Essays in Corporate Finance: Organizational Form, Financing and Innovation

by

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To My Family

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A few years ago, I left my parents, fiancé, friends and a reasonably well paying job to do my Ph.D. This was clearly decision making under severe uncertainty since I knew very little about either Finance or about life after Ph.D. I was clearly taking a bet just based on my curiosity about the subject. It was certainly not comforting when I quickly realized in my first economics course that risk averse agents would have rationally behaved quite unlike me. Thankfully, since things are uncertain, ex post some gambles do pay off. Six years later as I get ready to 'rationally' take more such gambles in an area that I have become passionately curious about, I believe that this fulfilling academic journey would not have been possible if not for numerous people.

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CHAPTER 1

Introduction

A firm's value consists of the value of its assets in place and the value of its growth options. A large body of work in finance is devoted to understanding drivers of these components. In my dissertation I focus on understanding how a firm's internal organization and capital structure interact with its growth options – and hence its value. In particular, I examine how these corporate finance decisions affect or are themselves affected by the firm's R&D productivity. The dissertation consists of five chapters. I will briefly describe below what each of these chapters entails.

In the second and third chapters the focus is on understanding how R&D productivity is influenced by differences in the internal organizational structure of a firm. In these chapters I restrict my attention to diversified firms since information on various aspects of internal organization of these firms is easily available. More specifically, in Chapter 2, I empirically examine how the central feature of a diversified firm – its internal capital market – influences the innovativeness of the firm. I show that firms that are more reliant on internal capital markets to reallocate resources across divisions produce both a lesser number of innovations and also less novel innovations. Importantly, I use a quasi-experiment to show that the link between organizational form and R&D productivity is causal. Finally, I show that the drop in R&D productivity is costly for the firm since it results in a lower market value.

In Chapter 3, I argue that lack of commitment, weak incentives and asymmetric information are responsible for the impact organizational form has on R&D productivity. Following this, I empirically investigate whether firms take any steps to mitigate these problems. I show empirically that centralization of R&D budgets, incentives for divisional managers and CEO skill reduce the negative impact activeness of internal capital markets has on R&D

productivity of the diversified conglomerate.

In the fourth chapter I examine whether innovative firms make their capital structure decisions taking their future R&D strategy into account. In the context of the dissertation, this chapter departs from Chapters 2 and 3 that were focused on internal organization of the firm keeping external financing fixed. The basic hypothesis in this chapter is that certain external financing arrangements are more conducive to innovative activity than others. In particular, I argue that arms length financing (such as public debt and equity) allows for more discretion on long term projects and is preferred by more innovative firms; whereas less innovative firms tend to use relationship-based borrowing (such as bank borrowing). Empirical support is shown for this hypothesis in a large panel of US firms. This chapter is based on a co-authored paper with Julian Atanassov and Vikram Nanda and a version of this paper appeared in Julian's dissertation.

The final chapter of the dissertation briefly summarizes the results of this research and concludes.

CHAPTER 2

Do Conglomerates Stifle Innovation?

2.1 Introduction

The diversified conglomerate form has drawn the attention of economists, historians and scholars in finance and corporate strategy for many years. Alchian [1969], Williamson [1975], and Stein [1997], among others, have put forth the view that conglomerates, by virtue of exerting centralized control over the capital allocation process, may do a better job in directing investments than the external capital markets. This "bright side" view of internal capital markets has, however, been challenged by finance scholars who show that the average conglomerate trades at a significant discount relative to a portfolio of comparable single-segment firms (e.g., Lang and Stulz [1994] and Berger and Ofek [1995]).[1] They, however, do not offer any definitive explanation in support of their findings. As a result, the actual operations of this corporate form still remains very much of a mystery. In this chapter, I take a first step of peering inside this black box.

Chandler [1990] and Porter [1992] were, perhaps, among the first to point to a specific deficiency in this organizational form. Porter [1992] claims that " ... the decline in rate of return to R&D spending in the United States in 1980s is rooted in the large, diversified American corporations". If true, this would be a serious charge, since conglomerates account for more than 50% of corporate R&D spending in the U.S. In fact, in 2004, 10 out of the 15

[1] A number of other papers have taken issue with the idea that the diversification discount reflects value destruction (e.g., Campa and Kedia [2002]; Graham, Lemmon and Wolf [2002]; Villalonga [2004]). Broadly, these papers argue that the discount is tainted by endogeneity bias, because relatively weak firms are the ones that choose to diversify in the first place. However, as Stein [2003] notes, taking these caveats into account significantly reduces–though may not eliminate–that part of the discount which one can think of as reflecting a causal link from diversification to fundamental value.

top R&D spenders in the U.S. were diversified conglomerates. Even if Porter's charge were to stick, we still have to deal with the curious observation made by Business Week magazine in 2005:"...[diversified] firms exist on both sides of the innovative spectrum. While firms like G.E. and 3M are among the most innovative, a host of other conglomerates produce the least innovative R&D".

In this chapter, I posit the hypothesis that it is precisely in the area of research activities that allocations of capital by the headquarters of a conglomerate may have detrimental effects. Novel research projects are especially characterized by significant informational asymmetries between researchers and outside evaluators. Faced with the possible threat of reallocation of resources by corporate headquarters, researchers in divisions may have the incentive to manipulate the information they transmit to corporate bosses. Recognizing this problem, high-level managers may be reluctant to embark on novel projects in the first place. Thus, it is precisely those organizations that attempt to exploit the efficiencies of a centralized capital allocation process that may end up fostering mediocrity in their divisional R&D activities.[2]

I measure the scale of a company's R&D output by the number of patents its research generates. In addition, I measure the novelty of its research program by the average number of citations its patents receive in subsequent patent applications. Evaluating these measures for Compustat firms over 1980-1998, I find that while the average multi-segment firm is twice as large in terms of sales as the average single-segment firm, they have a similar degree of research intensity, as measured by R&D expenses to sales ratio. However, the average single-segment firm generates 5 patents per year vs. 3 for the average multi-segment firm. What is more, each such patent garners about 1.06 citations (adjusted for time and technology class effects) as compared to about 0.84 citations for the average patent obtained by the multi-segment firms. Clearly, there is evidence to support the hypothesis that multi-segment firms, on average, do less novel research than their single-segment counterparts.

Moreover, as per the observation by Business Week quoted earlier, these averages hide a considerable degree of variation even among patenting multi-segment firms. For example, the level of citations per patent ranges from a minimum of .08 to a maximum of 3.55. It is also the case that multi-segment firms with less cited patents are valued at a discount compared to a portfolio of comparable single-segment firms. Correspondingly, those with

[2]This argument is more formally presented in a simple model sketched out in Section A.1.

highly cited patents trade at a significant premium to a similar benchmark. Clearly, then, this is not a case of the financial markets systematically discounting the value of R&D activities undertaken by multi-segment firms. But the central puzzle still remains: *Why* do multi-segment firms, on average, engage in less ambitious research?

I use information in the Compustat files and from the 423,640 patents granted by the United States Patent and Trademark Office (USPTO) during the sample period to shed light on this question. I am able to show that conglomerates with more active internal capital markets do, on average, conduct less novel research. I find that this result is robust to several measures of internal capital market intensity. In particular, proxies for internal capital market intensity proposed by Billett and Mauer [2003] and by Rajan, Servaes and Zingales [2000] both yield similar results. In addition, I construct a novel measure of R&D competition between divisions of a multi-segment firm by assigning each patent to the corporate division responsible for it. I find that when the implied competition for R&D resources is high, as proxied by the relative patenting prowess of divisions, the novelty level of aggregate R&D suffers. In other words, I produce considerable evidence in support of the contention that conglomerates, in attempting to efficiently allocate capital across divisions, end up producing mediocrity in their research activity.

