Technological Uniqueness and Firm Performance

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Abstract

Technological uniqueness, defined as the degree to which a firm's patented technology portfolio differs from its industry competitors, can have an unclear relationship with firm performance. On the one hand, recent empirical work in economics suggests that technological uniqueness can act as a barrier to incoming technology spillovers and impede firm performance. Alternatively, technological uniqueness could be a strategic resource which reduces outgoing technology spillovers and is costly to imitate. We empirically examine these competing arguments and find evidence that the strategic resource argument dominates in the data with technologically unique firms outperforming. At the same time, we show that pursuing technological uniqueness is costly, as unique firms indeed benefit less from technology spillovers, are harder to understand by equity analysts and have higher costs of equity capital.

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1. Introduction

A foundational premise of the resource-based view is that the possession of unique, valuable, and difficult to imitate resources is a necessary condition for superior performance (Barney, 1991). Such uniqueness in resources possessed is often simply an artifact of securing them at prices below their future value in use—below the prices other competitors must pay for similar resources (Barney, 1986). These unique and valuable resources—access to low-cost labor, a unique production or product technology, a brand, or some other resource—allow firms to generate unique products and services that deliver superior performance. Of course, causality may also operate in the opposite direction—a capacity to envision unique products or a unique strategy may enable firms to identify and secure resources that are underpriced relative to their value in use (Barney, 1986; Felin, Kauffman and Zenger, 2023).

Frequently cited as foremost among advantage-providing resources are unique or firm-specific technology and knowledge (Grant, 1996; Kogut and Zander, 1992). But knowledge is a resource quite unlike physical resources that are easily bought and sold in factor markets. Technological resources can be self-produced, widely shared, and often easily absorbed by others (Cohen and Levinthal, 1990). Knowledge is a scale free resource (Arrow, 1962; Levinthal and Wu, 2010) which eases its deployment within the firm, but also enables its absorption by and from others. The choice to pursue uniqueness in technology or knowledge generation presents the firm and strategist with a paradox. While a firm's decision to elevate its technological uniqueness may enable valuable product uniqueness readily deployable within the firm, it may also dampen a firm's capacity to absorb valuable knowledge from peers (Cohen and Levinthal, 1990) through beneficial spillovers (Bloom, Schankerman, and Van Reenen, 2013). Moreover, while technology's value depends on its novelty, having novel technology's value recognized by capital markets requires communication of this value. Yet, communicating technology's novel value to investors is often particularly difficult and may demand sharing the knowledge itself, which further undermines its value (Arrow, 1962). Because of both effects, the decision of whether to pursue uniqueness in technology as a path to increased firm performance is less straightforward than the resource-based view might imply. At a minimum, the choice to pursue technological uniqueness as a basis for generating product uniqueness comes at a cost.

In this paper we empirically explore both the substance of the tradeoff faced in pursuing unique technology, and the net result on firm performance. We construct a novel measure of technological uniqueness based on the patent classes in which a firm chooses to participate to protect its intellectual property, relative to a group (centroid) vector of patent classes selected by industry peers. We then examine how the uniqueness of a firm's patenting vector influences the scope of knowledge spillovers it enjoys, the cost of capital it pays, and the financial performance it generates. The main empirical finding is that more technologically unique firms outperform less unique industry rivals. More precisely, a one standard deviation greater technological uniqueness score is associated with 2.1% higher sales growth, 6.8% higher Tobin's Q, and roughly 0.8% higher profitability and ROA. These sales growth, profitability, and ROA effects are persistent at least four years into the future.

A distinct contribution of our analysis is to establish credible causal estimates of the performance effects of technological uniqueness. If higher technological uniqueness causes better firm performance, there are at least some firms that will benefit from pursuing more technologically unique strategies. To establish such causality, we use three distinct natural experiments—changes in industry-level technology trends, variation in local R&D tax credits, and variation in patent expiration. Our results suggest not only that higher technological uniqueness causes better firm performance, but that lower uniqueness also causes underperformance. Furthermore, we empirically characterize the set of firms for which these causal estimates apply, using complier analysis as suggested by Angrist and Pischke (2009). This analysis provides empirical characterizations of firms for which the causal effects of technological uniqueness are especially strong, thereby providing strategically useful predictions, which apply to some competitors but not for others (Barney, 1986).

At the same time, our results also suggest that the pursuit of technological uniqueness comes at a cost. We document that technologically unique firms benefit from fewer technological spillovers from their industry peers and pay higher costs of equity capital. We follow Litov et al. (2012) and explore the mechanism behind this latter finding of higher equity costs. We find that equity analysts consistently struggle to recognize technological uniqueness as a positive predictor of future firm performance. They are also are more likely to drop coverage of technologically unique firms, and expend more effort if they choose to cover these technologically unique firms.

Technologically unique firms appear harder for those outside the firm to understand as they must access private information, as argued by Benner and Zenger (2016). This asymmetric information problem, in addition to elevating equity costs, also explains why technological uniqueness is often hard to imitate and potentially risky to pursue.

In Section 2, we further develop our theory and hypotheses. In Section 3, we describe our new measure of technological uniqueness and the underlying data for our study. Section 4 discusses econometric issues and how we address them. Section 5 presents our main results. Section 6 offers robustness checks and section 7 discusses implications.

2. Theory: The Technological Uniqueness Paradox

2.1 Corporate Strategy and Technological Resources

Our conceptual starting point is a paradox at the heart of corporate strategy: On the one hand, unique strategic choices are needed for firms to differentiate themselves from competitors. On the other hand, such uniqueness raises the costs of evaluating strategies in capital markets. This "Uniqueness Paradox" was first established by Litov et al. (2012) and was further developed by Benner and Zenger (2016) and Oemichen et al. (2021). However, neither Litov et al. (2012) nor any of the studies following it, specified the nature of resources at the heart of the Uniqueness Paradox, partly because the empirical measure used by Litov et al. (2012) was based on uniqueness of industry segments. At the same time, which resource is pursued matters for our understanding of corporate strategy, since a strategy based on technology and patents can be very different in nature from a strategy based on a physical resource, talent, or an effective management team (Levinthal and Wu, 2010). We, therefore, push beyond the previous literature on the Uniqueness Paradox by focusing on the technology space – a domain in which an entirely novel set of considerations emerges.

Technology is often highlighted as a particularly important source of unique and valuable resources (Wernerfelt, 1984). However, technology and other forms of knowledge are resources quite unlike physical resources that are easily bought and sold. Knowledge, including knowledge found within patentable technologies, is "non-rival" (Romer, 1990) or "scale-free" (Levinthal and Wu, 2010). While a rival good has the property that its use by one party "precludes its use by another" (Romer, 1990),[2] knowledge can be infinitely replicated and shared, at a small or no cost and without loss of its inherent value (though with obvious loss to its competitive value). For example, the use of an algorithm by one division does not diminish the ability of another division to use the same algorithm, an example of a "within-firm spillover". Such within-firm spillovers are especially potent for large corporations, which, for example, can simultaneously deploy the same technology across many different geographic markets (Winter and Szulanski, 2001). For example, a company like Uber can concurrently re-use its proprietary technology across many local geographic markets[3] and every improvement in its technology will spill-over into all its local markets. In contrast, for rival or "non-scale free" resources (Levinthal and Wu, 2010), use by one local division will reduce usage by another division. If Uber's key resource were an effective management team instead of its technology, then adding more geographic markets would reduce the limited time and attention the management team can devote to each individual market (Levinthal and Wu, 2010). Non-rival technological resources also contrast with other rival resources, such as firm-specific equipment or human capital, which is typically redeployed as opportunities shift (Helfat and Eisenhardt, 2004; Lieberman, Lee and Folta, 2017; Dickler and Folta, 2020), but cannot be simultaneously deployed like a non-rival resource.

The scale-free nature of technology also enables the possibility of technological spillovers across firms, as the invention of a new technology by one firm allows other firms to also benefit. In this context, we are interested in technological uniqueness, defined as the degree to which a firm's patented technology portfolio differs from its industry competitors. Our main conceptual insight is that across-firm spillovers implied by the scale-free nature of technological uniqueness will lead to a new "Technological Uniqueness Paradox": On the one hand, technological uniqueness can be costly, because of reduced incoming spillovers. On the other hand,

[2] We follow Romer (1990) in distinguishing the concept of non-rivalry, which is a physical attribute of technology, from the concept of excludability, which is a function of physical attributes and the legal system. Romer writes that "A good is excludable if the owner can prevent others from using it." Patented technologies are an example of a non-rival, but partially excludable good, since patent owners can force others to pay a fee for the usage of the patented technology.

[3] At the same time, much of the traditional literature on corporate strategy and diversification has argued that even technical resources are subject to limited fungibility, so that technology becomes less valuable when used in applications and industries far from the purpose they were first developed for, see Levinthal and Wu (2010). Our empirical analysis takes such limits in fungibility into account.

technological uniqueness can be beneficial because of higher imitation barriers and reduced outgoing spillovers.

2.2 Reduced Outgoing Across-Firm Spillovers as a Benefit of Technological Uniqueness

Patents are commonly used as a proxy for advantage-generating technological resources based on the idea that patents are essentially "surrogates for inimitable and non-substitutable resources" and are as stipulated by US patent law "useful, novel and non-obvious" (Markman et al., 2004). Legal barriers make these resources somewhat costly to imitate, as mimicking inventors must "invent around" a patented technology. Consistent with this logic, substantial strategy and innovation literature has focused on measuring patent portfolios as valuable resources by simply summing the number of patents that a firm holds (Hsu and Ziedonis, 2013) or generating a value-weighted sum of patents (Kogan et al., 2017; Markman et al., 2004). But the uniqueness of a firm's technological position is more than the sum of individual patents, as patents may be technologically dissimilar or differentially important (e.g., exploratory patents versus exploitative patents (Sarnecka and Pisano, 2021)). Moreover, firms are fundamentally bundles of resources (Penrose, 1959; Rubin, 1973) that represent in part sequences of investment choices about what technologies to pursue (and, of course, their historical success in those pursuits). Independent of the inherent uniqueness of individual patents, the pattern by which technology trajectories are pursued (which we measure by participation in patent classes) will vary in uniqueness. Our measure of technological uniqueness is therefore precisely this: the uniqueness of a firm's patent portfolio, as measured by participation in patent classes, relative to the patent class portfolio of their industry peers, as measured by their participation in patent classes (henceforth "technological uniqueness"). In the spirit of Schumpeter's fundamental insights around novel recombinations being essential to "creative destruction", the argument follows that firms pursuing more unique combinations of technological trajectories are more likely to create uniquely valuable offerings (Wang, He, and Mahoney, 2009). For example, Apple introduced the iPhone in 2007, which was on many technical dimensions an inferior cellphone, but combined with new touch-screen technology and a new app-ecosystem turned out to be uniquely valuable to customers.

A strong focus in strategy and economic research that parallels or builds on resource-based logic is that by pursuing unique technology firms have the potential to generate superior firm performance (Hall, 1993; Schankerman, 1991; Bloom and Van Reenen, 2002).[4] Very unique patent combinations will be hard to copy, because imitating such unique portfolios requires investment in multiple new and different technology areas, many unfamiliar to competitors. Moreover, such technological uniqueness from a patent portfolio perspective involves many potential interdependencies (Simon, 1976; Rivkin, 2000) in ways not visible within individual patent disclosures, which makes imitation disproportionately costly.[5] Without such a barrier to outgoing across-firm spillovers, competitors are likely to easily imitate technologies of a focal firm, which limits its growth and reduces its profitability (Barney, 1991).[6]

This theoretical motivation for our portfolio-level measure of technological uniqueness naturally distinguishes our approach from other studies on technological resources. For example, in contemporaneous work, Arts, Cassiman, and Hou (2021) compose a measure of a firm's technological differentiation using patent descriptions, but their approach does not measure how the composition of technological areas in the patent portfolio differs from competitors – a critical feature for in-imitability. Our technological uniqueness measure also complements the work by Wang, He, and Mahoney (2009) which uses a firm's patent self-citation rate to measure the firm-specificity of knowledge resources. However, their work emphasizes the need to embody firm-specific knowledge in human capital,[7] which transforms it into a rival resource. In contrast, the scale-free nature of technological uniqueness is at the heart of both the benefits and costs of technological uniqueness.[8] We turn to the costs of technological uniqueness next.

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[4] As stated in Barney (1991): "By definition, valuable firm resources possessed by large numbers of competing or potentially competing firms cannot be sources of either a competitive advantage or a sustained competitive advantage. (...) If a particular valuable firm resource is possessed by large numbers of firms, then each of these firms have the capability of exploiting that resource in the same way, thereby implementing a common strategy that gives no one firm a competitive advantage. The same analysis applies to bundles of valuable firm resources used to conceive of and implement strategies."

[5] Specifically, while individual patents might be easy to "invent around" it will be much more challenging to invent around – for example - ten patents sourced in independent technology classes. To wit, if the probability to copy any individual patent is 50%, and all patents come from independent technology classes, then the joint probability of mimicking a combination of ten patents is merely 0.1% ($0.001 = 0.5^{10}$).

[6] Barney (1991) states: "However, valuable and rare organizational resources can only be sources of *sustained* competitive advantage if firms that do not possess these resources cannot obtain them. (...) these firm resources are imperfectly imitable."

[7] Wang et al. (2009) state that "rarely can a firm automatically achieve superior economic performance from its firm-specific knowledge resources. Instead, a firm usually requires its key employees to make complementary investments in human capital in the process of absorbing and deploying firm-specific knowledge."

