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R&D Spending: Dynamic or Persistent?

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It is well established that returns to spending on research and development are positive and accrue over several years—that is, firms benefit from higher levels of cumulative R&D spending. We study how a given amount of such spending is best allocated, over time, to optimize R&D performance. Under a *persistent* policy, allocations remain nearly constant irrespective of circumstances; under a *dynamic* policy, R&D spending increases (resp., declines) when opportunities arise (resp., fail to materialize). We use a sample of 3,711 publicly listed companies, observed for seven years (on average) between 1982 and 2003, to compare the outcomes of these R&D allocation policies. We find that a dynamic allocation strategy is associated with worse R&D performance in terms of patent quantity and quality. Our results indicate that the originality of an invention, and also the firm's familiarity with an invention's technological basis, are factors that can mitigate or amplify the harm caused by variability. Finally, we establish that R&D performance suffers from the unpredictable part of dynamic spending; the predictable part has either no effect or a positive one.

Key words: R&D strategy; R&D spending; variability in R&D spending; innovation; Arellano–Bond GMM estimation

1. Introduction

Should the management of research and development be persistent in its approach to funding R&D or rather allow for quick reaction and dynamism? Practitioners give conflicting answers to this question. To exemplify the perplexity that abounds on this score, we note two seemingly contradictory principles advocated by the practitioners Roussel et al. (1991) in their influential book on R&D management. After writing that, "because [. . .] R&D plans [. . .] are integral to corporate and business plans, flexibility and adaptability must characterize the R&D component of corporate plans" (p. 175), they turn around and—*on the same page*—proclaim that "[j]erking R&D around in a shortsighted response to short-term conditions is particularly destructive. There must be steadiness of course."

Intuition tells us that both constancy—what we refer to as persistence—and dynamism can result in good R&D performance. In essence, these funding strategies exemplify two general management styles: a relatively stable style that is primarily concerned with long-term capability building; and a more involved style that is mainly concerned with strategic positioning. Persistence provides continuity and stability whereas dynamism facilitates rapid adaptation to a changing landscape of opportunities.

These management styles translate into two competing approaches to allocating R&D resources. On the one hand, a faith in persistence presumes that R&D investments yield their benefits only over a long time horizon. Any investment induces lagged results: building expertise requires time as, for example, researchers are hired and become productive in their respective research fields and organizational contexts. Yet withdrawing R&D investment may lead to an instantaneous loss of knowledge—as when, for example, researchers leave the company or are reassigned to new fields. Therefore, alternating between investment and withdrawal invariably reduces productivity. Hence the management of R&D must create and *preserve a research environment whose continuity is sustained by persistent investment*, from which it follows that variability in R&D spending should be avoided.

In contrast, the dynamic style assumes that—in an inherently uncertain environment—opportunities for research are continuously opening and closing. Entire research fields become exciting prospects or lose their appeal as new discoveries are made. Projects must therefore be slowed down or sped up when technical insights trigger reorientation. Managers who are of this mind will adjust their R&D allocation in response to the shifting opportunities encountered by the firm. Dynamism, and hence variability in R&D spending, is a form of *rebalancing the company's strategy so as to mitigate or exploit the effects of uncertainty*.

The first aim of our study is to identify which of these two temporal R&D allocation policies, dynamism or persistence, is (on average) preferable in terms of R&D productivity—while holding the level of R&D spending constant, of course. We structure our reasoning around a single construct that unifies dynamism and persistence: *variability* in R&D spending. Thus dynamism implies the presence of variability and persistence the lack thereof. Our question is then: For a given level of overall R&D spending, is variability or instead constancy in R&D spending more conducive to R&D productivity?

Second, we seek to identify specific contexts in which variability is notably more conducive or harmful to R&D productivity. In particular, we focus on the effects of variability on original (i.e., novel) inventions and explore how an original invention's "technological distance"—from the company's pre-existing portfolio of activities—affects the relation between R&D spending variability and R&D output.

Our third aim is to identify managerial actions for mitigating the potentially negative effects of R&D spending variability and enhancing its positive ones. Because overarching management concerns may necessitate both persistence and dynamism regardless of their effects on R&D output, it is imperative to identify management actions that could accentuate their respective benefits while mitigating their drawbacks. Thus we explore whether predictable and unpredictable variability have different effects on R&D output and whether that distinction gives rise to a spending approach capable of exploiting the advantages of dynamism but without incurring its costs.

The setting for our empirical analysis is publicly traded US firms during the period 1982–2003. We estimate a firm-level dynamic panel data model, via the "system general method of moments" (S-GMM) approach (Arellano and Bond 1991, Blundell and Bond 1998), that combines financial information from the Compustat database with patent data provided by the National Bureau of Economic Research (NBER).

We find that the R&D outcomes of firms implementing a dynamic allocation strategy are *worse* in terms of both the quantity and quality of their patents. The interaction of variability and originality (i.e., novelty) reveals that, the more a company increases the originality of its innovation portfolio, the more a dynamic allocation hurts R&D performance. Decomposing the set of original inventions into subsets of technologically distant and technologically close inventions, we find that technologically close innovations amplify the harmful effect of variability on original patents whereas technologically distant innovations suffer less from a dynamic allocation strategy. Finally, decomposing variability into its predicted and unpredicted parts allows us to show that only the unpredicted part of spending variability harms performance; the predicted part may actually have a positive effect. Our findings are exceptionally robust to alternative variable constructions, model specifications, and sample choices.

This paper should not be interpreted as an condemnation of dynamism and adaptation; after all, strategic reasons may well justify a dynamic R&D spending policy. However, managers should be aware of its consequences for R&D productivity, of the circumstances under which such a policy can be especially harmful, and of the actions that can be taken to alleviate any negative consequences. So beyond establishing a new factor in the literature on the determinants of R&D productivity, we intend to help managers conceptualize sound principles for application in research and development.

2. Literature Review

Schumpeter's conjectures on the "relation between innovation, market structure and firm size" (Cohen 2010, p. 131) have spawned many avenues of research; in particular, they have initiated a prolonged and productive discussion of the determinants of R&D productivity. True to Schumpeter's original hypothesis, the resulting literature initially focused on the role of firm size and established two main insights. First, an increase in absolute R&D spending leads to an increase in absolute R&D output. That generalization holds whether R&D spending is defined narrowly (Lööf and Heshmati 2006) or accounts for the costs associated with a wide range of innovation activities, such as continuous improvement efforts (Hall et al. 2009); whether R&D output is measured in terms of patents (Crépon et al. 1998, Lööf and Heshmati 2002) or of innovation sales (Jefferson et al. 2006); and whether the focal sector is manufacturing (Lööf and Heshmati 2002) or the service industry (Lööf and Heshmati 2006). The second and perhaps more interesting insight from this literature—notwithstanding some skeptical voices (Cockburn and Henderson 2001, Henderson and Cockburn 1996)—is that firm R&D productivity declines as firm size increases (Cohen and Klepper 1996b, Bound et al. 1984, Geroski 1995, Lerner 2006) because larger firms lose managerial control (Scherer and Ross 1990), are more inclined to pursue incremental innovation (Prusa and Schmitz 1991, Henderson 1993), or focus on process rather than product R&D (Cohen and Klepper 1996a).

However, interest has now moved beyond the question of firm size and has begun to address how a multitude of other factors affect the relation between R&D spending and R&D output. Some of those factors are a function of strategy. Researchers studying economies of scope report that innovation success increases with the number of research programs in the pharmaceuticals industry (Henderson and Cockburn 1996, Cockburn and Henderson 2001) and with the level of technology diversification in US biotech firms (Quintana-Garcia and Benavides-Velasco 2008). Confirmation that a firm's strategic intent can influence R&D productivity is offered by Ahuja and Lampert (2001), who find a curvilinear relation between the amount of exploration in which a firm engages and the number of its breakthrough inventions, and by Rosenkopf and Nerkar (2001), who demonstrate that firms engaged in broader search efforts also have a broader subsequent impact. Other topics of study in this area include: the effect of a company's network position on its R&D productivity (Ahuja 2000); the value of links with competitors, customers, suppliers, and the science establishment (Cockburn and Henderson 1998, Lööf and Heshmati 2002, Revilla and Fernández 2012); and how best to answer the "make or buy" question (Cassiman and Veugelers 2006).

Different organizational factors have also been shown to affect R&D productivity. Among these factors, the structure of the R&D organization features prominently. Firms with centralized R&D organizations patent more per R&D dollar than do decentralized firms (Arora et al. 2014) and also generate more patents that are frequently and broadly cited (Argyres and Silverman 2004)—perhaps because centralized R&D efforts tend to be more scientific in nature and broader in scope (Arora et al. 2011) and tend to focus less on "imitative" innovation (Leiponen and Helfat 2011). Research and development productivity is likewise associated with the firm's ability to integrate knowledge across disciplines (Henderson and Cockburn 1994, 1996), different knowledge management practices including conference attendance (Lööf and Heshmati 2006, Kremp and Mairesse 2004), and the source of knowledge (Katila 2002). Long-term incentives have been shown to boost firm innovativeness (Lerner and Wulf 2007, Francis et al. 2011, Chang et al. 2015). Even the individual characteristics of decision makers (e.g., overconfidence) have been positively linked with R&D productivity (Galasso and Simcoe 2011).

Related work has explored the effects of financial decisions on R&D productivity. Both institutional ownership (Aghion et al. 2013) and private equity backing (Lerner et al. 2013) support innovativeness, as do geographical dispersion of ownership (Jefferson et al. 2006) and the adoption of anti-takeover provisions (Chemmanur and Tian 2017). Of particular interest is Almeida et al.'s (2013) finding that financial constraints may benefit innovation by improving the efficiency of innovative activities.

There is an extensive body of literature (for a summary see Hall et al. 2009) that—rather than focus on the link between R&D spending and R&D outcomes—discusses how the level of R&D spending relates to overall firm outcomes. Using total factor productivity models, researchers have confirmed a positive relation between R&D investment and firm productivity (Griffith et al. 2006, Rogers 2010), market value

(Ciftci et al. 2011, Hall and Oriani 2006), and to a lesser extent accounting profit (Ding et al. 2007, Lev and Sougiannis 1996). The literature has also identified many factors that moderate the relationship between R&D spending and overall firm outcomes; examples include investments in information technology (Arkali et al. 2008), the firm's orientation vis-à-vis commercialization (Lin et al. 2006), managers' firm-specific experience (Kor and Mahoney 2005), product line freshness (Terwiesch et al. 1998), early supplier and lead user involvement (Langerak and Hultink 2005), and certain project-level activities (Kleinschmidt et al. 2007).

Notwithstanding this wealth of considered factors, the literature has largely neglected one important class of predictors of R&D productivity: the *temporal pattern* of R&D spending, or how a given amount of R&D spending is distributed over time. The little research addressing this topic is concerned with whether (or not) particular patterns of R&D spending affect firm outcomes and/or R&D outcomes. In particular, Mudambi and Swift (2014) examine how extraordinary, compact, and significant increases in R&D spending affect the number and quality of firm patents; they find a small positive relation. In contrast, Kor and Mahoney (2005) hypothesize that spending increases should generally lead to increased productivity. These authors use the average percentage increase in R&D as a predictor variable and test their hypothesis on a sample of 218 firms; they find no significant relation (and their coefficient is actually negative).

Our work transcends this literature in three important ways. First, we take a more systematic approach to studying temporal patterns in R&D spending. Thus we employ the overarching concept of spending variability and its effect on R&D productivity while controlling for the overall level of R&D spending. This more holistic temporal measure yields results that differ sharply from those reported in the extant work based on specialized temporal measures. Second, we specify contingencies depending on the type of innovation—more specifically, we investigate whether the effect of R&D spending variability differs as a function of innovations' originality and familiarity to the firm. Third, we identify actions that managers can take to mitigate the potentially negative effects of R&D spending variability or enhance its positive effects.