Having established a link between internal capital markets and research output, I next examine the possible value consequences of such a link. By using the "excess value" criterion of Lang and Stulz [1994] and Berger and Ofek [1995], I am able to demonstrate that conglomerates with more novel research do, indeed, have significantly higher values. This association is particularly strong for conglomerates which have divisions operating in industries that are more innovative. Specifically, estimates suggest that a one standard deviation increase in citations per patent produced by a conglomerate whose divisions are in innovative industries is associated with a 3.7% increase in its excess value, a large impact relative to the mean excess value of about -7% for conglomerates with divisions in innovative industries. These findings suggest that the costs to research incentives wrought by incentive conflicts inherent in the capital allocation process are quite substantial.

Note that the results outlined above, in the end, only show a strong association between internal capital markets and research output. To the ardent skeptic, the results would be suggestive but not conclusive evidence of a direct, causal relationship. In order to address such concerns, I conduct a quasi-experiment which examines what happens to R&D

output of a firm which engages in a merger. My specific experimental design combines the elements of a case-control methodology with elements of a placebo-controlled clinical trial. Using a difference-in-difference specification I show that, compared to a control group of targets whose merger attempt failed due to reasons unrelated with their R&D activities, targets successfully acquired in a conglomerating merger suffer a significant fall (about 65%) in novelty of their research output. What is more, I find that the drop in novelty is significantly more in targets that were acquired by firms which already had an active capital market in operation. Notably, the control sample and the targets involved in non-conglomerating mergers did not exhibit any change in their R&D output pre and post the scheduled merger date. The quasi-experiment thus, shows that indeed, the very internal workings of a conglomerate bring about a reduction in the novelty of research conducted there.

This chapter is clearly related to prior studies in finance that examine the costs of conglomeration. Scharfstein [1998] and Rajan, Servaes and Zingales [2000], in particular, also demonstrate that active internal capital markets have costs associated with them.[3] In addition, Scharfstein and Stein [2000] outline alternative rationales for such costs and Stein [2003] discusses the difficulty of providing proper incentives to divisional managers in the absence of divisional stock prices. However, this chapter is the first to empirically examine an explicit avenue through which conglomeration affects value. In doing so, the chapter provides empirical evidence that relates to capital-allocation centric point of view on the boundaries of the firm (e.g., Bolton and Scharfstein [1998]; Holmstrom and Kaplan [2001]).

This chapter also relates to a considerable literature on R&D activities of firms. Griliches [1990] provides a useful survey of use of patent-based metrics to measure innovative activity. In particular, Hall et al. [2005] relate patent-based metrics to firm value without distinguishing between conglomerates and single-segment firms. Argyres and Silverman [2005] also examine the relationship between organization structure and R&D output by evaluating the impact of centralization of R&D activities in a firm. My chapter adds to this literature by showing that aspects of organizational design can explain differences in innovation across firms.[4]

[3]These findings have been challenged by Chevalier [2004] who shows that the effects highlighted in these papers are also observed in the investment behavior of conglomerate divisions in the years before they merged.

[4]The chapter also provides additional insights into the popular view on entrepreneurial spawning. Gompers, Lerner and Scharfstein [2005] find that individuals become entrepreneurs since firms are unwilling to

Finally, at a broader level, this chapter relates to a voluminous literature on the role of technological progress in growth started by Solow [1957]. While the endogenous growth literature of recent times (e.g., Aghion and Howitt [1997] and Romer [1990]) emphasizes the role of technological progress in promoting growth at the aggregate level, it does not look at the inner workings of firms. This chapter is also an attempt, therefore, at augmenting this literature on the margin.

The rest of the chapter is organized as follows. Section 2.2 presents the hypotheses and develops testable predictions. Section 2.3 describes the main data and sample construction. Section 2.4 presents preliminary results, while Section 2.5 explores the impact of internal capital markets on research output. Section 2.6 discusses the quasi-experiment used to establish causality, while Section 2.7 presents value implications. Section 2.8 presents additional robustness tests and Section 2.9 concludes.

2.2 Hypothesis Development and Predictions

In this section I develop the hypothesis that diversified firms may not be conducive for innovative activity. I also discuss when the agency problem related to R&D projects is likely to be more severe and the characteristics of organizational design that might mitigate the problem.

2.2.1 Theoretical Considerations

R&D Productivity and the Agency Problem within Conglomerates

Stein [1997] argues that the principal benefit of a conglomerate structure is that the headquarter (HQ) can use its informational advantage and control rights to better allocate resources within the firm as compared to the external capital market. HQ can elicit verifiable (hard) information from divisions about the profitability of projects better than outside capital markets can. As a consequence, an internal capital market (ICM) may be more efficient in allocating resources compared to an external market. In addition, given the set of decision rules used by the HQ in allocating capital, divisional managers have the

take advantage of entrepreneurial opportunities in their core business. The findings in the chapter suggest that firms operating in multiple areas of research face an *ex post* commitment problem and as a result may attract a less entrepreneurial type of an employee. Moreover, individuals with "entrepreneurial spirit" would most likely leave the diversified firm because it would be reluctant to fund their entrepreneurial ideas.

appropriate incentives to produce verifiable information that HQ can use in its capital allocation process.

The "bright side" characterization of ICMs sketched above assumes that information asymmetries between the HQ and the divisions are either absent or are small in magnitude. While this may be a reasonable assumption for, say, the capital budgeting process or optimizing operational plans[5], it may not be as tenable for project selection that is reliant on soft information. In these cases, divisions may be in a better position to evaluate information available to them than HQ. More importantly, divisions may choose to withhold or hype such information in order to obtain better treatment by the HQ. In such situations, the imposition of *ex ante* specified allocation rules by the HQ may very well be detrimental to the firm as a whole.

Research and Development (R&D) activities, in particular, are characterized by significant information asymmetries between divisions and HQ. Initial stages of research are likely to generate signals that may be open to widely varying interpretations about future prospects. As Scherer [1984] points out, managers closest to the R&D process are likely to be in possession of significant soft information that may be hard to communicate. Furthermore, they may be in a position to suppress unfavorable information that may emerge during the research phase. Therefore, in firms reliant on novel innovations for generating value, a heightened emphasis on ICMs to reallocate resources may actually hurt rather than enhance the value of the firm.[6]

There are at least two ways to think why this may be the case. First, as Brusco and Panunzi [2005] argue, in a long-term project, the threat of reallocation by HQ can blunt the incentives of divisional managers.[7] The notion is that if divisional managers are aware that the "fruits of their labor" might be shared at a later date, perhaps because a more lucrative investment opportunity shows up in another division, they might not have the incentives to exert optimal effort *ex ante.* This problem is likely to have more bite for uncertain R&D projects and, as a result, could affect the quantity and quality of R&D output the firm produces.[8]

[5]For instance, Maksimovic and Philips [2002] and Schoar [2002] show that plants run by conglomerates are more productive than those run by their stand-alone counterparts.

[6]Novel R&D has been shown to yield high returns and add to firm value (Hall et al. [2005]).

[7]Interestingly, R&D managers have commonly reported in surveys (e.g., Booz Allen Hamilton [2006]) that the firms that conduct novel R&D have top management that is committed to sticking with the ideas even if initially they might not seem promising.

