**Financial Distress and Risky Innovation**

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**Abstract**

We investigate the relation between financial distress and the riskiness of innovation as indicated by the degree to which new patents differ from a firm’s existing patent base. We find that firms with higher debt levels, less cash, a lower market-to-book ratio, or poorer past performance all subsequently choose more risky innovation. The effect is shown to be unrelated to financial constraints, per se, emphasizing the importance of anticipated financial distress. We also find that firms increase the riskiness of innovations just before they cease generating patents and also prior to being delisted. Our results suggest that firms moving toward financial distress shift their research activities toward more risky endeavors.

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When it comes to research and development, firms can safely exploit and refine existing technologies or engage in a more risky search for new technologies that can dramatically and positively transform their business. While a great deal of attention has been focused on how financial and governance characteristics affect the overall magnitude and efficiency of innovation activity, little attention has been given to the determinants of the balance between these two approaches – the degree to which firms pursue more risky innovation. Using a measure that captures the extent to which new patents represent a departure from the existing knowledge base of a firm, we explore whether firms facing financial distress shift the balance of their innovation toward more sure or more drastic alternatives.

The importance of innovation to a firm’s future performance has been documented extensively, though the level of risk associated with that innovation has been examined to a much smaller degree. The possibility that financial distress might drive firms to engage in risky behavior was first clearly articulated by Jensen and Meckling (1976), who pointed out that equity holders, being residual claimants, have an incentive to choose more risky investments over safer alternatives and thereby appropriate value from debt holders. In contrast, both Amihud and Lev (1981) and Goel and Thakor (2008) note that rational risk-averse managers will choose less risky investment decisions to hedge their employment risk and Myers (1977) suggests firms may underinvest if benefits accrue to debt holders. These early studies suggest that the degree of risk taking by a firm will be related to firm characteristics. Of course, firms may find optimal contracts that alleviate these concerns (see Anderson and Carverhill (2011) and work cited therein) and empirical evidence is inconclusive – a survey by Graham and Harvey (2001) found little concern for these issues, whereas Eisdorfer (2008) provides evidence of risk shifting for financially distressed firms.

We examine the riskiness of innovation using a large data set of patent holdings and a measure of riskiness based the degree to which new patents differ from a firm’s existing patent base.[[1]](#footnote-1) Our measure captures whether innovation is novel relative to past research, the degree of the shift toward the new activities, and adjusts for the magnitude of technology spillover that would be expected between new and past research activities. Our measure can be thought of as a measure of the “distance” between a firm’s new patents and its existing patent base where the location of patents is described in relation to the technological classes introduced by Hall et al. (2001).[[2]](#footnote-2) Specifically, we quantify the current distribution of a firm’s patents across these patent classes and then measure the degree of difference between this distribution and the analogous distribution calculated for new patents and adjusted for the expected degree of knowledge spillovers expected between patent classes (adjusted, therefore, for the “closeness” of patent classes). Data is available for our analysis from 1980 to 2002 and includes 22,136 firm-year observations spanning a wide range of public firms and industries.

We find that measures of financial distress – the degree of debt financing, the level of cash holdings, lower profitability, and lower Tobin’s Q – are positively associated with large distance between new patents and the existing patent base of a firm. Our results are robust along a number of dimensions: they hold for different innovation measurement horizons; if we only consider organic innovation and eliminate the impact of mergers; and under different statistical test specifications that account for distributional properties of our distance measure. We also control for financial constraints, per se, to distinguish between behaviors that might limit the extent of innovation (limit the magnitude of patent creation) and those that might give rise to a desire to increase the risk of innovation.

We supplement the above cross-sectional results with an analysis of the time series of innovation choices. Financial distress is associated with detrimental changes in firm characteristics. We examine a subsample of firms with long patent histories who then cease patenting. Of those cessations, some are associated with subsequent mergers or acquisitions and other delisted from a stock exchange due to poor performance. Given the importance of patenting to the firms, cessation of patenting itself is a likely sign of financial distress. We find that the in the sample of cessations that are followed by a delisting and the simple cessations are associated with statistically significant increases in innovation risk the year before (and in some cases two years before) the cessation. There is no evidence of such a change for the merged and acquired sample. Finally, we look at changes in other firm characteristics as the firms approach the cessation of patenting and find that for the two classifications with increased innovation risk, firm performance is declining.

In the process of examining the effects of financial distress, we document a variety of other relations between firm characteristics and the degree of innovation. We find that larger firms, firms with more subsidiaries, and firms with more diverse subsidiaries also tend to pursue more risky innovation.[[3]](#footnote-3) The results on size confirm the expectation that large firms, being more diversified, can withstand more extreme innovation (Henderson and Cockburn, 1996). The results also support the studies of innovation based on optimal search that suggest more complex firms will search more widely for innovations (Kauffman 1993, Kauffman et al. 2000). The results are inconsistent with the possibility that bounded rationality (Nelson and Winter 1982) or informational asymmetries that accompany increased firm size (Stein 2002) will lead complex firms innovate within familiar territory.[[4]](#footnote-4)

Our results are related to a number of recent research streams. A number of papers have used patent data to explore and the level and quality of innovation (Manso (2010), Li (2011) and Hirshleifer, Hsu, and Li (2011)). Building on Aghion and Tirole’s (1994) observation that innovation may be most effectively encouraged by linking outcomes to incentives and organizing research in small, independent units, recent papers have explored the relation between innovation and mergers and acquisitions (for example Phillips and Zandanov (2011), Seru (2011), venture capital (for example, Kortum and Lerner (2000), Fulghieri and Sevilir (2009), Tian and Wang (2010)), and private equity (Lerner, Sorensen, and Stromberg (2010)). A long stream of literature investigates how financial constraints and access to resources affect capital expenditures and R&D investments (see, e.g., Weitzman (1979), Kaplan and Zingales (1997), and Scharfstein and Stein (2000), Hsu, Tian, Xu (2010)). These papers, as with many others, consider the aggregate level of innovation, as measured by research and development expenditures in early papers or the number and quality of patents in more recent papers, whereas we focus on the degree (the riskiness) of innovation.

Papers that examine the degree of innovation include Bhattacharya and Mookherjee (1986), Dasgupta and Maskin (1987), and Klette and de Meza (1986), who observe that competing firms facing a payoff that rewards a single winner may choose more risky innovation than they would in the absence of such competition, Amihud and Lev (1981), who suggest that diversifying mergers are taken by risk averse managers to hedge employment risk, and Gervais, Heaton, and Odean (2009), who note that overconfidence encourages a risk-averse manager to take riskier projects, which reduces the cost of providing compensation incentives to do so. While focused on issues related to the riskiness of firm investment, these studies do not address the impact of financial constraints on innovation.

The remainder of this paper is organized as follows. In Section 2 we discuss our data and define our distance measure. Section 3 provides details regarding our sample selection, data sources, and variables of interest. Section 4 and 5 proceed with our core analysis and robustness tests. Section 7 concludes the paper and offers a discussion of the results.

# Measuring the Degree (Riskiness) of Innovation

While we cannot observe the exact allocation of resources between various R&D activities we can observe the resulting patents. The patenting activity is considered by the literature (see, e.g., Jaffe(1986)) to be a close proxy of the pursued R&D activity. In this study we propose a measure of the degree (riskiness) of innovation that is based on the observable results of R&D activity (patents) at different points in time. We build upon intuition provided by Stuart and Podolny (1996) and Jaffe (1986) who evaluate the distance between firms or industries via analysis of patents in different technological classes defined by USPTO and/or Hall et al (2001). We characterize innovation by measuring the degree of change in the composition of the patent portfolio from the perspective of technological knowledge at different points in time exploiting the NBER data that categorizes all patents into 37 two-digit technological classes developed by Hall et al. (2001). Our measure acknowledges both the distribution of patents across different classes as well as the degree of relatedness of patent classes.

First, we represent the patent activity of a firm as a column vector equal in length to the number of technological classes where each element reflects the proportion of patents in that patent class. Specifically, we let  be the column vector characterizing the composition of firm *i*’s existing patent portfolio in year , and  the column vector that characterizes the composition of firm *i*’s new (innovation) patent portfolio in year *t*. Element *j* of the each vector is equal to the percentage of patents in technology class *j* at time *t*. In the case of the patents used to construct the weight are the sum of patents over the previous five years.