3. Theory and Hypotheses

Before building a theory that accounts for the benefits of persistence and dynamism, we must clarify our most important terms.

3.1. R&D Spending Variability and R&D Performance

As mentioned previously, we structure our reasoning around a theme that unifies both dynamism and persistence: temporal variability in R&D spending. We conceptualize this variability as the period-to-period changes in the level of resources allocated to R&D (see Section 4.1 for the mathematical definition). A firm that consistently spends the *same* amount on R&D exhibits no variability in R&D spending; in contrast, a firm that either increases or decreases allocations to R&D between periods exhibits R&D spending variability. Thus dynamism implies the presence of variability while persistence implies the lack of it.

Conceptualizing R&D performance is more complicated because R&D output is multifaceted. Research and development explores and develops new opportunities; it provides not only technical knowledge, production-ready prototypes, and novel production processes but also technical support to manufacturing functions. It is therefore impossible to devise a straightforward notion that captures all aspects of R&D performance. The existing literature has focused on the two most salient aspects, of which one is the sheer *quantity* of inventions (e.g., Hall et al. 2001, Ahuja 2000, Arora et al. 2011, Cockburn and Henderson 1998, Lerner and Wulf 2007). According to this view of R&D performance, innovation results from incremental refinements and improvements to existing ideas (Freeman 1982, Moch and Morse 1977, Norman and Verganti 2014). Each improvement contributes a small amount to overall progress, and their sum ultimately leads to a significant economic benefit (Hacklin et al. 2004, Hollander 1965). The other most frequently studied aspect of R&D performance is the *quality* of inventions, which is crucial because focusing only on quantity fails to acknowledge the variation in inventions' importance (Hall et al. 2005, Aghion et al. 2013, Arora et al. 2011, Lerner et al. 2013, Ahuja and Lampert 2001). In this view, some inventions are disproportionately more beneficial to the firm than are others and so quality considerations must be incorporated into any discussion of R&D performance. Together, the quantity and quality of inventions form the basis for discussing our research question.

3.2. Effects of R&D Spending Variability on the Quantity of Inventions

3.2.1. The Negative Argument Variability in funding levels implies that the R&D organization must regularly adapt to new budgets. However, adaptation entails a cost to the company in the form of productivity losses. There are two main reasons why productivity declines under altered funding levels.

Gestation Period of R&D Investment. Frequently starting and then stopping work, especially R&D work, is inefficient. An R&D organization that starts new activities or raises its level of activity does not immediately attain its optimal steady-state level of knowledge creation. The organization faces an adaptation period as, for example, new equipment is sourced and placed in service, new staff is hired, new outside partners are found, and/or new work routines and a new work culture are established. Given that, on average, more than two thirds of R&D spending is related to personnel (Cameron 1996), an increase in R&D expenditures often implies that new researchers must be hired, and existing researchers reoriented, and that new organizational structures must be built. These implications have consequences on both the individual and the organization level. On the *individual* level, researchers who are new to a technical domain must immerse themselves in it before becoming fully productive (Baard et al. 2014, Jones 1986, Smith et al. 2013). In addition to mastering a highly specialized technical field, they must undergo a socialization phase

(Bauer et al. 2007, Van Maanen and Schein 1979) in which they adapt to new working routines, new corporate cultures, and new teams. Newcomers must also build informal networks that help them navigate the organization and gain access to its knowledge; they need to understand how the firm's chain of command works in practice and what their role is in the company (Kim et al. 2005, Klein and Weaver 2000). On the *organizational* level, entering a new R&D field requires new organizational routines and often new formal and informal structures (Massini et al. 2005). Until those routines and structures evolve into their most beneficial state, the organization must go through a phase of trial and error. Analogous arguments can be made with regard to tangible R&D equipment. We therefore conclude that a gestation period is required to build R&D competencies and to realize returns from them.

In contrast, there is an immediate interruption in the flow of new knowledge when R&D spending is reduced. Researchers and research managers leave the company, or are reoriented, and hence can no longer advance their original field's knowledge agenda. Equipment is reappropriated, sold, or decommissioned. This asymmetry implies that alternating increases and decreases in R&D spending will reduce R&D productivity overall: A firm that alternates between "up" and "down" spending will repeatedly need to bridge an unproductive phase because of the asymmetric lags; hence it will suffer as compared with a firm that spends the same cumulative amount on R&D but employs a persistently even-keeled investment policy.

Diseconomies of Scale. The second primary reason for the negative effect of variable resource allocation is that the relation between R&D inputs and R&D outputs is concave. There is ample evidence that, beyond a threshold of relevance, adding additional resources to a knowledge creation effort scales the output not proportionally but rather subproportionally. At the *project* level, it is difficult to partition a given activity into multiple discrete tasks with no operational and communication interactions. Adding resources to R&D projects therefore creates additional coordination overhead, and increases in output taper off or may even become negative; as a consequence, productivity declines (Edmondson and Nembhard 2009, Ostrom et al. 1999). At the *portfolio* level, rational R&D managers allocate their limited available resources to the most promising R&D projects (Chao and Kavadias 2013, Loch and Kavadias 2002). However, for a relatively larger R&D budget such priorities entail a lower average return per unit of invested resources. The concavity of this translation function implies that the functional value of the average output is higher than the average of any two individual function values. So even if we abstract from the aforementioned issue of gestation times, it follows from concavity that consistently providing the average level of R&D financial support is preferable to investing the same overall amount unevenly.

3.2.2. The Positive Argument The argument for variability in R&D spending presumes that uncertainty is at the heart of innovation (Nelson and Winter 1977). Technical uncertainty is constantly being resolved, either within the company or by outside entities; this progress may render past inventions obsolete or increase their importance. Such developments may require management to adapt at both the portfolio level and the project level and hence might end up requiring adjustments in allocations to R&D.

At the *portfolio* level, innovation is a quest for new territories. Survival in many industries depends on early entry into new fields that open up (Kessler et al. 2007), and this truism holds especially in high-tech industries because technology becomes obsolete rapidly (Bernstein and Singh 2008). Early entrants enjoy more freedom in their R&D pursuits because the field has yet to be extensively explored by competitors. The learning curve of early entrants is steep, yet they are quick to extend the frontier of current knowledge. Their inventions follow suit. A firm that seeks rapid entry into new technology fields, or that wants to abandon fields that have become unattractive, may need to change the focus or direction of its research efforts. As far as R&D budgets are concerned, such changes may balance out (or nearly so); but often the changes and shifts will likely require budget adjustments—and sometimes quick ones. For example, budget changes are often associated with radical purges of the R&D portfolio or expansion into a new field. It follows that achieving the goal of rapidly responsive flexibility may require shifts in R&D allocations.

At the *individual project* level, discoveries made in the course of a project may cast doubt on its technical feasibility, resource requirements, and (ultimately) the firm's current course of action. In particular, truly innovative projects often require a quick readjustment to technical learning (Pich et al. 2002, Sommer et al. 2009). It is only by remaining flexible—adding resources when needed and releasing them when not—that the discovery process is effective and efficient. So even though some project expansions coincide with reductions in other projects, flexibility with respect to the research portfolio's content will most often require flexibility in spending patterns; hence the company is led to employ a dynamic approach to R&D allocations.

3.2.3. Weighing the Negative and Positive Arguments Because R&D performance reflects both of these opposed effects, the overall effect's direction is ambiguous. We therefore provide two competing hypotheses, as follow.

HYPOTHESIS 1a (H1a). *Increased variability in R&D spending leads to reduced R&D performance in terms of* ***quantity*****.**

HYPOTHESIS 1b (H1b). *Increased variability in R&D spending leads to increased R&D performance in terms of* ***quantity*****.**

3.3. Effects of R&D Spending Variability on the Quality of Inventions

Most of the arguments, both negative and positive, about the effect of R&D spending variability on innovation quantity apply also with regard to innovation quality—though by a slightly different line of reasoning. A negative argument we discussed previously is that researchers need time before they can start innovating; extant work has similarly demonstrated that a threshold degree of immersion in the topic at hand is required before a researcher can develop ideas and innovation of high quality. The quality of ideas exhibited by those who have related experience in a field is higher than that exhibited by those who lack such experience (Chan et al. 2014, Mecca and Mumford 2014, Rietzschel et al. 2007, Sawyer 2011, Weisberg 2011), and the most creative and productive inventions are typically made only after an extensive period of immersion in the focal field (Jain 2013, Simonton 1997). These patterns are consistent with findings at the organization level. For instance, Pruett and Thomas (2008) study the slopes of learning curves and report that a company's past internal innovation experience fosters both learning and long-term success.

In short, innovation quality requires a gestation period—and perhaps even more so than does innovation quantity. Hence we again point to an asymmetric lag in the effects of R&D spending variability. It takes time for R&D investments to become quality inventions, but the destruction of quality is immediate when R&D resource allocations are reduced.

Yet the opposite can also be argued. At the *portfolio* level, two arguments favor quick adaptation to foster high-quality inventions. First, a company that enters a nascent field can freely choose its own technology position (Fleming and Sorenson 2003). A so-called first mover may be positioned to make "foundational" inventions that strongly affect the field for many years to come, often by way of setting basic definitions and standards. For example, Texas Instruments was the first company to work on commercial applications of the silicon planar transistor; it thus secured the foundational patent that all other semiconductor manufacturers had to license if they wanted to manufacture integrated circuits (Weber 1990). Second, entering a field early has implications for second- and third-generation inventions because first-generation experience has a positive effect on the quality of subsequent inventions (Bilgram et al. 2008, Von Hippel 2009). Both arguments favor quick entries into new fields as they emerge. And although entries can be financed by redistribution of means among existing projects, they would in general seem to call for dynamic R&D spending.

At the *individual project* level, agility and fast reactions directly affect the influence on the quality of inventions. This relationship is demonstrated by Kessler and Bierly (2002), who link development cycle time and product quality, and by Griffin (1997), who links development cycle time and "newness" (which can be viewed as a dimension of quality). Again, flexibility in actions usually requires flexibility in means.

Weighing the arguments for and against variability in R&D funding levels, we again cannot arrive at an obvious conclusion regarding innovation quality. Hence we again offer two competing hypotheses.

HYPOTHESIS 1c (H1c). *Increased variability in R&D spending leads to reduced R&D performance in terms of* ***quality.***

HYPOTHESIS 1d (H1d). *Increased variability in R&D spending leads to increased R&D performance in terms of* ***quality.***

3.4. Technological Originality and R&D Spending Variability

Our first hypothesis posits how, for the average firm, a given amount of R&D spending is best allocated over time so as to optimize R&D performance. The argument in favor of *persistence* maintains that adjustments in R&D spending entail an adaptation cost resulting from gestation periods and that diseconomies of scale (and their concavities) render variable investments suboptimal. The argument in favor of *dynamism* stresses the importance of budget flexibility in the face of inherent uncertainty.

However, the relative strength of these two arguments—and hence the optimal allocation of R&D resources over time—most certainly depends on the type of innovation in which the firm engages. We first focus on the concept of technological *originality*, which we define (in accordance with extant literature) as the degree to which an invention is new to the world. We say that an invention is "original" or "pioneering" if it is based on a new technology that does not build on existing work inside or outside the company (Ahuja and Lampert 2001, Quintana-Garcia and Benavides-Velasco 2008). For example, the modules that enable cars to drive autonomously constitute a pioneering invention whereas an improved gearbox is more of an incremental invention. Pioneering technology often has the potential to redefine markets and so may be of exceptional economic value. So with regard to originality, we ask how the nature of an invention (pioneering or incremental) influences the balance—between the positive and negative arguments—as regards both the quantity and the quality of inventions.

