Technological Uniqueness and Competitive Advantage

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Abstract

Technological uniqueness, defined as the degree to which a firm's patented technologies differ from its industry competitors, has 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 innovation spillovers and impede firm performance. Alternatively, technological uniqueness could be a strategic resource which confers competitive advantage and is costly to imitate. We empirically examine these competing arguments and find evidence that the strategic resource argument dominates in the data with technological uniqueness generating competitive advantage. At the same time, we show that pursuing technological uniqueness is costly, as unique firms are harder to understand by equity analysts and consequently have higher costs of equity capital.

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1. Introduction

Across nearly all industries, investment in innovation and technology is vital to value creation and comparative performance. Firms face difficult choices, however, in selecting paths for investment in technological progress. A particularly critical choice involves deciding whether to pursue a unique and differentiated technological strategy or one that is common among competitors. The choice is by no means obvious. On the one hand, the positioning and resource-based theories of the strategy literature highlight the value of a unique strategy. A unique technological path enables firms to generate unique and valuable knowledge, and technological resources that can be leveraged into unique and sought-after products, allowing firms to occupy unique product market positions that create competitive advantage (Barney, 1991; Lippman and Rumelt, 1982; Wernerfelt, 1984).

On the other hand, choosing unique technological paths impose at least two important strategic costs. First, selecting a unique technological strategy limits the scope of beneficial knowledge spillovers from other competitors. Dating as far back as Marshall (1890), innovation spillovers have been viewed as a vital source of technological progress. Recent work by Bloom, Schankerman, and Van Reenen (2013) suggests that firms that are technologically dissimilar to their industry peers benefit less from these valuable innovation spillovers. By contast, those with technology paths more similar to their competitors absorb more knowledge from their industry peers (Cohen and Levinthal, 1989), and may as a result enjoy higher performance (e.g., higher sales growth or greater profitability). Second, the technology, resources, and products that result from pursuing a unique technological path elevate the costs imposed on market participants tasked with evaluating the future performance prospects of the firm. In particular, the pursuit of a unique technological trajectory may impose high evaluation costs on analysts (Litov, Moreton, and Zenger, 2012), which could in turn increase the cost of capital, and thereby indirectly dampen corporate performance.

In this paper, we empirically evaluate the presence of each of these effects. To do so, 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 chosen by their industry peers. We then examine how the uniqueness of a firm's patenting vector influences the scope of knowledge spillovers it enjoys, the pattern of analyst coverage it receives, and its firm's performance.

The main finding of our empirical analysis is that more technologically unique firms outperform less unique industry rivals. More precisely, a one standard deviation greater technological uniqueness score is associated with 2.4% higher sales growth, 6.8% higher Tobin's Q, and roughly 0.7% higher profitability and ROA. These sales growth, profitability, and ROA effects are persistent at least four years into the future. At the same time, the pursuit of technological uniqueness comes at a cost. We document that technologically unique firms benefit from fewer technological spillovers from their peers in the industry 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, are more likely to drop coverage of technologically unique firms, and must expend more effort if they choose to cover these technologically unique firms. Technologically unique firms are simply harder to understand, as firm outsiders must access private information, as argued by Benner and Zenger (2016). This asymmetric information problem in addition to elevate 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 and Hypothesis Development

2.1 Strategic Resources and Absorptive Capacity

The economic rents a firm enjoys derive from the scarcity of the resources it possesses (Barney, 1991; Becker, 1971; Ricardo, 1817; Wernerfelt, 1984). Barney (1991) explicitly defines resources that generate competitive advantage as those that are valuable, rare, and costly-to-imitate. Within this literature, technology is often highlighted as a particularly important source of these valuable resources (Wernerfelt, 1984). Patents are commonly used as a proxy for competitive 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). Moreover, legal barriers make them costly to imitate, as mimicking inventors must "invent around" a patented technology. In this manner, patents help "isolate or buffer firms from competitors" (Hsu and Ziedonis, 2013), and allow firms to deliver value uniquely in ways that competitors cannot.

Much of the literature has focused on measuring patent portfolios as valuable resources by summing the number of patents held (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). Therefore, independent of the inherent uniqueness of individual patents, the pattern of technological categories (i.e., patent classes) in which a firm participates may be unique. Our measure of technological uniqueness is precisely this: the uniqueness of a firm's patent portfolio, as measured by the patent classes in which it participates, relative to the patent class portfolio of their industry peers (henceforth "technological uniqueness").

A strong focus in strategy and economic research is that by pursuing uniqueness in technological positions firms have the potential to generate a competitive advantage (Hall, 1993; Schankerman, 1991; Bloom and Van Reenen, 2002).[2] Very unique patent combinations will be hard to copy, because imitating such unique portfolios requires investment in multiple new technologies, many unfamiliar to competitors. Moreover, if these unique technologies are uniquely configured to be complementary[3] (see Porter, 1996; Rivkin, 2000) and in ways not visible within

[2] 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."
[3] 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 disclosures, imitation is all the more costly—a pivotal condition to sustained competitive advantage (Barney, 1991)[4]. Therefore, from a resource-based perspective, technological uniqueness, as we measure it, should be associated with a competitive advantage and superior corporate performance.

However, there is an essential counter argument to such resource-based logic. Knowledge, including knowledge found within patentable technologies, is unlike other resources in that knowledge is "non-rival" (Romer, 1990) or "scale-free" (Asmussen, 2015). While a rival good has the property that its use by one party "precludes its use by another" (Romer, 1990) [5], the use of a non-rival good such as knowledge does not have this property, as the resource can be infinitely replicated, at a small or no cost. For example, the use of an algorithm by one firm does not diminish the ability of another firm to use the same algorithm. This non-rival nature of patented technology gives rise to the possibility of technological spillovers, as the invention of a new technology by one firm, can lead other firms to benefit from the same technology. Indeed, the patent system, while providing legal protection, encourages spillovers as those who file patents are forced to provide detailed public descriptions of the technology. But firms are likely to differ in their ability to absorb or benefit from these technological spillovers (Cohen and Levinthal, 1990). A key performance implication of differences in absorptive capacity is that firms with deficient absorptive capacity are likely to lag behind their competitors technologically. One way to elevate absorptive capacity is to actually pursue technologies more similar to competitors, thereby enabling a greater learning from and absorption of knowledge from competitors. Bloom et al. (2013) measure the technological similarity of patent portfolios and find that firms that are technologically similar to their peers benefit more from R&D spillovers. Therefore, ignoring the strategic benefits of uniqueness described above, this absorptive capacity logic predicts that

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% $(0.001 = 0.5^{10})$.

[4] 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."

[5] 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.

technologically unique firms will learn less from competitors, and potentially underperform non-unique firms due to the loss of spillovers.