Second, we construct a matrix which represents the degree of relatedness between patent classes. In particular, the matrix *Rt* is a 37 by 37 matrix where each element *rkl* represents the proportion of all patent citations in technological class *l* that cite patent class *k*:

|  |  |
| --- | --- |
|  | (1) |

We are therefore using the degree of patent citations as in indicator of relatedness. The relatedness matrix is updated as of time *t*. [[5]](#footnote-5)

Third, we construct our riskiness measure at time *t*, which we denote as *di,t* since it is a variant of Euclidean distance.[[6]](#footnote-6) This measure is defined as

|  |  |
| --- | --- |
|  | (2) |

This measure captures the how a firm’s patent portfolio is evolving over time. It allows us to gauge the extent to which a firm is venturing into new technological areas while acknowledging the relatedness of those areas – that technological classes are not independent and have significant knowledge spillover. We can therefore discriminate between firms that venture into a completely new patent class (e.g., a software firm venturing from computers into transportation) and firms that venture into a related area (e.g., a chemical company that ventures from organic compounds to resins).

An intuitive way to interpret the distance measure is as follows. Each column of the matrix *Rt* represents the composition of knowledge necessary to produce a patent in a respective technological class. The product  represents total knowledge accumulated by a firm as a result of its R&D/patenting activity and  represents knowledge necessary to generate the innovation/new patents. Our measure of the degree of innovation measures the distance between these knowledge bases.

Figure 1 plots the *Rt* matrix in a form of a heat map. To compute *Rt* we utilize over 3.2 million citations for more than 1.5 million patents issued between 1976-1999 and available through the NBER patent database.[[7]](#footnote-7) In our core results we compute *Rt* dynamically for 37 NBER technological classes defined by Hall et al. (2001). For each year we use the past five years of citation data to compute the elements of *Rt*. One can see that while most citations take place within one technological class, a significant share of citations (sometimes up to 30%) take place between technological classes. This emphasizes that some technological classes cannot be considered unrelated to one another. Overall, the rolling nature of the *Rt* matrix allows us to account for the changing landscape of technological knowledge while providing a steady measure of interrelatedness.

We present a detailed example of technological search distance calculations in the Appendix. It illustrates that while our new distance measure builds on the work of Stuart and Podolny (1996) and Jaffe(1986), we further the approach and propose a measure that allows to capture not only the direction of the patenting across technological classes but also the depth and inter-relatedness of such activities.

# Data and Sample Selection

Following the methodology above we measure technological search distance for U.S. public corporations based on the NBER patent data for firms that applied for at least one patent between 1980-2002. Our sample contains 1,022,478 such patents and spans a wide variety of industries ranging from electronics and medical equipment to business services and pharmaceuticals. We limit our sample to firm-year observations dated between 1980 and 2002 for two reasons. First, in order to build a robust *Rt* matrix we need sufficient past citation history prior to 1980. Second, we are hesitant to expand our sample beyond 2002 because the NBER data suffers from truncation bias in more recent years (Hall et. al. 2001) as the patent information about recent inventions is omitted from the data. Such truncation bias might hinder our ability to fully capture more recent changes in firms’ R&D portfolio decisions.

Between 1980-2002 the NBER data contains patent information for 46,259 firm-year observations. In our core set of tests the portfolio vector  is built based on patents applied for (and eventually granted) over past five years (years through ) thus ensuring that we capture a firm’s existing technological expertise. *[[8]](#footnote-8)* Similarly, the innovation vector is based only on patents applied for in year . Consequently, we eliminate all firm-years with no patent applied for over the past five years and/or no patent applied for during the current year. This reduces our sample to 26,558 firm-year observations (we refer to this sub-sample as the *NBER-distance sample*). Such filtering is necessary because the distance measure is non-informative when either the portfolio or innovation vectors are missing. Finally, we map the NBER data to Compustat annual data, which further limits our sample.[[9]](#footnote-9) Our final sample contains 3,696 distinct firms and 22,136 firm-year observations. Table 1 presents the temporal distribution of our sample and compares it to the temporal distributions of the complete Compustat and NBER samples. One can see that our sample includes about 50% of all NBER database observations and they are similarly distributed across years.

Table 2 presents the industry representation for our sample alongside the industry representation for the complete NBER-Compustat merged database. Our inability to compute the distance measure, either due to absence of new patents applied for by a firm or insufficient data to compute the existing patent portfolio leads us to lose about 26% of the unique firms and 44% of the firm-year observations as compared to the sample in Hall et. al. (2001). Nonetheless, the distribution of patents across technological classes is similar to that of the NBER data. As Table 2 shows, the following five industries each account for approximately 10% of the sample: medical equipment, pharmaceutical products, machinery, computers, and business services (software). The distribution of firms across industries is consistent with the distribution of patents across technological classes.

Table 3 illustrates that the financial characteristics of firms in our sample are comparable to those in the NBER-Compustat sample. The two samples are very similar on a number of financial characteristics including size, leverage, profitability, and R&D activity. The firms in our sample are a bit larger both in terms of total assets (sales) and the size of their patent portfolio. This is not surprising since larger, more mature firms are more likely to patent annually and have viable technological distance values every year as opposed to younger firms that patent more sporadically.

## R&D Portfolio Search Distance

For our core set of empirical tests we build the distance measure using Equations (1) and (2). Specifically, we build the existing patent portfolio vector  using patents applied for during the five years prior to the end of fiscal year *.* The new patent portfolio vector  is constructed using only new patents applied for during fiscal year *t*. Matrix *Rt* is computed each year using citations over the past five-year horizon (years  through ). Table 3 provides summary statistics of our core distance measure alongside the characteristics of the existing patent portfolio vector (number of patents and number of technological classes). One can see that the average firm in our sample occupies 5 technological classes and on average applies for 4 patents every year. The patent portfolios tend to be fairly concentrated with the HHI index of patent portfolio being 0.38 on average. Finally our technological search distance measure is fairly skewed with mean of 0.13 and the median of 0.05. Figure 2.A presents the histogram of the technological search distance measure used in our core set of empirical tests. One can see that a significant share of firm-year observations has a zero search distance. To further explore the statistical properties of the distance measure distribution, Figure 2.B presents a histogram of the log of technological search distance. Here we drop all firm-year observations with zero technological search distance. One can see that once we exclude all zero distance observation the distribution shows properties close to normal distribution.

## Explanatory Variables

One of the core advantages of our empirical approach is the ability to combine search distance and organizational/financial information for a wide range of firms and industries. We focus on four measures of financial distress: (i) cash on hand, (ii) return on equity and return on assets, (iii) book value and market value leverage, and (iv) Tobin’s Q. We explain these in turn.

As a firm approaches financial distress, the firm will choose to lower the level of cash below what might be its typical optimal (unconstrained) level. We look at the ratio of cash to assets. Similarly, return on equity and return on assets capture firm performance, which will certainly decline as a firm approaches financial distress. The book value and market value of leverage capture the degree to which the firm faces incentives to shift risk and thereby gain from debt holders. Finally, Tobin’s Q, computed as a ratio of market value of the firm to book value of the firm, captures beliefs about future economic potential of a firm. Higher values of Tobin’s Q correspond to firms further from financial distress.[[10]](#footnote-10)

Table 4 presents correlations between all the variables of interest that we analyze in this paper. Within each group of variables we observe consistent but less than perfect correlation between measures of financial distress. This suggests that the introduced variables of interest agree in their assessment of distress but may reflect differing elements of distress.

Research on innovation suggests a number of firm characteristics that would affect the degree of innovation. For example, large firms are more capable of taking on the risk associated with more distant innovation. We measure the size of a firm’s operations using *Log of Total Assets* and *Log of Sales*. Managers facing more complex decision environments tend to limit the scope of their searching and innovation closer to their core competency. To capture this characteristic we consider the number of business segments within the firm (*Number of Business Segments*) and the Herfindahl-Hirschman index (HHI) of business segment sales (*HHI of Business Segments*).[[11]](#footnote-11) In addition we also evaluated *Number of Geographic Segments* and *HHI of Geographic Segments* as proxies for organizational complexity. The results were qualitatively similar to those reported here (details are available upon request). The number of business segments captures the sheer number of moving parts in the organization. The HHI of business segment sales allows us to discriminate whether a decision maker faces a large number of equal-size segments or a dominant segment that demands most of the decision-maker’s attention. We posit that the former leads to a more complex decision because the manager’s attention will be split between business segments, leading to significant interactions when making decisions. The latter is not as complex because the decision maker can focus attention on one segment.

Following this intuition we augment the set of proxies for organizational complexity with the *HHI of Patent Portfolio*. Here we consider the distribution of a firm’s existing patents across technological classes as of the end of . If a firm is engaged in a wide variety of patenting activities the managerial decision to finance further innovation becomes more complex.

Alongside the core variables of interest that capture financial distress and organizational characteristics such as complexity, we control for a variety of factors that might affect a firm’s decision regarding the riskiness of their innovation. Specifically we control for the following characteristics: (i) *R&D Intensity*, computed as the ratio of R&D to sales; (ii) *R&D Effectiveness* computed as R&D expenditure per patent applied for in a given year; (iii) *PPE Intensity* computed as the ratio of PPE to sales; and (iv) *Rate of Innovation* computed as the ratio of new (innovative) patents in a given year to the number of patents in the existing patent portfolio. These control variables have been used by other studies on innovation.