3.4.1. The Negative Argument A company that develops a portfolio of especially pioneering innovations may exacerbate any problems stemming from gestation arguments (see also Chao and Kavadias (2008)). The technological uncertainty associated with such a portfolio is relatively high, and the firm may need even more time and effort to build its R&D operations. The company may need to acquire new physical and intellectual assets that are not readily available on the market. It may also be forced to create entirely new processes because its existing ones are ill suited to the new technology (or because there simply are no existing processes). Furthermore, adaptation may require the firm to create entirely new mental models and new routines for the purpose of reshaping such organizational aspects as leadership behaviors and invention mind-sets. All of these activities may prolong the time it takes a company to become effective after increasing its R&D investment. But just as for all inventions, knowledge creation ceases immediately when funding is cut. Hence the gestation argument may carry even more weight in the case of pioneering inventions.

In addition, the argument based on concave returns to R&D spending may likewise become more relevant. Especially innovative portfolios often result from new fields opening up. The first movers can pick which projects to pursue, unencumbered by the competition. Thus, entering a brand-new field may yield the company extremely beneficial opportunities mixed in with more usual ones. These circumstances imply that investment opportunities may exhibit strongly concave characteristics.

In sum, both the quantity and the quality of ideas may suffer disproportionately from variability for portfolios characterized by large technological originality.

3.4.2. The Positive Argument However, the same logic can be used to argue the other way. The gestation argument rests on the assumption that experience is valuable—that knowledge is cumulative. Yet pioneering portfolios may be characterized by such high levels of technological uncertainty that experience becomes irrelevant. A company entering a new technological field has yet to establish appropriate mental models, routines, assets, and processes. At the outset, one intellectual asset, mental model, or routine is as good as the other; there simply do not exist refined assets, models, and routines already adjusted to the situation. There is no deep process knowledge base that new resources must acquire, and there is no experience of value. In this situation, the gestation argument may become less salient: no entrant into the field holds an advantage with respect to reaching the productivity frontier; basic talent is all that matters. As a result, gestation times are short.

Moreover, an argument based on the concave link between R&D investments and R&D outcomes becomes less compelling as uncertainty increases. That argument requires the firm to be capable of distinguishing ex ante between projects that are more versus less worthwhile. If information about individual projects becomes more ambiguous, then there can be little ex ante understanding of project payoffs and so project outcomes become largely random. Hence the firm does not have enough situational understanding to establish a concave investment curve ex ante. In short, high levels of originality and hence high levels of uncertainty tend to vitiate the arguments based on gestation and concavity.

We remark also that high levels of uncertainty may reinforce the arguments in favor of variability in R&D spending. At the level of an individual project, unexpected events require constant adaptation. The team must react to its environment by quickly acquiring or shedding resources. At the portfolio level, more uncertainty makes the outcome of each project less predictable. Underperforming projects need to be ended quickly, and new project alternatives (as may emerge during the development effort) must be initiated. Such strategic maneuvering requires that the firm continuously evaluate and rebalance its innovation portfolio. In sum: the best response to increased uncertainty is increased managerial flexibility, which in turn requires a more flexible budget.

3.4.3. Weighing the Negative and Positive Arguments With respect to pioneering inventions, then, the main arguments both for and against variability in R&D spending may become more persuasive. Hence we cannot determine a priori how the level of technological originality modulates the effect of R&D variability, which means that two competing hypotheses are in order.

HYPOTHESIS 2a (H2a). *The more original are a firm's innovation activities, the more pronounced are the effects of variability in R&D spending on its R&D performance in terms of both* ***quantity and quality.***

HYPOTHESIS 2b (H2b). *The more original are a firm's innovation activities, the less pronounced are the effects of variability in R&D spending on its R&D performance in terms of both **quantity and quality**.*

3.5. Technological Familiarity, R&D Spending Variability, and Technological Originality

There is an important distinction to be made when one analyzes pioneering innovation. New-to-the-world (pioneering) technology can be close to a company's existing technological base, or it can be distant from anything the company has developed before. Does the extent of this technological familiarity alter the effects of R&D variability on pioneering innovation?

We define technology *familiarity* as the degree to which the company is familiar with the broader technical field that spawned the invention (Freeman and Soete 1997). Some of the literature has characterized this familiarity in terms of technology search distance (March 1991, Stuart and Podolny 1996, Ahuja and Lampert 2001, Quintana-Garcia and Benavides-Velasco 2008). A technology is "close" to a company that has mastered the same field but is "distant" to companies that are unfamiliar with the field. Thus, for example, the autonomous vehicle is a close invention for Tesla but would be a distant invention for Pfizer.

On the one hand, a company cannot "embed" into its existing knowledge base any original inventions that are distant from its technological base. The reason is that those inventions cannot make use of the firm's existing intellectual and physical assets, processes, mental models, and routines. The company must develop new assets, processes, models, and routines, and that development may take time. Hence the gestation period may be extended. In this sense, portfolios of original inventions that are technologically distant from the firm's base should suffer even more (than technologically closer portfolios) from variability in R&D spending.

On the other hand, extant knowledge may be irrelevant and perhaps even harmful. Existing routines, mental models, processes, and intellectual and physical assets may not be well adapted to a new technology that is distant from the company's existing technological base. Applying and transferring them to the new setting may complicate the firm's experimentation with these components in its efforts to identify most quickly the most appropriate setup. As a consequence, the gestation-period argument may have less force. Yet the advantages of flexibility and quick adaptation to a constantly changing environment—on both the project level and the portfolio level—persist and are magnified for original portfolios that are distant from the firm's technology base. So in this sense, portfolios of "distant" original inventions should benefit the most from R&D spending variability.

Which of these arguments should prevail? Or, more fundamentally: Does variability affect pioneering inventions differently depending on whether they are close to or far from the company's technological base? Since we cannot determine the answer on theoretical grounds, we again offer two competing hypotheses.

HYPOTHESIS 3a (H3a). *The more distant are a firm's pioneering innovation activities from its existing technology base, the more pronounced are the effects of variability in R&D spending on its R&D performance in terms of both* ***quantity and quality.***

HYPOTHESIS 3b (H3b). *The more distant are a firm's pioneering innovation activities from its existing technology base, the less pronounced are the effects of variability in R&D spending on its R&D performance in terms of both* ***quantity and quality.***

3.6. Predicted and Unpredicted Variability

If the negative arguments hold then our hypotheses, despite their intellectual or academic appeal, send a negative message to practitioners: changes in R&D spending may reduce the quantity and quality of a firm's inventions. Thus it seems that any adaptation comes at the cost of a decline in R&D performance. Taking another angle, we focus here on ways to mitigate (resp. accentuate) the negative (resp. positive) effects of variability in R&D spending.

At the root of our argument is the distinction between predicted and unpredicted variability—that is, changes in R&D spending that are (respectively) foreseeable or entirely unexpected. For the case of predicted variability, management can prepare the organization for impending measures and thus reduce adaptation cost. Strategic and forward-looking managers adapt their behavior to accommodate expectations about the future (Case 2012, March 1994) and thus anticipate foreseeable decreases or increases in R&D resources. Managers can then, for example, plan hiring in advance and thereby shorten the time needed to find qualified candidates; they can also limit the damage of any staff cuts by finding alternative scenarios for employing the most talented among those candidates. Managers can moderate negative "diseconomy of scale" effects by promoting choices that are the least damaging to individual projects and to the R&D portfolio overall. In other words, managers can generally protect past R&D investment by addressing and assessing each potential variation of R&D inputs. Such planning activities mitigate the negative effects of R&D spending variability. Thus predictability changes the relative weight of the negative and the positive arguments concerning R&D spending variability in favor of the *positive* ones.

In contrast, unpredicted variability amplifies the cost of adaptation because managers cannot anticipate the effect of any change. Suppose that funding increases are unpredicted; then managers may rush activities and end up compromising performance. Unpredicted changes affect the R&D organization in a more subtle way as well. Past experience with unpredicted changes makes managers uncertain about future allocations (cf. the notion of "affective forecasting" discussed by Dane and George 2014), and this uncertainty inclines managers to build buffers into their operating plans so they can deal more easily with shortages should the need arise. Yet in the absence of such shortages, those buffers constitute excess spending and thus entail negative effects for research productivity. As a result, unpredicted variability changes the weight of the negative and positive arguments concerning R&D spending variability in favor of the *negative* ones.

We can summarize as follows: splitting variability into its predicted and unpredicted parts changes the relative weight of positive and negative arguments and therefore affects the trade-off between them. These considerations lead to our final hypotheses.

HYPOTHESIS 4a (H4a). *Unpredicted (resp. predicted) variability in R&D spending leads to reduced (resp. increased) R&D performance in terms of* ***quantity*****.**

HYPOTHESIS 4b (H4b). *Unpredicted (resp. predicted) variability in R&D spending leads to reduced (resp. increased) R&D performance in terms of* ***quality*****.**

4. Data and Variables

Our sample consists of publicly traded firms featured in the Compustat US industrial annual database for the 30-year period from 1976 to 2006, which we use to retrieve accounting information that includes R&D spending. According to the Statement of Financial Accounting Standards 2 of 1975, all R&D expenditures must be expensed in the period incurred and, in particular, cannot be capitalized.[1] Although there is some accounting discretion with respect to the boundaries of R&D spending and other cost categories, companies tend to categorize such fringe cases consistently. This means that US R&D spending data is ideally suited to a study of the temporal aspects—here, variability—of R&D spending. In fact, R&D spending data is often used in the accounting literature as a reliable representation of the underlying reality. Thus scholars have used such data to identify real-world funding decisions that advance managers' agendas yet are not in the firm's best interest (Roychowdhury 2006, Graham et al. 2005). We combine the Compustat data with information on patent applications and approvals from the NBER Patent Data Project (Hall et al. 2001), which provides details on all 2,812,428 US utility patents granted during the period 1976–2006. For each patent filing, these details include the year of filing/approval, the assignees, and a "corrected" count of citations (Hall et al. 2001, 2005). The correction is necessary because a raw citation count not only includes self-citations but also underestimates the citation count of more recent patents, which have had less time to accumulate citations.

To combine the financial information from the Compustat database with the patent information, we use the "concordance files" provided by the Patent Data Project. These files resolve two important issues. First, they correct for spelling discrepancies between the two databases. Second, companies often hold patents in subsidiaries and special-purpose legal entities with names and addresses that differ from the parent public corporation covered by the Compustat database. The concordance files consolidate patents received by all such assignees to their legal parent entity.

After merging the databases, we identify 11,698 firms that have been granted at least one patent during the period extending from 1976 to 2006. Throughout this 30-year period, we follow the patenting activity

[1] In line with general accounting principles, however, tangible (and some intangible) assets with alternative uses that are employed by the R&D department can (must) be capitalized and depreciated over their economic life.

of these firms as well as their financial details; the result is a raw yearly panel data set consisting of 139,867 firm-year events. We clean our data set in three ways. First, and in line with existing research, we consider only the data from 1982 onward because a structural change in the application of patent law renders incommensurate the data from before and after that year (Hall et al. 2001, Somaya 2003). Second, we follow Hall et al. (2001) in omitting the years 2003–2006 because the correction for future citations is insufficiently accurate in the last three years of the Project data set. Finally, in accordance with how researchers have previously assessed the effects of R&D investment (Kothari et al. 2002, Pandit et al. 2011), we restrict our attention to firms with significant R&D outlays. Thus we consider only firms that spent more than 5% of their sales revenue on R&D at least once during the period under study (although the effects of several other cutoff values are evaluated under "Robustness Tests" in Section 6). Our final sample contains 3,711 firms for which we have data from 1982 to 2003—a total of 28,034 firm-year events.