[8] Our work extends beyond these studies in two additional ways. First, we seek to explore the mechanisms underlying the relationship between technological uniqueness and firm performance more deeply, including mechanisms that imply the "Technological Uniqueness Paradox" discussed above. We examine the mechanisms that suggest increased

2.3 Lost Incoming Across-Firm Spillovers as a Cost of Technological Uniqueness

Firms are likely to differ in their ability to absorb or benefit from across-firm technological spillovers (Cohen and Levinthal, 1990). One way to elevate absorptive capacity is to strategically pursue technologies similar to competitors, which provides the knowledge, language and related technologies required to readily absorb the knowledge that competitors produce (Giustiziero, Kaul and Wu, 2019). Indeed, Cohen and Levinthal (1990) write that "the ability to evaluate and utilize outside knowledge is largely a function of the level of prior related knowledge". This absorptive capacity logic can be understood as the flipside of the theoretical mechanisms that reduce outgoing across-firm spillovers in the previous section. If more technological uniqueness disables competitors from learning about a focal firm's technology, then logic also suggests that less technological uniqueness also disables the focal firm from learning or absorbing knowledge from competitors. Therefore, ignoring the strategic benefits of uniqueness described above, this absorptive capacity logic predicts that technologically unique firms will enjoy more limited spillovers from competitors, and thereby potentially perform worse than less technologically unique firms.

Consistent with this logic, Bloom et al. (2013) find that firms that are technologically similar to their peers, as measured by the similarity of their patent portfolios, benefit more from R&D spillovers. Additionally, Giustiziero et al. (2019) find in fine-grained, duopolistic medical device manufacturing markets that technologically distant incumbents benefit less from technological spillovers by entrants. However, neither of these studies has contrasted the absorptive capacity logic of incoming spillovers with the resource-based view on how technological uniqueness reduces outgoing spillovers. It is the balance of these two effects that is at the heart of the new "Technological Uniqueness Paradox" in this paper, so that the net effect of strategically choosing technological uniqueness on firm performance is potentially ambiguous.

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technological uniqueness may undermine performance. Specifically, we examine the decreased beneficial spillovers associated with a firm increasing its technological distance from its industry peers. We also provide evidence that capital markets face increased cost in evaluating firms with greater technological uniqueness, which is reflected in paying an increased cost of capital. Second, we use three natural experiments to examine evidence of causality in the relationship between technological uniqueness and firm performance.

2.4 Technological Uniqueness and the Cost of Capital

A second factor may further mute any positive effect of technological uniqueness on firm performance. Technological uniqueness increases the information burden placed on capital market participants tasked with evaluating the focal firm's unique technology. While this information burden discourages competitors from imitation (Lippman and Rumelt, 1982; Barney, 1996), it also discourages investors. As argued by Litov et al. (2012) and Benner and Zenger (2016), capital markets are akin to "markets for strategy", wherein investors must evaluate strategies to decide which companies to invest in and what cost of capital to charge these companies. However, like competitors, investors in public capital markets are mostly firm outsiders and they may find it costly to gain information necessary for evaluation, and are therefore unable to properly evaluate a firm's strategy.

This information asymmetry between corporate insiders and capital market participants is rooted in at least two facts. First, firm outsiders lack (by insider trading statutes) access to relevant private information to complement information publicly available about individual patents. Second, technologically unique firms are likely to possess difficult to access knowledge about combinations of technologies (see Lippman and Rumelt, 1982; Rivkin, 2000). While equity analysts exist to help remedy such information asymmetries, technological uniqueness renders their task more challenging (Litov et al., 2012). These equity analysts face time constraints and career concerns, which often push them to specialize by industry or technology. Therefore, firms adopting more complex and novel combinations of technologies are anticipated to be more difficult to evaluate. We predict technologically unique firms will require equity analysts to exert more effort, and this will in turn discourage coverage by equity analysts, all else equal. Of course, the predicted higher returns associated with these technologically unique firms may also elevate demand for analyst coverage, leaving the net effect on the amount of analyst coverage an empirical question. Either way, if technologically unique firms are harder for investors to understand than non-unique firms, then as a reflection of this elevated uncertainty, the cost of capital should be systematically higher for unique firms. Furthermore, if equity analysts add value by reducing information asymmetries between investors and firms, then technologically unique firms that are not covered by equity analysts should be subject to disproportionately higher equity cost of capital.

In summary, while resource-based logic points to technological uniqueness as a potentially necessary condition for superior performance among technology firms, the reduced spillovers that accompany technological uniqueness as well as the higher cost of capital render the net effect ambiguous. In our empirical analysis we seek both to explore the net effect, as well as direct evidence of these two mechanisms that reduce the performance benefits of technological uniqueness.

3. Data and Measurement

To address these empirical questions, we construct a data set from several sources. We obtain patenting activity of public firms based on data from Kogan et al. (2017) and merge this to the CRSP, Compustat, and I/B/E/S databases. We base our industry classification on the Global Industry Classification Standard (GICS) and exclude firms from the financial (sector 40) and utilities (sector 55) sectors. Our final baseline sample covers a panel of 3,630 firms and 27,722 firm-year observations over 1983-2016.

3.1 Measuring Technological Uniqueness

Our measure of technological uniqueness follows Litov et al. (2012) in defining uniqueness relative to the activities of industry "peer" firms. However, our measure has two important differences. First, we classify industries according to the Global Industry Classification Standard (GICS) since it is a classification system commonly used by the global financial community.[9] Second, instead of measuring uniqueness by comparing a firm's revenue activity in different product segments, we measure uniqueness by comparing the firm's recent patenting activity against the patenting activities of firms within the same 6-digit level GICS, which after excluding industries with a low number of competitors leaves us with 32 broad industries. We use industry competitors as a reference, since a large literature in corporate strategy has argued that fungibility or the "degree to which the value of resources may be diminished as resources are leveraged in settings more distant from the original context" (Levinthal and Wu, 2010) is limited for technology. At the same time, we believe that the usage of 32 industry categories is quite broad

[9] The GICS is widely adopted as one of the standard industry analysis frameworks by the global financial analysis community, the others being the Industry Classification Benchmark (ICB) and the Thomson Reuters Business Classification (TRBC). Of the three, the GICS offers the most granularity in terms of classification (sub-industries).

and allows for economies of scope from unique technologies. Additionally in Online Appendix A2, we show that our results are robust to using either broader or narrower industry categories.

For each firm i, we define a 129x1 vector $F_{i,t} = [f_{1,i,t} \dots f_{129,i,t}]'$ that captures the firm's patenting activity across 129 patent technology classes at time t.[10] Each entry $f_{n,i,t}$ records the number of firm i's patents, in technology class n[11] during a rolling three-year period ending in t.[12] This vector is then divided by the total number of patents granted to firm i during the three-year window. For each GICS industry I, we also define the industry centroid as a 129x1 vector $I_t = \left[i_{1,t} \dots i_{129,t}\right]'$. Each entry $i_{n,t}$ records the number of patents from firms in the industry in technology class n[13] during a rolling three-year period ending in t.[14] This vector is then divided by the total number of patents in the industry during the three-year window.

To determine each firm's technological uniqueness each year ($TU_{i,t}$), we use the negative of the cosine similarity between the firm's patenting activity vector $F_{i,t}$ and the firm's industry centroid I_t , see Jaffe (1986):

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[10] The 129 patent technology classes are based on the USPTO's *Cooperative Patent Classification* (CPC) scheme (https://www.uspto.gov/patents/search/classification-standards-and-development). Since 2013, the USPTO has replaced the United States Patent Classification (USPC) with the CPC and the former is no longer being updated. The 129 technology classes represent the section and class designations of the CPC. However, a patent can be assigned multiple CPC designations by the USPTO but for the first majority of the patents, the first three values of the assigned CPC is the same. For example, GE's patent 7268237 was assigned the CPC values of C07C51/367 and C07C65/24. Based on the first three alpha-numeric values, GE's patent would be categorized into technology class C07. In Online Appendix A3, we show that our results get even stronger if we use finer 4-digit patent classes, which result in 665 different technology classes.

[11] Since a patent may be assigned to several different to technology classes, our main results utilize an equally-weighted technology class assignment algorithm where patents are assigned to all listed technology classes equally. We believe that our choice of an equally-weighted technology class assignment reflects the most conservative approach to matching patents with their technology classes, see Online Appendix A4 for a detailed example. As we show in the Online Appendix A5, the results still hold qualitatively when we assign technology classes using other methods.

[12] We use three-year rolling windows to reduce random lumpiness in patenting due to the patent granting process, which can lead to random gaps in the technological uniqueness measure. The use of moving averages will therefore reduce at least some measurement error related to random lumpiness. Additionally, we show that using 5-year moving averages produces similar results in Online Appendix A6.

[13] Since a patent may be assigned to several different to technology classes, our main results utilize an equally-weighted technology class assignment algorithm where patents are assigned to all listed technology classes equally. We believe that our choice of an equally-weighted technology class assignment reflects the most conservative approach to matching patents with their technology classes, however as we show in the Online Appendix Table A03, the results still hold qualitatively when we assign technology classes using other methods.

[14] In cases where a patent is assigned multiple technology classes, we apply equal weighting to each of the technology classes. As a robustness test, we also experiment with different technology class weights, including a value-weighted approach, and find qualitatively similar results. See the Online Appendix Table A03 for additional details.

$$TU_{i,t} = -\frac{F_{i,t}'I_{i,t}}{\sqrt{F_{i,t}{}'F_{i,t}}\sqrt{I_{i,t}{}'I_{i,t}}} \quad (1)$$

To facilitate interpretation of results later, we standardize TU around a mean of 0 with unit standard deviation. Intuitively, technological uniqueness is higher, the lower is the correlation of a firm's technology classes with the average technology classes used by other firms in the same GICS industry.

[Table 1]

Table 1 provides examples of how the technological uniqueness measure is calculated for firms in the Aerospace & Defense industry in 2015. Not all patent technology classes are shown but patenting behavior is noticeably different across the four firms. For reference, the industry centroid is displayed in the last column. For the typical firm in the Aerospace & Defense the most prominent technology classes are "Performing Operations: Aircraft; Aviation; Cosmonautics" with 8.4% of patents, "Physics: Measuring; Testing" with 7.9% of patents and "Physics: Computing; Calculating; Counting" with 6.2% of patents. Some firms, like Lockheed have similar priorities in their patenting with 11.1% of patents begin generated in "Physics: Measuring; Testing" and 9.3% of patents generated in "Physics: Computing; Calculating; Counting". As a result, the standardized technological uniqueness score for Lockheed is -0.877. However, other firms, such as General Dynamics pursue very different technologies. Its largest patent technology class is "Electricity: Electric Communication Technique" with 32% of patents generated compared to 5% for the industry. Its next largest patent class is "Mechanical Engineering: Lighting:Weapons" , which accounts for 12.5% of General Dynamics' patents, compared to almost 1.5% for the average Aerospace & Defense industry firm. As a result, General Dynamics' standardized technological uniqueness score is 0.019.

Our measurement approach complements the independently developed measure by Arts, Cassiman and Hou (2021), who use patent text similarity to measure technological differentiation and show that it is positively correlated with firm performance. Beyond the conceptual differences we discussed in section 2.2, there are also important empirical differences. For example, Arts et al. state that "our new *tech differentiation* measure only weakly correlates with *tech differentiation (class)* (corr=0.109), *tech differentiation (subclass)* (corr=0.013), and *tech differentiation (citation)* (corr=-0.074)". In this context, our measure of technological uniqueness corresponds to what Arts et al. call "tech differentiation (class)" and as they state, our measure and theirs is only very weakly correlated. This highlights that our measure of technological uniqueness captures variation that is very distinct from Arts et al.'s measure of technological differentiation.

3.2 Measurement of Technology Shocks

Our theory discussion predicts that a focal firm's technological uniqueness reduces the benefits from technological spillovers that it receives. One way to investigate this is to measure the impact of in-bound technological spillovers on the focal firms. Such in-bound technological spillover shocks can be defined as innovations by other firms that might benefit the focal firm. To quantify how much a focal firm might benefit from innovations by other firms, we use data on how intensively specific technology classes were cited by the patents of the focal firm in the last 4 years (Jaffe, Trajtenberg, and Fogarty, 2000). A technological spillover shock is then measured as the total market value of all patents generated by industry peers in technology classes that the focal firm heavily cites.[15] If this measure is constructed correctly, more patenting by other firms in technology classes that the focal firm uses to compose its own patents should boost its own performance and innovation based on the focal firm's ability to absorb similar technologies.

A different type of in-bound technology shock for a focal firm occurs if competitors successfully generate patents that result in more technological differentiation. Such (in-bound) technological differentiation shocks can potentially reduce a focal firm's performance, in contrast to technological spillovers within patent classes in which the firm patents. We measure such "technological differentiation shocks" as the sum of patents occurring in patenting areas that are *atypical* for firms within a given GICS industry.[16]

[15] First, we identify commonly cited technology classes of the focal firm during the past 4 years. Next, for each focal firm in each GICS industry, we obtain the value of all patents – measured by the Kogan et al. (2017) stock market values of patents – by peer firms in these commonly cited technology classes. Then, these technology class shocks are citation-weighted and aggregated to the annual firm level and standardized such that more heavily cited technology classes by the focal firm and more valuable patents, have the largest spillover impact on the focal firm.

[16] We define *atypical* as the technology classes for each industry in which less than 50% of all assigned technology classes from patents granted to firms in the industry are classified into over the past 4 years. Similar to the construction of our technology spillover shock measure, patents in these irregular patenting areas are value-weighted first, then citation-weighted at the firm level, and finally aggregated to the industry-year level and standardized.

3.3 Performance measures

We use Compustat data to construct our performance measures: *sales growth*, *Tobin's Q*, *Profitability*, and *ROA*.