Of course, in practice, technological uniqueness is likely to exhibit both resource- and absorptive capacity-related performance effects. Nevertheless, a first step in our analysis will be to investigate whether resource- or spillover-related performance effects dominate. We state these competing effects in hypothesis form as follows:

Hypothesis 1*: If strategic resource effects of technological uniqueness dominate, then more unique firms will outperform competitors with less unique patent positions. If on the other hand, absorptive capacity effects of technological uniqueness dominate and technological uniqueness is a significant spillover barrier, then more unique firms will underperform these more commonly positioned competitors.*

2.2 Costs of Technological Uniqueness 1: Spillover barrier

Regardless of whether technological uniqueness positively or negatively affects performance in aggregate, the pursuit of technological uniqueness should still generate impediments to technological spillovers. For firms pursuing such uniqueness, such impediments should deter imitators and thereby help sustain any potential competitive advantage created through technological uniqueness. Yet, as discussed previously, the pursuit of technological uniqueness should also should dampen firms' capacity to absorb technological spillovers from their competitors which are by definition pursuing more distant technology. Specifically, we conjecture that:

Hypothesis 2*: In response to technological spillover shocks, more technologically unique firms will benefit less from technological spillovers sourced from competitors.*

2.3 Costs of Technological Uniqueness 2: Asymmetric Information and Cost of Capital

A second cost of technological uniqueness relates to 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 push them to often 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 will also discourage coverage by equity analysts.

Hypothesis 3a*: Greater technological uniqueness is costlier to evaluate by equity analysts and therefore increases the required effort of covering technologically unique firms. As a result, analysts are less likely to provide and more likely drop coverage of technologically unique firms.*

This capital market perspective also allows us to directly quantify another cost to imitating technological uniqueness. If technologically unique firms are harder to understand for investors than non-unique firms, then costs of capital for unique firms should be systematically higher. Furthermore, if equity analysts add value by reducing information asymmetries between investors and firms, then firms that are not covered by equity analysts should be subject to disproportionately higher equity cost of capital.

Hypothesis 3b*: If not covered by analysts, more technologically unique firms have higher costs of equity capital.*

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

To measure a firm's uniqueness, we follow Litov et al. (2012) by defining a firm's uniqueness relative to the activities of industry "peer" firms. However, our definition of uniqueness 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[6]. 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 GICS.

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.[7] Each row of the vector records the total number of technology classes assigned to the firm's patents by the USPTO,[8] based on the

[6] 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).

[7] 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.

[8] 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.

patents awarded to the firm during a rolling three-year period.[9] For each GICS industry *I*, we also define the industry centroid as a 129x1 vector $I_t = [i_{1,t} \dots i_{129,t}]'$ that captures the industry's patenting activity across the same 129 patent technology classes at time *t*. Both patenting vectors are normalized by dividing each element of the vector by the total number of assigned technology classes.

To determine each firm's technological uniqueness each year ($TU_{i,t}$), we measure the distance between the firm's patenting activity vector $F_{i,t}$ to the firm's industry centroid I_t, using

$$TU_{i,t} = -\frac{F'_{i,t} I_{i,t}}{\sqrt{F_{i,t}{}' F_{i,t}}\sqrt{I_{i,t}{}' I_{i,t}}} \tag{1}$$

To facilitate interpretation of results later, we standardize TU around a mean of 0 with unit standard deviation. Our measure of technological uniqueness is the negative of "cosine similarity", which in turn is an uncentered measure of covariance, as shown by Jaffe (1986). Intuitively, technological uniqueness in (1) is higher, the lower the correlation of a firm's technology classes is 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. While Lockheed Martin's patenting behavior is similar to that of the Aerospace & Defense industry centroid, General Dynamics and Orbital ATK exhibit very different patenting profiles.

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. 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)", highlighting that we offer an analysis of a distinct empirical measure.

[9] 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.

3.2 Measurement of Technology Shocks

Hypothesis 2 predicts that a focal firm's technological uniqueness reduces the benefits from technological spillovers that it receives. One way to investigate this hypothesis 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 value of all patents generated by other firms in technology classes that the focal firm heavily cites.[10] 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 its 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. We measure such "technological differentiation shocks" as the sum of patents in occurring in patenting areas that are *atypical* for competitors in a given GICS industry.[11]

3.3 Performance measures

Our performance measures include growth, valuation, and relative profitability measures as these are likely the same metrics that financial analysts utilize when covering firms. Using Compustat data, we construct *sales growth*, *Tobin's Q*, *Profitability*, and *ROA.*

[10] 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. 2013 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.

[11] 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.

3.4 Analyst Coverage variables

Our analyst coverage model studies the impact of the firm's technological uniqueness choice on analyst coverage behavior. Three dependent variables that we consider are: *Adjusted Coverage, Analyst Attention,* and *Analyst Effort.* All three variables are constructed using I/B/E/S data and measure the analyst' coverage behavior of the focal firm. *Adjusted Coverage*, described previously, is the number of analysts currently covering 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.

3.5 Cost of capital variables

To measure the impact of the firm's technological uniqueness choice on the firm's cost of capital, we construct four measures of the firm's cost of capital. These four measures of the firm's cost of capital based on prior work (Claus and Thomas, 2001; Easton, 2004; Gebhardt et al., 2001; Ohlson and Juettner-Nauroth, 2005). Each of the four cost of capital measures are 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 will capture a variety of performance outcomes, such as sales growth, profitability, ROA or 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

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

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, (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 meaure 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 of the effect of technological uniqueness on firm performance, 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, our instrumental variables strategy uses changes in the average industry patent portfolio as measured by the industry patenting centroid ("centroid changes") as instrumental variable (IV). Formally, the first stage of our IV estimator is given by

$$TU_{i,t} = \gamma_1 \cdot \Delta C_{s,t-1} + \gamma_2 \cdot \Delta C_{s,t-2} + controls_{i,t} + D_i + D_l \times D_t + e_{i,t} \quad (3)$$

Where, $e_{i,t}$ is an error term and $\Delta C_{s,t-1}, \Delta C_{s,t-2}$ are once and twice lagged centroid changes. The IV second stage can then be written as

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

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

This IV has several advantages. First, centroid changes directly address reverse causality, since firms are mostly too small to impact industry centroids by their own patenting behavior. At the same time, centroid changes reflect patenting by a firm's industry rivals and therefore generate an incentive by the focal firm to respond. Additionally, we provide further results in the online appendix showing that our main results are robust to using more aggregate industry classification (Table A04) or using "leave-out centroid" changes (Table A05) as instruments. 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, which states that IV estimates will only be unbiased if centroid changes do not directly impact performance at the focal firm. Formally, the exclusion restriction states that

$$Cov(\Delta C_{s,t-1}, \epsilon_{i,t}) = 0 \quad (5)$$
$$Cov(\Delta C_{s,t-2}, \epsilon_{i,t}) = 0$$

It is well known, that IV exclusion restrictions are not testable (see Angrist and Pischke, 2009). However, in our case, any centroid changes are driven by changes in patenting direction of industry rivals, which they would only pursue if it benefits them. But innovations that benefit rival firms are likely to hurt the focal firm on average, e.g. $Cov(\Delta C_{s,t-1}, \epsilon_{i,t}) < 0$, which in turn biases IV results against finding a positive performance impact of technological uniqueness at the focal firm.