4.1. Definition of Variables

4.1.1. R&D Performance We consider two measures of R&D performance: *PAT*, or the number of patents filed by a firm and its related legal entities, and *CP*, the number of citations generated by these patents; the former (resp. latter) measure captures raw R&D performance via a quantity (resp. quality) dimension. Not surprisingly, both patents and citations are concentrated in the most productive firms. We follow the usual practice when analyzing such variables and apply a "log plus 1" transformation.

4.1.2. R&D Spending Patterns Our main explanatory variables capture some aspects of the level of variability in R&D spending. However, we must first define our most important control variable—namely, R&D stock. Previous research indicates that the level of R&D spending is a key driver of R&D performance (Hall et al. 2009). Our hypothesized effects of variability in R&D spending are in addition to the baseline effect of R&D allocation levels, so examining the former requires that we first control for the latter.

R&D Stock. Spending on R&D seldom affects firm outcomes in the same year only. More typically, annual R&D spending augments a cumulative body of knowledge that can be exploited for a number of years before its value decays. Hall et al. (2009) suggest using the notion of R&D stock (*SRD*) to capture this cumulative knowledge. We follow their suggestion and employ the widely used depreciation rate of 15% (Corrado et al. 2009, Czarnitzki et al. 2014, Griliches and Mairesse 1984, Hall et al. 2010). Formally, we use XRD_{it} to denote firm i's reported expenditures on R&D in year t and put $k = 15\%$. Then

$$SRD_{it} = XRD_{it} + (1-k)SRD_{i(t-1)}. \tag{1}$$

Aggregate R&D Variability. We define intertemporal variability in R&D (*VRD*) as an aggregate of the absolute year-to-year differences in R&D spending. As for the R&D stock, we discount past years. Formally,

$$VRD_{it} = \left|XRD_{it} - XRD_{i(t-1)}\right| + (1-k)\,VRD_{i(t-1)}. \tag{2}$$

Predicted and Unpredicted Variability. We split aggregate variability into changes that are predicted (i.e., they follow extrapolated past trends) and changes that are unpredicted (they are at variance with those trends). Specifically, for each given year we calculate the R&D expenses that would result from a linear extrapolation of the past two years' trend for such expenses. The predicted variability in R&D spending (*VRDP*) is then the absolute difference between real past expenses and extrapolated future ones, while the unpredicted variability (*VRDU*) is the absolute difference between the predicted and actual expenses. (In Section 6 we report, under "Robustness Tests", the estimates obtained when using other predictive models.) Thus we have

$$\begin{aligned} VRDP_{it} &= \left|XRD_{it}^{P} - XRD_{i(t-1)}\right| + (1-k)\,VRDP_{i(t-1)}, \\ VRDU_{it} &= \left|XRD_{it} - XRD_{it}^{P}\right| + (1-k)\,VRDU_{i(t-1)}. \end{aligned}$$

4.1.3. Types of Innovation Hypotheses 2 and 3 concern the interaction between R&D spending variability and the originality of firm innovations. Following Ahuja and Lampert (2001), we say that an innovation is "original" or "pioneering" when a granted patent cites no other patent inside or outside the firm—that is, when the underlying technology is new to both the firm and the world. Then we can define the pioneering ratio PNR_{it} for firm i in year t by dividing by the number of pioneering patents by the total number of patents the firm is granted in that year.

Second, we split the ratio of original patents into those that are technologically distant and those that are technologically close. We follow Ahuja and Lampert (2001) in defining a patent as technologically "close" if it is part of a technology class–as delineated by the US Patent & Trademark Office–in which the firm holds *other* patents; patents that are not part of such a class are considered to be technologically "distant". Using $nclose_{it}$ (resp. $ndistant_{it}$) to denote the number of original patents of firm i in year t granted in a technology class in which the firm has already (resp. never) been granted a patent, we obtain:

$$PNR_{it} = PNRC_{it} + PNRD_{it} = \frac{nclose_{it}}{npatent_{it}} + \frac{ndistant_{it}}{npatent_{it}}. \tag{3}$$

In Section 6 (under "Robustness Tests") we test different constructions of pioneering innovation and technological distance.

4.2. Control Variables

Opportunities Available. In addition to variability, the productivity of any R&D investment depends on the extent of opportunities available to the company. Capital expenditures (*CAPX*, as a percentage of sales) is a well-known proxy for such opportunities (Kothari et al. 2002).

Market-to-Book Ratio. Another proxy used to account for the marginal effect of growth opportunities (Kothari 2001) is the market-to-book ratio (*MB*).

Capital Intensity. Capital intensity—the amount of fixed capital in relation to labor—is a known predictor of R&D performance (Hall and Ziedonis 2001). Our variable for capital intensity (*CAPIN*) is computed as (the logarithm of) the ratio of property, plant, and equipment (*PPE*) to the number of employees (*EE*).

Liquidity. A metric much used by bankruptcy analysts, liquidity (*LIQ*) captures the firm's ability to cover short-term debts (Hirshleifer et al. 2012). We define liquidity as the ratio of a firm's working capital (for more details on why we use working capital instead of cash, see Hall and Kruiniker 1995) to the value of its tangible assets—excluding intangible, financial, and current assets (Fazzari et al. 1988, Harhoff 1998).

Firm Age. Firm age controls for the maturity of the firm in its innovation process. For each year we compute the logarithm of the firm's age (*LAGE*), where by "age" we mean the time elapsed between its first appearance in Compustat and the current year.

Firm Size. In line with a wealth of literature on operating performance in the fields of accounting, finance, and economics, we include the logarithm of the firm's total assets (*LAT*) and also its square (*LAT2*) as controls for firm size.

Industry Concentration. Changes in industry concentration, which can result from acquisitions by competitors, may change the industry's level of competitiveness and hence its financial strength (Hendricks and Singhal 2008). Our estimates therefore include the normalized Herfindahl index of the applicable 3-digit Standard Industrial Classification (SIC) industry codes (*HERF*) and its square (*HERF2*); see Atanassov (2013), Chemmanur and Tian (2017).

Industry Sales Growth. Different industries experience different cycles of expansion and stagnation over time. Expansion is generally associated with industry profitability while stagnation increases competition and thus erodes profits. Our regressions incorporate industry sales growth (*SALG*) at the 3-digit SIC level (Hendricks and Singhal 2008).

Table 1 gives summary statistics for the variables used in our analysis. There is substantial within-firm variation in R&D variability; hence we can use a model with fixed effects. Table 2 reports the correlations among all variables. As described in Section 4.1.2, we decompose VRD into $VRDP$ and $VRDU$ (which explains why VRD is so highly correlated with both $VRDP$ and $VRDU$). However, VRD never appears in the same estimation with either of its components.

5. Model Specification and Estimation

It is intuitive that a firm's current R&D performance is affected by its past performance. Thus R&D performance is "sticky" because accumulated R&D efforts build innovation capabilities (Teece et al. 1997, Teece 2000), which in turn affect the quantity and quality of inventions over a multiyear period. In addition, companies seeking to protect their intellectual property may do so via a patenting policy that builds a "fence"

		Mean	**Standard Deviation**			**N**	
Variables			*Overall*	*Between*	*Within*	*# Firms*	*# Obs.*
Patents (PAT)	log--count	0.938	1.474	1.127	0.559	3,711	28,034
Citations per patent (CP)	log--ratio	1.172	1.553	1.163	0.963	3,711	28,034
R&D Variability (VRD)	$ Mn	67.112	315.044	215.603	174.215	3,707	27,974
Predicted Variability (VRDP)	$ Mn	60.254	291.863	204.117	157.556	3,707	27,974
Unpredicted Variability (VRDU)	$ Mn	76.055	431.057	313.028	257.033	3,707	27,974
Pioneering Ratio (PNR)	ratio	0.017	0.087	0.063	0.075	3,711	28,034
Distant Pioneering Ratio (PNRD)	ratio	0.005	0.053	0.031	0.049	3,711	28,034
Close Pioneering Ratio (PNRC)	ratio	0.012	0.068	0.048	0.057	3,711	28,034
R&D Stock (SRD)	$ Mn	387.143	1,975.103	1,252.689	937.348	3,711	28,034
Total Assets (LAT)	log--$ Mn	3.934	2.511	2.211	0.718	3,710	27,762
Squared Total Assets (LAT2)	sq.log--$ Mn	21.777	23.437	18.688	6.325	3,710	27,762
Capital Expenditure (CAPX)	% of sales	0.464	18.145	16.312	14.719	3,623	26,516
Capital Intensity (CAPIN)	log--ratio	3.105	1.063	0.967	0.539	3,603	26,131
Liquidity (LIQ)	ratio	2.286	53.196	39.465	44.508	3,540	22,890
Market-to-Book Ratio (MB)	ratio	3.382	135.271	87.093	120.654	3,647	26,419
Age (LAGE)	log--years	2.368	0.730	0.680	0.330	3,711	28,034
Industry Concentration (HERF)	ratio	0.151	0.162	0.143	0.070	3,710	28,004
Squared Ind. Conc. (HERF2)	ratio--sq	0.049	0.200	0.161	0.107	3,710	28,004
Industry Sales Growth (SALG)	%	0.100	0.343	0.147	0.319	3,711	28,031

Table 1 Summary statistics

		[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]	[11]	[12]	[13]	[14]	[15]	[16]	[17]	[18]	[19]
[1]	*PAT*	1.00																		
[2]	*CP*	0.73	1.00																	
[3]	*VRD*	0.48	0.23	1.00																
[4]	*VRDP*	0.47	0.22	0.96	1.00															
[5]	*VRDU*	0.37	0.16	0.94	0.94	1.00														
[6]	*PNR*	0.17	0.15	0.05	0.04	0.03	1.00													
[7]	*PNRD*	0.03	0.05	-0.01	-0.01	-0.01	0.63	1.00												
[8]	*PNRC*	0.20	0.15	0.06	0.06	0.05	0.80	0.03	1.00											
[9]	*SRD*	0.52	0.25	0.86	0.86	0.74	0.04	-0.01	0.06	1.00										
[10]	*LAT*	0.67	0.48	0.45	0.44	0.37	0.11	0.01	0.13	0.45	1.00									
[11]	*LAT2*	0.75	0.47	0.61	0.60	0.51	0.11	0.00	0.14	0.63	0.90	1.00								
[12]	*CAPX*	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	-0.01	1.00							
[13]	*CAPIN*	0.33	0.22	0.19	0.19	0.16	0.07	0.00	0.09	0.18	0.46	0.40	0.03	1.00						
[14]	*LIQ*	0.00	0.00	-0.01	-0.01	-0.01	0.00	0.00	0.00	-0.01	0.06	-0.01	0.00	-0.01	1.00					
[15]	*MB*	0.01	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00				
[16]	*LAGE*	0.30	0.16	0.18	0.18	0.14	0.05	0.00	0.06	0.22	0.30	0.36	-0.02	0.09	-0.03	0.00	1.00			
[17]	*HERF*	-0.07	-0.08	-0.03	-0.03	-0.03	-0.02	0.00	-0.02	-0.02	-0.07	-0.04	-0.01	-0.05	0.00	0.00	0.05	1.00		
[18]	*HERF2*	-0.05	-0.05	-0.02	-0.02	-0.02	-0.01	0.00	-0.01	-0.02	-0.04	-0.03	0.00	0.00	0.00	0.00	0.04	0.87	1.00	
[19]	*SALG*	-0.02	0.01	-0.01	-0.02	-0.02	-0.01	0.00	-0.01	-0.01	-0.02	-0.02	0.00	0.01	0.00	0.00	-0.01	0.10	0.08	1.00