3.4 Analyst Coverage variables

Our analyst coverage model studies the impact of the firm's technological uniqueness choice on analyst coverage behavior. We consider three dependent variables: *Adjusted Coverage, Analyst Attention,* and *Analyst Effort.* All three variables are constructed using I/B/E/S data and measure analysts' coverage behavior of the focal firm. *Adjusted Coverage* is the number of analysts currently covering a firm, scaled by the total number of analysts covering the GIC industry. *Analyst Attention* is the total number of analysts covering the firm. *Analyst Effort* is the negative of the number of *other* firms that the analyst is covering besides the focal firm. The presumption is that the effort associate with analyzing a specific firm is negatively correlated with the number of other firms an analyst can cover.

3.5 Cost of capital variables

Based on prior work (Claus and Thomas, 2001; Easton, 2004; Gebhardt et al., 2001; Ohlson and Juettner-Nauroth, 2005), we compute four measures of the firm's cost of capital. Each of the four measures is winsorized at the 1% level to reduce the impact of annual firm outliers. We also define a variable, *analyst coverage loss*, as the negative of the number of analysts that are covering the focal firm each year. Thus, an increase in the firm's *analyst coverage loss* in any given year reflects a *reduction* in the number of total analysts covering that firm that year.

4. Empirical Approach

4.1 Firm Performance Analysis

Our dependent variables are denoted by $y_{i,t}$ for firm i at time t and capture our performance outcomes, such as sales growth, profitability, ROA and Tobin's Q. Our primary independent variable of interest is technological uniqueness as defined in the last section and is denoted $TU_{i,t}$. We include a complete set of firm fixed effects D_i to remove any selection on unobservable time-invariant firm characteristics, such as founder effects or very persistent characteristics, such as firm culture. Furthermore, we control for a full set of industry-by-time fixed effects $D_s \times D_t$, to ensure that differential industry trends do not drive our results. We also include a full set of location-by-time fixed effects $D_l \times D_t$ to remove location-specific time trends and location-based effects such as geographical knowledge spillovers. The baseline OLS specification can then be written as

$$y_{i,t} = \beta \cdot TU_{i,t} + controls_{i,t} + D_i + D_s \times D_t + D_l \times D_t + \epsilon_{i,t} \tag{2}$$

Where $\epsilon_{i,t}$ is an error term and $controls_{i,t}$ are additional, firm-level control variables. We control for firm size, using total sales and firm growth over the past 3 years, in order to address the possibility of mean reversion in outcomes. Since technological uniqueness is related to investments in intangibles, we include three measures of such intangible investments: R&D intensity, advertising intensity (i.e., advertising expenditures relative to sales), and book value of intangibles assets relative to total assets. To account for the idea that our measure of technological uniqueness might capture idiosyncratic risk, we include the coefficient of variation of earnings. Furthermore, we include the log number of shareholders as a control variable for dispersed ownership of firms (Oehmichen et al., 2021). We take a very general approach to control for potential product diversification effects by including separate dummy variables for firms with 2, 3, and more than 4 product segments. We control for potential market power effects by including a measure of both the average market share across business segments for each firm, as well as a "Main Market Concentration Index" (MMCI), which measures the average concentration (Herfindahl index) across all business segments. For both measures, the averages are sales-weighted.

4.2 Endogeneity Issue in Firm Performance Analysis and IV Approach

Despite our use of a comprehensive set of control variables, there may be reasonable concerns about using OLS regressions to establish a causal effect of technological uniqueness on firm performance. On the one hand, OLS might lead to an upward bias in estimating the effect of technological uniqueness on firm performance. This could occur, for example, because only some firms are able to afford the R&D needed to generate a technologically unique portfolio of patents. On the other hand, OLS might lead to a downward bias of the effect of technological uniqueness on firm performance if technologically unique firms tend to prioritize exploration and therefore tend to exhibit low profitability in the present (March, 1991), which is an example of a strategy selection bias (Hamilton and Nickerson, 2003). To address these concerns, we introduce several instrumental variables to establish the causal relationship between technological uniqueness and firm performance.[17]

4.2.1 Centroid IV

The first instrumental variable is based on changes in the average patenting portfolio of firms in the industry ("industry centroid") and is therefore referred to as "Centroid IV". The key idea of this IV is as follows: when companies in the same industry pursue similar technology trends, they inadvertently leave unaddressed niches, which create opportunities. A focal firm can stand out by specializing in these technological niche areas and, therefore, more easily create a unique technology portfolio. For example, in the early 2000s, major cellphone manufacturers such as Nokia and Research-in-Motion, which produced the "Blackberry", focused on technologies surrounding 3-G call quality, GPS, phone battery life, message encryption, and keyboard quality. Apple's iPhone, introduced in 2007, lagged behind in all those dimensions but had the unique feature of a touchscreen, which ended up becoming the dominant design feature. We construct a shift-share (or "Bartik" style) IV, based on the idea that firms in technology locations with high local clustering with other firms in the same industry will pay more attention to industry centroid changes. The first stage of our IV estimator is given by:

$$TU_{i,t} = \gamma \cdot Z_{i,t} + controls_{i,t} + D_i + D_s \times D_t + D_l \times D_t + e_{i,t} \quad (3)$$

Where $Z_{i,t} = s_{s,l} \times \Delta C_{s,t-1}$ is the instrument, with $s_{s,l}$ as initial industry shares in terms of revenue in location l and $\Delta C_{s,t-1}$ as lagged changes in the "leave-out-mean" (or "Hausman-IV") industry patenting centroids. As we discuss below, we use leave-out-means to purge out any direct effects of changes in patenting of the focal firm, which might lead to a mechanical correlation between our IV and technological uniqueness. The combination of exogenous industry-level shocks and local exposure shares have recently been widely used in applied econometric work, see Borusyak et al. (2022). Importantly, the use of the shift-share IV allows us to add a full set of industry-by-year fixed effects $D_s \times D_t$ and location-by-year fixed effects $D_l \times D_t$, as the identifying variation

[17] For the clustering of standard errors, we follow in the spirit of Abadie et al. (2022) and use cluster at the level of the exogenous variation, which is industry-by-time clusters for the IVs in section 4.2.1 and 4.2.3 and region-by-time cluster for the IV in section 4.2.2.

in the first (3) and the second stage (4) estimates, as the IV estimation relies on the interaction of industry shocks and local cross-sectional variation.

The second stage is given by:

$$y_{i,t} = \beta \cdot \widehat{TU}_{i,t} + controls_{i,t} + D_i + D_s \times D_t + D_l \times D_t + \epsilon_{i,t} \tag{4}$$

$\widehat{TU}_{i,t}$ are conceptually the predicted values from the first stage, even though we estimate (3) and (4) simultaneously.

This IV has several advantages. First, leave-out-mean centroid changes directly address reverse causality, since these changes by construction, omit the focal firm. At the same time, lagged centroid changes reflect patenting by a firm's industry rivals and therefore generate an incentive by the focal firm to respond. Finally, since local industry clustering is more likely to be exogenous, a shift-share style IV should provide more robust estimates, with the additional advantage that we are able to include a full set of industry-by-year fixed effects.

Second, we retain a full set of firm fixed effects, thereby allowing us to focus on the within-firm patenting response to exogenous changes in the industry patent portfolio. This helps to address selection bias on permanent unobservables. Third, our IV strategy is also attractive in the context of the necessary IV exclusion restriction. To understand this, let us fix ideas by denoting with $\tilde{x}$ any variable x, from which we removed the impact of the control variables and fixed effects listed under (3) and (4). Then, the IV estimate can be written as:

$$\hat{\beta}_{IV} = \beta + \frac{Cov\left(\tilde{\epsilon}_{i,t}, \tilde{Z}_{s,t}\right)}{Cov\left(\widetilde{TU}_{i,t}, \tilde{Z}_{s,t}\right)} \tag{5}$$

with $Cov\left(\widetilde{TU}_{i,t}, \tilde{Z}_{s,t}\right) > 0$, as the first stage will establish that industry centroid changes increase uniqueness at the focal firm. The IV estimate will be biased towards finding that more technological uniqueness increases firm performance if $Cov\left(\tilde{\epsilon}_{i,t}, \tilde{Z}_{s,t}\right) > 0$. However, this is unlikely, since our shift-share Centroid-IV is a leave-out-mean, which means $\tilde{Z}_{s,t}$ only reflects changes in technology trends at competing firms. In turn, competitors in an industry will only patent technologies they anticipate to be profit-maximizing, which should reduce profits at the focal firm. In other words, if competitors in the industry only patent technologies that they believe will increase their own profits, then it should be true that $Cov(\tilde{\epsilon}_{i,t}, \tilde{Z}_{s,t}) < 0$, which will lead to an underestimate of the true causal performance effect of technological uniqueness.

4.2.2 R&D tax credit IV

Our second identification strategy is based on state-level changes in R&D tax credits. This exogenous variation has previously been used by Bloom et al. (2013), but we utilize it in a novel way. Specifically, we hypothesize that higher R&D tax credits will incentivize firms to increase R&D spending on marginal innovations instead of radical innovations, since these are easier to obtain and will still earn the tax deductions from the R&D tax credits. Such marginal innovations in turn are by definition very similar to already existing patented technologies and will therefore tend to reduce firms' technological uniqueness. This allows us to estimate a different type of causal performance effect of technological uniqueness. The Centroid-IV estimates the positive performance effects of technological uniqueness: more technological uniqueness causes firms to outperform. However, it is theoretically possible for less technologically unique firms to deliver average performance instead of under-performing. The R&D tax credit allows us to test whether there are negative performance effects of less technological performance: firms that reduce their technological uniqueness consequently underperform.

We follow Bloom et al. (2013) and construct exogenous R&D capital stocks using exogenous changes to federal and state-level R&D tax credits:

$$Z_{i,t} = \beta_0 + \beta_1 * \log(FTC_{i,t}) + \beta_2 \log(STC_{i,t}) + D_i + D_s + D_l \tag{6}$$

where $Z_{i,t}$ are (log) R&D expenditures of firm i at time t and $FTC_{i,t}$ and $STC_{i,t}$ are the Federal R&D and State R&D tax credits, based on the location (state) of the firm i at time t. We use firm fixed effects D_i, location fixed effects D_l and industry fixed effects D_s. We then use the exogenous R&D capital stock as an instrument to predict technological uniqueness:

$$TU_{i,t} = \gamma \cdot Z_{i,t} + controls_{i,t} + D_i + D_s + D_l + \epsilon_{i,t} \tag{7}$$

We expect that $\gamma < 0$, because R&D tax credits are likely to stimulate marginal innovations that mimic peers and reduce technological uniqueness. This prediction concerning how R&D tax credits affect technological uniqueness is novel and not recognized in the original work by Bloom et al. (2013). In the second stage, the predicted TU values are used as an IV for firm performance:

$$y_{i,t} = \beta \cdot \widehat{TU}_{i,t} + controls_{i,t} + D_i + D_s + D_l + \epsilon_{i,t} \tag{8}$$

Our prediction is that $\beta > 0$, which in the case of $\gamma < 0$ will only be true if firms with higher values of $Z_{i,t}$ have lower performance. To see this, define the reduced form as

$$y_{i,t} = \delta \cdot Z_{i,t} + controls_{i,t} + D_i + D_s + D_l + \epsilon_{i,t} \tag{9}$$

Then it can be shown that:

$$\hat{\beta}_{IV} = \frac{\hat{\delta}}{\hat{\gamma}} \tag{10}$$

In the case of the R&D Tax Credit IV, our prediction is that $\hat{\gamma} < 0$ so that $\hat{\beta}_{IV} > 0$ only if $\delta < 0$, which in turn means that firms with higher values of $Z_{i,t}$ tend to lower firm performance $y_{i,t}$.

Again, a critical question is whether the exclusion restriction holds and as before we base our discussion on equation (5) with $\tilde{x}$ denoting any variable x, from which we removed the impact of the control variables and fixed effects listed under (3) and (4):

$$\hat{\beta}_{IV} = \beta + \frac{Cov\left(\tilde{\epsilon}_{i,t}, \tilde{Z}_{s,t}\right)}{Cov\left(\widetilde{TU}_{i,t}, \tilde{Z}_{s,t}\right)}$$

Where, due to the first stage, we expect $Cov\left(\widetilde{TU}_{i,t}, \tilde{Z}_{s,t}\right) < 0$. Under this condition, the IV estimate will only overestimate the impact of technological uniqueness on firm performance if $Cov\left(\tilde{\epsilon}_{i,t}, \tilde{Z}_{s,t}\right) < 0$. In other words, tax-credit induced R&D needs to directly reduce firm performance to induce an upwards bias on our IV estimates. At the same time, the empirical findings in Bloom et al. (2013) have shown that exogenous R&D, in fact, tends to increase firm performance as measured by productivity and Tobin's Q. Therefore, our analysis suggests that if anything, IV estimates using R&D tax credits will tend to underestimate the effect of technological uniqueness on firm performance.

4.2.3 Patent Expiration IV

Our third IV is based on industry-level patent expiration shocks. The key idea of this empirical approach is that if many patents in the industry expire mandatorily, this will tend to reduce technological uniqueness at a focal firm, since it is now legally allowed to use technologies with mandatorily expired patents for its upcoming inventions. As in the case of the Centroid-IV, we construct the Patent Expiration IV using a leave-out-mean, which facilitates identification, as discussed below. As in the case of R&D Tax Credits, this Patent Expiration IV will estimate negative performance effects of technological uniqueness, as we expect less technologically unique firms to underperform.

