>0.000302*</td>
<td>0.000462***</td>
</tr>
<tr>
<td>Environmental Uncertainty&lt;it-1&gt;</td>
<td>-0.991</td>
<td>0.0390</td>
<td>-0.215</td>
<td>-0.0324</td>
<td>-0.243**</td>
</tr>
<tr>
<td>Constant</td>
<td>0.558</td>
<td>0.0704***</td>
<td>0.455***</td>
<td>0.132*</td>
<td>-0.204**</td>
</tr>
<tr>
<td>Year Dummies</td>
<td>included</td>
<td>not included</td>
<td>not included</td>
<td>not included</td>
<td>not included</td>
</tr>
<tr>
<td>Technology Class Dummies</td>
<td>included</td>
<td>included</td>
<td>not included</td>
<td>not included</td>
<td>not included</td>
</tr>
<tr>
<td>Observations</td>
<td>10,550&lt;sup&gt;d&lt;/sup&gt;</td>
<td>9,147</td>
<td>1,403</td>
<td>3,494</td>
<td>7,056</td>
</tr>
</tbody>
</table>

z-statistics in parentheses (*** p<0.01, ** p<0.05, * p<0.1)

a. Predicted (Uncertainty<it-1>) is the lagged predicted uncertainty from the first stage Table 3, Model 2.
b. T-test compares the coefficients of Predicted (Uncertainty<it-1>) across the pairs of subsamples.
c. Variables are logged.
d. Observations reduced from 1st stage regressions due to the lagging of predicted uncertainty.
e. Scaled by 1,000
f. Scaled by 100
Table 5: Differences in firm attributes between treated and non-treated firms

<table>
<thead>
<tr>
<th>Firm Attributes</th>
<th>Non-treated Firms&lt;sup&gt;a&lt;/sup&gt;</th>
<th>Treated Firms&lt;sup&gt;a&lt;/sup&gt;</th>
<th>T-statistics&lt;sup&gt;b&lt;/sup&gt;</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mean</td>
<td>Std Dev</td>
<td>Mean</td>
</tr>
<tr>
<td>Technological Specialization&lt;sub&gt;t&lt;/sub&gt;</td>
<td>0.09</td>
<td>0.25</td>
<td>0.28</td>
</tr>
<tr>
<td>Uncertainty&lt;sub&gt;t&lt;/sub&gt;</td>
<td>0.37</td>
<td>0.16</td>
<td>0.76</td>
</tr>
<tr>
<td>Innovativeness&lt;sub&gt;t-1&lt;sup&gt;c&lt;/sup&gt;&lt;/sub&gt;</td>
<td>0.01</td>
<td>0.07</td>
<td>0.16</td>
</tr>
<tr>
<td>Firm Size&lt;sub&gt;t-1&lt;sup&gt;e&lt;/sup&gt;&lt;/sub&gt;</td>
<td>2.54</td>
<td>1.77</td>
<td>2.88</td>
</tr>
<tr>
<td>Downstream Assets&lt;sub&gt;t-1&lt;sup&gt;c,d&lt;/sup&gt;&lt;/sub&gt;</td>
<td>0.01</td>
<td>0.00</td>
<td>0.01</td>
</tr>
<tr>
<td>Cash&lt;sub&gt;t-1&lt;sup&gt;c,d&lt;/sup&gt;&lt;/sub&gt;</td>
<td>0.01</td>
<td>0.00</td>
<td>0.01</td>
</tr>
<tr>
<td>Diversification&lt;sub&gt;t-1&lt;/sub&gt;</td>
<td>0.84</td>
<td>0.61</td>
<td>0.87</td>
</tr>
<tr>
<td>Debt Equity&lt;sub&gt;t-1&lt;/sub&gt;</td>
<td>1.19</td>
<td>1.81</td>
<td>2.14</td>
</tr>
</tbody>
</table>

<sup>a</sup> Treated firms are observations that are active in Fuel Cell in 2001 (Policy Shock<sub>t</sub>*Fuel Cell<sub>t</sub>=1), and non-treated firms are all other observations.

<sup>b</sup> Compares difference in firm attribute between non-treated and treated firms.

<sup>c</sup> Scaled by 1,000.

<sup>d</sup> Variables are not logged here.