Table 2 Correlation table

of minor patents around a flagship patent. Finally, some companies file foundational patents within their domains; in this way the firm can establish "must cite" references for followers. We remark that a foundational patent retains that status for many periods. In order to account for serial correlation in our dependent variables, we estimate the following *dynamic panel data model*:

$$PAT_{it} = \alpha_{11} PAT_{i(t-1)} + \alpha_{12} VRD_{it} + \alpha_{13} PNR_{i(t-1)} + \alpha_{14} VRD_{it} PNR_{i(t-1)} + \alpha_{15} X_{i(t-1)} + \varepsilon_{it}; \quad (4)$$

$$CP_{it} = \alpha_{21} CP_{i(t-1)} + \alpha_{22} VRD_{it} + \alpha_{23} PNR_{i(t-1)} + \alpha_{24} VRD_{it} PNR_{i(t-1)} + \alpha_{25} X_{i(t-1)} + \varepsilon_{it}. \quad (5)$$

The first regression equation captures the effect of variability in R&D spending on the number of granted patents (*PAT*), or the quantity aspect of R&D performance; the second focuses on the number of citations per patent (*CP*), or the quality aspect. Our panels are each of dimension $N \times T$ and may be unbalanced. Recall that VRD_{it} denotes variability in R&D spending and PNR_{it} the pioneering ratio; the term X_{it} is a vector of our controls. Depending on the hypothesis being tested, we estimate different versions of these equations with different constructs for VRD_{it} and PNR_{it}. In addition, all the controls $X_{i(t-1)}$ (with the exception of R&D stock, *SRD*) are taken at the beginning of the period to avoid any simultaneity bias due to feedback effects (Czarnitzki et al. 2014). We instrument all other variables (viz., *SRD* and our predictor variables) as explained later. In addition, we lag the pioneering ratio variables $PNR_{i(t-1)}$ because otherwise the definition of PNR_{it} would itself contain an outcome variable (for more on such problems see Angrist and Pischke 2008, p. 67).

In both models, firm fixed effects eliminate estimation biases due to unobserved time-invariant R&D-related differences across firms (e.g., differences in R&D abilities, culture, and management). Year fixed effects control for any unobserved effects due to aggregate trends that influence the entire sample.

A dynamic panel data model raises a methodological challenge for the estimation strategy. Applying ordinary least-squares (OLS) estimators to such models disregards an important fact: the lagged dependent variable is, by construction, correlated with the fixed effects in the error term. It follows that an OLS estimator would give rise to "dynamic panel bias" (Nickell 1981, Roodman 2009), especially in the "small T, large N" configuration that we face. Another challenge for this estimation strategy is that our predictor variables may be prone to endogeneity. We therefore use a GMM method introduced by Arellano and Bond (1991) and augmented by Blundell and Bond (1998) and Windmeijer (2005). This approach allows us to use lags of variables as instruments for the lagged performance measures as well as for our predictor variables (and our most important control). As compared with a two-stage least-squares estimation strategy, the generalized method of moments approach is more efficient given our "small T, large N" configuration and the heteroskedasticity we must brace for.

Both the "difference GMM" (*D-GMM*) introduced by Arellano and Bond (1991) and the "system GMM" (*S-GMM*) proposed by Blundell and Bond (1998) and refined by Windmeijer (2005) address the problems just outlined and also match our model's requirements. However, our models incorporate lags of dependent variables whose distributions are close to persistence (see the coefficient, reported by Table 3 in Section 6, for the one-year lagged dependent variable). Persistence often implies weak instruments in a D-GMM framework, and when estimating an ad hoc OLS regression we do find (but do not report) that the instruments for our predictor variables are weak in this framework. We therefore use the S-GMM approach suggested by Blundell and Bond (1998), Bond (2002), and Windmeijer (2005).

We run our estimation using the *xtabond2* function in Stata, which includes the two-step S-GMM estimator with the Windmeijer (2005) correction. We ensure that all our tests—Hansen's J test for overall exogeneity, difference-in-Hansen tests to check on the exogeneity of each endogenous variable, and Arellano–Bond $\mathrm{AR}(p)$ tests to identify the starting point of each instrument's lag structure (see Roodman 2007)—are valid, that we have the lowest number of instruments (for details see Roodman 2007, 2009), and that we have enough information incorporated through moment conditions to derive reliably precise estimates.

6. Results

Table 3 displays the results of our study. Each column header denotes the hypothesis tested, with the first four columns of results subsuming performance in terms of quantity (number of patents) and the last four columns in terms of quality (number of citations per patent).

Aggregate R&D Variability. In columns H1.a/b and H1.c/d of Table 3, the coefficients for VRD indicate a significant and negative effect of R&D spending variability on patents ($-0.129\text{e}{-3}$, $p = 0.004$) and also on citations ($-0.310\text{e}{-3}$, $p = 0.009$). These findings support both H1a and H1c: variability in R&D spending reduces both the quantity and the quality of patents. Thus a certain amount of steadfastness is necessary when investing in R&D or else the firm's R&D performance will decline.

Table 3 shows that, after missing values (mainly for control variables) are taken into account, the final sample for estimating our models consists of 3,267 companies. We define 108 instruments for the estimation of *PAT* and 105 for the estimation of *CP*. Thus our ratio of instruments to companies is extremely low (Roodman 2007), which indicates that these tests are reliable and relevant. The high p-values associated with our exogeneity tests confirm this reliability, which assures that our instruments are in fact valid. Because all the Arellano–Bond $\mathrm{AR}(p)$ tests yield $p = 3$, we instrument our variables starting at lag 3. Similar considerations apply with respect to the other hypotheses, so we shall not repeat this information.

To develop a sense of this effect's magnitude, consider a hypothetical firm that reflects the average (annual) characteristics of our sample. If this firm were to increase its VRD by one standard deviation, then it would be granted 4.1% fewer patents and garner 10.1% fewer citations.

Technological Originality. Firms fund R&D projects whose level of technological originality ranges from incremental to pioneering, and the effects of R&D spending variability may differ depending on which end of this spectrum is the focus of a firm's R&D investment. Columns H2.a/b.p and H2.a/b.cp of Table 3 test the corresponding hypotheses. We find that the interaction between variability and the ratio of pioneering patents in firms' portfolios is significant and negative for both the number of patents and the number of

	Patents (PAT)				Citations per patents (CP)			
	H1.a/b	H2.a/b.p	H3.a/b.p	H4.a	H1.c/d	H2.a/b.cp	H3.a/b.cp	H4.b
Variables	Variability in R&D Spending	Interaction w/ Originality	Search Distance	Role of Forecasting	Variability in R&D Spending	Interaction w/ Originality	Search Distance	Role of Forecasting
1-yr Lagged Dependent Variable	934.9 ***	927.3 ***	964.2 ***	907.1 ***	907.5 ***	893.9 ***	893.7 ***	814.1 ***
R&D Stock (SRD)	0.013 *	0.002	-0.008	0.009	0.048 **	-0.001	-0.016	-0.016
Total Assets (LAT)	-7.728 .	-16.53 **	-2.96	-12.262 *	11.697	-0.813	3.07	21.72 .
Squared Total Assets (LAT2)	5.004 ***	5.347 ***	2.288	5.349 ***	1.878	3.107 *	2.892 .	4.389 **
Capital Expenditure (CAPX)	0.122	0.086	0.123	0.103	-0.185	-0.193	-0.207	-0.163
Capital Intensity (CAPIN)	-19.20 ***	-20.88 ***	-23.26 ***	-20.18 ***	-31.86 ***	-34.68 ***	-34.44 ***	-33.99 ***
Liquidity (LIQ)	0.065	0.060 .	0.024	0.058	0.018	0.022	0.013	-0.049
Market-to-Book Ratio (MB)	0.014	0.013	0.012	0.017	0.063	0.068	0.066	0.078
Age (LAGE)	-4.283	-7.035	-2.874	-2.072	2.316	0.851	3.757	-11.641
Industry Concentration (HERF)	-113.2 **	-56.00	-36.6	-74.9 .	-175.87	-133.991	-168.2 .	-253.3 *
Squared Ind. Conc. (HERF2)	78.98 ***	53.72 *	34.14	62.72 **	114.68	91.397	105.4 .	149.8 *
Industry Sales Growth (SALG)	4.036 **	3.767 *	3.520 *	3.769 *	1.931	2.318	1.911	3.454
Pioneering Ratio (PNR)		1,883.9 ***		1,560.2 ***		1,813.2 **		566.8
Distant Pioneering Ratio (PNRD)			-1,116.8				-331.0	
Close Pioneering Ratio (PNRC)			1,723.7 **				1,798.7 *	
R&D Variability (VRD)	**-0.129** **	**-0.026**	**0.051**		**-0.310** **	**0.000**	**0.050**	
Interaction VRD x PNR (INTER1)		**-2.026** ***				**-1.865** *		
Interaction VRD x PNRC (INTER2)			**-2.35** **				**-1.139** *	
Interaction VRD x PNRD (INTER3)			**7.597** *				**-5.638**	
Predicted Variability (VRDP)				**0.144** .				**0.359**
Unpredicted Variability (VRDU)				**-0.155** ***				**-0.250** *
GMM Estimation Method	system	system	system	system	system	system	system	system
Company Fixed Effects	YES	YES	YES	YES	YES	YES	YES	YES
Year Fixed Effects	YES	YES	YES	YES	YES	YES	YES	YES
Number of Observations	19,585	19,585	19,585	19,585	19,585	19,585	19,585	19,585
Number of Firms	3,267	3,267	3,267	3,267	3,267	3,267	3,267	3,267
Number of instruments	108	207	199	171	105	201	208	174
Percentage of Instruments	3%	6%	6%	5%	3%	6%	6%	5%
Arellano-Bond Test for AR(1)[1]	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Arellano-Bond Test for AR(2)[2]	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Arellano-Bond Test for AR(3)[3]	0.667	0.404	0.969	0.354	0.504	0.401	0.491	0.475
Hansen J-test for Overidentifying Restrictions[4]	0.303	0.223	0.231	0.242	0.601	0.744	0.725	0.867
Diff.-in-Hansen Test of Exogeneity of:[5]								
Dep. Var.	0.800	0.250	0.274	0.708	0.964	0.928	0.940	0.720
VRD	0.530	0.515	0.281		0.411	0.307	0.276	
SRD	0.499	0.616	0.525	0.244	0.537	0.714	0.692	0.651
PNR		0.377		0.560		0.465		0.859
INTER1		0.256				0.558		
PNRD			0.249				0.304	
PNRC			0.790				0.396	
INTER2			0.475				0.201	
INTER3			0.454				0.680	
VRDP				0.433				0.551
VRDU				0.421				0.978

*** -- 0.1% level, ** -- 1% level, * -- 5% level, . -- 10% level
All controls are lagged by 1 year and coefficients are scaled by a factor of 1000 for better readability
1 - H0 = no 1st-order serial correlation in residuals
2 - H0 = no 2nd-order serial correlation in residuals
3 - H0 = no 3rd-order serial correlation in residuals
4 - H0 = model specification is correct
5 - H0 = instruments are exogenous

Table 3 Model estimates

citations per patent ($-2.026\text{e}{-3}$, $p = 0.001$ and $-1.865\text{e}{-3}$, $p = 0.018$, resp.). Hypothesis 2a is strongly supported because, the more a firm engages in original invention, the more R&D variability hurts R&D performance in terms of quantity and quality. Focusing on the main effect of originality, we uncover an interesting fact: the more a company is engaged in pioneering innovation, the better its invention performance in both quantity and quality (PNR is positive and significant with $1883.9\text{e}{-3}$, $p = 0.000$ and $1813.2\text{e}{-3}$, $p = 0.006$ for quantity and quality, resp.). These results suggest that a pioneer can cement technological leadership and pre-empt scarce assets (see Lieberman and Montgomery 1988, p. 44).