In addition to these measures we consider a number of control variables specific to our study. To capture the fact that the number of patent classes a firm can expand to is limited to 37 we control for the number of patent classes a firm already occupies. Specifically, we include first and second-degree polynomial terms for *log number of portfolio patent classes.* By doing so we effectively control for the fact when a firm occupies only one technological class, it has a wide set of patent classes available to pursue exploratory innovation, while a firm that occupies a larger set of technological classes has a more limited set and is more likely to remain in its current technological space by definition. We further control for the sheer size of the patent portfolio (*log number of patents in portfolio*) to control for so called “defensive patenting” (Blind, Cremers, and Mueller 2009) or “patent blocking” (Cohen, Nelson, and Walsh 2000). Litigation activities in the patent space have recently exploded, which compels firms to devote significant effort to defend their technological know-how via incremental patents that are minor changes and are aimed only at protecting the patents a firm already owns. Including *log number of patents in portfolio* allows us to capture such phenomena in patenting*.*

Finally, we include both year and industry dummies that capture not only annual trends in patenting law and economic activity but also structural differences across industries (and years) in terms of their reliance/dependence on innovation. All standard errors are clustered at the industry level. [[12]](#footnote-12)

# Empirical Tests

Table 5 presents the core cross-sectional results. The dependent variable in all specifications is search distance as defined by Equations (1) and (2). In Table 5, regression specifications (1) through (4) include different proxies for financial distress and specification (5) includes all such proxies in one regression. All specifications uniformly agree that high likelihood of financial distress is positively associated with more distant patent activity. Larger firms (both in terms of total assets and sales), firms with more business segments, firms with less concentrated segments (lower HHI of business segments), and firms with more diverse patent portfolios (HHI of existing patent portfolio) on average pursue innovation activities further away from their existing patent portfolio as measured by our distance measure. All coefficients of interest in specifications (1) through (4) are significant at the 1% level. The fact that three of four variables of interest in specification (5) are statistically significant further confirms the robustness of the results.

The cross-sectional tests consider whether firms that have characteristics associated with financial distress choose more risky innovation on average. One can also put the question in a time-series context – as firms approach financial distress do they pursue more risky innovation. To address this issue we look at firms that cease to patent. This cessation may be a choice of firms like any other investment decision, though in this case they no longer invest in innovation. Given the importance of innovation to firms, we consider this a sign of financial distress itself. Not surprising, a large number of these cessations are followed immediately or within a few years by a delisting event.

We construct a subsample of firms with a long time series of innovation decisions. Specifically, we look for firms that have 8 years of new patents prior to patent cessation with at most one year’s gap in the sequence and a cessation that lasts at least 4 years for cessations that start before 1998 and for cessations that start after 1998 they must continue through 2002 (to have at least one observation with no patents, our sample in this case ends in 2001). We then look to see if there is a delisting event (as indicated in the CRSP data sets) within two years of this cessation. For those where CRSP offers a delisting indicator, we group those that were merged, acquired, or switched exchanges into one group and those that were delisted for poor performance in another group. A third grouping has the firms that simply ceased patenting.

The merged or delisted group may or may not face financial constraints. This provides something of a control group – there is no ex ante evidence to suggest the merged firms would believe they were approaching financial distress. Put another way, there is no reason to believe the merger or acquisition date would be known in advance and the firms would, therefore, have timed their search behavior. On the other hand, firms that delisted for not meeting delisting requirements would be expected to know they were approaching financial distress and the group that ceases to make patents while having done so for eight years are likely acting from constraints imposed by poor performance.

Our results are presented in Table 6 and in Figure 1. In table 6 we approach the question of statistical significance in two ways. We are looking for a change in strategy as firms approach distress so we focus on the significance of the two years before cessation of patenting relative to the choices in the six years prior to that point. The first approach is to look at the medians over time and test whether the median in years 0 and -1 differ from the medians (the mean of the time-series of medians) in the -2 to -7 period. We use the time-series standard deviation of the medians to test for significance. In effect, we avoid problems with the skewed nature of the distance measure, eliminate the effects of outliers, and assume only that each year’s median in the sample is independent of the prior year. These results are presented in Panel A. The second test is a traditional test of the difference between the means of two samples – the mean of the period 0 (or period -1) sample relative to the mean of the period -2 to -7 sample. This result is presented in Panel B.

A downside to requiring a long and nearly contiguous time series from which to generate a time series standard deviation for the test of the medians is that the sample is much reduced. Out of 3,696 firms in the cross section, we have 1,202 firms with such a time series before a cessation of patenting. As an alternative, we looked for only four years of continuous patenting and the sample is increased to 2,144 firms. This sample is presented along with the 8-year sample in Panel B, but given the lack of a meaningful time series, we only present the test of significance based on means.

In general we observe strong statistical and economically meaningful changes in distance for the delisted and patent-ceasing samples. The results are consistent with a change in strategy as a firm approaches financial distress. As confirmation that the firms’ characteristics are consistent with financial distress, in Figure 1 we plot, along with the time series of patent distance, a few measures of firm performance. Specifically, we plot the mean distance, market value of leverage, return on assets, and stock price for the patent-ceasing sample. Consistent once again with financial distress, the return on assets and share price decline and the level of leverage increases.

# Robustness Tests

The preceding empirical analysis is based on the measure of search distance proposed in Section 3 of this study. As we have already mentioned, to avoid endogeniety problems, we lag all independent variables by one year relative to the year in which we measure new patents. In this section we explore additional issues that might bias our results, and provide variety of robustness tests.

## Timing of R&D decisions versus timing of patenting

One might argue that the decision to pursue innovation and the actual observed patent application might be separated by a significant amount of time. It is also possible that while some innovation projects financed today might come to fruition within one fiscal year, others would require more time to deliver patentable ideas. Thus the financial conditions in year *t*-1 might affect the innovation patented in some later period beyond year *t*. Following this argument we explore alternative ways to measure the difference between existing and new patents. Specifically, in building  we consider the following:[[13]](#footnote-13)

1. one year lagged innovation: patents applied for during year (as opposed to year in our core tests);
2. longer time horizon for innovation: patents applied for over the 5 year horizon from year *t* through year ;
3. one year lagged innovation and longer time horizon: patents applied for from year  through year *.*

Exploring the change in the innovation portfolio over different time horizons allows us to account for the potential criticism of the timing of innovation.

## Measuring the relatedness matrix

The relatedness matrix *Rt* used in our core distance measure is aimed at capturing the interrelatedness between technological classes. We compute *Rt* using citation data over a 5-year horizon prior to the end of fiscal year . This ensures that information about new patents (innovation in year *t*) is omitted from the *Rt* matrix and that the current state of the technological knowledge is fully captured. One might argue, however, that a 5-year horizon is too short to capture the current state of science and technology. Current patent law states that the term for a patent filed before 1995 is 17 years, while the term for a patent filed after 1995 is 20 years. Following this argument we compute *Rt* over both short-term (5 year) and long-term (15 year) horizons.

We have also constructed relatedness matrices in which we attempt to capture cross-citations. In other words, rather than focus on how a given patent class cites others, we count the total number of citations both from a patent class and to a patent class and base the relatedness measure on this data. The results, not reported, are little changed.

## Organic innovation versus acquired innovation

The NBER patent data captures both organic innovation as well as innovation that the company acquired through mergers and acquisitions. From one perspective combining organic and acquired innovation in computing our distance measure is appropriate because an acquisition may be the result of a strategic choice by a firm to acquire technological expertise (Zhao 2009, Seru 2009). On the other hand, acquired innovation could be the result of a strategic acquisition to expand market share and might have nothing to do with the acquisition of technological knowledge. Some mergers might be pursued for liquidity reasons (Almeida, Campello and Hackbarth 2010). There is also empirical evidence that financial constraints are not necessarily binding if a company wants to pursue an acquisition.

To address this issue empirically we consider the distance from an existing patent portfolio that contains all owned (including previously acquired) innovations to a portfolio that contains only organic innovation. The NBER data records patents changing the core owner (as defined by Compustat GVKEY identifier) well after the patent was applied for/granted. We exploit this feature of the data and classify a patent as organic innovation in  if its first year of assignment to considered economic entity coincides with its application year. Similarly, we classify a patent as acquired innovation if belonged to a different economic entity (as defined by GVKEY) at the application year and was reassigned to the considered firm part time into its life.