The main disadvantage of our baseline centroid-IV in (3) and (4) is that we cannot use a full set of industry-by-year fixed effects, as this tends to remove much of the identifying variation of industry level centroid changes. We therefore check the robustness of our IV results using a shift-share (or "Bartik") IV, based on the idea that firms in locations with high local clustering of other firms in the same industry will tend to pay more attention to industry centroid changes. Exogeneity of local industry shares is also used by recent work in labor economics, as described by Goldsmith-Pinkham et al. 2020. First stage of the shift-share identification strategy becomes

$$TU_{i,t} = \varphi \cdot \left(s_{s,l} \times \Delta C_{s,t-1}\right) + controls_{i,t} + D_i + D_s \times D_t + D_l \times D_t + e_{i,t} \tag{6}$$

where $s_{s,l}$ are initial industry shares in terms of revenue in location l. Importantly, the use of the shift share IV allows us to add a full set of industry-by-year fixed effects $D_s \times D_t$, as the identifying variation in the first stage (6) and the second stage (4), as the IV estimation now relies on the interaction of industry shocks and local cross-sectional variation.

4.3 Responses to Shocks

Hypothesis 2 is directly testable using the following interaction regression:

$$y_{i,t} = \psi_1 \cdot TU_{i,t} + \psi_2 \cdot \left(TU_{i,t} \times \xi_{i,t}\right) + \psi_3 \cdot \xi_{i,t} + D_i + controls_{i,t} + D_l \times D_t + \epsilon_{i,t} \tag{7}$$

Where D_i are firm fixed effects, $D_l \times D_t$ is a full set of location-by-year fixed effects and $\xi_{i,t}$ are measures of technology shocks. For Hypothesis 2, $\xi_{i,t}$ measures technology spillover shocks, and we will also investigate technological differentiation shocks, both discussed in section 3.2.

4.4 Analyst Regressions and Cost of Capital

The analyst coverage and analyst effort regressions take the form

$$A_{i,t} = \delta \cdot TU_{i,t} + controls_{i,t} + D_i + D_s \times D_t + D_l \times D_t + \epsilon_{i,t} \tag{8}$$

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 (5), 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 (8) where analyst attention is the dependent variable.

In addition to the OLS specifications in (8), 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:

$$\ln\left(\frac{h_i(t)}{h_{i,0}(t)}\right) = \phi \cdot TU_i + controls_i + u_i \tag{9}$$

where $h_i(t)$ is a hazard function, capturing the probability of the event (analyst beginning coverage of firm i or analyst dropping 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 (8), 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:

$$\begin{aligned} r_{i,t} = \kappa_1 \cdot TU_{i,t} + \kappa_2 \cdot \left(A_{i,t} \times TU_{i,t}\right) + \kappa_3 \cdot A_{i,t} + controls_{i,t} + D_i + D_s \times D_t \\ + D_l \times D_t + \epsilon_{i,t} \end{aligned} \tag{10}$$

Where $A_{i,t}$ denotes changes in analyst coverage from (8) 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 from Hypothesis 3 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 following Hypothesis 1 and analyzing the correlation of firm performance and technological uniqueness in Table 3.

[Table 3]

The main result from Table 3 is that firms with unique technologies consistently outperform. They 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 2.4% higher sales growth rate, a 6.8% higher Tobin's Q, and 0.7% higher profitability and ROA per year—all rather economically significant relationships.

Although the results in Table 3 are not causal, they are remarkably robust, as we remove 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 that unobservable, omitted and time-varying firm-level factors might drive the correlation of firm performance and technological uniqueness, the results in Table 3 suggest that technological uniqueness is a robust predictor of firm performance. As such, it should be used by equity analysts to forecast performance of publicly traded firms.

As discussed in section 2, a key prediction of the resource-based view (Barney, 1991) is that costly imitation implies that competitive advantage is persistent. Table 3 shows that firms which increase their technological uniqueness also 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 the competitive advantage associated with technological uniqueness is very persistent. Performance improvements associated with higher technological uniqueness are statistically significant even 4-5 years after the increase in technological uniqueness. These results raise the question of whether and how technological uniqueness helps to sustain competitive advantage. We approach this question in two steps. In section 5.2 and 5.3 we offer a deeper investigation of whether technological uniqueness causes performance improvements and analyze the mechanism of how firms benefit from being technologically unique. In sections 5.4 and 5.5 we will then investigate costs of technological uniqueness that can act as a barrier to imitation, thereby contributing to the sustainability of competitive advantage.

5.2 Causal Performance Effects from Technological Uniqueness

Table 5 displays our main results from our IV strategy discussed in section 4.2. The first column confirms that centroid changes are indeed relevant instruments.

[Table 5]

The remaining columns then show that higher technological uniqueness causes better firm performance. Throughout the table, the IV results are qualitatively consistent with our OLS results from Table 3. In addition, the magnitudes of the IV coefficients are an order of magnitude larger than the OLS results. There are at least two reasons for why the IV estimated performance effects are larger than the corresponding OLS results. On the one hand, our measure of technological uniqueness is likely to be subject to classical measurement error, which implies attenuation of estimated regression coefficients towards zero (see Angrist and Pischke, 2009). On the other hand, the quantitative differences between IV and OLS are likely too large to be explained by measurement error alone. Instead, the difference between OLS and IV results is likely driven by the omission of time-varying firm-specific omitted variables, as discussed in section 4.2. In this context, our results imply that OLS is biased downwards as would be the case if there is a time-varying firm-level variable that is positively correlated with technological uniqueness but negatively correlated with current performance. As we argued in section 4.2, one such variable could be the relative importance of exploration or exploitation, which is time-varying, if firms follow vacillating pattern of emphasizing exploration, then exploitation, as described in Boumgarden, Nickerson, and Zenger (2012), Nickerson and Zenger (2002), and Yen et al. (2022).

5.3 The Mechanism Driving Performance Effects

In this section we explore further explore the mechanism through which technological uniqueness increases firm performance. In particular, we explore if in pursuing technological uniqueness, firms are benefiting from 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 of competitors should reduce the focal firm's performance. 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 competitors will leave the focal firm unaffected.

[Table 6]

As Table 6 shows, the main effect of increased technological differentiation[12] 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. As before, in practice, technological uniqueness is likely to affect competitive advantage through both, vertical and

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

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 normalized the competitive technological differentiation shocks to have a unit standard deviation. As a result, Table 6 shows that a one standard deviation increase in technological differentiation at competing firms implies 1.8% lower sales growth and 1.3% lower profitability. A somewhat more surprising result is that competitive technological differentiation also leads to an increase in Tobin's Q. A possible explanation for this result might be that investors are positively surprised by a wider range of technological opportunities revealed by patenting in uncommon technology classes and that this effect outweighs the negative performance consequences for the focal firm.

The third row of Table 6 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.

5.4 Costs of Technological Uniqueness 1: Spillover-Barriers

Our first step in analyzing the persistence of competitive advantage for technologically unique firms follows from Hypothesis 2 and is shown in Table 7. As discussed in section 3.2, our technological spillover shocks capture in-bound technological spillovers from patenting of other firms in patent classes that the focal firm heavily cited in the prior four years.

[Table 7]

We find that technological spillover shocks consistently benefit the focal firm, as shown in the second row of Table 7. This result provides reassurance that our measurement of technological spillovers is correct, since the spillover shock has the theoretically correct sign and we saw in Table 6 that patenting by rival firms does not necessarily imply benefits, but often also leads to lower performance at the local firm. 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 normalized to have a unit standard deviation for ease of interpretation. Therefore, a one standard deviation increase in the spillover shock implies a 3.5% higher sales growth rate, a 9% higher Tobin's Q, a 1% higher profitability and a 0.6% higher ROA on an annual basis.