[8]Robinson [2006] uses similar intuition to explore the tradeoff between internal capital markets and

Second, divisional managers, concerned about reallocation of resources by HQ, may be unwilling to shut down projects even when the interim information they obtain is bad. They will, then, attempt to manipulate the release of such information to HQ. In anticipation of this manipulation, the HQ is likely to place less reliance on the divisional manager's information in making its own decision to continue with the project. Given that this problem is likely to be more acute for novel R&D projects, HQ may optimally decide not to embark on ambitious projects whose successful outcomes are *ex ante* more uncertain. Such behavior would show up in a deterioration of the *ex post* quality of R&D projects actually pursued. The second argument is more formally presented in a simple model sketched out in Section A.1.[9]

Both arguments presented so far assume that the R&D investment opportunities emerge in an exogenous fashion. However, opportunities generated at the divisional level may themselves also be influenced by organizational structure. If divisional managers need to put in effort to generate novel ideas in the first place, HQ control over resource allocation may adversely impact the incentives of divisional managers to do so. In particular, divisional managers may be concerned about being denied investment for projects that HQ finds difficult to evaluate after they have sunk in the effort. As a result, managers may want to propose only safe and incremental ideas–that HQ can evaluate and monitor better (Rotemberg and Saloner [1994]). In summary, both this argument and the ones above would suggest that conglomerates where the role of ICM is important would embark upon and produce less-novel R&D.

My first three predictions follow from the discussion thus far. First, since single-segment firms do not suffer from a similar agency problem, I expect them, on average, to be more innovative than diversified firms. Thus:

Prediction 1: *Ceteris paribus, conglomerates will produce less-novel innovations than stand-alone firms.*

Prediction 1 distinguishes between conglomerates and single-segment firms. However, even within conglomerates, there exist significant differences to the extent to which divisions

strategic alliances. He finds that alliances cluster in risky, high-growth, high-tech industries, and that they typically occur between industries with different risk characteristics.

[9] More generally, the notion that lack of commitment by a player can affect the project choice it makes can also be found in the literature on soft budget constraints (Maskin [2003]). Since large firms or governments may be unwilling to shut down projects once they have begun, they are reluctant to invest in projects that are *ex ante* more uncertain.

are granted autonomy in their operations. HQs that employ ICMs more intensively to redeploy resources between divisions are less likely to be able to credibly commit to a non-diversion of resources based on information available to them. Consequently, these conglomerates will allow the pursuit of less-novel projects than those with relatively hands off HQs. This observation is summarized in the next prediction.

Prediction 2: *Ceteris paribus, conglomerates with more ICM intensity will produce innovations that are less novel.*

Third, while ICMs are responsible for allocating capital for all types of investments, the intensity of the ICM with respect to R&D may be measured better by divisional competition for R&D resources themselves. In other words, all else being equal, HQ is more likely to reallocate R&D resources, and the consequent agency problem will likely be more severe, when the competition for R&D resources inside the conglomerate is higher.

Prediction 3: *Ceteris paribus, conglomerates with more competition for R&D resources will produce innovations that are less novel.*

2.3 Data and Sample Construction

2.3.1 Segment and Value Information

To construct the primary sample, I begin with all firms listed on Compustat's industry segment files for 1980-1998. I then refine the sample by excluding the following firms: (i) those with incomplete segment information on sales, assets or capital expenditures; (ii) those with segments in the one-digit SIC codes of 6 (financial firms) or 9 (government firms); (iii) those with sales less than $10 million and (iv) those with data missing on either market value of equity or cash flow statement items. Following Berger and Ofek [1995], I also drop firms if: (i) the sum of the segment sales is not within 1% of the total net sales and if the sum of segment assets is not within 25% of the firm assets. For remaining firms, a multiple is applied such that the sum of the recomputed segment assets adds up to total assets; and (ii) the imputed value of the conglomerate is missing. Imputed value of the diversified firm is the sum of the segment values, with each segment valued using median sales and asset multipliers of single-segment firms in that industry. The industry definitions are based on the narrowest SIC grouping that includes at least five firms.

Imposing all the filters described above, results in a sample of 12,090 diversified firm-years and 32,018 single-segment firm-years evenly spread out over the sample period. There are 6,500 firm-years with 2 segments, 3,300 with 3 segments, 1,250 with 4 segments and 1,040 with 5 or more segments.

Excess Value

I follow Lang and Stulz [1994] and Berger and Ofek [1995] to compute the excess value (EV) of the conglomerate as the log of the ratio of firm value to its imputed value. In the sample, the median (mean) excess value for diversified firms using Berger and Ofek's sales multiplier method is -13.03% (-16.14%) and -14.03% (-13.27%) using Lang and Stulz's asset multiplier method. These means and medians are all significantly negative at the 1% level.

Measures of Importance of ICM

ICMs assume greater importance when there is a greater degree of mismatch between the inflows and outflows of divisions. To measure the degree of importance of ICMs for a multi-division firm, a number of proxies have been suggested in the literature. I employ three of these in the analysis.

The first measure, *Reallocate*, closely follows Billett and Mauer [2003]: it captures the gap between the cash surplus in some divisions and the cash deficit in others. The degree of disparity in cash needs across divisions is measured by the sum of absolute values of the difference between cash flow from operations and capital expenditure across all the divisions. This is standardized by the absolute value of total investments less the total cash from operations to correct for potential differences in availability of total capital. Finally, the variable is normalized by the total assets of the conglomerate. More formally, for each year, $Reallocate_i = \frac{\sum_{j=1}^{n}|I_j - CF_j| - |\sum_{j=1}^{n}(I_j - CF_j)|}{Assets}$, where $Assets$ are the total assets of the conglomerate, I_j is segment j's investments, CF_j is its cash flow from operations and n is the number of segments. A higher value of this variable proxies for the importance of the ICM for the firm for that year. In the sample, *Reallocate* ranges from 0 to 4.90 with a mean value of 1.83.[10]

The second measure, *Diversity* is derived from Rajan, Servaes and Zingales [2000] (henceforth RSZ [2000]). It is defined as the standard deviation of the segment-asset

[10]Notably if the firm relied primarily on external financing, this measure would be small–highlighting the fact that ICMs are not important for the firm in question.

weighted (imputed) market-to-book ratio, Q, divided by the equally weighted average (imputed) segment Q. More formally, $Diversity_i = \frac{\sqrt{\sum_{j=1}^{n}\frac{(w_jQ_j - \overline{w_jQ_j})^2}{n-1}}}{\frac{\sum_{j=1}^{n} Q_j}{n}}$, where w_j is segment j's share of total assets, Q_j is imputed Q, n is the number of segments and $\overline{wQ}$ is the average asset weighted Q_j. This measure seeks to encompass three distinct features of an ICM: the number of different divisions, the correlation of investment opportunities between the divisions, and the size differences between these divisions. As RSZ [2000] point out, a higher value of the variable can indicate a greater number of divisions, less correlation in the segments' investment opportunities, and/or segments of relatively similar size. All of these are scenarios where the role of ICM is expected to be important In my sample, *Diversity* ranges from 0.02 to .96 with a mean value of 0.29.

Finally, the third proxy measuring ICM importance is the *Diversification Index*, measured as the inverse of the Herfindahl index of sales of various segments in the firm, i.e., $Diversification\ Index_i = \frac{1}{\sum_{j=1}^{n}\{\frac{Sales_j}{\sum_{j=1}^{n} Sales_j}\}^2}$, where $Sales_j$ are segment j's sales, and n is the number of segments. A higher value signifies more fragmentation in the conglomerate–a setting where the role of ICM is expected to be more important. In the sample, *Diversification Index* ranges from 1.09 to 6.03 with a mean value of 2.32.

In the empirical analysis, I will refer to conglomerates with high (low) ICM importance in a given year as having high (low) ICM intensity for that year.