## Robustness Results

Table 7 presents the results of our core regressions where the dependent variable is computed taking into account the various robustness tests described above. Panel A presents the results for the organic and acquired innovations combined (total innovation) and the distance matrix computed over 15 year horizon prior to innovation measurement (long-term distance matrix). Panel B presents the results for total innovation and short-term distance matrix (prior 5 year horizon). Panel C presents the results for organic innovation and short-term distance matrix used to compute distance measure. In all panels, specifications, (1) through (3) consider innovation applied for during fiscal year (one year removed innovation), specifications (4) though (6) consider innovation between years  through , and, specifications (7) through (9) consider longer horizon innovation covering fiscal years *t* through . Only coefficients of interest are reported and all regressions contain the full set of control variables described in Section 4.3.

All the robustness tests confirm that increased financial distress is associated with more risky innovation. Larger firms, firms with more business segments, firms with more diverse business segments, firms with less internal capital (cash), firms with more existing debt, and those with lower growth potential are, on average, more likely to pursue innovation further removed from their traditional areas of competency. The majority of the coefficients of interest are significant at the 1% level.

## Dependent Variable Distribution

The empirical analysis presented in Tables 5 is conducted via OLS regressions where the standard errors are clustered at the industry level. The coefficients of the regression equation are estimated under an implicit assumption that the error term of our regression is normally distributed. This assumption, while acceptable for a majority of empirical studies, might not be appropriate in our setting. As reported in Table 3 our distance variable is highly skewed to the left. It is not bounded between 0 and 1, varies from 0 to a maximum value of 1.4, and the median value is 0.26. To evaluate whether our results are biased due to the fact that our dependent variable is not normally distributed we proceed as follows.

First, we categorize the dependent variable into 20 percentile groups each containing 5% of the distance distribution and assign values from 1 to 20 to the dependent variable in the corresponding groups. By discretizing the distance measure we smooth its distribution and remove the skewness. Panel A of Table 8 reports this robustness test where all distance measures (as presented in the robustness tests, Table 6) are categorized. Only coefficients of interest are reported and all regressions contain the full set of control variables described in Section 4.3.

Secondly, we run an ordered logit regression where the dependent variable is categorized as above. The ordered logit not only smooth the distribution of the dependent variable it allows for categories to have different distribution of the error term. The results of the ordered logit are presented in Panel B of Table 8.

Finally, we implement our analysis with the dependent variable equal to the log of the initial distance measure. As noted earlier, the log of the distance measure present very attractive properties of close to normal distribution, however in this case we are forced to drop from consideration all firm-years with zero distance. Such sample filtering leads to significant changes in the distribution of the independent variables as well (specifically log of assets and log of sales) as smaller companies are more likely to be dropped from consideration. The results of this analysis are presented in Panel C of Table 8.

Regardless of the way we compute the distance measure and irrespective of adopted statistical analysis approach, the regression results strongly support the notion that greatere financial distress is associated with more distant search.

# Conclusions and Discussion

Innovation and R&D are the pillars of economic growth. Over the past few decades, innovation research has matured from studies that aim to understand the sheer volume of innovative activity (i.e. R&D spending or R&D intensity) to the study of more nuanced measures that are focused on the managerial elements of R&D. Certainly innovation efficiency and innovation quality are of great concern. While innovation, to the extent it is associated with unproven technologies (at least unproven in the market), is often considered inherently risky, we note that there can be a substantial degree of variation in that risk. One can choose to patent in familiar areas and increment existing knowledge (lower risk innovation) or one can look much further afield and for more dramatic innovations (higher risk innovation). This distinction has received little attention.

While one would expect the riskiness of innovation activities to be influenced by a variety of firm, industry and market characteristics, and one would also expect the level of innovation might be affected by financial constraints, one would not typically expect the nature of the innovation choices to be affect by financial considerations in the absence of some form of agency problem. There are two potential agency issues that might sway firms to take more, or less, risky bets on new innovation. Risk averse managers may play it safe when conditions worsen to preserve their positions.

On the other hand, managers acting in the interest of shareholders who are residual claimants relative to debt holders have an incentive to increase risks when distress is near to increase the option value of the equity claim. The evidence in this paper is consistent with this so-called asset substitution effect.

**Appendix – Technological Search Distance Calculations: Numerical Example**

In this appendix we provide a detailed example of how our distance measure is computed. Consider the current state of technology characterized by the citations between technology classes 1, 2, and 3 over past five years (*t* - 5 through *t* - 1) and captured by the following *Rt* matrix:



This would be the case if patent class 1 is essentially unrelated to the other two patent classes, whereas patent classes 2 and 3 are relatively closely related (20% of patents over the past five years in patent class 2 cite patent class 3 and 40% of patents in patent class 3 cite patent class 2).

Consider a firm that currently generates all (100%) of its patents in patent class 2: . This firm has a “technological knowledge base” that is not necessarily concentrated in patent class 2 but rather includes some capabilities in patent class 3 – but no capabilities in patent class 1. Now assume that this firm innovates and all the new patents are in class 2: . This represents a portfolio that is identical to its existing portfolio and the distance represented by the innovation is zero. The calculation in equation (1) would be

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On the other hand, if the firm were to generate new patents exclusively in patent class 2, then  and the distance calculation would be

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Finally, if the firm were to generate all it’s patents in patent class 3, then  and the distance calculation would be

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The effect of patent relatedness is quite clear in this example. In both the second and third examples the firm’s new patents are in a new patent class. However, the past patents, while exclusively in patent class 2, do confer a measure of knowledge in patent class 3 to the extent that the citations demonstrate relatedness. Thus, the distance to a new portfolio all in patent class 2 represents a greater distance from the current knowledge base of the firm than a new portfolio all in patent class 1.

The example above demonstrates that our distance measure captures the interrelatedness of the technological knowledge between patent classes. Note that by looking at the relative proportion of patents in each patent class, the distance measure also reflects the degree of venture activity. For example, if the firm makes a relatively small step into patent class 1 with a single patent and generates 7 patents in patent class 2, then the innovation vector is  and the distance is 0.16 whereas a more significant step that generates 3 patents in patent class 1 while generating the same 7 patents in patent class 2 generates an innovation vector  and the distance more than doubles to 0.39.

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Figure 1

Heat Mapping of Patent Citations



Figure 2.A

Histogram of the Technological Search Distance Measure

Figure 2.B

Histogram of the Log of the Technological Search Distance

**Figure 3**

**Time Series of Performance Measures**

This figure shows the time series of the median levels of technological search distance and measures of firm performance relative to the last year a firm is observed to have a new patent before ceases to patent. The firms are classified further as to whether they were delisted within two years of ceasing to patent due to not meeting delisting requirements, were merged or acquired, or simply ceased to patent.

 

 

**Table 1**

**Sample Selection**

This table presents annual sample distributions of our sample and compares it to the distribution of two core dataset contributing to our sample formation: Compustat and NBER. NBER-Distance stands for the sample of firm-years where the distance measure can be computed. Our sample stands for sub-sample of NBER-distance that has been merged with Compustat data.

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| ***Year*** | ***Compustat*** | ***NBER*** | ***NBER-Distance*** | ***Our sample*** |
| 1980 | 6,385 | 1,523 | 858 | 512 |
| 1981 | 6,414 | 1,507 | 856 | 516 |
| 1982 | 6,853 | 1,520 | 865 | 549 |
| 1983 | 7,109 | 1,542 | 882 | 595 |
| 1984 | 7,176 | 1,546 | 891 | 636 |
| 1985 | 7,482 | 1,585 | 942 | 910 |
| 1986 | 7,741 | 1,626 | 989 | 909 |
| 1987 | 7,816 | 1,658 | 978 | 916 |
| 1988 | 7,696 | 1,681 | 974 | 887 |
| 1989 | 7,592 | 1,672 | 948 | 914 |
| 1990 | 7,624 | 1,703 | 1,012 | 935 |
| 1991 | 7,761 | 1,746 | 1,039 | 1,058 |
| 1992 | 8,172 | 1,873 | 1,185 | 1,155 |
| 1993 | 9,362 | 1,979 | 1,275 | 1,228 |
| 1994 | 9,845 | 2,078 | 1,390 | 1,243 |
| 1995 | 10,724 | 2,314 | 1,490 | 1,470 |
| 1996 | 10,907 | 2,494 | 1,636 | 1,455 |
| 1997 | 10,654 | 2,612 | 1,579 | 1,427 |
| 1998 | 11,003 | 2,809 | 1,675 | 1,466 |
| 1999 | 11,087 | 2,836 | 1,625 | 1,374 |
| 2000 | 10,593 | 2,781 | 1,496 | 1,150 |
| 2001 | 9,978 | 2,659 | 1,234 | 692 |
| 2002 | 9,525 | 2,515 | 739 | 139 |
| ***Total number of firm-years*** | 199,499 | 46,259 | 26,558 | 22,136 |
| ***Percent relative to Compustat population*** | 100% | 23% | 13% | 11% |

**Table 2**

**Industry Representation**

This table presents sample distributions by Fama-French 48 industries. Panel A presents the industry distribution of firms in our sample as compared to industry distribution of firms in the NBER-Compustat merged dataset. Similarly Panel B presents similar comparison for firm-years.