At the same time, Table 7 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 Table 7 shows that technologically unique firms benefit substantially less from technology spillovers. For example, the same one standard deviation spillover shock translates into only a 1.5% increase in sales growth for a firm with a one standard deviation higher technological uniqueness score ($0.0153 = 0.0355 - 0.0202$). Similarly, a firm with a one standard deviation higher technological uniqueness exhibits only a 3.36% increase in Tobin's Q compared the 9% increase for the average firm. The muted spillover effects also carry over to profitability and ROA. Overall these results are quantitatively sizeable 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. The results also confirm that technological uniqueness does tend to attenuate the benefits of technology spillovers, as lowers a firm's absorptive capacity, even if this effect does not dominate.

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

In this section we follow Hypothesis 3 and 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 8.

[Table 8]

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 8 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 less 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 8. 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 8 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 9]

Table 9 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 0.036% 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 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) are 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. We also extend our analysis to consider the implications of technological uniqueness for investment patterns.

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 10]

Table 10 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 10 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 business segments differ from the average business segments used by the firms in its industry.

[Table 11]

Table 11 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-basd 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. If technologically unique firms are really riskier, we would expect that technological uniqueness is positively correlated with these three forms of exit.

[Table 12]

Table 12 shows that there is no evidence for technological uniqueness being correlated with either form of exit from the Compustat data.

6.4 Investment Patterns of Technologically Unique Firms

Much of our analysis focused on documenting and understanding technological uniqueness as a resource and taking it as given. A potentially interesting extension of our analysis is to understand technological resources as starting point for the development and deployment of future resources and capabilities. Indeed, some work in finance, such as Sanford and Yang (2022) suggests that innovation creates growth options that can then be exercised via investments. A follow up question we can then analyze is: Is technological uniqueness correlated with higher investment and if so, which types of investment are affected?

To analyze these questions, we use the same control variables we discussed in section 3, but add two additional variables. First, we include Tobin's Q as control variable, as long-standing work in economics and finance has argued that it is a key predictor of investments (see Hayashi, 1982 and Abel and Eberly, 1994). Second, we add cash flow as a fraction of assets as a control variable, although there is a debate in finance whether this variable captures the influence of financial frictions (Fazzari et al., 1988) or is really a better measure of future profit opportunities than Tobin's Q (Alti, 2003).

[Table 13]

Table 13 collects our evidence on how technological uniqueness is correlated with investment patterns. As shown in column 1, more innovative firms as measured by technological uniqueness exhibit systematically higher capital expenditure. This is consistent with the idea that technological uniqueness creates growth opportunities that can then be implemented using capital expenditures (see Sanford and Yang, 2022). However, Table 13 goes further in establishing that a variety of different investment expenditures are affected. Specifically, technologically unique firms systematically invest more in R&D, which suggests that they create further innovation opportunities that they strive to exploit. Additionally, we consider SG&A as including measures of investment in organizational capital, as argued by Ewens, Peters, and Wang (2021). Our results in column 3 of Table 13 suggest that technologically unique firms also invest more heavily in organizational capital, which is consistent with the notion that innovation requires novel organizational forms to be properly implemented.

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 advantage is sustained because of two distinct mechanisms that make technological uniqueness costly to imitate for competitors. First, technological uniqueness can be challenging to evaluate by financial and product market participants, such as equity analysts, investors, and competitors (Barney, 1986; Benner & Zenger, 2016; Litov et al., 2012; R. P. Rumelt, 1984). Second, unique firms benefit less from technological spillovers (Bloom et al., 2013; Cohen & Levinthal, 1990).

Our work complements a recent empirical study by Arts, Cassiman and Hou (2021), who independently from us, develop a measure of technological differentiation based on patent text. and show that it is positively correlated with firm performance. We go further than Arts et al. (2021) by establishing causal effects of technological uniqueness, investigating the mechanisms driving our performance effects and documenting the costs of technological uniqueness, in terms of reduced spillovers and equity analyst coverage and increased costs of capital. 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. Importantly, this strategy has to be understood as ongoing and dynamic, as competitive advantages from technological uniqueness are persistent but ultimately anticipated to unravel.

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 & 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.

References

Abel, A. B., & Eberly, J. C. (1994). A Unified Model of Investment Under Uncertainty. *The American Economic Review*, *84*(5), 1369–1384.

Alti, A. (2003). How Sensitive is Investment to Cash Flow when Financing is Frictionless? *The Journal of Finance*, *58*(2), 707–722.

Angrist, J. D., & Pischke, J.-S. (2009). *Mostly Harmless Econometrics*. Princeton University Press.

Arts, S., Cassiman, B. and J. Hou. (2021). Technology Differentiation and Firm Performance. Harvard Business School Working Paper.

Asmussen, C. G. (2015). Strategic Factor Markets, Scale Free Resources, and Economic Performance: The Impact of Product Market Rivalry. *Strategic Management Journal*, *36*(12), 1826–1844.

Barney, J. B. (1986). Organizational Culture: Can It Be a Source of Sustained Competitive Advantage? *Academy of Management Review. Academy of Management*, *11*(3), 656–665.

Barney, J. B. (1991). Firm Resources and Sustained Competitive Advantage. *Journal of Management*, *17*(1), 99–120.

Barney, J. B. (1996). The Resource-Based Theory of the Firm. *Organization Science*, *7*(5), 469–469.

Barth, M. E., Kasznik, R., & McNichols, M. F. (2001). Analyst Coverage and Intangible Assets. *Journal of Accounting Research*, *39*(1), 1–34.

Becker, G. S. (1971). *Economic Theory*. Alfred A. Knopf.

Benner, M. J., & Zenger, T. (2016). The lemons problem in markets for strategy. *Strategy Science*, *1*(2), 71–89.

Bloom, N., & Van Reenen, J. (2007). Measuring and Explaining Management Practices Across Firms and Countries. *The Quarterly Journal of Economics*, *122*(4), 1351–1408.

Bloom, N., Schankerman, M., & Van Reenen, J. (2013). Identifying Technology Spillovers and Product Market Rivalry. *Econometrica*, *81*(4), 1347–1393.

Bloom, N., & Van Reenen, J. (2002). Patents, Real Options and Firm Performance. *The Economic Journal*, *112*(478), C97–C116.

Boumgarden, P., Nickerson, J., & Zenger, T. R. (2012). Sailing into the Wind: Exploring the Relationships Among Ambidexterity, Vacillation, and Organizational Performance. *Strategic Management Journal*, *33*(6), 587–610.

Claus, J., & Thomas, J. (2001). Equity Premia as Low as Three Percent? Evidence from Analysts' Earnings Forecasts for Domestic and International Stock Markets. *The Journal of Finance*, *56*(5), 1629–1666.

Cohen, W. M., & Levinthal, D. A. (1989). Innovation and Learning: The Two Faces of R&D. *Economic Journal (London, England)*, *99*(397), 569.