2.3.2 Information on Innovation

The variables that measure R&D productivity are constructed from the NBER patent dataset created by Hall, Jaffe, and Trajtenberg [2001] (henceforth HJT). HJT match the assignees of the patents in the NBER dataset, by name, to manufacturing firms from Compustat, as of 1989.[11] The matched firms in the patent dataset are identified by the six-digit cusip number if the assignee is a public corporation or a subsidiary of a public corporation covered in Compustat. Using these cusip numbers, I merge the financial data with

[11]The match performed by HJT is a cumbersome procedure since it has to account for idiosyncrasies in names reported by assignees to USPTO. After the name match, HJT assign the patents to the firms from 1975–2002. For the firms that are matched, the data set provides annual information on patent assignee names, the number of patents, the number of citations received by each patent, the technology class of the patent and the year that the patent application is filed. The fact that the matching occurs for firms that existed on or before 1989 might introduce a survivorship bias, with older firms dominating the latter half of my sample. In the empirical analysis (Section 2.8), I control for this bias in a variety of ways and conclude that it does not affect my analysis.

the NBER patent dataset. For my analysis, I augment the HJT sample with all the firms in Compustat that operate in the same 4-digit SIC industries as the firms in the patent database but who do not have patents.[12] I take the patent count to be zero for these firms. Including these firms alleviates some of the sample selection concerns since the sampling procedure is independent of whether the firms patent or not. My sample spans the period of 1980–1998 since information on citations received by patents is reliably available over this period. The final Compustat-NBER merged base sample includes 6,635 firms that have publicly traded stock (44,108 firm years), 1,316 of which have registered a patent in one or more years during the sample period (9,270 firm years).

Measures of R&D Productivity

It has been common practice in the finance literature to use R&D expenditures as a proxy for the research intensity of the firm (e.g., Campa and Kedia [2002]). However, R&D expenditure combines the expenses incurred in both the research as well as the development phase. Since my predictions are on the productivity of the research that is undertaken by the conglomerate, rather than on the expenses incurred in developing the product/process, I focus on patent-based metrics. I am led to this choice by Trajtenberg [1990] and Griliches [1990] who show that patent-based metrics are better at measuring research productivity instead of R&D investments. Moreover, in contrast to R&D intensity, a patent signals to outsiders about the success of a firm's current R&D or its future R&D prospects. In addition, although patents provide an imperfect measure of innovation, there is no other widely accepted method that has been applied empirically to capture technological advances by firms (Griliches [1990]).[13] The first measure I employ is simply the patent count for a firm each year. Specifically, this variable counts the number of patent applications filed that year that were eventually granted.

The second metric of R&D productivity measures the importance of the output by accounting for the number of citations each patent receives in the subsequent years. Specifically, this measure is constructed by taking the total number of citations a firm receives

[12]Since 1989, the primary SIC code of a few firms has changed from manufacturing. As a result, in addition to manufacturing firms, I also include services and transportation companies.

[13]Using patents has its drawbacks (Griliches [1990]). Not all firms and industries patent their innovations because some inventions do not meet the patentability criteria and because the inventor might rely on secrecy or other means to protect its innovation. In addition, patents measure only successful innovations. In my analysis I control for industry-specific trends by using industry-and firm- fixed effects. Furthermore, I restrict my analysis to a sub-sample of industries with high patenting intensities and find similar results.

on all the patents it produces in a year and normalizing it by the total number of patents produced in that year. It is motivated by the recognition that the simple count of patents does not distinguish breakthrough innovations from less significant or incremental technological discoveries (e.g., Griliches, Pakes, and Hall [1987]). Consistent with this notion, Figure 1 shows that the distribution of the importance of patents is extremely skewed, with about 80% of the patents in the sample receiving less than 10 citations. Moreover, Trajtenberg [1990] and Hall et al. [2005] among others demonstrate that patent citations are a good measure of the value of innovations. Intuitively, the rationale behind using patent citations to identify important innovations is that if firms are willing to further invest in a project that builds on a previous patent, it implies that the cited patent is influential and economically significant.[14]

Both patents and citations suffer from several imperfections. First, there is a truncation bias in the number of patents toward the end of the sample, since it takes an average of two years from the time a patent is applied for to the time it is granted. Similarly, citations are received for many years after the patent is applied for and granted. As a result, patents towards the end of the sample tend to have fewer citations. Third, both patenting and citation intensities vary across industries. To adjust for these problems, I follow HJT and divide the number of patents (citations per patent) for each firm by the mean of the number of patents (citations per patent) in the same cohort to which the patent belongs. I use the year and technology class (finer industry classification used by USPTO to assign patents) to define these cohorts. The adjusted variables are called *Patent* and *CPatent*. In the sample, the median patents (citations per patent) produced by a firm is 0 (0), while among firms that patent, the median is 4 (0.76).

Attributing R&D Activity

While the NBER patent database provides patent and citations information at the aggregate firm level, it does not tell us anything about the division in the diversified firm that was responsible for a particular patent.[15] I use patent specific information (inventor

[14]It is not costless to cite a patent. By citing a patent, a firm narrows the scope of its property right and therefore, unless necessary, firms would prefer to not cite.

[15]The NBER patent dataset at the aggregate level has been used in different contexts in the finance literature (e.g., Atanassov, Nanda and Seru [2005], Lerner and Wulf [2006]). In contrast, my dataset is unique because I am able to match each patent produced by a conglomerate to the division that produced the innovation. This allows me to investigate the interplay between organization structure and R&D productivity.

location, inventor name, and claims) obtained from the United States Patent and Trademark Office website (www.uspto.gov) to match each of the 423,640 patents in the sample to the division that was responsible for the invention. I first search for the name of the subsidiary by examining the assignee name. For cases where the subsidiary name is not reported, I match the state of location of the inventors to the location of the subsidiary. To do this, I gather the information on the location of the subsidiaries of a conglomerate from the *Directory of Corporate Affiliations*. In many cases, the state of location is the same for different subsidiaries in a conglomerate. For these cases, I examine which technology class the patent was filed in and match it to the SIC code of the subsidiary. This match is not perfect since a technology class can correspond to a number of SIC codes. If the patent cannot be tracked to a unique division, I divide the patent equally among the subsidiaries that might be possible candidates.[16]

2.3.3 Other Financial Variables and Data

Besides information on sales, assets and capital expenditures at the segment level, I also collect information for both single and multi-segment firms on assets (*Assets*), sales (*Sales*), industry SIC, R&D expenditures (*RD*)[17], book equity (*Equity*), debt (*Debt*), net property plant and equipment (*PPE*), cash (*Cash*), operating profits (*EBIDTA*), market-to-book (Q) and retained earnings (*RetEarn*) from the main Compustat file. The data used to construct the market and firm stock returns come from the Center for Research in Security Prices (CRSP). I also use CRSP to construct the variable that measures the age of the firm (*Age*) based on the years from a firm's IPO as reported in CRSP. All the variables are winsorized at the 1st and 99th percentiles to prevent any influence of extreme outliers.

[16]The analysis is repeated after assigning the patents that are not uniquely tracked to a subsidiary in different ways. For instance, I also assigned the patent to only one (randomly chosen) subsidiary among the potential candidates. Doing so does not change the nature of the results.

[17]Note that many firms do not separately report R&D expenses and, thus, the variable is missing on Compustat for many firms. I assume that any firm that reports total assets but not R&D expenses had no R&D expenses in that year. Results in the chapter stay similar when an additional dummy variable that takes a value 1 for all the firms who do not report R&D expenses in a year is also included.