For each year for each industry *s,* we compute a vector of expiring patent-shares across all technology classes based on the prior patents granted to peer firms 18 or 20 years ago.[18] These expiring patent shares are then used to construct a Bartik-style IVs by multiplying them with firm-level variables that measure the initial distribution of patents a firm has across technology classes. This shift-share approach postulates that patent expirations should be more important for a focal firm if it uses the technology classes in which the patents expire more. The first stage of this IV approach is given by:

$$TU_{i,t} = \gamma \cdot Z_{i,t} + controls_{i,t} + D_i + D_s + D_l + e_{i,t} \tag{11}$$

With $Z_{i,t} = P_{s,T} \times \Delta P_{s,t}$, where $P_{s,0}$ is the initial industry-level patent granted shares and $\Delta P_{s,t}$ is the annual vector of expiring patents. As we discussed, we expect that $\gamma < 0$, since more patent expirations should lead to less technological uniqueness as all firms in an industry have free access to technology with expired patents. The predicted technological uniqueness from (8) is then used to predict firm performance, as before.

$$y_{i,t} = \beta \cdot \widehat{TU}_{i,t} + controls_{i,t} + D_i + D_s + D_l + \epsilon_{i,t}$$

As in the context of the R&D Tax Credits, our prediction is that $\beta > 0$, because firms with less technological uniqueness will tend to underperform.

There are at least two ways the exclusion restriction for the Patent Expiration IV might fail. On the one hand, the timing of patent expirations might be correlated with technological or growth opportunities. However, such a correlation is unlikely, since patents expire 20 years after they are being granted. For industry-wide patent expirations to be correlated with current technological or competitive conditions, firms would need to accurately forecast technological or industry forces 20 years into the future. We believe that accurate forecasts over such long horizons are implausible.

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[18] In 1994, the United States enacted the Uruguay Round Agreements Act which changed the patent term from based on the grant date of the patent to the application date of the patent. For patents with application dates after June 7, 1995, their patent terms last 20 years from the application date. This is the definition that we use to determine when patents expire.

On the other hand, patent expirations imply that intellectual property rights mandatorily expire, which might directly impact profits. To further understand the threat to the exclusion restriction criterion, we again denote with $\tilde{x}$ any variable x, from which we removed the impact of the control variables and fixed effects listed under (3) and (4). The IV estimator can therefore be written as

$$\hat{\beta}_{IV} = \beta + \frac{Cov(\tilde{\epsilon}_{i,t}, \tilde{Z}_{s,t})}{Cov(\widetilde{TU}_{i,t}, \tilde{Z}_{s,t})}$$

Since $Cov(\widetilde{TU}_{i,t}, \tilde{Z}_{s,t}) < 0$ for the Patent Expiration IV, the IV estimator will only be biased towards a positive coefficient if $Cov(\tilde{\epsilon}_{i,t}, \tilde{Z}_{s,t}) < 0$, i.e., more industry patent expirations reduce profits. However, the Patent Expiration IV is constructed as a leave-out-mean, which means that the patent expiration of the focal firm is not included. At the same time, patent expirations at competitors will tend to increase performance at the focal firm, which would imply $Cov(\tilde{\epsilon}_{i,t}, \tilde{Z}_{s,t}) > 0$, which suggests that our IV strategy likely underestimates the true causal effect.

4.2.4 Profiling Compliers

According to a prominent view, strategic management should tailor business policy recommendations to suit specific types of companies or particular circumstances instead of offering "universal best practices" (Barney, 1986; Porter and Siggelkow, 2008). Barney (1986) pointed out that it is more beneficial to understand what makes certain companies successful in specific contexts, rather than looking for common strategies that every company in an industry could use. This is because targeted strategies are more likely to provide a competitive edge. Complier analysis is a method to empirically characterize the companies for which uniqueness causes outperformance or underperformance. Therefore, complier analysis offers strategic recommendations that are more practical and directly applicable to certain firms but not others, making our guidance far more valuable for executives. At the same time, complier analysis allows us to empirically characterize how compliers differ empirically from the rest of the sample, leading to deeper understanding of why the quantitative magnitudes of IV estimates might differ from each other and from OLS results.

Complier firms are defined as firms that are responsive to an IV (Angrist and Pischke, 2009). The basic idea of this analysis is based on Angrist, Imbens and Rubin (1996) who showed that under some conditions, IV estimates reflect the causal effects of the treatment on the compliers instead of the whole sample of treated firms, which also includes "always takers", who would have taken treatment even without the encouragement of the instrument. We note that traditional complier analysis relies on binary instruments and binary treatment variables, in contrast to the continuous treatment variable of technological uniqueness and our continuous instrumental variables.[19] We therefore dichotomize the relevant variables in the following way. We construct a binary version of our instruments, denoted by E_i. E_i will be one for above average values for the Centroid IV, the R&D Tax Credit IV and the Patent Expiration IV. Our treatment variable T_i is derived from our measure of technological uniqueness. For the Centroid IV, our prediction is that stronger industry centroid changes will lead to more uniqueness at the focal firm, so we construct a treatment indicator T_i which is one if the technological uniqueness measure is above average and zero otherwise. In contrast for both the R&D Tax Credit IV as well as the Patent Expiration IV, our prediction is that higher values of the IV will induce less technological uniqueness. Therefore, for these variables, we construct a treatment indicator T_i which is one if the technological uniqueness measure is below average and zero otherwise. Following potential outcomes notation (Rubin, 1974), let $T_{1,i}$ denote the treatment value for firm i, when the instrument is $E_i = 1$ and $T_{0,i}$ for $E_i = 0$. Under this notation, and with the proper definition of treatment group T_i, compliers are defined as the set of firms for which $T_{1,i}, -T_{0,i} \geq 0$, which is also called the "monotonicity assumption" in Angrist, Imbens and Rubin (1996). Under these definitions and assumptions, the fraction of compliers in the overall sample can be calculated as:

$$P\left(T_{1,i} > T_{0,i}\right) = P(T_i|E_i = 1) - P(T_i|E_i = 0) \tag{12}$$

Furthermore, the percentage of compliers relative to all treated firms can be calculated as

$$P\left(T_{1,i} > T_{0,i} \mid T_i = 1\right) = \frac{P(E_i = 1) \cdot \left(P(T_i|E_i = 1) - P(T_i|E_i = 0)\right)}{P(T_i = 1)} \tag{13}$$

[19] We also note that standard complier analysis relies on a set of fully saturated controls. We have too many continuous control variables to generate saturated controls for all control variables and still have variation left over to analyze, and the literature does not currently offer a way to choose which control variables to saturate in a principled way.

To show the empirical differences between compliers and average firms in the sample, we follow Angrist and Pischke (2009) and define indicator variables X_i, which are one if firm i exhibits an above-average value of some characteristic X and zero otherwise. Based on this and our other definitions, we will calculate the quantity

$$\frac{P\left(X_i = 1 \mid T_{1,i} > T_{0,i}\right)}{P(X_i = 1)} = \frac{P(T_i|E_i = 1, X_i = 1) - P(T_i|E_i = 0, X_i = 1)}{P(T_i|E_i = 1) - P(T_i|E_i = 0)} \tag{14}$$

Equation (11) shows how to calculate the odds of how much more likely complier firms are to exhibit above-average values for characteristic X than average firms in the sample. For example, values such as $\frac{P\left(X_i=1| T_{1,i}>T_{0,i}\right)}{P(X_i=1)} = 1$ will mean that complier firms are about as likely to have above average characteristic X as the average firm in the sample. In contrast if $\frac{P\left(X_i=1| T_{1,i}>T_{0,i}\right)}{P(X_i=1)} = 2$, then compliers are twice as likely as average firms with have an above-average value of X.

4.3 Analyst Regressions and Cost of Capital

The analyst coverage and analyst effort regressions take the form

$$A_{i,t} = \delta \cdot TU_{i,t} + controls_{i,t} + D_i + D_s \times D_t + D_l \times D_t + \epsilon_{i,t} \tag{15}$$

Where $A_{i,t}$ is either adjusted analyst coverage or analyst effort. We include a full set of firm fixed effects, industry-by-year fixed effects and location-by-year fixed effects. For the firm-level controls in (15), we follow the literature on understanding analyst forecasts (Dong et al., 2021, Jackson, 2005, and Litov et al., 2012) and include log assets, market-to-book ratio, intangible asset ratio, stock price volatility, log stock turnover and stock return. The theoretical predictions from section 2 would predict that $\delta > 0$ for analyst effort as more technologically unique firms are harder to understand. On the flipside, high effort costs to understand technologically unique firms also imply low attention by analysts unwilling to invest this effort cost. Therefore, we predict $\delta < 0$ for (15) where analyst attention is the dependent variable.

In addition to the OLS specifications in (15), we also analyze the extensive margin of analyst coverage, i.e. time until analysts pick up coverage of technologically unique firms that are currently not covered and time until analysts drop technologically unique firms that are currently covered. For this purpose, we use Cox proportional hazard models:

$$\ln\left(\frac{h_i(t)}{h_{i,0}(t)}\right) = \phi \cdot TU_i + controls_i + u_i \tag{16}$$

where $h_i(t)$ is a hazard function, capturing the probability of the event (analyst begins coverage of firm i or analyst drops firm i from coverage) at time t. $h_{i,0}(t)$ is the baseline hazard of that event, so that the hazard model will capture whether technologically unique firms are more or less likely to be covered or dropped from coverage. As control variables we include the controls from (15), namely log assets, market-to-book ratio, intangible asset ratio, stock price volatility, log stock turnover and stock return.

We directly quantify the capital market costs of reduced equity analyst coverage using different measures for the cost of capital $r_{i,t}$ as dependent variable in the following regression:

$$\begin{aligned} r_{i,t} = \kappa_1 \cdot TU_{i,t} + \kappa_2 \cdot \left(A_{i,t} \times TU_{i,t}\right) + \kappa_3 \cdot A_{i,t} + controls_{i,t} + D_i + D_s \times D_t \\ + D_l \times D_t + \epsilon_{i,t} \end{aligned} \tag{17}$$

Where $A_{i,t}$ denotes changes in analyst coverage from (15) and we include the control variables using in the OLS performance regressions in (1), in addition to firm fixed effects, industry-by-year fixed effects and location-by-year fixed effects. The main prediction is that $\kappa_1 > 0$, because more technologically unique firms will be forced to pay higher costs of capital and unique firm with lower coverage by equity analysts will be forced to pay a disproportionate cost of capital premium, $\kappa_2 > 0$.

5. Results

5.1 Technological Uniqueness and Firm Performance

We begin by analyzing the relationship between firm performance and technological uniqueness in Table 3.

[Table 3]

The main result from Table 3 is that higher technological uniqueness is associated with better performance. Technologically unique firms exhibit higher sales growth as shown in column 1, and have higher long-run performance prospects as measured by Tobin's Q in column 2. At the same time, growth does not displace profitability but rather accompanies it. Technologically unique firms' current profitability and ROA is higher than their industry peers, as shown in columns 3 and 4 of Table 3. While these performance correlations do not rule out that more technological uniqueness acts as a barrier to inbound technological spillovers, they do suggest that the costs of such reduced beneficial spillovers are not dominating. Instead, the performance results show that technologically unique firms exhibit at least a temporary competitive advantage, consistent with the view that technological uniqueness is a type of strategic resource (Barney, 1991).

Technological uniqueness is associated with quantitatively large performance advantages. To understand these, it is useful to point out that our technological uniqueness measure is standardized to have a unit standard deviation. Therefore, firms which increase their technological uniqueness by one standard deviation exhibit 2.3% higher sales growth rate, a 6.9% higher Tobin's Q, and 0.8% higher profitability and ROA per year—all rather economically significant relationships.

Although the results in Table 3 are not estimated to support causal claims, they are remarkably robust, as they are estimated using a full set of firm fixed effects, industry-by-year fixed effects and region-by-year fixed effects, in addition to a large set of control variables shown in the table. And although this robustness does not rule out unobservable, omitted and time-varying firm-level factors driving the relationship between firm performance and technological uniqueness, the results suggest that technological uniqueness is a robust predictor of firm performance. The usage of the different fixed effects also matters for qualitatively interpreting the OLS performance estimates. Since all our specifications include firm fixed effects, the performance correlations measure changes in performance accompanying changes in technological uniqueness within firms. Furthermore, since we include a full set of industry-by-time fixed effects, the OLS estimates remove any time-varying industry differences. In particular, one might wonder whether changes in technological uniqueness are mostly driven by changes in patenting of the focal firm or changes in the industry centroid. However, due to the inclusion of industry-by-time fixed effects, all changes in technological uniqueness exclusively reflect changes in patenting composition by the focal firm, while controlling for industry centroid changes.

Table 3 shows that firms which increase their technological uniqueness exhibit a contemporaneous increase in sales, stock market valuation, profitability and ROA. But how persistent are these effects? The answer is displayed in Table 4, which estimates performance correlations up to 5 years after changes in technological uniqueness. We note that all specifications in Table 4 include the same set of controls as Table 3, but we only display the coefficients on technological uniqueness to save space.

[Table 4]

The main finding of Table 4 is that performance improvements associated with increased technological uniqueness persist as statistically significant for up to 5 years. These results raise the question of how technological uniqueness has this sustained effect. We approach this question in three steps. In section 5.2, we seek evidence of a causal relationship between technological uniqueness and firm performance. In section 5.3, we characterize the set of firms for which such causal effects are estimated. In section 5.4, we then analyze the mechanisms through which firms benefit from being technologically unique. Sections 5.4 and 5.5 then investigate the costs of technological uniqueness associated with restrained in-coming spillovers and elevated evaluation costs.

5.2 Causal Performance Effects from Technological Uniqueness

Table 5 displays our results from our different IV estimations discussed in section 4.2. The first column of each panel confirms that in each case we indeed have relevant instruments.

[Table 5]

Broadly our results in Table 5 confirm that increased technological uniqueness causes better firm performance. Throughout the table, the IV results are qualitatively consistent with our OLS results from Table 3. This consistency is especially reassuring, because the different IV approaches rely on very different natural experiments, including changes in industry technology trends for the Centroid-IV, changes in R&D tax-credits and industry waves of patent expirations. Additionally, all of our IV estimates include a full set of firm fixed effects, industry fixed effects and region fixed effects, and the Centroid-IV results also including industry-by-year and region-by-year fixed effects.