Technological Firm Search Distance. Columns H3.a/b.p and H3.a/b.cp of Table 3 test whether the effects of variability on originality are the same for technologically distant inventions as for technologically close ones. For this purpose we decompose the fraction of original inventions into a component that is technologically close and one that is technologically distant. The interaction between R&D variability and original technologies that are *close* to the company's technological base is negative and significant for both the number of patents ($-2.347\text{e}{-3}$, $p = 0.002$) and the quality of patents ($-1.139\text{e}{-3}$, $p = 0.048$). The arguments given for H2 apply here as well. When a company decides to develop novel technologies that are close to its existing technology base, variability hurts R&D productivity. (Just as for the main effect underlying H2, the main effect of novelty in close technologies is positive for both the quantity (1.723, $p = 0.002$) and quality (1.799, $p = 0.012$) of patents. However, it is no less interesting that the interaction between R&D variability and original technologies that are *distant* from the company's technological base is positive and significant for the number of patents ($7.597\text{e}{-3}$, $p = 0.026$) although not significant for the quality of patents ($-5.638\text{e}{-3}$, $p = 0.225$). We conclude that, when a company decides to develop novel technologies that are distant from its existing technology base, flexibility becomes a major driver of patent generation and does not reduce the quality of those patents. (The main effects in this case are negative but not significant.) Therefore, H3b is supported for quantity and partially supported for quality.

These results have an interesting interpretation. An argument about embeddedness can be made. Original innovation that is close to the firm's technological base benefits from the technical knowledge, routines, processes, and other intellectual assets that accumulated while the technology base was built. Variability in R&D spending obstructs development of the technology base and thereby provides fewer resources to the original invention projects which are close to the firm's technology base. The base technology thus "embeds" the innovation by establishing the equivalent of "absorptive capacity" for the original inventions (Cohen and Levinthal 1990). In contrast, inventions that are distant from the firm's technological base do not profit from existing routines, mental models, and assets. Because past experiences are less valuable, there is no technology base in which to embed the innovation.

Predicted versus Unpredicted Variability. Finally, Hypotheses 4 reflect our recognition that adaptive R&D spending cannot be unrelievedly negative; in other words, there should be some way to mitigate the negative effect of funding variability so that management can effect necessary changes in R&D spending with minimal harm. To test for the possibility of such a mitigation method, we decompose R&D spending variability into anticipated and unanticipated changes. The estimated effects are reported in columns H4.a and H4.b of Table 3.

We find that, for both patents and citations, the coefficients for predicted variability are positive and marginally significant in the case of patents ($0.144\mathrm{e}{-3}$, $p = 0.089$ and $0.359\mathrm{e}{-3}$, $p = 0.12$, resp.) whereas the coefficients for unpredicted variability are significant and negative ($-0.155\mathrm{e}{-3}$, $p = 0.001$ and $-0.250\mathrm{e}{-3}$, $p = 0.032$, resp.). Thus anticipated changes in R&D spending do not harm R&D performance and potentially may increase it whereas unanticipated changes clearly reduce it. This result confirms that managers can anticipate the consequences of changed R&D spending and so can prepare the organization for that eventuality. Hence Hypotheses 4a is supported and 4b–while not literally supported–is supported in the sense that the effect of predicted variability is much more positive than the effect of unpredicted variability.

In sum, our empirical results suggest that variability in R&D spending has an inherently negative effect that interacts with the type of innovation strategy. Even so, we identify a way to manage any required changes to R&D resource allocations: by adhering to a predictable method of effecting any necessary funding changes, managers can at least limit the negative consequences of those changes.

Robustness Tests

Table 4 and Table 5 summarize the results of alternative models with respect to the number of patents and the number of citations per patent, respectively. As a benchmark, we reproduce the original estimates (from Table 3) in row 1 of both tables; each subsequent row corresponds to a particular robustness check.

We test the robustness of our results to four types of alternative model specifications. We estimate autocorrelative specifications with alternative lag structures for our dependent variables (rows 2 and 3); we verify robustness with respect to a different number of instruments (rows 4 and 5); we construct alternative samples, including industry subsamples (rows 6–11); and we test alternative constructs of our main variables (rows 12–18). Of course–as must be expected–a few individual tests do not give further support to our analyses, but overall our results exhibit a remarkable level of robustness to all these different configurations.

Alternative Autocorrelative Model Specifications. Rows 2 and 3 of the tables concern the order of the autoregressive process for our dependent variables. Our main model introduces an autoregressive model of order 1; rows 2 and 3 test models of orders 2 and 3, respectively.

Alternative Number of Instruments. Following Roodman (2009), we test for a reduced and an elevated number of instruments—conditions that deviate from our configuration rules (see p. 20 in Section 5). Results are given in (respectively) rows 4 and 5 of the tables.

		H1.a/b	H2.a/b.p	H3.a/b.p		H4.a				
	#	VRD	INTER1	INTER2	INTER3	VRDP	VRDU	#obs	#firms	***Robustness Test Description***
Main Model	1	-0.013 **	-0.203 **	0.760 *	-0.235 **	0.014 .	-0.015 **	19,585	3,267	
Alternate DPD[1] Model Specifications	2	-0.011 *	-0.110 *	1.045 **	-0.247 **	0.015 .	-0.015 **	19,585	3,267	AR(2) model for dependent variable
	3	-0.011 *	-0.224 **	1.396 **	-0.273 **	0.014 .	-0.015 **	19,585	3,267	AR(3) model for dependent variable
Alternate Number of Instruments	4	-0.025 **	-0.273 **	1.056 **	-0.286 **	0.016 .	-0.016 **	19,585	3,267	62 | 165 | 200 | 176 instruments
	5	-0.014 **	-0.232 **	0.770 *	-0.205 **	0.008	-0.011 *	19,585	3,267	195 | 213 | 236 | 217 instruments
Alternate Sample Building	6	-0.010 *	-0.203 **	1.579 **	-0.641 ***	0.014	-0.014 **	22,999	3,646	Intensity > 3%
	7	-0.011 ***	-0.302 *	1.600 **	-0.665 ***	0.013	-0.013 **	21,369	3,458	Intensity > 4%
	8	-0.013 ***	-0.646 ***	0.867 **	-0.234 **	0.015 .	-0.019 ***	18,237	3,124	Intensity > 6%
	9	-0.020 **	-0.663 ***	2.629 **	-0.474 ***	0.011	-0.012 *	17,148	3,000	Intensity > 7%
	10	-0.014 *	-0.186 **	0.440	-0.164 *	0.002	-0.012 *	14,684	2,574	Strictly positive R&D spend
	11	-0.020 *	-0.174 *	1.308 **	-0.247 *	0.024	-0.025 **	14,509	2,180	Manufacturing subsample
Alternate Variable Specifications	12	-13.80 ***	0.0000 ***	35.925	-572.382 .	21.216 **	-16.712 ***	19,609	3,271	Scaled variables: SRD by AT, VRD by SRD
	13	-0.014	-0.3371 **	0.584	-0.308 *	0.001	-0.017 *	13,232	2,305	Industry-dependent amortization factor
	14	-0.017 **	-0.3257 *	2.238 *	-0.361 *	0.016	-0.023 *	19,585	3,267	Squared changes
	15					0.027	-0.025 **	19,585	3,267	5-point predicted variability
	16	-0.013 **	-0.259 **	1.397 **	-0.297 **	0.010	-0.014 **	19,585	3,267	Control for M&A
	17	-0.011 *	-0.263 **	1.333 **	-0.299 **	0.014 .	-0.014 **	19,585	3,267	Control for intangible assets
	18	-0.014 **	-0.265 **	0.133	-0.239 .	0.014	-0.017 **	18,612	3,160	Control for changes in intangible assets

Table 4 Robustness tests: Number of patents

		H1.c/d	H2.a/b.cp	H3.a/b.cp		H4.b				
	#	VRD	INTER1	INTER2	INTER3	VRDP	VRDU	#obs	#firms	***Robustness Test Description***
Main Model	1	-0.031 **	-0.187 *	-0.564	-0.114 *	0.036	-0.025 *	19,585	3,267	
Alternate DPD[1] Model Specifications	2	-0.032 *	-0.139 *	0.006	-0.498	0.026	-0.021 .	19,585	3,267	AR(2) model for dependent variable
	3	-0.019 *	-0.209 *	0.000	0.001	0.015	-0.018 *	19,585	3,267	AR(3) model for dependent variable
Alternate Number of Instruments	4	-0.016 **	-0.205 *	-0.309	-0.216 *	0.028	-0.022 *	19,585	3,267	93 | 121 | 159 | 160 instruments
	5	-0.021 *	-0.115 *	-0.630	-0.120 *	0.024	-0.023 **	19,585	3,267	151 | 259 | 219 | 220 instruments
Alternate Sample Building	6	-0.020 *	-0.197 *	-0.502	-0.124 **	-0.002	-0.005	22,999	3,646	Intensity > 3%
	7	-0.032 ***	-0.190 **	-0.328	-0.121 *	0.048 .	-0.030 *	21,369	3,458	Intensity > 4%
	8	-0.035 ***	-0.185 *	0.317	-0.203 *	0.018	-0.018 *	18,237	3,124	Intensity > 6%
	9	-0.031 **	-0.177 *	-0.111	-0.154 *	0.035	-0.025	17,148	3,000	Intensity > 7%
	10	-0.010	-0.196 *	0.185	-0.201 *	0.000	-0.012 .	14,684	2,574	Strictly positive R&D spend
	11	-0.020 **	-0.177 *	-0.044	-0.174 *	0.021	-0.017 *	14,509	2,180	Manufacturing subsample
Alternate Variable Specifications	12	-12.18 ***	0.0000 ***	0.0000 ***	0.0 ***	31.753 .	-28.004 **	19,609	3,271	Scaled variables: SRD by AT, VRD by SRD
	13	-0.018 *	-0.1586	-0.6947	-0.165 *	-0.004	-0.010	13,232	2,305	Industry-dependent amortization factor
	14	-0.038 *	-0.236 *	-0.389	-0.155 .	0.070 .	-0.049 *	19,585	3,267	Squared changes
	15					0.026	-0.028 **	19,585	3,267	5-point predicted variability
	16	-0.033 **	-0.176 *	0.032	-0.185 *	0.037	-0.025 .	19,585	3,267	Control for M&A
	17	-0.030 *	-0.130 *	0.033	-0.200 *	0.036	-0.024 *	19,585	3,267	Control for intangible assets
	18	-0.013 .	-0.181 .	-0.171	-0.177 .	0.040	-0.026 *	18,612	3,160	Control for changes in intangible assets

Table 5 Robustness tests: Citations per patent

Alternative Samples. In the main model, we considered companies for which R&D intensity (i.e., the ratio of R&D expenditures to firm sales) was greater than 5% at least once during the observation period. As a robustness test, rows 6–9 of the tables give results for models based on a sample of companies with a cutoff from 3% to 7%. The model of row 10 imposes the additional condition that R&D spending be strictly positive in each observation period. In order to rule out industry trends that might confound the results, in row 11 we verify our method's validity for the manufacturing industry (2-digit SIC codes from 20 to 39), which is a widely used subsample—see, for example, Crépon et al. (1998), Lööf and Heshmati (2002), Cassiman and Veugelers (2006), Leiponen and Helfat (2011), and Revilla and Fernández (2012).