2.4 Preliminary Results

2.4.1 Descriptive Statistics

Table B.1 describes some sample properties of the main variables. Panels A and B provide details on the distribution and summary statistics of patents across years. Given that a vast majority of the sample has no patents, the distribution of patent grants to firms is very right-skewed, and the 75^{th} percentile of the distribution is zero. Panel B reports the number of firms per patent class. Among the multi-segment (single-segment) firm-year observations, those with zero patents represent roughly 66% (84%) of the sample, firm-years with one to two patents and three to ten patents about 10% (7%) and 11% (5%), firm-years with eleven to one hundred patents about 10% (3%). The remaining 3% (1%) of the sample comprises firm-years with more than one hundred patent awards.[18] I also find (unreported) that there is a large variation in patenting both *across* and *within* industries. Notably, the five industries doing the largest amount of patenting are Chemicals and Pharmaceuticals, Electronic and Computing Equipment, Aircraft, Office Supplies, and Automobiles.

Panel C presents descriptive statistics for single and multi-segment firms. As indicated by the reported values, multi-segment firms are larger (sales of \$2 billion vs. \$1 billion per year), spend more on R&D (\$43 million vs. \$22 million per year), have a lower market-to-book ratio (0.87 vs. 1.21) and have divisions that belong to more concentrated industries (average Herfindahl index of 0.28 vs. 0.23) than single-segment firms.[19] Moreover, over the course of the sample period, the average patenting multi-segment firm produces fewer patents than the average patenting single-segment firm (3 vs. 5), and these patents receive fewer citations per patent than those produced by single-segment firms (.84 vs. 1.06). All these differences in various statistics between the two groups of firms are significant at the 1% level. These univariate comparisons are in line with the prediction that firms with no ICMs should be associated with more productive R&D. Note, however, that both groups have an R&D to sales ratio of about 2.10%.[20]

[18] To alleviate concerns that the results might be affected by many firms with no patents in the sample, I conduct all my tests on firms that have at least one patent in prior years and find that results are unaffected. This is discussed in more detail in Section 2.8

[19] For the multi-segment firm, this variable is taken to be the sales weighted average of the Herfindahl index of each of its divisions.

[20] The R&D intensity of the two groups is similar even after adjusting for industries in which the divisions of the multi-segment firm operate (around 1.5%). I follow the approach of Berger and Ofek [1995] and Lang and Stulz [1994] and find that the median conglomerate firm has similar R&D intensity relative to a comparable portfolio of single-segment firms.

Panel D presents relevant characteristics of patenting multi-segment firms. Firms with above mean citations per patent are, on average, larger, have higher R&D expenditures, have higher market excess values (EV) and have less active ICMs than those below the mean level. The differences in various statistics between the two groups of firms are significant at the 1% level. These univariate comparisons are in line with my prediction that multi-segment firms with more intense ICMs (as indicated by higher values of *Reallocate*, *Diversity* and *Diversification Index*) should produce less-novel innovations. Interestingly, consistent with the notion that firms that produce more novel innovations have higher values, diversified firms with patents that receive more citations also have higher excess values (EV).

2.4.2 R&D Productivity in Single vs. Multi-Segment Firms

The univariate comparison between single and multi-segment firms suggests that, even though the R&D intensity is the same across the two groups, R&D productivity of single-segment firms is higher. In this section, I examine whether this relationship is robust to multivariate analysis.

The analysis starts by taking the number of patents as the measure of R&D productivity. Specifically, in Table B.2, I use a fixed effects Poisson regression that takes the simple patent count, *Patent*, as a dependent variable:

$$\text{Patent}_{it} = \lambda_{it} = \exp\left\{ \beta_1 \text{Dummy}_{it}^{mseg=1} + \delta \mathbf{Z}_{it} + \text{Time F.E.} + \text{State F.E.} \right\}. \quad (2.1)$$

The coefficient estimate of interest (β_1) in these models is on the dummy variable that indicates whether or not the firm is a multi-segment firm ($Dummy^{mseg=1}$). Following the literature (Lerner [2006]; Hall et al. [2005]), $\boldsymbol{Z}$ is the matrix of systematic factors that are related to R&D productivity and includes size measured by sales (*Sales*), investments in innovative projects measured by R&D expenditures (RD), and investment opportunities measured by market-to-book ratio of the firm (Q). To control for financial constraints that may be faced by the firm, I include the profitability of the firm ($\frac{EBIDTA}{Assets}$), operating cash ($\frac{Cash}{Assets}$), retained earnings ($\frac{RetEarn}{Assets}$), book leverage and asset tangibility (*Tangible*). $\boldsymbol{Z}$ also includes firm age (Age) and age square (Age^2) to control for life cycle effects on innovativeness. Finally, I also include industry concentration measured by the sales Herfindahl index (HI) and its square to capture possible non-linearities between market competition and innovation (Aghion et al. [2005]). All regressions are estimated with time and state fixed effects and the standard errors are heteroskedastic consistent to control for over-dispersion.

Consistent with my first prediction, I find that the estimated coefficient β_1 is negative and significant at the 1% level in model (1).[21] This shows that multi-segment firms are associated with fewer innovations as compared to single-segment firms. In Column (2), I use firm fixed effects to control for unobservable firm specific factors that could affect the firm's innovative activity and find similar results. In Column (3), for robustness, I repeat the estimation using a negative binomial specification and find similar results. In all the regression models, other firm specific control variables are significant as well. This is in line with findings in the literature (e.g., Griliches [1990]), that larger firms, those with higher levels of R&D expenditure, those with greater investment opportunities, and those that face lesser financial constraints create more innovations (Himmelberg and Petersen [1994]).

In Columns (4) to (6), I use the same specifications as in the first three models with *CPatent* as the dependent variable. As mentioned earlier, this variable measures the significance of the firm's innovative activity by accounting for the citations each patent receives. Again, I find that conglomerates tend to be associated with less-novel innovations.

Note that the findings are not due to differences in R&D expenditures between single and multi-segment firms since R&D expenses have been controlled for. Moreover, the relationship generally holds even when differences in scale, cash flow, investment opportunities and firm fixed effects are taken into account. The results in Table B.2 are economically meaningful. Estimates in Column (2) suggest that, keeping other factors at their mean levels, single-segment firms are associated with 50% (exp{-.68}-1) more patents. Moreover, estimates in Column (5) indicate that patents of single-segment firms are also 90% (exp{-2.39}-1) more significant than those produced by conglomerate firms. Given the small mean values of the number of patents and citations per patent (adjusted for technology class and year), these differences may seem small. However, I will show in Section 2.7 that even small changes in the number of patents and their citations can lead to significant value implications for the conglomerate.

Overall, the results in this section are consistent with the notion that single-segment firms have a higher R&D productivity because they do not suffer from the problems as-

[21] This result is also consistent with the papers in the organizational management literature that argue that diversification might be harmful to innovation due to the difficulty in gauging performance inside the conglomerate (e.g., Argyres and Silverman [2004]). A notable exception is the study by Cardinal and Opler [1995] who find no statistically discernible effect of diversification on innovative efficiency in a sample of research-intensive firms between 1981 and 1988.

sociated with ICMs. To determine whether ICMs directly impact R&D productivity, I now examine how R&D output varies with the importance of ICMs within conglomerates. The expectation is that more important the ICM is in terms of allocating resources across divisions, the more severe will be the drop in R&D productivity for a conglomerate.

2.5 R&D Productivity within Diversified Firms

In this section I examine how R&D productivity varies with two aspects of the ICM among conglomerate firms. Section 2.5.1 discusses the variation in R&D productivity with ICM intensity; Section 2.5.2 examines how R&D output varies with divisional R&D competition.