Among our IV estimates, Panel A and Panel C show results of very similar magnitudes, while the effect sizes for the R&D tax credit IV are mostly larger. In addition, the magnitudes of all IV estimates are at least an order of magnitude larger than the OLS results. There are at least two reasons for these larger IV estimated effects of technological uniqueness on performance relative to the OLS estimates. First, our measure of technological uniqueness is likely subject to classical measurement error, which implies attenuation of estimated OLS coefficients towards zero (see Angrist and Pischke, 2009.) Attenuation bias is even stronger in panel data with a very detailed level of fixed effects, which is likely to lead to "over-differencing". In Online Appendix A7, we show OLS estimates using only firm and year fixed effects, which exhibit larger magnitudes than our estimates in Table 3, consistent with over-differencing. Second, each of the IVs is likely to induce only a small set of firms to respond, leading to very large effect sizes for the minority of firms that do. It is well-known that such Local Average Treatment Effects (LATE) can lead IV estimates to differ from OLS, even in the absence of measurement error or omitted variables bias (see Angrist and Pischke, 2009). We therefore next turn to a complier analysis of our different instruments.

5.3 Complier Analysis for Different IVs

To shed further light on which companies the different IV estimates apply to, we follow the methodology outlined in section 4.2.4 and provide a complier analysis in Table 6.

[Table 6]

Panel A of Table 6 shows that the percentage of compliers is moderate, ranging from 7.5% to 11.33% of the respective estimation samples. The instrument with the largest group of compliers is the Patent Expiration IV, for which compliers account of 11.33% of sample firms.

Panel B of Table 6 documents that the complier groups across all three IVs are very different. The key entries are the even number columns, i.e. column (2), (4) and (6) as these columns show how much more likely firms in the complier group are to have firms with above-average characteristic X, compared to average firms in the sample. For example, in the first row, the characteristic X is having "many geographic segments" and first entry of column (2) says that compliers of the Centroid IV are 2.45 times more likely to have above-average number of geographic segments than average firms. In other words, firms with many geographic segments disproportionately benefit from being able to simultaneously deploy their unique technologies across many local markets, exactly as we discussed in section 2.1. Centroid-IV compliers also are 32% more likely to have above-average number of business segments, are 41% more likely to have above-average market share, are 2.06 times more likely than the average firm to exhibit above-average growth. They are also 44% more likely to be above-average in R&D spending, 50% more likely to be above-average in advertising spending, and 32% more likely to have above-average intangible capital. Large and positive causal performance effects of higher technological uniqueness therefore especially apply to firms that can benefit from the scale-free nature of technological uniqueness while investing strongly in R&D, advertising and intangible capital.

Compliers for the R&D Tax Credit are very different in nature. They are firms that suffer large performance drops from lower technological uniqueness, as shown by the large IV estimates in Table 5. Table 6 shows that these complier firms are 2.08 times more likely to have high R&D. At the same time, R&D Tax Credit compliers are 47% less likely to have above-average market share and are 73% less likely to have above-average market growth. This suggests that lower technological uniqueness especially hurts if a firm does not have sufficient scale in the first place.

Patent Expiration-IV compliers tend to be as likely as average firms to have above-average growth rates or many geographic or business segments, but they are also 44% less likely to have above-average market shares. At the same time, Patent Expiration-IV compliers are 35% less likely to have above-average advertising expenses while they are 40% more likely to exhibit high intangible capital, compared to average sample firms. This combination highlights that small firms that strongly invest in intangible capital tend to be strongly hurt by becoming technologically similar to other firms.

As this complier analysis shows, the three groups of firms are empirically very distinct from each other. Yet, for all three groups of compliers, our IV analysis robustly finds causal impacts of technological uniqueness on firm performance: positive performance effects from more technological uniqueness and negative performance effects from less technological uniqueness. These findings are indicative of the robustness of the causal estimates.

5.4 Meeting the Strategic Challenge of Technological Uniqueness

A natural question is whether increased uniqueness of a focal firm induces performance losses at competitors, and thereby intensifies competition or if technological uniqueness leaves the level of competition unaffected. As we discussed in section 2.2, there is theoretical reason to believe that technological uniqueness enables uniquely valuable offerings. The example we use in section 2.2 is Apple's first iPhone, which was technologically unique in its use of touchscreen technology and its app-store platform, even if it lagged behind technologically in terms of call quality, message encryption etc. One strategic challenge for Apple's competitors in 2007 was the question of whether they should consider the iPhone as a threat to their market share. This in turn depends on whether technological uniqueness leads to vertical or horizontal differentiation. Vertical differentiation increases the value of a firm's product offerings for all customers, for example through higher quality or lower cost (Shaked and Sutton, 1982, Makadok, 2010, Makadok and Ross, 2013, and Costa, Cool, and Dierickx, 2013). If positive performance effects are due to vertical differentiation, then increased technological uniqueness by Apple reduces firm performance of competitors and is therefore a competitive threat. By contrast, horizontal differentiation generates increased value for a more narrow set of customers, while leaving others indifferent (Hotelling, 1929; Makadok, 2010; Makadok and Ross, 2013). Therefore, if horizontal differentiation explains the relationship, then more technological uniqueness by Apple will leave its competitors unaffected.[20] In other words, horizontal differentiation tends to leave the intensity of competition unchanged or might even reduce it.[21]

[Table 7]

Table 7 shows that the main effect of increased technological differentiation[22] at competing firms is to reduce sales growth and profitability at the focal firm. This is consistent with technological differentiation leading to more vertical differentiation and intensifying competition. As before, in practice, technological uniqueness is likely to affect firm performance through both,

[20] There is evidence that some of Apple's main competitors indeed thought of the iPhone providing horizontal differentiation, and therefore not a competitive threat. Former Research-in-Motion COO Larry Conlee stated about the iPhone that "It wasn't secure. It had rapid battery drain and a lousy [digital] keyboard." (https://www.wsj.com/articles/behind-the-rise-and-fall-of-blackberry-1432311912.)

[21] Makadok and Ross (2013) write: "if firms have similar efficiency, horizontal differentiation reduces competitive advantage by making a firm's product less appealing to the majority of the market".

[22] Defined in section 3.2 as "value of patents obtained by industry rivals, which are outside the most common technology classes".

vertical and horizontal product differentiation. Our results only suggest that the vertical differentiation results dominate and not that there are no horizontal differentiation effects.

For purposes of easy quantitative interpretation, we have standardized the competitive technological differentiation shocks to have a unit standard deviation. As a result, Table 7 shows that a one standard deviation increase in technological differentiation at competing firms implies 1.21 percentage point lower profitability, which is a large effect. A somewhat more surprising result is that competitors' technological differentiation also leads to an increase in Tobin's Q for the focal firm. A possible explanation for this result might be that investors are positively surprised by a wider range of technological opportunities revealed by competitors' patenting in uncommon technology classes.

The third row of Table 7 considers the possibility that under horizontal differentiation, more technological uniqueness might at least moderate the effects of competition (Makadok, 2010). We find some evidence for this being the case in sales growth, but fail to find evidence for this hypothesis when considering profitability or ROA as dependent variable.

5.5 Costs of Technological Uniqueness 1: Spillover-Barriers

As discussed in our theory section, technological uniqueness may carry two forms of cost. Our first step in analyzing potential costs of technological uniqueness and is shown in Table 8. As discussed in section 3.2, our technological spillover shocks capture in-coming technological spillovers from patenting of other firms in patent classes that the focal firm heavily cited in the prior four years.

[Table 8, Panel A]

We find that technological spillover shocks consistently benefit the focal firm, as shown in the second row of Table 8. This result provides reassurance that our measurement of technological spillovers is correct, since the spillover shock has the theoretically correct sign even though as we saw in Table 7 patenting by rival firms does not necessarily imply benefits for the focal firm, but instead often leads to lower performance. Confounding spillover and technological differentiation shocks might indeed incorrectly show zero effects of patenting by rival firms on the focal firm, a problem we seem to have successfully addressed here. The technology spillover shock is also large in magnitude. As before, the spillover shock variable is standardized to have a unit standard deviation for ease of interpretation. Therefore, a one standard deviation increase in the spillover shock implies a 3.18% higher sales growth rate, a 7.55% higher Tobin's Q, a 1.04% higher profitability and a 0.76% higher ROA on an annual basis.

At the same time, Panel A of Table 8 also shows that technologically unique firms do pay a cost for their uniqueness, as shown in row 3. Across the different columns, row 3 of Panel A shows that technologically unique firms benefit substantially less from technology spillovers. For example, the same one standard deviation spillover shock translates into only a 1.03% increase in sales growth for a firm with a one standard deviation higher technological uniqueness score $(0.0103 = 0.0318 - 0.0215)$. Similarly, a firm with a one standard deviation higher technological uniqueness exhibits only a 2.39% increase in Tobin's Q compared the 7.55% increase for the average firm $(0.0239 = 0.0755 - 0.0516)$. The muted spillover effects also carry over to profitability and ROA. Throughout, the attenuation of spillover effects is sizable, but technologically unique firms still tend to benefit from incoming spillovers – albeit less than less unique firms. Importantly, all specifications in Panel A of Table 8 also include controls for the number of recent patents as an alternative measure of absorptive capacity, as well as the interaction of the number of patents with the technological spillover shocks.[23] Overall these results are quantitatively large and qualitatively consistent with empirical results by Bloom et al. (2013), who considered the effect of R&D spillovers as function of technological distance across firms.

[Table 8, Panel B]

Panel B of Table 8 pushes the analysis of technological uniqueness as a spillover barrier further.[24] Specifically, this table analyzes whether more technologically unique firms are also citing patents by industry peers less, which is consistent with the view that technological uniqueness directly reduces learning from industry peers. Panel B of Table 8 uses two different measures of patent citations for this purpose: Column (1) uses number of patent citations to patents by competitors, while column (2) uses number of patent citations to patents in popular (or "core") technology classes used by industry competitors. For both measures, the results show that a focal firm with

[23] We gratefully acknowledge a suggestion by a reviewer to include this as a control variable.
[24] We gratefully acknowledge a suggestion by a reviewer to run the analysis in Panel B or Table 8.

more unique technology tends to cite their competitor's patents less, which supports the view that technological uniqueness reduces absorptive capacity for patented technology of competitors.

5.6 Costs of Technological Uniqueness 2: Information Problem and Costs of Capital

In this section we investigate both the mechanism and overall performance consequences of asymmetric information problems implied by technological uniqueness. Firm-level analyst coverage regressions are reported in Table 9.

[Table 9]

The first column shows that analyst coverage is systematically lower for technologically unique firms. At first this result might be surprising, especially given our performance results in Tables 3 and 4 which show that technological uniqueness is a strong predictor for firm performance and firm stock value. However, column 2 of Table 9 offers empirical support for the view that low analyst coverage is the consequence of high effort costs to understanding technologically unique firms. An increase in technological uniqueness by one standard deviation implies that on average analysts cover 0.14 fewer firms. Covering technologically unique firms requires high effort, which is especially costly for time constrained analysts.

We push this analysis further by considering how technological uniqueness impacts the time until a currently uncovered firm is picked up for coverage by equity analysts in column 4 of Table 9. The results in the last two columns use Cox proportional hazard models, and report implied hazard ratios, for which a value smaller than 1 implies that the variable contributes to a lower risk of analyst coverage take-up, and a longer time until that take-up occurs. Consequently, column 4 reports that technologically unique firms are systematically less likely to be covered by equity analysts or take longer until they are covered. Conversely, column 5 shows that currently covered firms are more likely to be dropped from coverage by equity analysts, if they are more technologically unique.

The analyst regressions in Table 9 confirm that it is challenging for outsiders to fully appreciate and correctly value technological uniqueness. An implication from these results is that technologically unique firms are likely to pay higher costs of capital, as investors more generally struggle to fully understand the profit prospects of unique technologies. Furthermore, firms that are not covered or are only superficially covered by equity analysts should exhibit a disproportionately higher cost of capital, since there is not even analyst reports to guide investors.

[Table 10]

Table 10 shows that this is indeed the case. For all four measures of implied cost of capital, we find that technologically unique firms that lost analyst coverage have to pay higher costs of capital. These results are robust across different measures of cost of capital and statistically significant. However, the penalty in terms of cost of capital is only moderate in size. A firm with a one standard deviation higher technological uniqueness score pays 0.035% higher cost of capital on an annual basis using the Claus and Thomas (2001) cost of capital measure. Our results also confirm that investors systematically struggle to correctly understand the value of unique technologies. Of course, if investors struggle to understand the value of unique technologies, then competitors may as well, and therefore fail to seize opportunities to imitate technologically unique firms. This suggests that asymmetric information (Benner and Zenger, 2016) and causal ambiguity (Lippman and Rumelt, 1982) may be powerful barriers to imitating technological uniqueness.

6. Robustness and Extensions

In this section we provide additional robustness checks, showing that the systematic relation between technological uniqueness and performance is not driven by other factors, such as the quantity or quality of patents, product market uniqueness or survivorship bias.

6.1 Controlling for Quantity and Quality of Patents

As we argued in section 2, our analysis of technological uniqueness is entirely novel within the empirical literature on strategic management and economics. However, as we also noted in that section, previous work used measures of the quantity or quality of patents to proxy for technological resources (see Markman et al., 2004 and Hsu and Ziedonis, 2013). A natural question is, therefore, whether technological uniqueness captures novel performance correlations or whether it merely reflects the quantity or quality of patents. For example, only firms that have many patents might be able to generate a technologically unique patent portfolio. Or the correlation of technological uniqueness with firm performance might be driven by the fact that firms with unique patent portfolios are also firms that create more valuable patents, and it might be this value of patents that truly drives the correlation of technological uniqueness with firm performance.