Alternative Variable Specifications. In row 12 of Tables 4 and 5 we present a model that controls for company size by scaling our variables of interest. Following Hall et al. (2005), we scale the R&D stock by the value of total assets. We scale our measures of R&D variability—aggregate R&D spending variability as well as its predictable and unpredictable parts—by the stock. Variables used for measuring originality are ratios, by construction.

In row 13 we use an alternative method for constructing the R&D stock and R&D spending variability. Instead of employing a common discount factor of 15% for all companies, we use the industry-specific factors estimated by Li and Hall (2016) for the ten most patent-intensive industries.

In row 14 we build the R&D variability according to yet another method: instead of aggregating discounted yearly absolute changes we aggregate discounted yearly squared changes.

Row 15 in each table concerns the predicted/unpredicted configuration. In our main analysis, the predicted annual R&D spending was obtained through a linear two-point extrapolation. Here we test the robustness of that construction by replacing the two-point approach with a five-point linear forecast.

In row 16, we introduce a dummy set to 1 whenever a company's *gvkey* changes, which implies a merger or an acquisition between public firms. In rows 17 and 18 we consider that in some cases companies can build also immaterial R&D assets, typically during merger and acquisition activity. Such immaterial positions are recorded as "intangible assets", although such assets comprise much more than intangible *R&D* assets. In our main regression, we control for this asset type indirectly because it constitutes part of our "total assets" control variable (*LAT*). In row 17 we include intangible assets directly as a separate control, and in row 18 we control for changes in the value of intangible assets.

7. Discussion and Implications

This paper provides empirical evidence concerning how the temporal distribution of R&D funding affects R&D outcomes. We show that investing a given sum of R&D funds in a persistent and not a dynamic fashion helps improve R&D performance: variation in R&D spending is negatively related to innovation performance in terms of both quantity and quality provided we control for overall investment in R&D. Flexibility comes with a loss of R&D efficiency, although the precise nature of this relation depends on the type of innovation in which a company engages. The more original is a firm's innovation portfolio, the more negative is the effect of variation on R&D performance. Differentiating between R&D settings even further, we find that research on an original portfolio of inventions close to (resp., distant from) the company's technology base tends to suffer (resp., to prosper) under variability. The implication is that variability in most of its forms is a detriment to R&D performance. Our subsequent analysis qualifies that impression, however. After decomposing R&D spending variability into its unpredictable and predictable components, we find that only unpredictable variability is harmful; predictable variability has no effect or potentially even a positive effect. So if the performance of R&D is a priority, then managers should strive to make any strategic repositioning in R&D funding as gradual as possible.

Our research contributes to a theoretical understanding of what determines R&D productivity and hence good R&D management. Yet this paper has important implications also for managerial practice. There are many reasons why managers may wish to alter the level of R&D spending. Some of these reasons (e.g., pursuing technological opportunities) reflect more positive intentions than do others (e.g., chasing targets for earnings). Whatever the rationale for a change in spending, our paper highlights the possible negative consequences that managers should consider; it also documents the contingencies under which adaptation is especially harmful and identifies policies for mitigating adaptation pains. Thus we offer managers a framework for conceptualizing principles about how best to invest in R&D. Our paper also issues this warning about the goal of hitting quarterly financial targets: If R&D spending is viewed as discretionary when such targets must be met—which is customary (as documented by Roychowdhury 2006) for some publicly traded companies—then one should expect to observe long-term negative consequences that cannot be reversed simply by later restoring or even increasing R&D investment.

As with any empirical study based on archival data, there are limits to generalizing the results. Although our sample is expansive, it considers only public firms. It may be that private firms, which can operate without the pressure of periodic financial reporting requirements, employ dynamic R&D spending strategies that lead to better outcomes than those described in this study.

We use accounting and patent data to draw our conclusions, and questions naturally arise about how well these data represent reality. For example, there may be innovation activities not captured by either type of data, and patent information might not accurately reflect a company's innovation efforts. The measures we use are also based on annual R&D spending data. Hence we observe only year-to-year changes, which might fail to reveal equally significant changes that transpire over shorter time periods. Extant accounting and reporting standards make it virtually impossible to observe changes at a finer level for a large set of companies. That being said, a collaborative study with a large firm featuring many divisions and frequent capital budgeting adjustments would almost certainly shed still more light on the nature of variability.

Owing to the nature of lags between R&D spending decisions and observable outcomes, our sample is focused on a period that goes back almost 40 years. The effects addressed in this study may well be timeless. Yet as a consequence of the changing nature of knowledge work and improved human resource systems, it is also possible that some organizations in fast-moving industries (e.g., information technology) have recently become more adept at managing flexibility but that there are too few such companies for this effect to show up in the data collected so far.

In conclusion, we believe that our study—in addition to improving our theoretical understanding of R&D productivity—can foster managerial discussions about the optimal level of dynamism in R&D spending.

References

Aghion P, Van Reenen J, Zingales L (2013) Innovation and institutional ownership. *AM ECON REV* 103(1):277–304.

Ahuja G (2000) Collaboration networks, structural holes, and innovation: A longitudinal study. *ADMIN SCI QUART* 45(3):425–455.

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

Almeida H, Hsu PH, Li D (2013) Less is more: Financial constraints and innovative efficiency. *SSRN* .

Angrist J, Pischke JS (2008) *Mostly harmless econometrics: An empiricist's companion* (Princeton university press).

Arellano M, Bond S (1991) Some tests of specification for panel data: Monte carlo evidence and an application to employment equations. *REV ECON STUD* 58(2):277–297.

Argyres N, Silverman B (2004) R&d, organization structure, and the development of corporate technological knowledge. *STRATEGIC MANAGE J* 25(8-9):929–958.

Arkali G, Bardhan I, Krishnan V (2008) R&d, information technology, and firm performance: A complementarity model. *UCSD Working Paper* 1–50.

Arora A, Belenzon S, Rios L (2011) The organization of r&d in american corporations: the determinants and consequences of decentralization. Technical report, NBER.

Arora A, Belenzon S, Rios L (2014) Make, buy, organize: The interplay between research, external knowledge, and firm structure. *STRATEGIC MANAGE J* 35(3):317–337.

Atanassov J (2013) Do hostile takeovers stifle innovation? Evidence from antitakeover legislation and corporate patenting. *J FINANC* 68(3):1097–1131.

Baard S, Rench T, Kozlowski S (2014) Performance adaptation a theoretical integration and review. *J MANAGE* 40(1):48–99.

Bauer T, Bodner T, Erdogan B, Truxillo D, Tucker J (2007) Newcomer adjustment during organizational socialization: A meta-analytic review of antecedents, outcomes, and methods. *J APPL PSYCHOL* 92(3):707.

Bernstein B, Singh PJ (2008) Innovation generation process: Applying the adopter categorization model and concept of "chasm" to better understand social and behavioral issues. *EUR J INNOVAT MANAG* 11(3):366–388.

Bilgram V, Brem A, Voigt KI (2008) User-centric innovations in new product development - Systematic identification of lead users harnessing interactive and collaborative online-tools. *IJIM* 12(03):419–458.

Blundell R, Bond S (1998) Initial conditions and moment restrictions in dynamic panel data models. *J ECONOMETRICS* 87(1):115–143.

Bond S (2002) Dynamic panel data models: a guide to micro data methods and practice. *PORT ECON J* 1(2):141–162.

Bound J, Cummins C, Griliches Z, Hall B, Jaffe A (1984) Who does r&d and who patents? Griliches ZE, ed., *R&D Patents and Productivity* (Chicago, IL.: University of Chicago Press for the NBER).

Cameron G (1996) On the measurement of real r&d: Divisia price indices for uk business enterprise r&d. *RES EVALUAT* 6(3):215–219.

Case D (2012) *Looking for information: A survey of research on information seeking, needs and behavior* (Bingley, UK: Emerald Group Publishing).

Cassiman B, Veugelers R (2006) In search of complementarity in innovation strategy: Internal r&d and external knowledge acquisition. *MANAGE SCI* 52(1):68–82.

Chan J, Dow S, Schunn C (2014) Do the best design ideas (really) come from conceptually distant sources of inspiration? *DES STUD* 1(1):1–28.

Chang X, Fu K, Low A, Zhang W (2015) Non-executive employee stock options and corporate innovation. *J FINANC ECON* 115(1):168–188.

Chao R, Kavadias S (2013) R&d intensity and the new product development portfolio. *IEEE T ENG MANAGE* 60(4):664–675.

Chao RO, Kavadias S (2008) A theoretical framework for managing the new product development portfolio: When and how to use strategic buckets. *Management Science* 54(5):907–921.

Chemmanur T, Tian X (2017) Do anti-takeover provisions spur corporate innovation? a regression discontinuity analysis. *J FINANC QUANT ANAL* .

Ciftci M, Lev B, Radhakrishnan S (2011) Is research and development mispriced or properly risk adjusted? *J ACC AUD FINANCE* 26(1):81–116.

Cockburn I, Henderson R (1998) Absorptive capacity, coauthoring behavior, and the organization of research in drug discovery. *J IND ECON* 46(2):157–182.

Cockburn I, Henderson R (2001) Scale and scope in drug development: unpacking the advantages of size in pharmaceutical research. *J HEALTH ECON* 20(6):1033–1057.

Cohen W (2010) Fifty years of empirical studies of innovative activity and performance. *Handbook of the Economics of Innovation* 1:129–213.

Cohen W, Klepper S (1996a) Firm size and the nature of innovation within industries: the case of process and product r&d. *REV ECON STAT* 232–243.

Cohen W, Klepper S (1996b) A reprise of size and r & d. *ECON J* 925–951.

Cohen W, Levinthal D (1990) Absorptive capacity: a new perspective on learning and innovation. *ADMIN SCI QUART* 35:128–152.

Corrado C, Hulten C, Sichel D (2009) Intangible capital and us economic growth. *REV INCOME WEALTH* 55(3):661–685.

Crépon B, Duguet E, Mairessec J (1998) Research, innovation and productivity: An econometric analysis at the firm level. *Economics of Innovation and new Technology* 7(2):115–158.

Czarnitzki D, Hall B, Hottenrott H (2014) Patents as quality signals? the implications for financing constraints on r&d. Technical report, NBER.

Dane E, George J (2014) Unpacking affective forecasting and its ties to project work in organizations. *ACAD MANAGE REV* 39(2):181–201.

Ding Y, Stolowy H, Tenenhaus M (2007) R&D productivity: An exploratory international study. *Review of Accounting and Finance* 6(1):86–101.

Edmondson A, Nembhard I (2009) Product development and learning in project teams: The challenges are the benefits. *JPIM* 26(2):123–138.

Fazzari S, Hubbard R, Petersen B (1988) Financing constraints and corporate investment. *BPEA* 1:146–206.

Fleming L, Sorenson O (2003) Navigating the technology landscape of innovation. *SLOAN MANAGE REV* winter:15–23.

Francis B, Hasan I, Sharma Z (2011) Incentives and innovation: Evidence from ceo compensation contracts. *SSRN* .

Freeman C (1982) *The Economics of Industrial Innovation* (Cambridge, MA: MIT Press).

Freeman C, Soete L (1997) *The economics of industrial innovation* (Psychology Press).

Galasso A, Simcoe T (2011) Ceo overconfidence and innovation. *MANAGE SCI* 57(8):1469–1484.

Geroski P (1995) Market structure, corporate performance, and innovative activity. *OUP Catalogue* .

Graham J, Harvey C, Rajgopal S (2005) The economic implications of corporate financial reporting. *J ACCOUNT ECON* 40(1):3–73.

Griffin A (1997) The effect of project and process characteristics on product development cycle time. *J MARKETING* 34(1):24–35.