2.5.1 Variation with Internal Capital Market Intensity

In Panel A of Table B.3, I use a specification similar to (2.1) using *Patent* as the dependent variable in Columns (1) to (3) and *CPatent* as the dependent variable in Columns (4) to (6):

$$\mathrm{y}_{it} = \lambda_{it} = \exp\left\{ \beta_1 \text{ICM Intensity}_{it} + \delta \mathbf{Z}_{it} + \text{Time F.E.} + \text{Firm F.E.} \right\}. \tag{2.2}$$

The sample for this estimation includes all multi-segment firms. As explained earlier, I predict a negative relationship between proxies for ICM intensity (*Reallocate*, *Diversity* and *Diversification Index*) and innovations i.e., $\beta_1 < 0$. Consistent with this prediction, I find that the estimated coefficient β_1 is negative and significant at the 1% level in all the models. This implies that, controlling for financials and R&D expenditures, the more active the ICM, the fewer the number of patents produced by the conglomerate. Moreover, the coefficient estimates on *CPatent* suggest that these innovations are more incremental in nature. This relationship is robust to controlling for differences in scale, cash flow, investment opportunities and time invariant firm-specific factors. The results are economically meaningful: estimates in Column (4) suggest that a 1 SD increase in ICM intensity (1.8) inside a conglomerate is associated with a 75% (exp{-.762*1.8}-1) decrease in citations per patent, when compared to an average patenting conglomerate.

The regressions reported above ignore the fact that firms in more mature industries may have both (i) lesser potential to innovate and (ii) greater benefits from conglomeration through the use of ICMs. Such an association would introduce a selection bias. To ameliorate this bias, I construct measures of innovation for the multi-segment firm relative to innovation level of a comparable portfolio of single-segment firms in the same industries as the divisions of the diversified firm (*Patent*^{d} and *CPatent*^{d}). Subsequently, in Panel B, I estimate the following model using *Patent*^{d} as a dependent variable in Columns (1) to (3) and *CPatent*^{d} as the dependent variable in Columns (4) to (6):

$$\mathrm{y}_{it} = \left\{ \ \alpha + \beta_1 \text{ICM Intensity}_{it} + \ \delta \mathbf{Z}_{it} + \text{Time F.E.} + \text{Firm F.E.} \ \right\}. \tag{2.3}$$

Note that I switch to an OLS specification from a Poisson one since adjusting the measures of R&D productivity for the industry makes some of the values negative. Consistent with Prediction 2, I find that the estimated coefficient β_1 is negative and significant at the 1% level in the models. The economic magnitude of the estimates is large, though smaller than in the models in Panel A. For instance, estimates in Column (4) suggest that a 1 SD increase in ICM intensity inside a conglomerate is associated with a 65% ($\frac{-.112*1.8}{.30}$) decrease in citations per patent, as compared to an average patenting conglomerate (mean *CPatent*^{d} =0.3).

The results of this section confirm that ICMs significantly reduce the novelty of innovations produced by a conglomerate. While I find some evidence of a selection bias, it cannot entirely explain the relationship between ICM intensity and R&D productivity. For brevity, I will present most of the remaining results in the chapter using only citations per patent adjusted for industry effects (*CPatent*^{d}) to measure R&D productivity.[22]

2.5.2 Variation with Divisional R&D Competition

The proxies for measuring the intensity of the ICM with respect to R&D have so far been imperfect. Since ICMs are responsible for allocating capital for all types of investments, the intensity of ICM with respect to R&D may be better measured by divisional competition for R&D resources themselves. In this section, I use a measure of R&D competition to examine whether higher competition for R&D resources inside the conglomerate affects the novelty of the innovations it produces.[23]

[22] All results are qualitatively similar when the number of patents or other alternative variables that measure innovation (e.g., one that controls for self-cites) are employed.

[23] While I expect competition for resources to have a negative impact on the type of innovation the conglomerate engages in, there might be countervailing forces. For instance, if an effort-related moral hazard at the divisional level (Inderst and Laux [2005]) has a large impact on the type of innovation produced, an

To capture R&D competition, one can, in principle, use either R&D inputs or output. Since R&D inputs are not available at the divisional level, I exploit the annual information on the number of patents produced by each division in a conglomerate to construct a measure of R&D competition. Specifically, I use the inverse of the Herfindahl index of patents produced in the preceding year by *each division* inside the conglomerate, weighted by the sales of the division (*Compete*). I assume the value of this variable to be 1 if none of the divisions in the conglomerate produced a patent in the preceding year (i.e., no competition). *Compete* will have a large value if there are a number of divisions that produce innovations (more competition). On the other hand, the measure will have a value closer to 1 if there is a single division that largely produces innovations inside the conglomerate. The median value of *Compete* in the sample is 1.88.

To test my prediction, I estimate variants of the following model using *CPatent*^{d} as a dependent variable:

$$\text{CPatent}_{it}^{d} = \left\{ \alpha + \beta_1 \text{ICM Intensity}_{it} + \beta_2 \text{Compete}_{it} + \delta \mathbf{Z}_{it} + \text{Time F.E.} + \text{Firm F.E.} \right\} \quad (2.4)$$

As per Prediction 3, more competition for R&D resources lead the conglomerate to produce less-novel innovations; therefore, the coefficient on *Compete* is expected to be negative ($\beta_2 < 0$). I find evidence consistent with this in model (1) in Table B.4. In Column (2), I also include firm-fixed effects and find that the results are not affected. The estimates are economically significant. From Column (2), a 1 SD increase in competition for R&D resources (1.2) is associated with a 57% ($\frac{-.144*1.2}{.3}$) decrease in citations per patent.

In columns (3) to (5), variables that were employed earlier to proxy for ICM intensity (*Diversity*, *Reallocate* and *Diversification Index*) are added along with *Compete*. I find that in these models *Compete* retains its significance along with *Diversity* and *Reallocate.* Notably, the estimate on *Compete* remains the same even in the presence of these variables. This confirms the earlier premise that there are aspects of ICM affecting R&D that are not being adequately captured by the ICM intensity variables. In subsequent tests, I will employ *Compete* along with *Diversity* and *Reallocate* to proxy for the role of the ICM pertinent for R&D activities.

I end this section by conducting two robustness tests. First, in the construction of *Compete*, firms with no innovations in the previous year have been assumed to have no

increase in competition might actually improve incentives and lead to more novel innovations.

R&D competition (since the Herfindahl index is not defined for these firms). Therefore, a dummy variable indicating whether or not a firm produced an innovation in the preceding year is added in Column (6). I find qualitatively similar results. Second, to alleviate concerns that patents produced every year might not accurately capture the R&D activity of a division, I also construct an alternative measure of R&D competition taking patents produced by each division in the last three years. The results are unchanged when this measure is employed instead.

2.6 Causal Link? Evidence from a Quasi-Experiment

The results thus far show that features of the diversified organizational form are associated with its innovative ability. Admittedly, though suggestive, these results cannot conclusively establish a causal link between the diversified organizational form and R&D productivity. This is a challenge due to concerns about omitted variables and reverse causality. For instance, one could see a relationship between low R&D productivity and diversification because firms with low R&D productivity might be natural targets for bidders from different industries because it is easier to value such targets. In this section, I use a quasi-experiment to examine whether the diversified organizational form *causes* R&D productivity to go down.