To analyze the empirical value added of technological uniqueness, we control for the quantity of and quality of patents. To control for the quantity of patents, we measure the total number of patents in the same previous 3-year period we used to calculate technological uniqueness. To measure quality of patents, we use the total implied stock market value of patents in the previous 3 years, based on the patent values provided by Kogan et al. (2017).

[Table 11]

Table 11 shows that the correlation of technological uniqueness and firm performance is robust and not driven by either the quantity or quality of patents. Additionally, the total number of patents does not seem to be positively correlated with firm performance, but instead negatively correlated. This is negative correlation one might expect if firms with exploration strategies generate more patents, using costly resources to do so, and if there exists an exploration-exploitation trade-off (March, 1991), whereby a successful focus technology development comes at the cost of less effective commercial exploitation of that technology.

Panel B of Table 11 also highlights that technological uniqueness remains systematically correlated with various measures of firm performance, even if we control for the total value of patents in the last 3 years. As expected the total value of patents is positively correlated with Tobin's Q, which should not be surprising, as the patent values are quantified using stock market impact of patent grants in Kogan et al. (2017). At the same time, technological uniqueness remains highly significant, even if we control for this value of patents.

6.2 Controlling for Product Differentiation

Much of our conceptual discussion of the performance effects of technological uniqueness used the lens of strategic positioning and the resource-based view. However, a natural question is whether technological uniqueness really just captures the effects of product uniqueness instead of the distinct effects of technological resources. To investigate this potential issue, we follow Litov et al. (2012) and measure product uniqueness, defined as the degree to which a firm's vector of sales across business segments differs from the centroid vector of sales across business segments of all firms within its industry.

[Table 12]

Table 12 shows that technologically unique firms outperform other industry peers, even if we control for product uniqueness. This is consistent with the view that technological uniqueness captures distinct effects from product uniqueness, which is consistent with Wernerfelt's (1984) argument that resource-based logic complements the traditional analysis of product market competition.

6.3 Survivorship Bias

Another potential issue is that our performance results might be driven by survivorship bias. Specifically, there are two distinct ways in which the set of continuing public firms might be sample selected. On the one hand, technologically unique firms might generally be more risky, which leads badly performing technologically unique firms to go into bankruptcy (see Yang, Li, and Kueng, 2021). If this would be the case, the fact that technologically unique firms outperform non-unique firms might just reflect the higher risk that technologically unique firms exhibit. On the other hand, even if worse performing technologically unique firms do not exit the sample through bankruptcy, they might exit through LBOs or acquisitions, again leaving the outperforming technologically unique firms as a reflection of sample selection in our data.

We analyze both of these possible concerns by taking advantage of Compustat's exit variables, that encode whether firms exit the data because of bankruptcy, LBOs or acquisitions.[25] If technologically unique firms are really riskier, we would expect that technological uniqueness is positively correlated with these three forms of exit.

[Table 13]

Table 13 shows that there is no evidence for technological uniqueness being correlated with either form of exit from the Compustat data.

7. Discussion

This paper provides systematic evidence of technological uniqueness as a valuable strategic resource. We document that technologically unique firms grow persistently faster and are more profitable than non-unique competitors, and provide evidence that higher technological uniqueness causes superior corporate performance. Furthermore, we provide evidence that such competitive

[25] The number of exit events we observe in our sample of patenting Computat firms are 23 for bankruptcy, 19 for LBO and 710 for acquisitions.

advantage is balanced by two distinct mechanisms that make technological uniqueness costly. First, technologically unique firms benefit less from incoming technological spillovers (Giustiziero et al., 2019; Bloom et al., 2013; Cohen & Levinthal, 1990). Second, technological uniqueness can be challenging to evaluate by investors, which implies higher costs of capital (Barney, 1986; Benner & Zenger, 2016; Litov et al., 2012). Together, the presence of benefits and costs of technological uniqueness constitute a new "Technological Uniqueness Paradox." Beyond our key findings, we highlight two additional insights.

First, our analysis reconciles the resource-based/competitive positioning and absorptive capacity views on how technological uniqueness shapes performance. Although the strategic effects of technological uniqueness dominate in the data analysis, predictions from the absorptive capacity view of technological uniqueness also hold, as more technologically unique firms benefit less from technological spillovers. As a result, these absorptive capacity effects reinforce the interpretation of technological uniqueness as a strategic resource, as they constitute additional costs of mimicking technologically unique corporations.

Second, our results have important implications for corporate strategy, going beyond the principle that diversification should match resources or "core competencies" (Wernerfelt, 1984; Prahalad and Hamel, 1990; Peteraf, 1993). Specifically, our results suggest that firms must carefully manage their technology portfolios relative to product market competitors and expand patents towards more technologically unique areas. Additionally, our complier analysis highlights that firms with large initial market shares, many geographic and business segments and aggressive R&D and intangible investment strategies can disproportionately benefit from technological uniqueness, consistent with the logic of economies of scale and scope from non-rival technologies.

There are several limitations of our analysis, which suggest avenues for future research. For example, our empirical analysis focuses on the sample of publicly traded firms, which implies that the firms in our research tend to be very large and mature. At the same time, understanding technological uniqueness as a strategic resource is potentially similarly important for startups and private firms and the role technological uniqueness may play in their success. We pursue these questions in ongoing research.

Another limitation is that our measure of technological uniqueness focuses on patented technologies. This ignores other types of technologies, such as intellectual property that can be protected by copyrights (Heath and Mace, 2020) as well as organizational or management practices that can be protected by trade secrets (Bloom and Van Reenen, 2007; Guernsey, John and Litov, 2022).

8. Conclusion

In this study, we provide evidence that the choice of pursuing unique and differentiated strategies can be a valuable proposition for a firm. We find that technologically unique firms grow faster, are more valuable, more profitable, and have higher ROAs. Moreover, this competitive advantage seems to last at least four years into the future. This result is consistent with the resource-based view of uniqueness that classifies technological uniqueness is a strategic resource (Barney, 1991).

On the other hand, we also demonstrate that unique strategies can be costly for the firm in at least two different ways. First, technologically unique firms benefit less from technological spillovers of peers, acting as a spillover barrier, a result consistent with recent works by Bloom et al. (2013). Second, technologically unique firms may also face higher costs of equity capital as a direct consequence of equity analysts finding it challenging to evaluate firms whose strategies are more unique. We show that this higher evaluation cost is associated with (i) increases in effort cost imposed on the consensus analyst, (ii) reductions in the number of analysts covering the firm, and (iii) a delay in analyst coverage of the firm.

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Table 1: Measurement Example for Technological Uniqueness

CPC	Description	Firm Vector (129x1)	Firm Vector (129x1)	Firm Vector (129x1)	Firm Vector (129x1)	Industry Vector (129x1)
		General Dynamics	**Lockheed Martin**	**Raytheon**	**Orbital ATK**	**Aerospace and Defense**
A61	Human Necessities: Medical or Veterinary Science; Hygiene	0.000	0.021	0.008	0.021	0.005
B01	Performing Operations: Physical or Chemical Processes	0.000	0.019	0.002	0.010	0.006
B21	Performing Operations: Shaping; Punching Metal	0.000	0.000	0.001	0.005	0.004
B22	Performing Operations: Casting; Powder Metallurgy	0.000	0.009	0.002	0.000	0.005
B64	Performing Operations: Aircraft; Aviation; Cosmonautics	0.000	0.029	0.022	0.036	0.084
B82	Performing Operations: Nanotechnology	0.000	0.024	0.006	0.000	0.007
C06	Chemistry; Metallurgy: Explosives; Matches	0.000	0.003	0.001	0.062	0.001
F01	Mechanical Engineering: Machines or Engines in General	0.000	0.002	0.002	0.000	0.047
F02	Mechanical Engineering: Lighting: Combustion Engines	0.000	0.010	0.006	0.047	0.038
F41	Mechanical Engineering: Lighting: Weapons	0.125	0.037	0.051	0.130	0.015
F42	Mechanical Engineering: Lighting: Ammunitions; Blasting	0.016	0.017	0.051	0.140	0.011
G01	Physic: Measuring; Testing	0.031	0.111	0.140	0.057	0.079
G02	Physic: Optics	0.016	0.045	0.048	0.005	0.018
G06	Physic: Computing; Calculating; Counting	0.047	0.093	0.125	0.000	0.062
H01	Electricity: Basic Electric Elements	0.078	0.115	0.129	0.031	0.055
H03	Electricity: Basic Electric Circuitry	0.016	0.021	0.029	0.000	0.011
H04	Electricity: Electric Communication Technique	0.328	0.070	0.111	0.000	0.050
	Technological Uniqueness Score	**-0.544**	**-0.802**	**-0.740**	**-0.543**	
	(Standardized) Technological Uniqueness Score	**0.019**	**-0.876**	**-0.661**	**0.021**	

Table 2: Summary Statistics

Variables	Mean	Median	Std. Dev	Min	Max
A: Performance Analysis					
Technology Uniqueness (standardized)	-.132	-.212	0.950	-1.482	1.821
Shift-Share IV (standardized)	-.071	.445	1.084	-2.938	.77
Sales Growth (1-year)	.117	.074	0.321	-.47	1.375
Tobin's Q	2.142	1.611	1.505	.719	7.585
Profitability	.032	.086	0.197	-.74	.283
ROA	-.022	.04	0.209	-.829	.238
Sales ($) (log)	5.571	5.565	2.124	.737	9.973
Sales Growth (past three years)	.075	.051	0.172	-.259	.747
Earnings Coef. of Variation	1.655	.853	2.114	.046	10.306
# of firms in industry (GIND)	244.213	228	114.655	24	531
Number of Shareholders (log)	3.483	3.378	1.221	1.431	6.564
Dummy variable *Segment 1*	.134	0	0.340	0	1
Dummy variable *Segment 2*	.516	1	0.500	0	1
Dummy variable *Segment 3*	.096	0	0.295	0	1
Dummy variable *Segment 4*	.254	0	0.435	0	1
Average market share	.168	.129	0.116	.037	.541
Average HHI	.061	.011	0.106	0	.457
R&D Intensity	.134	.065	0.180	0	.759
Advertising Intensity	.009	0	0.021	0	.112
Intangible Assets	.105	.036	0.144	0	.526
B: Equity Analyst Analysis					
Adjusted Coverage	0.014	0.006	0.022	0.000	0.352
Analyst Coverage Dummy	0.669	1.000	0.467	0.000	1.000
Technology Uniqueness (Standardized)	-0.062	-0.145	0.990	-1.476	1.836
Analyst Effort	-6.661	-6.000	4.059	-47.000	0.000
Analyst Attention	9.206	6.000	8.833	1.000	62.000
Assets (log)	5.919	5.749	1.866	0.718	12.718
Market-Book	3.890	2.438	5.603	-18.844	68.953
Intangible Assets	0.125	0.042	0.177	0.000	0.908
Volatility	0.044	0.030	0.044	0.001	0.430
Share Turnover (log)	14.041	14.075	0.920	9.084	17.472
Return	0.165	0.073	0.638	-0.898	6.520
C: Technology Shocks and Cost of Capital					
Knowledge Spillover Shock (non-standardized)	7.340	7.565	2.161	0.000	13.234
Competitive Shock (non-standardized)	8.783	8.967	1.569	2.292	12.659
Cost of Capital (Claus and Thomas, 2001)	0.082	0.079	0.050	0.000	0.847
Cost of Capital (Gebhardt et al., 2001)	0.083	0.082	0.029	0.000	0.492
Cost of Capital (Easton, 2004)	0.108	0.100	0.050	0.000	0.569
Cost of Capital (Ohlson and Juettner-Nauroth, 2005)	0.112	0.106	0.041	0.012	0.655
Analyst Coverage Loss	-9.693	-6.000	9.299	-62.000	-1.000

Notes: R&D intensity and advertising intensity are defined relative to total operating expenses.

Table 3: Technological Uniqueness and Firm Performance

Variable (end of prior fiscal year)	**Sales Growth**	**Tobin's Q**	**Profitability**	**ROA**
	OLS	OLS	OLS	OLS
Models	(1)	(2)	(3)	(4)
Technological Uniqueness	0.0231***	0.0695***	0.00867***	0.00889***
	(0.00657)	(0.0245)	(0.00252)	(0.00279)
Sales (log)	-0.0733***	0.450***	-0.0352***	-0.0333***
	(0.00954)	(0.0430)	(0.00419)	(0.00490)
Sales Growth (past three years)	0.167***	-0.225***	0.0877***	0.0737***
	(0.0103)	(0.0370)	(0.00471)	(0.00504)
R&D intensity	-0.284***	0.437***	0.0294***	0.0216*
	(0.0313)	(0.0937)	(0.00974)	(0.0116)
Advertising intensity	-0.00200*	-0.0241***	-0.00143***	-0.00114**
	(0.00109)	(0.00363)	(0.000393)	(0.000468)
Intangibles/assets	0.000545	0.00371***	-0.0000932	-0.0000430
	(0.000369)	(0.00138)	(0.000139)	(0.000198)
CV Earnings	0.00493	-0.209***	-0.00984	-0.0123
	(0.0186)	(0.0706)	(0.00673)	(0.00846)
Number of Shareholders (log)	-0.0226	-0.210***	-0.0297***	-0.0323***
	(0.0209)	(0.0774)	(0.00795)	(0.00967)
Business segments: 2	-0.0198	-0.244***	-0.0344***	-0.0360***
	(0.0213)	(0.0779)	(0.00790)	(0.00979)
Business segments: 3	0.0306	0.0467	-0.0108	-0.0266
	(0.0523)	(0.179)	(0.0196)	(0.0216)
Business segments: 4 or more	-0.197***	-0.185	-0.0996***	-0.0897***
	(0.0644)	(0.191)	(0.0211)	(0.0242)
Average Market Share	-0.157*	-0.0692	-0.149***	-0.307***
	(0.0831)	(0.285)	(0.0297)	(0.0358)
MMCI	0.352	1.301	-0.295**	-0.419***
	(0.287)	(1.485)	(0.144)	(0.161)
Firm FE	YES	YES	YES	YES
Industry-by-Year FE	YES	YES	YES	YES
Region-by-Year FE	YES	YES	YES	YES
R-squared	0.0789	0.0559	0.180	0.121
Observations	23,050	23,050	23,050	23,050

Notes: Technological uniqueness is measured as normalized distance from average industry patent portfolio. Sample is restricted to only include patenting firms. Average market share measures sales-weighted market share of firm across all its business segments. MMCI is sales-weighted average of industry concentration (Herfindahl index) across all business segments the firm is active in. Standard errors are clustered at the firm level and are reported in parentheses. Statistical significance levels: *: 10%, **: 5%, ***: 1%.