Griffith R, Harrison R, Van Reenen J (2006) How special is the special relationship? Using the impact of U.S. R&D spillovers on U.K. firms as a test of technology sourcing. *AM ECON REV* 96(5):1859–1875.

Griliches Z, Mairesse J (1984) Productivity and r&d at the firm level. Griliches Z, ed., *Patents, and Productivity* (Chicago: University of Chicago Press).

Hacklin F, Raurich V, Marxt C (2004) How incremental innovation becomes disruptive: The case of technology convergence. *Engineering Management Conference, 2004. Proceedings. 2004 IEEE International*, volume 1, 32–36 (IEEE).

Hall B, Jaffe A, Trajtenberg M (2001) The NBER patent citation data file: Lessons, insights and methodological tools. *NBER Working Paper Series* No. 8498.

Hall B, Jaffe A, Trajtenberg M (2005) Market value and patent citations. *RAND J ECON* 36(1):16–38.

Hall B, Kruiniker H (1995) The role of working capital in the investment process.

Hall B, Lotti F, Mairesse J (2009) Innovation and productivity in smes: empirical evidence for italy. *SMALL BUS ECON* 33(1):13–33.

Hall B, Mairesse J, Mohnen P (2010) Measuring the returns to R&D. *Handbook of the Economics of Innovation* 2:1033–1082.

Hall B, Oriani R (2006) Does the market value R&D investment by european firms? Evidence from a panel of manufacturing firms in France, Germany, and Italy. *INT J IND ORGAN* 24(5):971–993.

Hall B, Ziedonis R (2001) The patent paradox revisited: An empirical study of patenting in the u.s. semiconductor industry, 1979-1995. *RAND J ECON* 32:101–128.

Harhoff D (1998) R&d and productivity in german manufacturing firms. *Economics of Innovation and New Technology* 6(1):29–50.

Henderson R (1993) Underinvestment and incompetence as responses to radical innovation: Evidence from the photolithographic alignment equipment industry. *RAND J ECON* 248–270.

Henderson R, Cockburn I (1994) Measuring competence? exploring firm effects in pharmaceutical research. *STRATEGIC MANAGE J* 15(S1):63–84.

Henderson R, Cockburn I (1996) Scale, scope, and spillovers: the determinants of research productivity in drug discovery. *RAND J ECON* 32–59.

Hendricks KB, Singhal VR (2008) The effect of product introduction delays on operating performance. *MANAGE SCI* 54(5):878–892.

Hirshleifer D, Low A, Teoh S (2012) Are overconfident ceos better innovators? *J FINANC* 67:1457–1498.

Hollander S (1965) *The Sources of Increased Efficiency: A Study of Du Pont Rayon Plants* (Cambridge, MA: MIT Press).

Jain A (2013) Learning by doing and the locus of innovative capability in biotechnology research. *ORGAN SCI* 24(6):1683–1700.

Jefferson G, Bai H, Guan X, Yu X (2006) R&d performance in chinese industry. *Economics of Innovation and New Technology* 15(4-5):345–366.

Jones G (1986) Socialization tactics, self-efficacy, and newcomers adjustments to organizations. *ACAD MANAGE J* 29(2):262–279.

Katila R (2002) New product search over time: past ideas in their prime? *ACAD MANAGE J* 45(5):995–1010.

Kessler E, Allocca M, Rahman N (2007) External knowledge accession and innovation speed in the small and medium sized enterprise (SME). *SER* 15(1):1–21.

Kessler E, Bierly P (2002) Is faster really better? An empirical test of the implications of innovation speed. *IEEE T ENG MANAGE* 49(1):2–12.

Kim T, Cable D, Kim S (2005) Socialization tactics, employee productivity, and person-organization fit. *J APPL PSYCHOL* 90(2):232.

Klein H, Weaver N (2000) The effectiveness of an organizational-level orientation training program in the socialization of new hires. *PERS PSYCHOL* 53(1):47–66.

Kleinschmidt E, De Brentani U, Salomo S (2007) Performance of global new product development programs: A resource-based view. *JPIM* 24(5):419–441.

Kor Y, Mahoney J (2005) How dynamics, management, and governance of resource deployments influence firm-level performance. *STRATEGIC MANAGE J* 26(5):489–496.

Kothari S (2001) Capital markets research in accounting. *J ACCOUNT ECON* 31(1):105–231.

Kothari S, Laguerre T, Leone A (2002) Capitalization versus expensing: Evidence on the uncertainty of future earnings from capital expenditures versus R&D outlays. *REV ACC STUD* 7(4):355–382.

Kremp E, Mairesse J (2004) Knowledge management, innovation, and productivity: A firm level exploration based on french manufacturing cis3 data. Technical report, NBER.

Langerak F, Hultink E (2005) The impact of new product development acceleration approaches on speed and profitability: Lessons for pioneers and fast followers. *IEEE T ENG MANAGE* 52(1):30–42.

Leiponen A, Helfat C (2011) Location, decentralization, and knowledge sources for innovation. *ORGAN SCI* 22(3):641–658.

Lerner J (2006) The new new financial thing: The origins of financial innovations. *J FINANC ECON* 79(2):223–255.

Lerner J, Sorensen M, Stromberg P (2013) Private equity and investment in innovation: Evidence from patents. *J APPL CORP FIN* 25(2):95–102.

Lerner J, Wulf J (2007) Innovation and incentives: Evidence from corporate R&D. *REV ECON STAT* 89(4):634–644.

Lev B, Sougiannis T (1996) The capitalization, amortization, and value-relevance of R&D. *J ACCOUNT ECON* 21(1):107–138.

Li W, Hall B (2016) Depreciation of business r&d capital. *NBER Working Paper Series* No. 22473.

Lieberman M, Montgomery D (1988) First-mover advantages. *STRATEGIC MANAGE J* 9(S1):41–58.

Lin BW, Lee Y, Hung SC (2006) R&d intensity and commercialization orientation effects on financial performance. *J BUS RES* 59(6):679–685.

Loch C, Kavadias S (2002) Dynamic portfolio selection of NPD programs using marginal returns. *MANAGE SCI* 48(10):1227–1241.

Lööf H, Heshmati A (2002) Knowledge capital and performance heterogeneity:: A firm-level innovation study. *Int. J. Prod. Econ.* 76(1):61–85.

Lööf H, Heshmati A (2006) On the relationship between innovation and performance: A sensitivity analysis. *Economics of Innovation and New Technology* 15(4-5):317–344.

March J (1991) Exploration and exploitation in organizational learning. *ORGAN SCI* 2(1):71–87.

March J (1994) *A Primer on Decision Making: How Decision Happens* (New York, NY: Free Press).

Massini S, Lewin A, Greve H (2005) Innovators and imitators: Organizational reference groups and adoption of organizational routines. *RES POLICY* 34(10):1550–1569.

Mecca J, Mumford M (2014) Imitation and creativity: Beneficial effects of propulsion strategies and specificity. *J CREATIVE BEHAV* 48(3):209–236.

Moch M, Morse E (1977) Size, centralization and organizational adoption of innovations. *AM SOCIOL REV* 42(5):716–725.

Mudambi R, Swift T (2014) Knowing when to leap: Transitioning between exploitative and explorative r&d. *STRATEGIC MANAGE J* 35(1):126–145.

Nelson R, Winter S (1977) In search of useful theory of innovation. *RES POLICY* 6(1):36–76.

Nickell S (1981) Biases in dynamic models with fixed effects. *ECONOMETRICA* 1417–1426.

Norman D, Verganti R (2014) Incremental and radical innovation: Design research vs. technology and meaning change. *DES ISSUES* 30(1):78–96.

Ostrom E, Burger J, Field CB, Norgaard RB, Policansky D (1999) Revisiting the commons: local lessons, global challenges. *SCIENCE* 284(5412):278–282.

Pandit S, Wasley C, Zach T (2011) The effect of R&D inputs and outputs on the relation between the uncertainty of future operating performance and R&D expenditures. *J ACC AUD FINANCE* 26(1):121–144.

Pich M, Loch C, DeMeyer A (2002) On uncertainty, ambiguity and complexity in project management. *MANAGE SCI* 48(8):1008–1023.

Pruett M, Thomas H (2008) Experience-based learning in innovation and production. *R&D MANAGE* 38(2):141–153.

Prusa T, Schmitz J (1991) Are new firms an important source of innovation?: Evidence from the pc software industry. *ECON LETT* 35(3):339–342.

Quintana-Garcia C, Benavides-Velasco C (2008) Innovative competence, exploration and exploitation: The influence of technological diversification. *RES POLICY* 37(3):492–507.

Revilla A, Fernández Z (2012) The relation between firm size and r&d productivity in different technological regimes. *TECHNOVATION* 32(11):609–623.

Rietzschel E, Nijstad B, Stroebe W (2007) Relative accessibility of domain knowledge and creativity: The effects of knowledge activation on the quantity and originality of generated ideas. *J EXP SOC PSYCHOL* 43(6):933–946.

Rogers M (2010) R&D and productivity: Using UK firm-level data to inform policy. *EMPIRICA* 37(3):329–359.

Roodman D (2007) A short note on the theme of too many instruments. Working paper 125, Center for Global Development.

Roodman D (2009) How to do xtabond2: An introduction to difference and system gmm in stata. *STATA J* 9(1):86–136.

Rosenkopf L, Nerkar A (2001) Beyond local search: boundary-spanning, exploration, and impact in the optical disk industry. *STRATEGIC MANAGE J* 22(4):287–306.

Roussel P, Saad K, Erickson T (1991) *Third Generation* R&D (Watertown, MA: Havard Business School Press).

Roychowdhury S (2006) Earnings management through real activities manipulation. *J ACCOUNT ECON* 42(3):335–370.

Sawyer R (2011) *Explaining creativity: The science of human innovation* (Oxford, UK: Oxford University Press).

Scherer F, Ross D (1990) *Industrial market structure and economic performance* (Houghton Mifflin Company), 3th edition.

Simonton D (1997) Creative productivity: A predictive and explanatory model of career trajectories and landmarks. *PSYCHOL REV* 104(1):66–89.

Smith L, Amiot C, Smith J, Callan V, Terry D (2013) The social validation and coping model of organizational identity development a longitudinal test. *J MANAGE* 39(7):1952–1978.

Somaya D (2003) Strategic determinants of decisions not to settle patent litigation. *STRATEGIC MANAGE J* 24(1):17–38.

Sommer S, Loch C, Dong J (2009) Managing complexity and unforeseeable uncertainty in startup companies: An empirical study. *ORGAN SCI* 20(1):118–133.

Stuart T, Podolny J (1996) Local search and the evolution of technological capabilities. *STRATEGIC MANAGE J* 17(S1):21–38.

Teece D (2000) Strategies for managing knowledge assets: the role of firm structure and industrial context. *Long Range Plann.* 33(1):35–54.

Teece D, Pisano G, Shuen A (1997) Dynamic capabilities and strategic management. *STRATEGIC MANAGE J* 18(7):509–533.

Terwiesch C, Loch CH, Niederkofler M (1998) When product development performance makes a difference. *JPIM* 15(1):3–15.

Van Maanen J, Schein E (1979) Towards a theory of organizational socialization. *RES ORGAN BEHAV* 1:209–264.

Von Hippel E (2009) Democratizing innovation: The evolving phenomenon of user innovation. *IJIS* 1(1):29–40.

Weber J (1990) Toshiba will pay TI royalty on chip patents. *Los Angeles Times* December 12.

Weisberg R (2011) Frank Lloyd Wright's Fallingwater: A case study in inside-the-box creativity. *CREATIVITY RES J* 23(4):296–312.

Windmeijer F (2005) A finite sample correction for the variance of linear efficient two-step gmm estimators. *J ECONOMETRICS* 126(1):25–51.