My research design in this section draws heavily on techniques employed in medical sciences. I combine elements of case-control technique used to study infrequent events like deaths from cancer (Doll [2002]) with elements of "placebo-controlled" clinical trials (Pocock [2004]). Specifically, I assemble a "treatment group" comprising of firms taken over in a friendly merger and compare their R&D productivity pre and post-merger with those of a "control group". The control group is assembled from a sample of targets whose mergers failed to go through.[24] What I hope to find through such comparison is that a conglomerating merger brings about a drop in the novelty of innovations produced by the acquired target compared to targets which remained independent. However, since all successful mergers are not conglomerating mergers, I am then able to implement, in addition, a placebo-controlled test to examine whether the extent of dilution of innovation levels is affected by the nature of the merger itself. In particular, my research design is able to

[24]Similar case-control experiment has been used in the Finance literature by Eckbo [1983] and Savor [2006].

establish a causal link between conglomeration and dilution of incentives to engage in novel R&D if it emerges that targets in non-conglomerating mergers behave in a similar fashion to the control group, whereas those involved in conglomerating ones evidence diminished research output.[25]

2.6.1 Sample Construction

The basic sub-sample used for this test comes from the SDC Database. I focus only on all the friendly mergers since, unlike the hostile takeover, targets in friendly deals are less likely to change their R&D policies in any irreversible way in order to block the merger. I include all friendly deals (conglomerating and non-conglomerating) between 1980 and 1999. After applying filters to the deals (explained in Table B.5), I arrive at the treatment group, which consists of 2,321 (1,697 stock and 624 cash) mergers. To estimate the R&D productivity of a target once it has been acquired requires additional data collection. I use the approach in Section 2.3.2 to match innovation data to divisions to track the innovation of the target once it has been acquired.

The control group consists of mergers that can be considered to be unrelated to innovation incentives. To construct this group, I start from all friendly deals that were not completed during the sample period (422; 316 stock and 106 cash). Next, I only keep deals where the news articles from Lexis-Nexis and Factiva did not mention R&D activity of the target or the bidder as a reason for the failure. Broad categories under which deals were screened out can be found in Appendix II. The final control sample contains only those bids that did *not complete* because of: (i) objections by regulatory bodies, (ii) unexpected legal action or market conditions (e.g., 1987 crash), or (iii) competing offers. Regulator action takes the form of anti-trust complaints (or threats thereof) by the Department of Justice, the Food and Drug Administration, Federal Trade Commission, Federal Energy Regulatory Commission, European Union Commission, local authorities or by the Securities and Exchange Commission. Competing offers are bids that emerged subsequent to the first offer and the news did not mention that the interest of any of the bidders was due to innovativeness of the target. The control group consists of 175 deals out of the 422 deals

[25]Technically, this is equivalent to having an over-identification test of my theory. The identification comes from the unsuccessful targets that were going to conglomerate acting as a counterfactual for how the successful targets would have performed R&D *after* the merger, had they not been acquired by conglomerates. The over-identification comes from the targets in a non-conglomerating merger being used as a placebo to validate the experiment.

that had failed. Of the 175 deals, categories (i), (ii) and (iii) account for 44%, 42% and 14%, respectively.

The final sample consists of 14,590 observations before (13,460 control and 1,130 treatment) and 11,480 observations after (10,167 control and 1313 treatment) the intended merger date. Out of these, 3,860 involve acquisitions by multi-segment acquirers before (3,420 control and 440 treatment) and 2,982 after (2,660 control and 322 treatment) the intended merger date.

2.6.2 Pre-Merger Analysis: Validation of Control Sample Construction

To make inferences about subsequent changes in innovativeness of the control and treatment groups after the intended merger date (*event date*), it is important for the two groups to have similar sample characteristics, i.e., the two groups should look "balanced". The reason is that the quasi-experiment assumes that the only randomization between the control group and the treatment group is whether or not the merger succeeded. Panel A of Table B.6 shows this to be case. The two groups are similar in terms of sales, R&D expenditures, profitability and R&D productivity. To examine if this is also the case in a multivariate setting, I estimate a logit regression.

In the test I pool all target firms and examine whether the characteristics of the targets at any time $t-1$ can predict the deal's success at time t. I take all the years till the year in which the deal either succeeds or fails (inclusive). More specifically the specification is:

$$Prob\left(\text{Success}_{it}=1\right)=\Phi\left(\alpha+\ \gamma\text{Firm Financials}_{it-1}+\beta_1\text{CPatent}_{it-1}^{3yr_{avg}}+\text{Time F.E.}\ \right) \quad (2.5)$$

where Φ denotes the logit distribution function. The dependent variable *Success* takes a value 1 for the treatment group in the event year and 0 otherwise. The key explanatory variables include proxies for size of the target (*Size*), its R&D expenditure, its past three-year average R&D productivity ($Patent^{3yr_{avg}}$ and $CPatent^{3yr_{avg}}$), and its financial health (*EBIDTA/TA*, *Cash/TA* and *Leverage*). The regression is estimated with time-fixed effects and with robust standard errors.

As reported, the key explanatory variables are insignificant. This is in line with evidence in Panel A, and suggests that the pre-merger characteristics of the control and the treatment sample are quite similar and are, therefore, unable to predict which deal will subsequently succeed.[26] Notably, estimates on variables that measure past R&D productivity of the target are also insignificant (Columns (4) and (5)). This confirms that the control sample, indeed, consists of deals that fail for reasons exogenous to the innovation characteristics of the targets. Since some of the failed deals are due to anti-trust/competitive issues, this makes it likely that failure due to these reasons is more likely to occur if the bidder is from a related industry. To examine this, I add dummy variables that capture whether the bidder was from a related industry. These variables take a value 1 if the *bidder* is in the same SIC ($Dummy^{A_{dind}}$) as the target and when the bidder is a multi-segment firm ($Dummy^{A_{mseg}}$). I do find that the probability of the deal succeeding increases when the bidder is a conglomerate or is in a different SIC than the target (Column (3)). Overall, the analysis in this section validates the methodology that was used to construct the control sample.[27]

2.6.3 Post-Merger Analysis: Difference in Difference

Before a formal analysis, I provide a graphical snapshot of the R&D productivity of the targets in the treatment and control groups. Figures B.2 to B.4 depict the Epanechnikov kernel density of citations per patent corrected for technology and time effects (*CPatent*). Figure B.2 shows that the density of *CPatent* is similar in control and treatment groups before the event date. This is consistent with the evidence reported in the previous section. Figures B.3 and B.4 depict the kernel density of *CPatent* before and after the event date for the control and treatment groups, respectively. Figure B.3 shows that, for the control group, the density of *CPatent* is similar before and after the event date. In contrast, Figure B.4 shows that after the intended merger date, the treatment group suffers a fall in R&D productivity. The leftward shift of the density in Figure B.4 is significant since a Kolmogorov-Smirnov test for equality of distribution functions is rejected at the 1% level.

These figures suggest that, on average, R&D productivity falls in the treatment group. However, my primary interest is in determining whether the fall is confined to targets that undergo conglomeration. To examine this graphically, I plot the trend of *CPatent* for at

[26] An F-test for joint significance of the variables is rejected at 10% in Column (1). Moreover, the results are robust to using a firm-fixed effects specification (Column (2)), though observations are lost with firm fixed effects.

[27] Note that the predicted probabilities of control group range from 0.70 to 0.99, for the treatment group these range from 0.73 to 0.99. The high *ex ante* probability of a friendly deal going through is in line with what Baker and Savasoglu [2002] report.

least five years before and after the event. While *CPatent* of the control group remains at about an average of 0.77, it falls for the treatment group after the merger (by about 0.20 from an average of 0.70). Moreover, this fall occurs primarily in those targets engaged in unrelated mergers–mergers where the primary SIC code of the bidder is different from the SIC code of the target. This pattern is consistent with my expectation. To examine this more formally, I turn next to a difference in difference (DD) specification.