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
|  | ***Fama-French Industry*** | ***NBER- Compustat*** | ***Our Sample*** | ***Percent Coverage*** | ***NBER- Compustat*** | ***Our Sample*** | ***Percent Coverage*** |
|  |  | **Panel A: Firms** | | | **Panel B: Firm-Years** | | |
| 1 | Agriculture | 18 | 11 | 61% | 107 | 45 | 42% |
| 2 | Food Products | 99 | 68 | 69% | 858 | 493 | 57% |
| 3 | Candy and Soda | 2 | 2 | 100% | 35 | 27 | 77% |
| 4 | Alcoholic beverages | 8 | 8 | 100% | 153 | 100 | 65% |
| 5 | Tobacco Products | 11 | 8 | 73% | 70 | 40 | 57% |
| 6 | Recreational Products | 84 | 54 | 64% | 538 | 274 | 51% |
| 7 | Entertainment | 40 | 19 | 48% | 203 | 68 | 33% |
| 8 | Printing and Publishing | 36 | 19 | 53% | 214 | 63 | 29% |
| 9 | Consumer Goods | 186 | 138 | 74% | 1547 | 904 | 58% |
| 10 | Apparel | 57 | 35 | 61% | 504 | 183 | 36% |
| 11 | Healthcare | 33 | 24 | 73% | 174 | 68 | 39% |
| 12 | Medical Equipment | 386 | 299 | 77% | 2810 | 1584 | 56% |
| 13 | Pharmaceutical Products | 455 | 367 | 81% | 3340 | 1993 | 60% |
| 14 | Chemicals | 163 | 131 | 80% | 1496 | 1047 | 70% |
| 15 | Rubber and Plastic Products | 103 | 78 | 76% | 771 | 401 | 52% |
| 16 | textiles | 42 | 28 | 67% | 401 | 196 | 49% |
| 17 | Construction Materials | 150 | 108 | 72% | 1184 | 669 | 57% |
| 18 | Construction Materials | 41 | 19 | 46% | 237 | 99 | 42% |
| 19 | Steel Works, Etc. | 99 | 74 | 75% | 986 | 538 | 55% |
| 20 | Fabricated products | 37 | 30 | 81% | 317 | 136 | 43% |
| 21 | Machinery | 342 | 276 | 81% | 3182 | 2053 | 65% |
| 22 | Electrical Equipment | 120 | 105 | 88% | 1118 | 729 | 65% |
| 23 | Miscellaneous | 128 | 102 | 80% | 1349 | 924 | 68% |
| 24 | Automobiles and Trucks | 30 | 25 | 83% | 339 | 260 | 77% |
| 25 | Aircraft | 9 | 6 | 67% | 101 | 59 | 58% |
| 26 | Shipbuilding, Railroad Equip | 14 | 12 | 86% | 174 | 130 | 75% |
| 27 | Defense | 13 | 7 | 54% | 103 | 28 | 27% |
| 28 | Precious Metals | 17 | 11 | 65% | 152 | 65 | 43% |
| 30 | Coal | 1 | 1 | 100% | 19 | 15 | 79% |
| 31 | Petroleum and Natural Gas | 101 | 75 | 74% | 928 | 533 | 57% |
| 32 | Utilities | 78 | 45 | 58% | 624 | 225 | 36% |
| 33 | Telecommunication | 85 | 55 | 65% | 511 | 270 | 53% |
| 34 | Personal Services | 18 | 8 | 44% | 140 | 52 | 37% |
| 35 | Business Services | 600 | 357 | 60% | 3421 | 1312 | 38% |
| 36 | Computers | 382 | 280 | 73% | 2917 | 1669 | 57% |
| 37 | Electronic Equipment | 500 | 418 | 84% | 4555 | 2719 | 60% |
| 38 | Measuring and Control Equip | 201 | 160 | 80% | 1903 | 1164 | 61% |
| 39 | Business Supplies | 93 | 77 | 83% | 1088 | 674 | 62% |
| 40 | Shipping Containers | 19 | 16 | 84% | 284 | 175 | 62% |
| 41 | Transportations | 42 | 30 | 71% | 384 | 131 | 34% |
| 42 | Wholesale | 82 | 51 | 62% | 794 | 300 | 38% |
| 43 | Retail | 65 | 33 | 51% | 402 | 132 | 33% |
| 44 | Restaurants, Hotel, Motel | 18 | 6 | 33% | 96 | 17 | 18% |

**Table 3**

**Descriptive Statistics**

This table reports information on the distribution characteristics for firms that we were able to computed distance for (Pane A), and for the full sample of NBER-Compustat merged firm-year observations (Panel B).

|  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | ***Mean*** | ***Std. Dev.*** | ***25%*** | ***Median*** | ***75%*** |  | ***Mean*** | ***Std. Dev.*** | ***25%*** | ***Median*** | ***75%*** |
|  | **Panel A: Our Sample** | | | | |  | **Panel B: Merged NBER-Compustat Sample** | | | | |
| Total Assets ($ mil) | 4,112 | 18,525 | 55 | 266 | 1,688 |  | 3,217 | 17,583 | 37 | 164 | 1,015 |
| Sales ($mil) | 3,263 | 11,081 | 50 | 294 | 1,719 |  | 2,415 | 9,460 | 30 | 172 | 1,048 |
| Cash/Total Assets | 10.8% | 15.8% | 1.4% | 4.2% | 13.3% |  | 11.9% | 16.5% | 1.5% | 4.9% | 15.3% |
| Book Value Leverage | 22.2% | 15.9% | 9.3% | 20.5% | 31.9% |  | 23.6% | 17.6% | 9.1% | 21.5% | 34.4% |
| Market Value Leverage | 21.8% | 19.5% | 5.3% | 16.8% | 33.5% |  | 22.6% | 20.8% | 4.9% | 16.9% | 35.1% |
| Tobin-Q | 2.34 | 3.71 | 1.07 | 1.45 | 2.36 |  | 2.33 | 3.55 | 1.06 | 1.45 | 2.35 |
| ROE | 2.55% | 10.28% | 0.60% | 4.84% | 8.02% |  | -0.64% | 15.36% | -2.57% | 3.94% | 7.27% |
| R&D Intensity | 31.7% | 120.8% | 1.8% | 4.8% | 12.0% |  | 37.5% | 134.9% | 1.9% | 5.7% | 15.1% |
| R&D/Total Assets | 8.8% | 11.1% | 2.1% | 5.0% | 10.9% |  | 10.2% | 13.0% | 2.2% | 5.7% | 12.7% |
| CAPEX/Total Assets | 6.85% | 5.54% | 3.34% | 5.62% | 8.80% |  | 6.20% | 5.45% | 2.67% | 4.89% | 8.05% |
| PPE Intensity | 39.6% | 56.7% | 14.9% | 23.8% | 40.1% |  | 41.4% | 64.6% | 13.0% | 22.6% | 40.5% |
| Number of Business Segments | 2.05 | 1.54 | 1 | 1 | 3 |  | 1.83 | 1.35 | 1 | 1 | 2 |
| Number of Geo Segments | 2.17 | 1.32 | 1 | 2 | 3 |  | 2.05 | 1.35 | 1 | 2 | 3 |
| HHI of Business Segments | 0.78 | 0.28 | 0.51 | 1 | 1 |  | 0.82 | 0.26 | 0.58 | 1 | 1 |
| HHI of Geo Segments | 0.76 | 0.25 | 0.54 | 0.81 | 1 |  | 0.79 | 0.24 | 0.57 | 0.94 | 1.00 |
| Number of Patents in Port. | 162.71 | 660.41 | 5 | 15 | 58 |  | 96.32 | 539.07 | 2 | 6 | 22 |
| Number of New Patents | 36.66 | 186.05 | 1 | 4 | 13 |  |  |  |  |  |  |
| Number of Tech Classes | 7.38 | 7.37 | 2 | 5 | 10 |  |  |  |  |  |  |
| Patent Portfolio HHI | 0.46 | 0.29 | 0.23 | 0.38 | 0.63 |  |  |  |  |  |  |
| R&D per New Patent | 5.18 | 10.88 | 0.80 | 1.92 | 4.69 |  |  |  |  |  |  |
| Search Distance | 0.132 | 0.189 | 0.012 | 0.0495 | 0.165 |  |  |  |  |  |  |