Cohen, W. M., & Levinthal, D. A. (1990). Absorptive Capacity: A New Perspective on Learning and Innovation. *Administrative Science Quarterly*, *35*(1), 128–152.

Costa, L. A., Cool, K., & Dierickx, I. (2013). The Competitive Implications of the Deployment of Unique Resources. *Strategic Management Journal*, *34*(4), 445–463.

Dong, R., Fisman, R., Wang, Y., & Xu, N. (2021). Air Pollution, Affect, and Forecasting Bias: Evidence from Chinese Financial Analysts. *Journal of Financial Economics*, *139*(3), 971–984.

Easton, P. D. (2004). PE Ratios, PEG Ratios, and Estimating the Implied Expected Rate of Return on Equity Capital. *The Accounting Review*, *79*(1), 73–95.

Ewens, M., Peters, R., & Wang, S. (2021). *Measuring Intangible Capital with Market Prices*.

Fazzari, S., Hubbard, R. G., & Petersen, B. (1988). Investment, Financing Decisions, and Tax Policy. *The American Economic Review*, *78*(2), 200–205.

Gebhardt, W. R., Lee, C. M. C., & Swaminathan, B. (2001). Toward an Implied Cost of Capital. *Journal of Accounting Research*, *39*(1), 135–176.

Griliches, Z. (1979). Issues in assessing the contribution of research and development to productivity growth. *The Bell Journal of Economics*, *10*(1), 92.

Guernsey, S., John, K., Litov, L. (2022). Actively Keeping Secrets from Creditors: Evidence from The Uniform Trade Secrets Act, *Journal of Financial and Quantitative Analysis*, forthcoming.

Hall, R. (1993). A Framework Linking Intangible Resources and Capabilities to Sustainable Competitive Advantage. *Strategic Management Journal*, *14*(8), 607–618.

Hamilton, B. H., & Nickerson, J. A. (2003). Correcting for Endogeneity in Strategic Management Research. *Strategic Organization*, *1*(1), 51–78.

Hayashi, F. (1982). Tobin's Marginal q and Average q: A Neoclassical Interpretation. *Econometrica: Journal of the Econometric Society*, *50*(1), 213–224.

Heath, D., & Mace, C. (2020). The Strategic Effects of Trademark Protection. *The Review of Financial Studies*, *33*(4), 1848–1877.

Hotelling, H. (1929). Stability in Competition. *Economic Journal* , *39*(153), 41–57.

Hsu, D. H., & Ziedonis, R. H. (2013). Resources as dual sources of advantage: Implications for valuing entrepreneurial-firm patents. *Strategic Management Journal*, *34*(7), 761–781.

Jackson, A. R. (2005). Trade generation, reputation, and sell-side analysts. *The Journal of Finance*, *60*(2), 673–717.

Jaffe, A. B. (1986). Technological Opportunity and Spillovers of R&D: Evidence from Firms ' Patents, Profits, and Market Value. *American Economic Review*, *76*(5), 984–1001.

Jaffe, A. B., Trajtenberg, M., & Fogarty, M. S. (2000). Knowledge spillovers and patent citations: Evidence from a survey of inventors. *The American Economic Review*, *90*(2), 215–218.

Kogan, L., Papanikolaou, D., Seru, A., & Stoffman, N. (2017). Technological innovation, resource allocation, and growth. *The Quarterly Journal of Economics*, *132*(2), 665–712.

Lippman, S. A., & Rumelt, R. P. (1982). Uncertain Imitability: An Analysis of Interfirm Differences in Efficiency under Competition. *The Bell Journal of Economics*, *13*(2), 418–438.

Litov, L. P., Moreton, P., & Zenger, T. R. (2012). Corporate strategy, analyst coverage, and the uniqueness paradox. *Management Science*, *58*(10), 1797–1815.

Makadok, R. (2010). The Interaction Effect of Rivalry Restraint and Competitive Advantage on Profit: Why the Whole Is Less Than the Sum of the Parts. *Management Science*, *56*(2), 356–372.

Makadok, R. (2011). Invited Editorial: The Four Theories of Profit and Their Joint Effects. *Journal of Management*, *37*(5), 1316–1334.

Makadok, R., & Ross, D. G. (2013). Taking Industry Structuring Seriously: A Strategic Perspective on Product Differentiation. *Strategic Management Journal*, *34*(5), 509–532.

March, J. G. (1991). Exploration and Exploitation in Organizational Learning. *Organization Science*, *2*(1), 71–87.

Markman, G. D., Espina, M. I., & Phan, P. H. (2004). Patents as Surrogates for Inimitable and Non-Substitutable Resources. *Journal of Management*, *30*(4), 529–544.

Marshall, A. (1890). *Principles of Economics*. Macmillan.

Nickerson, J. A., & Zenger, T. R. (2002). Being Efficiently Fickle: A Dynamic Theory of Organizational Choice. *Organization Science*, *13*(5), 547–566.

Oehmichen, J., Firk, S., Wolff, M., & Maybuechen, F. (2021). Standing out from the crowd: Dedicated institutional investors and strategy uniqueness. *Strategic Management Journal*, *42*(6), 1083–1108.

Ohlson, J. A., & Juettner-Nauroth, B. E. (2005). Expected EPS and EPS Growth as Determinants of Value. *Review of Accounting Studies*, *10*(2–3), 349–365.

Penrose, E. T. (1959). *The Theory of the Growth of the Firm*. Oxford Academic.

Peteraf, M. A. (1993). The Cornerstones of Competitive Advantage: A Resource-Based View. *Strategic Management Journal*, *14*(3), 179–191.

Porter, M. E. (1996). What is Strategy? *Harvard Business Review*, *74*, 61–78.

Prahalad, C. K., & Hamel, G. (1990, May 1). The Core Competence of the Corporation. *Harvard Business Review*.

Ricardo, D. (1817). *On the Principles of Political Economy and Taxation*. John Murray.

Rivkin, J. W. (2000). Imitation of Complex Strategies. *Management Science*, *46*(6), 824–844.

Romer, P. M. (1990). Endogenous Technological Change. *The Journal of Political Economy*, *98*(5, Part 2), S71–S102.

Rubin, P. H. (1973). The Expansion of Firms. *The Journal of Political Economy*, *81*(4), 936–949.

Rumelt, R. P. (1984). Towards a Strategic Theory of the Firm. *Competitive Strategic Management*, *26*(3), 556–570.

Sanford, A., & Yang, M.-J. (2022). Corporate investment and growth opportunities: The role of R&D-capital complementarity. *Journal of Corporate Finance*, *72*, 102130.

Sarnecka, D., & Pisano, G., (2021) The Evolutionary Nature of Breakthrough Innovation: Re-Evaluating the Exploration vs. Exploitation, Academy of Management Proceedings, Vol, 2021, No.1.

Schankerman, M. (1991). How Valuable is Patent Protection?: Estimates by Technology Field Using Patent Renewal Data. *Rand J. Econ.*, *29*(1), 77–107.

Schumpeter, J. A. (1942). Creative Destruction. *Capitalism, Socialism and Democracy*, *36*, 132–145.

Shaked, A., & Sutton, J. (1982). Relaxing price competition through product differentiation. *The Review of Economic Studies*, *49*(1), 3.