Table 4: Persistence of Competitive Advantage from Technological Uniqueness

	Panel A: Sales Growth					
	t	t+1	t+2	t+3	t+4	t+5
Technological Uniqueness	0.0231***	0.0109*	0.00681	0.00836	0.00718	0.0154***
	(0.00657)	(0.00605)	(0.00547)	(0.00515)	(0.00526)	(0.00585)
Controls			See Table Notes			
Observations	23,050	20,244	17,960	16,165	14,672	13,322

	Panel B: Tobin's Q					
	t	t+1	t+2	t+3	t+4	t+5
Technology Uniqueness	0.0695***	0.0545**	0.0263	0.00695	-0.000264	0.0315
	(0.0245)	(0.0266)	(0.0279)	(0.0298)	(0.0304)	(0.0304)
Controls			See Table Notes			
Observations	23,050	20,255	17,989	16,204	14,715	13,365

	Panel C: Profitability					
	t	t+1	t+2	t+3	t+4	t+5
Technology Uniqueness	0.00867***	0.00726***	0.00678**	0.00582	0.00465	0.00241
	(0.00252)	(0.00277)	(0.00326)	(0.00357)	(0.00364)	(0.00364)
Controls			See Table Notes			
Observations	23,050	20,284	18,016	16,227	14,729	13,372

	Panel D: ROA					
	t	t+1	t+2	t+3	t+4	t+5
Technology Uniqueness	0.00889***	0.00851***	0.00764**	0.00709*	0.00469	0.000459
	(0.00279)	(0.00307)	(0.00357)	(0.00379)	(0.00385)	(0.00383)
Controls			See Table Notes			
Observations	23,050	20,284	18,016	16,227	14,729	13,372

Notes: Controls include firm fixed effects, region-by-year fixed effects and industry-by-year fixed effects, initial sales, sales growth over the past 3 years, R&D intensity, advertising intensity, intangibles as fraction of assets, earnings coefficient of variation, log number of shareholders, separate dummies for firms with 2, 3 and 4 or more business segments, average market share across business segments and average industry concentration across business segments. Standard errors are clustered at the firm level and are reported in parentheses. Statistical significance levels: *: 10%, **: 5%, ***: 1%.

Table 5: Causal Effects of Technological Uniqueness on Firm Performance

Panel A: Centroid IV

	Technological Uniqueness	**Sales Growth**	**Tobin's Q**	**Profitability**	**ROA**
	OLS	IV	IV	IV	IV
	(1)	(2)	(3)	(4)	(5)
Technological Uniqueness		1.249***	1.636**	0.251***	0.190***
		(0.309)	(0.731)	(0.0747)	(0.0730)
Centroid Shift-Share 1	0.0710**				
	(0.0348)				
Centroid Shift-Share 2	0.00340				
	(0.0339)				
Additional Controls	See Table Notes				
Fixed Effects	Firm, Industry-by-Year, and Region-by-Year				
Observations	23,050	23,050	23,050	23,050	23,050

Panel B: R&D Tax Credit IV

	Technological Uniqueness	**Sales Growth**	**Tobin's Q**	**Profitability**	**ROA**
	OLS	IV	IV	IV	IV
	(1)	(2)	(3)	(4)	(5)
Technological Uniqueness		3.637***	3.383***	0.837***	0.709***
		(0.675)	(1.230)	(0.165)	(0.155)
R&D Tax Credit	-0.160***				
	(0.0324)				
Additional Controls	See Table Notes				
Fixed Effects	Firm, Industry, and Region				
Observations	16,632	16,632	16,632	16,632	16,632

Panel C: Industry Patent Expiration IV

	Technological Uniqueness	**Sales Growth**	**Tobin's Q**	**Profitability**	**ROA**
	OLS	IV	IV	IV	IV
	(1)	(2)	(3)	(4)	(5)
Technological Uniqueness		1.094***	2.049**	0.114	0.149
		(0.339)	(0.988)	(0.0749)	(0.0999)
Patent Expiration IV	-0.0826***				
	(0.0203)				
Additional Controls	See Table Notes				
Fixed Effects	Firm, Industry, Region, Year				
Observations	15,619	15,619	15,619	15,619	15,619

Notes: Technological uniqueness is measured as normalized distance from average industry patent portfolio (centroid). Panel A instruments are the Bartik-style shift-share measures which are the product of the state-level industry's revenue-share (first and second lag) and industry centroid patent portfolio. Cragg-Donald F-Statistic for panel A is 11.08 and Kleibergen-Paap p-value is 0. Panel B instrument is the predicted R&D expenditures based on state and federal R&D tax credits. Cragg-Donald F-Statistic for panel B is 27.85 and Kleibergen-Paap p-value is 0. Panel C instrument is a Bartik-style IV constructed using expiring patent shares for each technology class at the industy level. Sample is restricted to only include patenting firms. Cragg-Donald F-Statistic for panel C is 31.37 and Kleibergen-Paap p-value is 0. Additional controls include separate dummies for 2,3,4 business segments; number of competitors in the same GIND industry, average market share across business segments, average industry concentration (Herfindahl) across business segments. Standard errors are clustered at the industry-year level for the shift-share and patent expiration IV; and region-year level for the R&D tax credit IV. Statistical significance levels: *: 10%, **: 5%, ***: 1%.

Table 6: Profiling Compliers Across Instruments

Panel A: Fraction of Compliers in Sample

	Centroid IV	R&D Tax Credit IV	Patent Expiration IV
	(1)	(2)	(3)
$P(E_i=1)$	65.63%	54.07%	68.03%
$P(T_i=1)$	40.00%	14.44%	20.06%
$P(T_{1i}-T_{0i})$	7.50%	7.98%	11.33%
Percentage compliers relative to all treated firms	12.32%	29.86%	38.42%

Panel B: Characterizing Compliers

	Centroid IV		R&D Tax Credit IV		Patent Expiration IV	
	(1)	(2)	(3)	(4)	(5)	(6)
	$P(T_{1i}-T_{0i}\|X_i=1)$	$P(X_i=1\|T_{1i}-T_{0i})$ $/P(X_i=1)$	$P(T_{1i}-T_{0i}\|X_i=1)$	$P(X_i=1\|T_{1i}-T_{0i})$ $/P(X_i=1)$	$P(T_{1i}-T_{0i}\|X_i=1)$	$P(X_i=1\|T_{1i}-T_{0i})$ $/P(X_i=1)$
Many geo. segments	17.90%	2.45	12.55%	1.61	12.98%	1.13
Many bus. segments	9.63%	1.32	-0.08%	0	12.95%	1.13
High Market Share	10.59%	1.41	4.28%	0.53	6.45%	0.56
High Growth	15.47%	2.06	2.16%	0.27	12.34%	1.08
High Market Concentr.	9.76%	1.30	15.01%	1.88	-10.05%	0
High R&D	10.85%	1.44	16.63%	2.08	9.07%	0.80
High Advertising	11.28%	1.50	10.78%	1.35	7.45%	0.65
High Intangible Capital	9.96%	1.32	-3.21%	0	15.92%	1.40

Notes: Complier results are estimated using a logistic regression. For the shift-share and R&D tax credit IV, fixed effects include firm, industry and region fixed effects. For the patent expiration IV, fixed effects include firm, industry, region, and year. For column (1) T_i is dummy variable that is one if a firm has above-average technological uniqueness (the "treatment group"). For columns (2), (3) T_i is dummy variable that is one if a firm has below-average technological uniqueness. E_i is a dummy that is one if the instrumental variable (Centroid IV, R&D tax credit IV, Patent Expiration IV) has an above-average value. Correspondingly, $P(T_i=1)$ is the fraction of treated firms; $P(Z_i=1)$ is the fraction of firms with above average instrument values; $P(T_{1i}-T_{0i})$ is fraction of "complier" firms, which are defined as responding to the instrument by increasing technological uniqueness; X_i is a dummy that is one for firms that have above-average values of characteristics X given in the rows of Panel B; $P(T_{1i}-T_{0i}|X_i=1)$ is the fraction of compliers, conditional on firms with above-average characteristic X; $P(X_i=1|T_{1i}-T_{0i})$ $/P(X_i=1)$ measures how much more likely compliers are to exhibit above-average characteristic X compared to average sample firms. Whenever estimates of $P(X_i=1|T_{1i}-T_{0i})$ are negative, we replace $P(X_i=1|T_{1i}-T_{0i})$ $/P(X_i=1)$ with a lower bound of zero. For more details, see text and Angrist and Pischke (2009).

Table 7: Competitive Effects of Technological Differentiation

Variable (end of prior fiscal year)	**Sales Growth**	**Tobin's Q**	**Profitability**	**ROA**
	OLS	OLS	OLS	OLS
	(1)	(2)	(3)	(4)
Technological Uniqueness	0.0281***	0.0799***	0.00919***	0.0111***
	(0.00662)	(0.0248)	(0.00251)	(0.00275)
Competitive Technological Differentiation	-0.0172	0.116**	-0.0121***	-0.00385
	(0.0107)	(0.0556)	(0.00435)	(0.00484)
Technological Uniqueness **X** Competitive Technological Differentiation	0.0141**	-0.00158	0.000943	0.000467
	(0.00633)	(0.0241)	(0.00219)	(0.00248)
Additional controls	see table notes			
Firm FE	YES	YES	YES	YES
Region-by-year FE	YES	YES	YES	YES
R-squared	0.0764	0.0681	0.199	0.133
Observations	22,138	22,138	22,138	22,138

Notes: Technological uniqueness is measured as normalized distance from average industry patent portfolio. Competitive technological differentiation shocks are defined as the value of patents by firms in the same industry, in uncommon technology classes. Uncommon technology classes are defined as classes that firms patent in less than 50% of the time. Number of patents is the number of patents granted to the firm in the last 3 years. Additional control variables include log number of shareholders, log sales, sales growth (past 3 years), coefficient of variation of earnings, number of firms in the industry, dummies for firms with 2,3,4+ business segments, average market share across segment industries, average Herfindahl index across industries of segments, R&D intensity, advertising intensity, intangibles as fraction of assets, number of patents granted in the last 3 years and interaction of number of patents and Competitive tech nological differentiation shocks. Sample is restricted to only include patenting firms. Standard errors are clustered at the firm level and are reported in parentheses. Statistical significance levels: *: 10%, **: 5%, ***: 1%.

Table 8: Technological Uniqueness as Spillover Barrier

Panel A: Technology Spillover Shocks

	Sales Growth	**Tobin's Q**	**Profitability**	**ROA**
	OLS	OLS	OLS	OLS
	(1)	(2)	(3)	(4)
Technological Uniqueness	0.0277***	0.0821***	0.00905***	0.0112***
	(0.00666)	(0.0254)	(0.00253)	(0.00279)
Technological Spillovers	0.0318***	0.0755***	0.0104***	0.00765***
	(0.00717)	(0.0236)	(0.00245)	(0.00279)
Technological Uniqueness X Technological Spillovers	-0.0215***	-0.0516***	-0.00594***	-0.00512**
	(0.00579)	(0.0198)	(0.00196)	(0.00218)
Number of Patents X Technological Spillovers	-0.000186***	0.000148	-0.000045***	-0.0000156
	(0.0000393)	(0.000210)	(0.0000143)	(0.0000160)
Additional Controls	see table notes			
Firm FE	YES	YES	YES	YES
Region-by-Year FE	YES	YES	YES	YES
R-squared	0.0805	0.0667	0.201	0.134
Observations	22,138	22,138	22,138	22,138

Panel B: Patent Citations

	Number of Citations to Industry Peers	**Number of Citations to Core* Industry Technology Classes**
	OLS	OLS
	(1)	(2)
Technological Uniqueness	-0.0405**	-0.163***
	(0.0192)	(0.0190)
Number of Patents (3-years)	0.00160***	0.000945***
	(0.000207)	(0.000203)
Additional Controls	see table notes	
Firm FE	YES	YES
Region-Year FE	YES	YES
Industry-Year FE	YES	YES
Observations	22,292	22,292

Notes: Technological uniqueness is measured as normalized distance from average industry patent portfolio. Panel A: Technology spillover shock is defined as the value of patents by other firms in technology classes the focal firm has cited in its own patents during the last 4 years. Panel B: Number of Citations to Industry Peers is the number of patent citations from the focal firm's granted patents to those patents granted to peer firms within the same industry. Number of Citations to Core Industry Technology Classes is the number of patent citations from the focal firm's granted patents to patents in the industry's core technology areas. Core technology areas by industry are based on the commonly assigned technology classes of patents granted to firms in the same industry over the past 4 years. Number of Patents are the number of granted patents to the firm in the past 3 years. Additional control variables in both panels include: number of patents granted to the firm in the last 3 years, log sales, sales growth (past 3 years), R&D intensity, advertising intensity, intangibles as fraction of assets, coefficient of variation of earnings, dummies for firms with 2,3,4+ business segments, average market share across segment industries, average Herfindahl index across industries of segments. Sample is restricted to only include patenting firms. Standard errors are clustered at the firm level and are reported in parentheses. Statistical significance levels: *: 10%, **: 5%, ***: 1%.