**Table 4**

**Correlations Between Core Variables of Interest**

|  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | ***Cash/Total Assets*** | ***Book Value Leverage*** | ***Market Value Leverage*** | ***Tobin Q*** | ***Return on Equity*** | ***Log of Total Assets*** | ***Log of Sales*** | ***Number of Business Segments*** | ***Business Segments HHI*** | ***HHI of Patent Portfolio*** |
| Cash/Total Assets | 1.000 |  |  |  |  |  |  |  |  |  |
| Book Value Leverage | -0.331 | 1.000 |  |  |  |  |  |  |  |  |
| Market Value Leverage | -0.367 | 0.776 | 1.000 |  |  |  |  |  |  |  |
| Tobin Q | 0.289 | -0.175 | -0.290 | 1.000 |  |  |  |  |  |  |
| Return on Equity | -0.254 | -0.013 | 0.243 | -0.123 | 1.000 |  |  |  |  |  |
| Log of Total Assets | -0.341 | 0.224 | 0.354 | -0.206 | 0.053 | 1.000 |  |  |  |  |
| Log of Sales | -0.456 | 0.231 | 0.363 | -0.262 | 0.08 | 0.939 | 1.000 |  |  |  |
| Number of Business Segments | -0.243 | 0.169 | 0.308 | -0.156 | 0.201 | 0.489 | 0.486 | 1.000 |  |  |
| HHI of Business Segments | 0.268 | -0.182 | -0.366 | 0.174 | -0.206 | -0.445 | -0.458 | -0.883 | 1.000 |  |
| HHI of Patent Portfolio | 0.222 | -0.109 | -0.188 | 0.142 | -0.154 | -0.480 | -0.485 | -0.327 | 0.343 | 1.000 |

**Table 5**

**Impact of Financial Distress on Search Distance**

This table reports regressions of the technological search distance measure. The unit of observation is the firm-year, from 1980 to 2002. All regressions also include year and industry fixed effects. T-statistics in parentheses are based on errors clustered at the industry level: \* significant at 10%; \*\* significant at 5%; \*\*\* significant at 1%.

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
|  | (1) | (2) | (3) | (4) | (5) |
|  |  |  |  |  |  |
| ***Financial Distress*** |  |  |  |  |  |
| Cash/Total Assets | -0.0528\*\*\* |  |  |  | -0.0404\*\*\* |
|  | (-5.528) |  |  |  | (-3.551) |
| Return on Equity |  | -0.0283\*\*\* |  |  | -0.0285\*\*\* |
|  |  | (-15.67) |  |  | (-9.776) |
| Market Value Leverage |  |  | 0.0233\*\* |  | 0.0213\* |
|  |  |  | (2.403) |  | (1.979) |
| Tobin Q |  |  |  | -0.000721\* | -0.000603 |
|  |  |  |  | (-1.843) | (-1.681) |
| ***Control Variables*** |  |  |  |  |  |
| KZ Index | -0.023 | 0.0001 | 0.0049 | -0.0001 | 0.0001 |
|  | (-0.2712) | -0.1623 | -0.2771 | (-0.0134) | -0.0932 |
| Log of Total Assets | 0.00678\*\*\* | 0.00837\*\*\* | 0.00794\*\*\* | 0.00807\*\*\* | 0.00672\*\*\* |
|  | (5.376) | (7.528) | (6.290) | (7.180) | (4.581) |
| # of Business Segments | -0.00496\*\*\* | -0.00463\*\*\* | -0.00494\*\*\* | -0.00453\*\*\* | -0.00460\*\*\* |
|  | (-2.979) | (-3.646) | (-3.890) | (-3.608) | (-3.215) |
| HHI of Business Seg. | -0.0403\*\*\* | -0.0415\*\*\* | -0.0406\*\*\* | -0.0407\*\*\* | -0.0366\*\*\* |
|  | (-3.527) | (-4.398) | (-4.559) | (-4.373) | (-3.839) |
| HHI of Patent Portfolio | -0.0927\*\*\* | -0.0969\*\*\* | -0.0953\*\*\* | -0.0970\*\*\* | -0.0949\*\*\* |
|  | (-9.889) | (-8.534) | (-8.366) | (-8.583) | (-8.711) |
| R&D Intensity | 0.0471 | 0.0364 | 0.0377 | 0.0390 | 0.0533 |
|  | (1.179) | (0.878) | (0.921) | (0.929) | (1.226) |
| R&D Effectiveness | 0.0989\*\* | 0.0789\*\*\* | 0.0780\*\*\* | 0.0793\*\*\* | 0.0950\*\* |
|  | (2.726) | (3.200) | (3.176) | (3.188) | (2.492) |
| PPE Intensity | -0.000132 | -0.000145 | -0.000150\* | -0.000147\* | -0.000150\* |
|  | (-1.565) | (-1.709) | (-1.818) | (-1.732) | (-1.758) |
| Rate of Innovation | -0.0161\*\*\* | -0.0555\*\* | -0.0542\*\* | -0.0547\*\* | -0.0504\*\* |
|  | (-3.889) | (-2.464) | (-2.503) | (-2.449) | (-2.612) |
| Log Number of Patents in Portfolio | -0.0629\*\*\* | -0.0638\*\*\* | -0.0635\*\*\* | -0.0636\*\*\* | -0.0611\*\*\* |
| (-30.89) | (-27.18) | (-26.73) | (-27.66) | (-28.37) |
| Log Number of Portfolio Patent Classes | -0.0836\*\*\* | -0.0871\*\*\* | -0.0865\*\*\* | -0.0875\*\*\* | -0.0833\*\*\* |
| (-9.324) | (-9.158) | (-8.933) | (-9.149) | (-8.366) |
| Log Number of Portfolio Patent Classes Squared | 0.0249\*\*\* | 0.0251\*\*\* | 0.0250\*\*\* | 0.0252\*\*\* | 0.0238\*\*\* |
| (10.76) | (11.35) | (10.90) | (11.28) | (10.19) |
| Year Dummies | + | + | + | + | + |
| Industry Dummies | + | + | + | + | + |
| Observations | 22,962 | 19,808 | 19,742 | 19,807 | 20,223 |
| R-squared | 0.262 | 0.244 | 0.244 | 0.244 | 0.231 |

**Table 6**

**Time Series Analysis for Firms that Stop Generating Patents**

This table reports the time series of distance values relative to the last year before which no patents are issued. This sample ends in 2001 to determine when a patent was issues in 2002 and comprises either the set with 8 patent observation in a row (with one possible gap) and the group with 4 patent observations in a row. Medians and means are reported, each with their own test as to whether the period -1 and 0 levels differ from the average median or mean, respectively. The test on the median values is based on the time series standard deviation of the medians which the test on the means is based on the standard deviation of the means in the values (a test of whether the mean of the distribution in period -1 or 0 differs from the mean of the distribution over period -7 to -2).

|  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  |  |  |  |  |  |  |  |  |  |  |
|  | -7 | -6 | -5 | -4 | -3 | -2 | -1 | 0 | Number | Average  -7 to -2 |
| **Panel A: Median Distance With Test of Significant Based on Times Series Variation Over Periods -7 to -2** | | | | | | | | | | |
| Merged or Acquired | 0.052 | 0.044 | 0.042 | 0.043 | 0.046 | 0.044 | 0.045 | 0.052\* | 192 | 0.045 |
| Delisted | 0.046 | 0.044 | 0.033 | 0.038 | 0.031 | 0.031 | 0.035 | 0.063\*\*\* | 37 | 0.037 |
| Stopped Patenting | 0.030 | 0.027 | 0.026 | 0.023 | 0.029 | 0.030 | 0.049\*\*\* | 0.103\*\*\* | 973 | 0.027 |
|  |  |  |  |  |  |  |  |  |  |  |
| **Panel B: Mean Distance With Tests of Significant Based on Distribution Values** | | | | | | | | | | |
| Merged or Acquired | 0.121 | 0.112 | 0.116 | 0.096 | 0.088 | 0.091 | 0.089 | 0.117 | 192 | 0.104 |
| Delisted | 0.088 | 0.100 | 0.080 | 0.103 | 0.071 | 0.095 | 0.077 | 0.124\* | 37 | 0.089 |
| Stopped Patenting | 0.092 | 0.080 | 0.068 | 0.078 | 0.070 | 0.078 | 0.099\*\*\* | 0.166\*\*\* | 973 | 0.078 |
|  |  |  |  |  |  |  |  |  |  |  |
| Merged or Acquired |  |  |  |  | 0.132 | 0.123 | 0.115 | 0.129 | 408 | 0.127 |
| Delisted |  |  |  |  | 0.118 | 0.123 | 0.109 | 0.155\*\* | 100 | 0.120 |
| Stopped Patenting |  |  |  |  | 0.108 | 0.101 | 0.119\*\*\* | 0.171\*\*\* | 1736 | 0.105 |
|  |  |  |  |  |  |  |  |  |  |  |