Wernerfelt, B. (1984). A Resource-Based View of the Firm. *Strategic Management Journal*, *5*(2), 171–180.

Yang, M.-J., Li, N., & Kueng, L. (2021). The Impact of Emerging Market Competition on Innovation and Business Strategy: Evidence from Canada. *Journal of Economic Behavior & Organization*, *181*, 117–134.

Yen, C. J., Yang, M.-J., Nickerson, J., & Zenger, T. (2022). Leadership Vacillation as a Pattern of CEO Succession. *Working Paper*

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**	
	Technological Uniqueness Score (S)	**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)	-0.13	-0.21	0.96	-1.48	1.84
Industry Centroid	-0.19	-0.37	0.50	-0.57	2.45
Sales Growth (1-year)	0.12	0.08	0.33	-0.48	1.44
Tobin's Q	2.15	1.61	1.53	0.71	7.84
Profitability	0.03	0.09	0.20	-0.76	0.29
ROA	-0.02	0.04	0.21	-0.86	0.24
Sales ($) (log)	5.55	5.56	2.13	0.63	9.79
Sales Growth (past three years)	0.08	0.05	0.18	-0.27	0.77
Earnings Coef. of Variation	1.66	0.87	2.13	0.05	10.43
# of firms in industry (GIND)	226.05	210	104.82	37	484
Number of Shareholders (log)	3.48	3.37	1.21	1.43	6.35
Dummy variable *Segment 1*	0.13	0.00	0.34	0	1
Dummy variable *Segment 2*	0.52	1.00	0.50	0	1
Dummy variable *Segment 3*	0.10	0.00	0.29	0	1
Dummy variable *Segment 4*	0.25	0.00	0.43	0	1
Average market share	0.17	0.13	0.12	0.04	0.54
Average HHI	0.06	0.01	0.10	0.00	0.45
R&D Intensity	0.14	0.07	0.18	0.00	0.77
Advertising Intensity	0.01	0.00	0.02	0.00	0.10
Intangible Assets	0.10	0.04	0.14	0.00	0.52
B: Equity Analyst Analysis					
Adjusted Coverage	0.01	0.01	0.02	0.00	0.35
Analyst Coverage Dummy	0.67	1	0.47	0	1
Technology Uniqueness (Standardized)	-0.06	-0.15	0.99	-1.48	1.84
Analyst Effort	-6.66	-6.00	4.06	-47.00	0
Analyst Attention	9.21	6	8.83	1	62
Assets (log)	5.92	5.75	1.87	0.72	12.72
Market-Book	3.89	2.44	5.60	-18.84	68.95
Intangible Assets	0.13	0.04	0.18	0.00	0.91
Volatility	0.04	0.03	0.04	0.00	0.43
Share Turnover (log)	14.04	14.08	0.92	9.08	17.47
Return	0.17	0.07	0.64	-0.90	6.52
C: Technology Shocks and Cost of Capital					
Knowledge Spillover Shock (non-standardized)	7.34	7.56	2.16	0.00	13.23
Competitive Shock (non-standardized)	8.78	8.97	1.57	2.29	12.66
Cost of Capital (Claus and Thomas, 2001)	0.08	0.08	0.05	0.00	0.85
Cost of Capital (Gebhardt et al, 2001)	0.08	0.08	0.03	0.00	0.49
Cost of Capital (Easton, 2004)	0.11	0.10	0.05	0.00	0.57
Cost of Capital (Ohlson and Juettner-Nauroth, 2005)	0.11	0.11	0.04	0.01	0.66
Analyst Coverage Loss	-9.70	-6.00	9.30	-62	-1

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	0.0244***	0.0683***	0.00727***	0.00720***
	(0.005)	(0.019)	(0.002)	(0.002)
Sales (log)	0.168***	-0.217***	0.0905***	0.0773***
	(0.008)	(0.028)	(0.003)	(0.003)
Sales Growth (past three years)	-0.262***	0.430***	0.0244***	0.013
	(0.025)	(0.075)	(0.008)	(0.010)
R&D intensity	-0.115*	0.0825	-0.155***	-0.311***
	(0.066)	(0.230)	(0.024)	(0.029)
Advertising intensity	0.464*	1.06	-0.295**	-0.391***
	(0.270)	(1.105)	(0.116)	(0.130)
Intangibles/assets	0.175***	-1.705***	-0.0594***	-0.113***
	(0.033)	(0.117)	(0.012)	(0.014)
CV Earnings	-0.00196**	-0.0244***	-0.00116***	-0.00106**
	(0.001)	(0.003)	(0.000)	(0.000)
Number of Shareholders (log)	-0.0784***	0.455***	-0.0370***	-0.0355***
	(0.008)	(0.031)	(0.003)	(0.004)
Business segments: 2	-0.00558	-0.196***	-0.00168	-0.00741
	(0.016)	(0.054)	(0.005)	(0.006)
Business segments: 3	-0.0330*	-0.242***	-0.0237***	-0.0301***
	(0.018)	(0.060)	(0.006)	(0.007)
Business segments: 4 or more	-0.0246	-0.257***	-0.0282***	-0.0329***
	(0.018)	(0.060)	(0.006)	(0.007)
Average Market Share	-0.175***	-0.141	-0.0966***	-0.0871***
	(0.051)	(0.144)	(0.016)	(0.018)
MMCI	0.0235	-0.0883	-0.0142	-0.0317*
	(0.042)	(0.137)	(0.016)	(0.018)
Firm FE	YES	YES	YES	YES
Industry-by-Year FE	YES	YES	YES	YES
Region-by-Year FE	YES	YES	YES	YES
R-squared	0.075	0.051	0.182	0.123
Observations	25,845	25,845	25,845	25,845

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. Average market share measures the sales-weighted market share of firm across all its business segments. MMCI is the sales-weighted average of industry concentration (Herfindahl index) across all business segments the firm is active in. Newey-West standard errors use 3 lags 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	0.0244***	0.00631	0.00846*	0.00443	0.00883*	0.0136**
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Controls			See Table Notes			
Observations	25,845	22,233	19,781	17,749	16,112	14,602

	Panel B: Tobin's Q					
	t	t+1	t+2	t+3	t+4	t+5
Technology Uniqueness	0.0683***	0.0500**	0.0232	0.00445	-0.0015	0.0145
	(0.019)	(0.021)	(0.021)	(0.022)	(0.023)	(0.024)
Controls			See Table Notes			
Observations	25,845	22,245	19,815	17,794	16,161	14,655

	Panel C: Profitability					
	t	t+1	t+2	t+3	t+4	t+5
Technology Uniqueness	0.00727***	0.00574**	0.00570**	0.00538**	0.00522**	0.00
	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)
Controls			See Table Notes			
Observations	25,845	22,285	19,848	17,823	16,178	14,667

	Panel D: ROA					
	t	t+1	t+2	t+3	t+4	t+5
Technology Uniqueness	0.00720***	0.00751***	0.00650**	0.00587**	0.00514*	0.00177
	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Controls			See Table Notes			
Observations	25,845	22,285	19,848	17,823	16,178	14,667

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. Newey-West standard errors with 3 lags reported in parentheses. Statistical significance levels: *: 10%, **: 5%, ***: 1%.