Table 9: Analyst Coverage of Technologically Unique Firms

Variable (end of prior fiscal year)	**Adjusted Analyst Coverage**	**Analyst Effort**	**Analyst Attention**	**Analyst Coverage Take-up**	**Analyst Coverage Drop**
	OLS		Negative Binomial	Cox Proportional Hazard (reported as hazard ratios)	
	(1)	(2)	(3)	(4)	(5)
Technology Uniqueness	-0.000604**	0.144*	-0.0233*	0.880***	1.294***
	(0.00025)	(0.074)	(0.012)	0.031	0.071
Assets (log)	0.00316***	-0.267***	0.311***	1.121***	0.467***
	(0.0004)	(0.071)	(0.014)	0.04	0.04
Market-Book	0.0000474***	0.00614	0.00570***	0.99	0.95
	(0.00002)	(0.005)	(0.001)	0.02	0.04
Intangible Assets	-0.000917	-0.0774	-0.0890**	1.00	0.718***
	(0.001)	(0.225)	(0.040)	0.04	0.06
Stock Volatility	0.00801***	0.018	0.153	1.088***	0.95
	(0.003)	(0.951)	(0.110)	0.03	0.09
Stock Turnover (log)	0.00202***	0.225***	0.192***	1.04	0.384***
	(0.0002)	(0.063)	(0.010)	0.04	0.04
Stock Return	-0.000152*	-0.152***	-0.0774***	1.079**	1.156**
	(0.0001)	(0.035)	(0.006)	0.03	0.08
Firm FE	YES	YES	YES	NO	NO
Industry-by-Year FE	YES	YES	YES	NO	NO
Region-by-Year FE	YES	YES	YES	NO	NO
R-squared	0.0557	0.004	0.061	-	-
Observations	34,866	22,181	23,707	10,325	16,563

Notes: Analysis is run on the analyst-year level from IBES. Dependent variables are: (1) Adjusted analyst coverage is defined as the ratio of the number of analysts covering a particular firm, divided by the number of analysts covering all firms in the industry of the firm. (2) Analyst effort is defined as the negative of the number of other firms a particular analyst is covering in addition to the focal firm. (3) Analyst attention is defined as the number of analysts covering a particular firm. (4) Analyst coverage take-up is a dummy that is one, if any equity analyst who previously did not cover a focal firm, starts covering it eventually. (5) Analyst coverage drop is a dummy that us one if a focal firm, which was covered by at least one equity analyst, eventually stops being covered by any equity analyst. Standard errors are clustered at the firm level and reported in parentheses. Statistical significance levels: *: 10%, **: 5%, ***: 1%.

Table 10: Technological Uniqueness and Cost of Capital

Variable (end of prior fiscal year)	Cost of Capital			
	OLS	OLS	OLS	OLS
	(1)	(2)	(3)	(4)
Technological Uniqueness	0.00157	0.00120	-0.000823	0.000604
	(0.00162)	(0.000825)	(0.00137)	(0.00119)
Analyst Coverage Loss	0.000279**	0.0000937	-0.0000577	-0.0000885
	(0.000111)	(0.0000652)	(0.000116)	(0.0000925)
Technological Uniqueness X Analyst Coverage Loss	0.000353***	0.000253***	0.000268***	0.000251***
	(0.0000922)	(0.0000538)	(0.0000901)	(0.0000757)
Sales (log)	0.0343***	0.00934***	0.0257***	0.0188***
	(0.00199)	(0.00114)	(0.00194)	(0.00159)
Sales Growth (past three years)	-0.0119***	0.000703	-0.00772***	-0.00536***
	(0.00205)	(0.00119)	(0.00201)	(0.00152)
R&D intensity	0.00603	-0.00581*	-0.0186***	-0.00781**
	(0.00427)	(0.00338)	(0.00472)	(0.00371)
Advertising intensity	-0.0000534	0.000101	0.000287	0.000189
	(0.000197)	(0.000107)	(0.000220)	(0.000175)
Intangibles/assets	-0.0000735	-0.0000371	-0.000172**	-0.000161***
	(0.0000674)	(0.0000438)	(0.0000751)	(0.0000555)
CV Earnings	-0.000866	0.00220	0.000409	0.00237
	(0.00304)	(0.00176)	(0.00353)	(0.00247)
Number of Shareholders (log)	-0.00177	0.00196	0.00447	0.00431
	(0.00327)	(0.00205)	(0.00395)	(0.00277)
Business segments: 2	0.00212	0.00316	0.00701*	0.00643**
	(0.00373)	(0.00213)	(0.00405)	(0.00297)
Business segments: 3	-0.0131	-0.00742	-0.00559	-0.0139*
	(0.00844)	(0.00491)	(0.0102)	(0.00798)
Business segments: 4 or more	0.0337***	0.0124**	0.0104	0.0233**
	(0.0100)	(0.00608)	(0.0109)	(0.00943)
Additional Controls	See Table Notes			
Firm FE	YES	YES	YES	YES
Industry-by-Year FE	YES	YES	YES	YES
Region-by-Year FE	YES	YES	YES	YES
Observations	13139	13231	12798	13034

Notes: Dependent variables are different measures of the cost of capital: (1) uses Claus and Thomas (2001), (2) uses Gebhardt, Lee and Swaminathan (2001), (3) uses Easton (2004) and (4) uses Ohlson and Juettner-Nauroth (2005). Technological uniqueness is measured as normalized distance from average industry patent portfolio. Sample is restricted to only include patenting firms. Additional controls include average market share across business segments and average industry concentration across business segments. Standard errors are clustered at the firm level. Statistical significance levels: *: 10%, **: 5%, ***: 1%.

Table 11: Controlling for Quantity and Quality of Patents

Variable (end of prior fiscal year)	A: Controlling for Quantity of Patents Sales Growth	Tobin's Q	Profitability	ROA
	OLS	OLS	OLS	OLS
Models	(1)	(2)	(3)	(4)
Technological Uniqueness	0.0254***	0.0609**	0.00889***	0.0103***
	(0.00668)	(0.0249)	(0.00254)	(0.00277)
Number of Patents (1000)	-0.0516***	-0.355***	-0.0118	-0.00395
	(0.0180)	(0.108)	(0.00827)	(0.00989)
Additional controls		see table notes		
Firm FE	YES	YES	YES	YES
Industry-by-Year FE	YES	YES	YES	YES
Region-by-Year FE	YES	YES	YES	YES
R-squared	0.0801	0.0610	0.179	0.120
Observations	22292	22292	22292	22292

Variable (end of prior fiscal year)	B: Controlling for Quality of Patents Sales Growth	Tobin's Q	Profitability	ROA
	OLS	OLS	OLS	OLS
Models	(5)	(6)	(7)	(8)
Technological Uniqueness	0.0262***	0.0693***	0.00912***	0.0104***
	(0.00667)	(0.0249)	(0.00254)	(0.00276)
Value of Patents ($10K)	-0.0306**	0.0701	-0.00314	0.00169
	(0.0119)	(0.0526)	(0.00429)	(0.00435)
Additional controls		see table notes		
Firm FE	YES	YES	YES	YES
Industry-by-Year FE	YES	YES	YES	YES
Region-by-Year FE	YES	YES	YES	YES
R-squared	0.0801	0.0581	0.179	0.120
Observations	22,292	22,292	22,292	22,292

Notes: Technological uniqueness is measured as the normalized distance of the firm's patent portfolio from the average industry's patent portfolio (centroid). The sample is restricted to only include patenting firms. Controls include firm fixed effects, region-by-year fixed effects and industry-by-year fixed effects, initial sales, sales growth over the past 3 years, R&D intensity, advertising intensity, intangibles as fraction of assets, earnings coefficient of variation, log number of shareholders, separate dummies for firms with 2, 3 and 4 or more business segments, average market share across business segments and average industry concentration across business segments. The sample is restricted to only include patenting firms. Average market share measures sales-weighted market share of firm across all its business segments. MMCI is sales-weighted average of industry concentration (Herfindahl index) across all business segments the firm is active in. Standard errors are clustered at the firm level. Statistical significance levels: *: 10%, **: 5%, ***: 1%.

Table 12: Controlling for Product Uniqueness

Variable (end of prior fiscal year)	Sales Growth	Tobin's Q	Profitability	ROA
	OLS	OLS	OLS	OLS
Models	(1)	(2)	(3)	(4)
Technological Uniqueness	0.0260***	0.0824***	0.00934***	0.00995***
	(0.00729)	(0.0284)	(0.00286)	(0.00318)
Product Uniqueness	-0.00957	-0.000258	0.0131	0.00680
	(0.0338)	(0.127)	(0.0136)	(0.0153)
Sales (log)	-0.0720***	0.459***	-0.0380***	-0.0362***
	(0.0102)	(0.0475)	(0.00460)	(0.00537)
Sales Growth (past three years)	0.170***	-0.235***	0.0946***	0.0800***
	(0.0110)	(0.0404)	(0.00502)	(0.00547)
R&D intensity	-0.293***	0.448***	0.0248**	0.0165
	(0.0319)	(0.0979)	(0.0102)	(0.0120)
Advertising intensity	-0.00165	-0.0258***	-0.00130***	-0.000974*
	(0.00118)	(0.00396)	(0.000435)	(0.000519)
Intangibles/assets	0.000732*	0.00406***	-0.000138	-0.0000856
	(0.000389)	(0.00152)	(0.000151)	(0.000216)
CV Earnings	0.00601	-0.211***	-0.0111	-0.0144
	(0.0194)	(0.0758)	(0.00727)	(0.00905)
Number of Shareholders (log)	-0.0228	-0.200**	-0.0313***	-0.0353***
	(0.0223)	(0.0840)	(0.00868)	(0.0105)
Business segments: 2	-0.0265	-0.223***	-0.0374***	-0.0398***
	(0.0230)	(0.0850)	(0.00865)	(0.0107)
Business segments: 3	-0.000692	-0.0513	-0.0194	-0.0372
	(0.0610)	(0.218)	(0.0227)	(0.0255)
Business segments: 4 or more	-0.213***	-0.282	-0.136***	-0.125***
	(0.0764)	(0.246)	(0.0263)	(0.0302)
Additional controls	see table notes			
Firm FE	YES	YES	YES	YES
Industry-by-Year FE	YES	YES	YES	YES
Region-by-Year FE	YES	YES	YES	YES
R-squared	0.0792	0.0550	0.189	0.128
Observations	20,401	20,401	20,401	20,401

Notes: Technological uniqueness is measured as the normalized distance of the firm's patent portfolio from the average industry's patent portfolio (centroid). The sample is restricted to only include patenting firms. Product market uniqueness is measured as normalized distance from average industry business segment portfolio. The sample is restricted to only include patenting firms. Additional controls include: Average market share measures, which are sales-weighted market share of firm across all its business segments and MMCI, which is a sales-weighted average of industry concentration (Herfindahl index) across all business segments the firm is active in. Standard errors are clustered at the firm level. Statistical significance levels: *: 10%, **: 5%, ***: 1%.

Table 13: Exit and Survivorship Bias

Variable (end of prior fiscal year)	**Bankruptcy**	**LBO**	**Acquisition**
	OLS	OLS	OLS
Models	(1)	(2)	(3)
Technological Uniqueness	0.000475	0.000175	-0.00344
	(0.000641)	(0.000469)	(0.00281)
Sales (log)	0.000950	-0.000383	-0.0187***
	(0.000910)	(0.000248)	(0.00389)
Sales Growth (past three years)	-0.00200***	-0.000587**	0.000856
	(0.000695)	(0.000277)	(0.00312)
CV Earnings	0.00252	-0.000935	-0.0111
	(0.00243)	(0.000749)	(0.00899)
Number of Shareholders (log)	0.0000923	0.000114	0.00114*
	(0.000118)	(0.000122)	(0.000671)
Business segments: 2	0.00000404	0.0000245**	0.000978***
	(0.0000250)	(0.0000122)	(0.000253)
Business segments: 3	0.00469**	0.000290	0.0118*
	(0.00222)	(0.000360)	(0.00706)
Business segments: 4 or more	0.00410*	0.000737	0.00725
	(0.00232)	(0.000777)	(0.00841)
MMCI	0.00312	0.000221	0.00327
	(0.00225)	(0.000595)	(0.00839)
Average Market Share	0.00107	-0.00101	0.00555
	(0.00331)	(0.00401)	(0.0214)
R&D intensity	0.00450	0.00508	-0.0216
	(0.00503)	(0.00501)	(0.0288)
Advertising intensity	-0.00884	-0.00461	-0.0676***
	(0.00674)	(0.00297)	(0.0227)
Intangibles/assets	-0.0285	-0.0235	-0.0521
	(0.0210)	(0.0156)	(0.119)
Firm FE	YES	YES	YES
Industry-by-Year FE	YES	YES	YES
Region-by-Year FE	YES	YES	YES
R-squared	0.270	0.292	0.234
Observations	23,050	23,050	23,050

Notes: Technological uniqueness is measured as the normalized distance of the firm's patent portfolio from the average industry's patent portfolio (centroid). The sample is restricted to only include patenting firms. The sample is restricted to only include patenting firms. Average market share measures sales-weighted market share of firm across all its business segments. MMCI is sales-weighted average of industry concentration (Herfindahl index) across all business segments the firm is active in. Standard errors are clustered at the firm level. Statistical significance levels: *: 10%, **: 5%, ***: 1%.