**Table 7**

**Robustness Tests: Measurement of Innovation**

This table reports regressions of the technological search distance measure computed over different time horizons and for different subset of a firm innovation portfolio (total innovation versus organic innovation). Only the coefficients of interest are reported. All regressions contain a full set of control variables as reported in Table 5. The unit of observation is the firm-year, from 1980 to 2002.Specification (1) through (3) measure innovation vector based on patents applied for in year t+1 (similar to the core tests reported in Table (5); specifications (4) through (6) measure the innovations over four year horizon starting one year after the portfolio vector is formed; specifications (7) through (9) measure the innovation vector over 5 year horizon immediately after the portfolio vector is formed. Panel A presents the analysis of total (organic and acquired) innovation where the D matrix is computed over 15 year horizon prior to and including year t. Panel B presents the analysis of total (organic and acquired) innovation where the D matrix is computed over 5 year horizon prior to and including year t. Finally, Panel C presents the analysis of only organic innovation where the D matrix is computed over 5 year horizon prior to and including year t. T-statistics in parentheses are based on robust standard errors clustered at the industry level: \* significant at 10%; \*\* significant at 5%; \*\*\* significant at 1%.

|  | **Innovation Measured  from *t*  to *t*+1** | | | **Innovation Measured  from *t*+1 to *t*+4** | | | **Innovation Measured  from *t* to *t*+4** | | |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
| **Panel A: Total Innovation & Long Term Distance Matrix** | | | | | | | | | |
| Cash/Total Assets | -0.0466\*\*\* |  |  | -0.0569\*\*\* |  |  | -0.0544\*\*\* |  |  |
|  | (6.54) |  |  | (5.03) |  |  | (6.32) |  |  |
| Book Value Leverage |  | 0.0269\*\*\* |  |  | 0.0409\*\*\* |  |  | 0.0307\*\*\* |  |
|  |  | (3.61) |  |  | (6.11) |  |  | (5.44) |  |
| Return on Equity |  |  | -0.0870\*\*\* |  |  | 0.00169 |  |  | -0.0920\*\*\* |
|  |  |  | (5.21) |  |  | (0.10) |  |  | (5.93) |
| Log of Total Assets | 0.00549\*\*\* |  |  | 0.00302\*\*\* |  |  | 0.00470\*\*\* |  |  |
|  | (4.82) |  |  | (3.07) |  |  | (5.38) |  |  |
| HHI of Business Segments |  | -0.0275\*\*\* |  |  | -0.0291\*\*\* |  |  | -0.0319\*\*\* |  |
|  | (6.41) |  |  | (7.10) |  |  | (7.91) |  |
| HHI of Patent Portfolio |  |  | -0.0943\*\*\* |  |  | -0.0156\* |  |  | -0.00314 |
|  |  |  | (9.33) |  |  | (1.86) |  |  | (1.41) |
|  |  |  |  |  |  |  |  |  |  |
| Observations | 20,534 | 22,644 | 20,098 | 21,542 | 23,995 | 21,229 | 25,703 | 28,382 | 24,970 |
| R-squared | 0.233 | 0.238 | 0.245 | 0.255 | 0.265 | 0.265 | 0.254 | 0.261 | 0.265 |

|  | **Innovation Measured  from *t*  to *t*+1** | | | **Innovation Measured  from *t*+1 to *t*+4** | | | **Innovation Measured  from *t* to *t*+4** | | |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
| **Panel B: Total Innovation & Short Term Distance Matrix** | | | | | | | | | |
| Cash/Total Assets | -0.0497\*\*\* |  |  | -0.0646\*\*\* |  |  | -0.0589\*\*\* |  |  |
|  | (5.71) |  |  | (5.37) |  |  | (6.09) |  |  |
| Book Value Leverage |  | 0.0313\*\*\* |  |  | 0.0447\*\*\* |  |  | 0.0330\*\*\* |  |
|  |  | (4.26) |  |  | (5.51) |  |  | (4.91) |  |
| Return on Equity |  |  | -0.0868\*\*\* |  |  | -0.0745 |  |  | -0.0943\*\*\* |
|  |  |  | (5.03) |  |  | (1.18) |  |  | (5.78) |
| Log of Total Assets | 0.00709\*\*\* |  |  | 0.00440\*\*\* |  |  | 0.00613\*\*\* |  |  |
|  | (5.11) |  |  | (3.73) |  |  | (5.66) |  |  |
| HHI of Business Segments |  | -0.0299\*\*\* |  |  | -0.0317\*\*\* |  |  | -0.0338\*\*\* |  |
|  | (6.14) |  |  | (7.01) |  |  | (7.73) |  |
| HHI of Patent Portfolio |  |  | -0.104\*\*\* |  |  | -0.0147 |  |  | -0.00541 |
|  |  |  | (8.69) |  |  | (1.56) |  |  | (1.57) |
| Observations | 20,534 | 22,644 | 20,098 | 21,542 | 23,995 | 21,229 | 25,703 | 28,382 | 24,970 |
| R-squared | 0.233 | 0.238 | 0.244 | 0.256 | 0.264 | 0.265 | 0.255 | 0.26 | 0.265 |
| **Panel C: Organic Innovation & Short Term Distance Matrix** | | | | | | | | | |
| Cash/Total Assets | -0.0428\*\*\* |  |  | -0.0556\*\*\* |  |  | -0.0555\*\*\* |  |  |
|  | (5.28) |  |  | (5.05) |  |  | (6.25) |  |  |
| Book Value Leverage |  | 0.0280\*\*\* |  |  | 0.0402\*\*\* |  |  | 0.0312\*\*\* |  |
|  |  | (3.39) |  |  | (6.18) |  |  | (5.23) |  |
| Return on Equity |  |  | -0.0954\*\*\* |  |  | -0.1170 |  |  | -0.0958\*\*\* |
|  |  |  | (5.56) |  |  | (1.50) |  |  | (6.37) |
| Log of Total Assets | 0.00776\*\*\* |  |  | 0.00464\*\*\* |  |  | 0.00581\*\*\* |  |  |
|  | (5.45) |  |  | (4.61) |  |  | (6.20) |  |  |
| HHI of Business Segments |  | -0.0283\*\*\* |  |  | -0.0349\*\*\* |  |  | -0.0349\*\*\* |  |
|  | (6.07) |  |  | (7.11) |  |  | (7.24) |  |
| HHI of Patent Portfolio |  |  | -0.0990\*\*\* |  |  | -0.0104 |  |  | -0.00473 |
|  |  |  | (9.58) |  |  | (1.63) |  |  | (1.55) |
|  |  |  |  |  |  |  |  |  |  |
| Observations | 20,606 | 22,717 | 20,164 | 21,700 | 24,175 | 21,397 | 25,719 | 28,407 | 24,996 |
| R-squared | 0.245 | 0.249 | 0.255 | 0.258 | 0.269 | 0.269 | 0.258 | 0.266 | 0.269 |

**Table 8**

**Robustness Tests: Distribution of the Dependent Variable**

This table reports various statistical analysis of the technological search distance. Panel A presents the OLS analysis where the technological search distance measure is ordered and then transformed into 20 categories (1 through 20) each containing 5% of the sample. Panel B presents the ordered logit analysis where the dependent variable is transformed similarly to Panel A. Finally, Panel C presents the OLS regression analysis where the dependent variable is equal to log of our original distance measure and all firm-year observations with zero distance are dropped from consideration. Only the coefficients of interest are reported. All regressions contain a full set of control variables as reported in Table 5. The unit of observation is the firm-year, from 1980 to 2002. Specification (1) through (3) measure innovation vector based on patents applied for in year t+1 (similar to the core tests reported in Table 5); specifications (4) through (6) measure the innovations over four year horizon starting one year after the portfolio vector is formed; specifications (7) through (9) measure the innovation vector over 5 year horizon immediately after the portfolio vector is formed. T-statistics in parentheses are based on robust standard errors clustered at the industry level: \* significant at 10%; \*\* significant at 5%; \*\*\* significant at 1%.