Table 5: Causal estimates of Firm Performance Effects from Technological Uniqueness

Panel A: Lagged Centroid IV

Variable (end of prior fiscal year)	Technological Uniqueness	Sales Growth	Tobin's Q	Profitability	ROA
	OLS	IV	IV	IV	IV
Models	(1)	(2)	(3)	(4)	(5)
Technology Uniqueness		0.543***	1.817***	0.156***	0.161***
		(0.133)	(0.470)	(0.040)	(0.045)
Lag Centroid Uniqueness	0.0479***				
	(0.013)				
2nd Lag Centroid Uniqueness	0.0419***				
	(0.012)				
Firm FE	YES	YES	YES	YES	YES
Region-by-Year FE	YES	YES	YES	YES	YES
Cragg-Donald F-stat	25.78				
Kleibergen-Paap p-value	0.00				
Observations	25,845	25,845	25,845	25,845	25,845

Panel B: Bartik (Shift-Share) IV

Variable (end of prior fiscal year)	Technological Uniqueness	Sales Growth	Tobin's Q	Profitability	ROA
	OLS	IV	IV	IV	IV
Models	(1)	(2)	(3)	(4)	(5)
Technology Uniqueness		1.099***	0.977*	0.220***	0.151**
		(0.322)	(0.593)	(0.077)	(0.070)
Shift-Share IV1	0.490***				
	(0.133)				
Shift-Share IV2	-0.0111				
	(0.0352)				
Firm FE	YES	YES	YES	YES	YES
Industry-by-Year FE	YES	YES	YES	YES	YES
Region-by-Year FE	YES	YES	YES	YES	YES
Cragg-Donald F-stat	17.41				
Kleibergen-Paap p-value	0.00				
Observations	25,844	25,844	25,844	25,844	25,844

Notes: Technological uniqueness is measured as the normalized distance of the firm's patent portfolio from the average industry's patent portfolio (centroid). Panel A instruments used are the first two lags of the changes in the industry centroid patent portfolio. Panel B instruments are the Bartik-style shift-share measures which are the product of the first and second lag of state-level industry's revenue-shares and the industry centroid patent portfolio. The sample is restricted to only include patenting firms. Additional controls include 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. Newey-West standard errors use 3 lags and are reported in parentheses. Statistical significance levels: *: 10%, **: 5%, ***: 1%.

Table 6: 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	0.0285***	0.0949***	0.00909***	0.00932***
	(0.0050)	(0.0183)	(0.0019)	(0.0022)
Competitive Technological Differentiation	-0.0170**	0.116***	-0.0128***	-0.00710*
	(0.009)	(0.039)	(0.003)	(0.004)
Technological Uniqueness **X** Competitive Technological Differentiation	0.0121***	-0.00782	0.00143	0.000668
	(0.0044)	(0.017)	(0.0016)	(0.0019)
Additional controls	see table notes			
Firm FE	YES	YES	YES	YES
Region-by-year FE	YES	YES	YES	YES
R-squared	0.072	0.058	0.201	0.137
Observations	25,360	25,360	25,360	25,360

Notes: Technological uniqueness is measured as the normalized distance of the firm's patent portfolio from the average industry's patent portfolio (centroid). 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. Additional control variables include 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. The sample is restricted to only include patenting firms. Newey-West standard errors with 3 lags are reported in parentheses. Statistical significance levels: *: 10%, **: 5%, ***: 1%.

Table 7: Technological Uniqueness as Spillover Barrier

Variable (end of prior fiscal year)	**Sales Growth**	**Tobin's Q**	**Profitability**	**ROA**
	OLS	OLS	OLS	OLS
	(1)	(2)	(3)	(4)
Technological Uniqueness	0.0293***	0.0915***	0.00925***	0.00945***
	(0.0050)	(0.0186)	(0.0019)	(0.0022)
Technology Spillover	0.0355***	0.0898***	0.0105***	0.00646***
	(0.005)	(0.018)	(0.002)	(0.002)
Technology Spillover **X** Technological Uniqueness	-0.0201***	-0.0589***	-0.00582***	-0.00417***
	(0.0041)	(0.014)	(0.0014)	(0.0016)
Additional controls	see table notes			
Firm FE	YES	YES	YES	YES
Region-by-year FE	YES	YES	YES	YES
R-squared	0.075	0.060	0.203	0.137
Observations	25360	25360	25360	25360

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. 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. Additional control variables include 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. The sample is restricted to only include patenting firms. Newey-West standard errors with 3 lags are reported in parentheses. Statistical significance levels: *: 10%, **: 5%, ***: 1%.

Table 8: 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: 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 9: 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	0.00192*	0.00132**	0.000865	0.00159**
	(0.00107)	(0.00053)	(0.00096)	(0.00079)
Analyst Coverage Loss	0.000293***	0.00	-0.0000989	-0.000112
	(0.00009)	(0.00005)	(0.00009)	(0.00007)
Technological Uniqueness X Analyst Coverage Loss	0.000369***	0.000239***	0.000255***	0.000246***
	(0.00006)	(0.00004)	(0.00006)	(0.00005)
Sales (log)	-0.0113***	0.000532	-0.00770***	-0.00536***
	(0.001)	(0.001)	(0.001)	(0.001)
Sales Growth (past three years)	0.00290	-0.00740***	-0.0150***	-0.00732***
	(0.003)	(0.002)	(0.003)	(0.003)
R&D intensity	-0.00808	-0.00949	-0.0016	-0.00479
	(0.008)	(0.006)	(0.008)	(0.006)
Advertising intensity	0.0818**	0.0364	0.0578*	0.0400
	(0.035)	(0.022)	(0.032)	(0.026)
Intangibles/assets	0.00318	0.0121***	0.00455	0.00567*
	(0.004)	(0.002)	(0.004)	(0.003)
CV Earnings	0.0001070	0.000178**	0.000353**	0.000290**
	(0.00017)	(0.00009)	(0.00017)	(0.00014)
Number of Shareholders (log)	0.0327***	0.00840***	0.0250***	0.0177***
	(0.001)	(0.001)	(0.001)	(0.001)
Business segments: 2	-0.00233	0.00195*	0.000554	0.00168
	(0.002)	(0.001)	(0.002)	(0.002)
Business segments: 3	-0.00208	0.00215*	0.00387	0.00396**
	(0.003)	(0.001)	(0.003)	(0.002)
Business segments: 4 or more	0.00158	0.00337**	0.00738***	0.00656***
	(0.003)	(0.001)	(0.003)	(0.002)
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	16,749	16,883	16,290	16,617

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. Newey-West standard errors with 3 lags in parentheses. Statistical significance levels: *: 10%, **: 5%, ***: 1%.

Table 10: 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	0.0272***	0.0668***	0.00713***	0.00804***
	(0.00511)	(0.0189)	(0.00199)	(0.00225)
Number of Patents (1000)	-0.0573***	-0.357***	-0.00979*	0.000634
	(0.0153)	(0.0665)	(0.00506)	(0.00668)
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	0.0768	0.0566	0.182	0.123
Observations	24819	24819	24819	24819

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	0.0281***	0.0750***	0.00731***	0.00805***
	(0.00511)	(0.0189)	(0.00199)	(0.00224)
Value of Patents ($10K)	-0.0290***	0.0783*	-0.00203	0.00269
	(0.00922)	(0.0411)	(0.00314)	(0.00356)
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	0.08	0.05	0.18	0.12
Observations	24,819	24,819	24,819	24,819

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. Newey-West standard errors use 3 lags and are reported in parentheses. Statistical significance levels: *: 10%, **: 5%, ***: 1%.