|  | **Innovation Measured  from *t* to *t*+1** | | | **Innovation Measured  from *t*+1 to *t*+4** | | | **Innovation Measured  from *t* to *t*+4** | | |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
| **Panel A: OLS Regressions with Ordered Categorical Distance Measure** | | | | | | | | | |
| Cash/Total Assets | -1.042\*\*\* |  |  | -1.180\*\*\* |  |  | -1.099\*\*\* |  |  |
|  | (5.53) |  |  | (2.91) |  |  | (3.59) |  |  |
| Book Value Leverage |  | 0.662\*\*\* |  |  | 1.229\*\*\* |  |  | 0.940\*\*\* |  |
|  |  | (3.65) |  |  | (6.75) |  |  | (6.03) |  |
| Return on Equity |  |  | -1.485\*\*\* |  |  | -1.652 |  |  | -2.178\*\*\* |
|  |  |  | (4.06) |  |  | (1.68) |  |  | (5.29) |
| Log of Total Assets | 0.127\*\*\* |  |  | 0.106\*\*\* |  |  | 0.169\*\*\* |  |  |
|  | (5.15) |  |  | (3.83) |  |  | (7.04) |  |  |
| HHI of Business Segments |  | -1.127\*\*\* |  |  | -1.156\*\*\* |  |  | -1.264\*\*\* |  |
|  | (9.57) |  |  | (7.77) |  |  | (8.30) |  |
| HHI of Patent Portfolio |  |  | -9.987\*\*\* |  |  | -8.116\*\*\* |  |  | -8.004\*\*\* |
|  |  |  | (34.22) |  |  | (25.34) |  |  | (32.12) |
|  |  |  |  |  |  |  |  |  |  |
| Observations | 20,553 | 22,672 | 20,118 | 21,562 | 24,023 | 21,245 | 25,732 | 28,421 | 24,995 |
| R-squared | 0.343 | 0.352 | 0.392 | 0.298 | 0.314 | 0.335 | 0.298 | 0.309 | 0.333 |

|  | **Innovation Measured  from *t* to *t*+1** | | | **Innovation Measured  from *t*+1 to *t*+4** | | | | | **Innovation Measured  from *t* to *t*+4** | | | | | |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | (1) | (2) | (3) | (4) | (5) | | (6) | | (7) | | (8) | | (9) | |
| **Panel B: Ordered Logit Regressions** | | | | | | | | | | | | | | | |
| Cash/Total Assets | -0.472\*\*\* |  |  | -0.584\*\*\* | |  | |  | | -0.535\*\*\* | |  | |  | |
|  | (4.22) |  |  | (5.39) | |  | |  | | (5.71) | |  | |  | |
| Book Value Leverage |  | 0.270\*\*\* |  |  | | 0.502\*\*\* | |  | |  | | 0.390\*\*\* | |  | |
|  |  | (3.67) |  |  | | (7.18) | |  | |  | | (6.22) | |  | |
| Return on Equity |  |  | -0.599\*\*\* |  | |  | | -0.182 | |  | |  | | -0.874\*\*\* | |
|  |  |  | (3.84) |  | |  | | (1.75) | |  | |  | | (5.05) | |
| Log of Total Assets | 0.0520\*\*\* |  |  | 0.0351\*\*\* | |  | |  | | 0.0548\*\*\* | |  | |  | |
|  | (5.12) |  |  | (3.85) | |  | |  | | (6.68) | |  | |  | |
| HHI of Business Segments |  | -0.363\*\*\* |  |  | | -0.384\*\*\* | |  | |  | | -0.401\*\*\* | |  | |
|  | (8.39) |  |  | | (9.29) | |  | |  | | (10.49) | |  | |
| HHI of Patent Portfolio |  |  | -3.630\*\*\* |  | |  | | -2.401\*\*\* | |  | |  | | -2.339\*\*\* | |
|  |  |  |  |  | |  | |  | |  | |  | |  | |
|  |  |  | (25.67) |  | |  | | (21.78) | |  | |  | | (23.89) | |
| Observations | 20,553 | 22,672 | 20,118 | 21,562 | | 24,023 | | 21,245 | | 25,732 | | 28,421 | | 24,995 | |
| **Panel C: Log of Distance as Dependent Variable** | | | | | | | | | | | | | | | |
| Cash/Total Assets | -0.491\*\*\* |  |  | -0.532\*\*\* | |  | |  | | -0.504\*\*\* | |  | |  | |
|  | (7.65) |  |  | (8.50) | |  | |  | | (7.00) | |  | |  | |
| Book Value Leverage |  | 0.209\*\*\* |  |  | | 0.372\*\*\* | |  | |  | | 0.319\*\*\* | |  | |
|  |  | (6.41) |  |  | | (10.05) | |  | |  | | (10.48) | |  | |
| Return on Equity |  |  | -0.168\*\* |  | |  | | -0.145 | |  | |  | | -0.209\*\*\* | |
|  |  |  | (2.17) |  | |  | | (1.47) | |  | |  | | (4.03) | |
| Log of Total Assets | 0.0102 |  |  | 0.0184\*\*\* | |  | |  | | 0.00746 | |  | |  | |
|  | (1.66) |  |  | (3.00) | |  | |  | | (1.35) | |  | |  | |
| HHI of Business Segments |  | -0.234\*\*\* |  |  | | -0.263\*\*\* | |  | |  | | -0.266\*\*\* | |  | |
|  | (8.84) |  |  | | (9.54) | |  | |  | | (8.74) | |  | |
| HHI of Patent Portfolio |  |  | -1.785\*\*\* |  | |  | | -1.519\*\*\* | |  | |  | | -1.566\*\*\* | |
|  |  |  | (15.27) |  | |  | | (16.98) | |  | |  | | (17.66) | |
|  |  |  |  |  | |  | |  | |  | |  | |  | |
| Observations | 18,799 | 20,804 | 18,599 | 19,917 | | 22,260 | | 19,794 | | 23,683 | | 26,239 | | 23,229 | |
| R-squared | 0.568 | 0.577 | 0.592 | 0.539 | | 0.552 | | 0.56 | | 0.548 | | 0.559 | | 0.567 | |

1. In exploring the R&D portfolio decisions we ideally would like to evaluate the exact budget allocation across all projects of varying riskiness. Unfortunately such allocations are unobservable. However, Griliches (1976, 1990), Jaffe (1986), and Fleming (2001), among others, argue that patents are close proxies for R&D resource allocation decisions. [↑](#footnote-ref-1)
2. See Jaffe (1986) and Stuart and Podolny (1996). [↑](#footnote-ref-2)
3. A large literature examines optimal strategies for searching out new innovations and the choosing and optimal research portfolio, including theoretical work by Weitzman 1979, Lipman and McCardle 1991, Rivkin and Sigglekow 2003 and empirical work by Stuart and Podolny 1996, Fleming 2001, Fleming and Sorenson 2004. [↑](#footnote-ref-3)
4. Chao and Kavadias (2008) note that evaluating the tradeoff between more certain and more risky innovation becomes more difficult as organizations become more complex due to, for example, increase in scale and scope. [↑](#footnote-ref-4)
5. As a robustness check, we compute an alternate relatedness matrix which is bi-directional – it acknowledges both citations of patent class *k* by patent class *l* and citations of patent class *l* by *k*. We find the results both economically and statistically similar to those reported in this paper. [↑](#footnote-ref-5)
6. If *Rt* is an identity matrix then our measure collapses to a traditional Euclidian distance measure. The traditional Euclidian distance, however, suffers from two major problems. First, it ignores the difference in scale across components of the vector, which is not a problem in our analysis since all components of the portfolio and innovation vectors are bound between 0 and 1 and hence similarly scaled. Secondly, the Euclidian distance treats all elements of the vector to be independent which present a problem since the technological classes cannot be considered completely independent of one another. [↑](#footnote-ref-6)
7. Unfortunately, the data on citation is not available past 1999 which limits our ability to capture the most recent interrelatedness between patent classes. Consequently, we use *Rt* as of 1999 to estimate the R&D portfolio distance in years 1999 through 2002. [↑](#footnote-ref-7)
8. Following prior studies of patents and innovation (citation) we record all patents based on application year rather than the actual patent grant year. This approach allows to better capture the actual innovation date as there is a significant lag (sometimes more than a year) between patent application date and patent granting date, and this lag has increased over time. [↑](#footnote-ref-8)
9. Here we exclude from consideration all firm-year observations with unreliable Compustat data. For example we exclude firms with negative cash holdings, firms with negative or negligible market value of equity, firms with stock price below one dollar,etc. [↑](#footnote-ref-9)
10. It is worth noting that the literature on financial constraints uses additional proxies to measure how financially constrained a firm is. In particular, the KZ Index developed by Kaplan and Zingales (1997) is featured prominently in the financial constraints literature as a measure of the likelihood that a firm faces financial constraints. We ran regressions with KZ Index and found results qualitatively similar to those reported here (details are available upon request). [↑](#footnote-ref-10)
11. The HHI index is widely used as a measure concentration and is often employed to measure industry competition. *HHI* = ∑ where *si* is the market share of a given firm and ∑ *si* = 1. Since higher HHI index is consistent with higher concentration, negative coefficients on HHI-type variables are consistent with a positive relationship between complexity and distance. [↑](#footnote-ref-11)
12. In Section 6 we explore alternative empirical test specifications that explicitly account for the significant skewness in our variable of interest, namely, the technological search distance. [↑](#footnote-ref-12)
13. We have empirically explored other possible time horizons to measure innovation (e.g., two year removed innovation over one year) and found the results to be quantitatively and qualitatively consistent with those reported in this study. [↑](#footnote-ref-13)