Table 11: 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	0.0281***	0.0826***	0.00789***	0.00818***
	(0.0056)	(0.0212)	(0.0022)	(0.0025)
Product Uniqueness	-0.021	-0.046	0.015	0.010
	(0.0283)	(0.0957)	(0.0102)	(0.0121)
Sales (log)	0.168***	-0.227***	0.0967***	0.0830***
	(0.0088)	(0.0304)	(0.0033)	(0.0038)
Sales Growth (past three years)	-0.266***	0.446***	0.0189**	0.00652
	(0.0264)	(0.0776)	(0.0086)	(0.0099)
R&D intensity	-0.099	0.016	-0.143***	-0.303***
	(0.0677)	(0.2340)	(0.0237)	(0.0291)
Advertising intensity	0.499*	1.412	-0.279**	-0.397***
	(0.3010)	(1.2400)	(0.1300)	(0.1470)
Intangibles/assets	0.192***	-1.691***	-0.0615***	-0.122***
	(0.0355)	(0.1250)	(0.0125)	(0.0154)
CV Earnings	-0.001690	-0.0250***	-0.00110***	-0.000998**
	(0.0011)	(0.0036)	(0.0004)	(0.0005)
Number of Shareholders (log)	-0.0748***	0.464***	-0.0395***	-0.0378***
	(0.0089)	(0.0338)	(0.0035)	(0.0041)
Business segments: 2	-0.00103	-0.188***	-0.00271	-0.00908
	(0.0167)	(0.0567)	(0.0057)	(0.0068)
Business segments: 3	-0.0322*	-0.235***	-0.0256***	-0.0339***
	(0.0190)	(0.0645)	(0.0066)	(0.0079)
Business segments: 4 or more	-0.027	-0.228***	-0.0311***	-0.0366***
	(0.0193)	(0.0644)	(0.0066)	(0.0079)
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	0.07	0.05	0.19	0.13
Observations	22,988	22,988	22,988	22,988

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. Newey-West standard errors use 3 lags and are reported in parentheses. Statistical significance levels: *: 10%, **: 5%, ***: 1%.

Table 12: Exit and Survivorship Bias

Variable (end of prior fiscal year)	Bankruptcy	LBO	Acquisition
	OLS	OLS	OLS
Models	(1)	(2)	(3)
Technological Uniqueness	0.000432	-0.0000972	-0.00333
	(0.00058)	(0.00042)	(0.00248)
Sales (log)	-0.00243***	-0.000544**	0.0000732
	(0.00080)	(0.00024)	(0.00279)
Sales Growth (past three years)	0.00425*	0.00	-0.0158*
	(0.00253)	(0.00065)	(0.00814)
R&D intensity	-0.0143**	-0.00418	-0.0701***
	(0.00718)	(0.00260)	(0.02020)
Advertising intensity	-0.0396*	-0.02	-0.10
	(0.02200)	(0.01390)	(0.11200)
Intangibles/assets	-0.00129	-0.000417	-0.0103
	(0.00197)	(0.00142)	(0.01430)
CV Earnings	0.000041	0.0000566	0.00106*
	(0.00012)	(0.00011)	(0.00062)
Number of Shareholders (log)	0.00107	-0.000263	-0.0152***
	(0.00086)	(0.00022)	(0.00352)
Business segments: 2	0.00269	0.00022	0.00732
	(0.00216)	(0.00029)	(0.00644)
Business segments: 3	0.00223	0.000435	0.00146
	(0.00224)	(0.00063)	(0.00800)
Business segments: 4 or more	0.00171	0.0000863	-0.000708
	(0.00207)	(0.00051)	(0.00791)
Average Market Share	0.00441	0.005	-0.0155
	(0.00503)	(0.00478)	(0.02790)
MMCI	0.00090	-0.00117	-0.00189
	(0.00359)	(0.00386)	(0.01980)
Firm FE	YES	YES	YES
Industry-by-Year FE	YES	YES	YES
Region-by-Year FE	YES	YES	YES
R-squared	0.276	0.28	0.231
Observations	25,845	25,845	25,845

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. Newey-West standard errors use 3 lags and are reported in parentheses. Statistical significance levels: *: 10%, **: 5%, ***: 1%.

Table 13: Technological Uniqueness and Investment

Variable (end of prior fiscal year)	**Capex/Assets**	**R&D intensity**	**SGA intensity**	**Advertising intensity**
	OLS	OLS	OLS	OLS
Models	(1)	(2)	(3)	(4)
Technological Uniqueness	0.00970**	0.102***	0.0306**	0.00465
	(0.00437)	(0.03750)	(0.01410)	(0.00334)
Tobin's Q	0.00684*	0.0736**	0.0436***	0.00430***
	(0.00382)	(0.02980)	(0.01090)	(0.00109)
Cash flow / assets (log)	-0.0617**	-1.097***	-0.528***	-0.0635***
	(0.02890)	(0.22000)	(0.08920)	(0.01440)
Sales (log)	-0.0518***	-0.711***	-0.0591**	-0.000732
	(0.00971)	(0.08830)	(0.02860)	(0.00333)
Sales Growth (past three years)	-0.181***	-2.612***	-0.0857	-0.01
	(0.03540)	(0.25800)	(0.08650)	(0.01150)
Intangibles as fraction of assets	0.0625**	0.731***	0.289***	0.0172
	(0.02770)	(0.24300)	(0.08970)	(0.01240)
CV Earnings	-0.00253***	-0.0247***	-0.00280**	-0.0000451
	(0.00050)	(0.00413)	(0.00129)	(0.00018)
Number of Shareholders (log)	0.0287***	0.379***	0.00633	-0.000235
	(0.00981)	(0.08780)	(0.02420)	(0.00265)
Business segments: 2	0.0359**	0.149	-0.0555	0.0081
	(0.01570)	(0.11100)	(0.04840)	(0.00502)
Business segments: 3	0.0444***	0.250**	-0.0256	0.00766
	(0.01620)	(0.11300)	(0.04970)	(0.00513)
Business segments: 4 or more	0.0471***	0.281**	0.00383	0.00661
	(0.01700)	(0.12000)	(0.05100)	(0.00525)
Average Market Share	0.134***	1.494***	0.0185	0.00503
	(0.02610)	(0.22800)	(0.08850)	(0.01130)
MMCI	-0.0591**	-0.395	0.0685	-0.00166
	(0.02630)	(0.26100)	(0.11400)	(0.01100)
Firm FE	YES	YES	YES	YES
Industry-by-Year FE	YES	YES	YES	YES
Region-by-Year FE	YES	YES	YES	YES
R-squared	0.03	0.10	0.04	0.06
Observations	25,555	23,015	25,793	8,725

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. Newey-West standard errors use 3 lags and are reported in parentheses. Statistical significance levels: *: 10%, **: 5%, ***: 1%.