The DD specification compares the novelty of innovations of targets *within* the treatment and control groups before and after the event dates and then compares the difference *across* the two groups. Specifically, the specification that is estimated in Panel C is:

$$CPatent_{it} = \left\{ \begin{array}{l} \alpha + \gamma_1 \text{After}_{it} + \gamma_2 \text{After}_{it} * Treat_i + \delta \mathbf{Z}_{it} \\ + \gamma_3 \text{After}_{it} * Treat_i * Dummy_{it}^{A_{mseg}} \\ + \gamma_4 \text{After}_{it} * Treat_i * Dummy_{it}^{A_{mseg}} * ICMIntensity_{it} \\ + \gamma_5 \text{After}_{it} * Treat_i * Dummy_{it}^{A_{dind}} + \text{Firm F.E.} + \text{Time F.E.} \end{array} \right\}. \quad (2.6)$$

After is an indicator variable that takes a value 1 for all the years after the event date and 0 otherwise. *Treat* is an indicator variable that takes a value 1 for targets in the treatment group. To examine how the R&D productivity changes in targets that are engaged in conglomerating (unrelated) mergers, I include $After*Dummy^{A_{mseg}}$ and $After*Dummy^{A_{dind}}$. All the regressions are estimated with time and firm fixed effects.

Columns (1) and (2) show that while R&D productivity falls after the event in the treatment group (by about 30%$=\frac{.22}{.7}$), no drop is observed in the control group. This is consistent with the evidence presented in Figures B.3 and B.4. To investigate whether the fall is confined to targets that are engaged in unrelated mergers, I add terms $After*Treat*Dummy^{A_{mseg}}$ and $After*Treat*Dummy^{A_{dind}}$ in Columns (3) and (4). Consistent with the results in Figure B.5, I find that all the drop in the R&D productivity in the treatment group is confined to targets who are engaged in unrelated mergers. This provides evidence towards validity of the experiment–since the "placebo" (non-conglomerating mergers) did not see any change in R&D productivity.

Next, I examine whether the reduction in R&D productivity among targets in the treatment group that are acquired by multi-segment firms is related to ICM characteristics of the acquirer. More concretely, in Columns (5) to (7), I include $After*Treat*Dummy^{A_{mseg}}*$*ICM Intensity*. Here *ICM Intensity* is the average of ICM intensity variables of the multi-segment acquirer prior to the event date. Coefficient estimates on the interaction terms indicate that a significant proportion of the drop (about 80%) in novelty of innovations is found in cases where the ICM intensity of the multi-segment acquirers is high prior to the merger. This provides direct evidence that it is primarily the activity of the ICM that affects novelty of innovations.

I also examine if the acquisition of the target results in any change in the novelty of innovations for the entire conglomerate (excluding the target). One can, for instance, conjecture that while the novelty of innovations in the target falls, innovation in the entire conglomerate increases as a result of refocusing/restructuring of the target. To examine this, I estimate the change in R&D productivity of the multi-segment acquirers before and after the merger (using (2.6)). I find no evidence of any substitution between R&D productivity of the target and the acquirer.

Does this drop in R&D productivity occur because the conglomerates cut back on R&D expenditures? Although I do not have data on R&D of the targets once they are acquired, I can make some inferences based on the aggregate R&D spending of the conglomerate. In particular, consistent with Hall [1999], I find no significant change in the sales weighted average R&D of the target and the multi-segment bidder before the merger as compared to R&D expenditure of the combined entity after the merger. This suggests that managers in multi-divisional firms are not cutting R&D investments but rather are producing less-novel innovations for each dollar they invest in R&D.

The drop in R&D productivity suggested by the coefficient estimates is economically large. In particular, comparing the estimate on $After*Treat*Dummy^{A_{mseg}}$ (γ_3=-.45) in Column (3) with the average citations per patent produced by the target in the treatment group (.70) suggests a drop of about 65% ($\frac{-.45}{.70}$). Interestingly, comparing this number with the estimates from Table B.2 (Column (5)) suggests that more than two-thirds of the 90% drop in novelty of innovations found earlier can be attributed to the diversified form affecting R&D productivity. In value terms, this drop is around -2.1% and compares well with the -2.3% announcement returns that have been documented in diversifying mergers by Morck, Shleifer and Vishny [1990].

Summarizing, I find strong evidence that the novelty of innovations falls in targets engaged in conglomerating mergers, with the drop being more severe for conglomerates having more active ICMs. There is no evidence of such a reduction in the novelty of innovations by targets whose deal failed for reasons exogenous to R&D or in targets that were involved in non-conglomerating mergers. This evidence strongly suggests that the diversified organizational form *itself* causes R&D productivity to go down.

A caveat associated with the analysis, of course, is that one can only make inferences about innovative firms. Moreover, the analysis does not attempt to address whether it is optimal for conglomerates to undertake such mergers. While I show a particular cost associated with the conglomeration, this could be only part of the story. For instance, there might be private benefits that the manager might be getting by undertaking the acquisition. This has been argued for by Morck, Shleifer and Vishny [1990] when they found negative stock market reactions to such mergers. Likewise, there might be other benefits of a conglomerating merger–e.g., better efficiency of operations or winner picking (Guedj and Scharfstein [2005])–that are not captured by this analysis.

2.7 Novelty of Innovations and Value

I have shown that the quality of R&D output is affected by measures that proxy for the importance of ICM. The question that remains is whether R&D output has valuation consequences. In other words, does the dilution of incentives to produce more novel innovations hurt the market value of a conglomerate? To examine this question, I use the "excess value" (EV) criterion of Berger and Ofek [1995] to see how much a conglomerate suffers in value terms compared to a portfolio of comparable single-segment firms. The model I estimate is:

$$\mathrm{EV}_{it} = \left\{ \alpha + \beta_1 \mathrm{CPatent}_{it} + \delta \mathbf{Z}_{it} + \text{Time F.E.} + \text{Firm F.E.} \right\}, \tag{2.7}$$

where $\mathbf{Z}$ includes other factors that have been used in the literature to explain the value of a multi-segment firm (*Size*, *Leverage*, $\frac{Capx}{Assets}$, $\frac{EBIDTA}{Assets}$ and $\frac{Cash}{Assets}$).[28] The results are reported in Panel A of Table B.7. The estimate in Column (1) shows that conglomerates that produce more novel innovations tend to be associated with higher excess value ($\beta_1 > 0$). In Column (2), I repeat the estimation including firm fixed effects and using $CPatent^d$ as the dependent variable to control for the industries the divisions of the conglomerate operate in. The results are similar. The estimate in Column (2) suggests that a 1 SD increase in novelty of innovations (0.70) produced by an average patenting conglomerate is associated

[28] Since I am explaining differences in value *among* conglomerates rather than explaining absolute levels, criticisms about inferring value destruction from the EV measure are not applicable (e.g., see Campa and Kedia [2002]).

with a 3.2% ($.047 * .70$) increase in its EV. This effect should be compared with the mean EV of -13% for the whole conglomerate sample reported earlier.

Next, I investigate the effect for those conglomerates whose divisions operate in innovative industries. The expectation is that R&D productivity will be most valuable for these conglomerates. Specifically, in Column (3), I include the interaction of $CPatent^d$ with an indicator variable ($Dummy^{P>0}$) that takes a value 1 if at least one of the divisions of the conglomerate operates in an industry that produces more than the median patents produced across industries in a given year. Consistent with my expectation, the effect of high R&D productivity on value is stronger when the conglomerate operates in innovative industries. The estimate suggests that a 1 SD increase in citations per patent by such a conglomerate is associated with a 3.7% ($.052 * .70$) increase in its EV. This impact is quite large especially in comparison with the -7% mean EV of conglomerates with divisions in innovative industries.

The question that now remains is whether, consistent with the arguments in the chapter, the measures that proxy for *ICM Intensity* have more bite when the divisions of the conglomerate operate in innovative industries. To examine this in Panel B, I include *ICM Intensity* variables interacted with $Dummy^{P>0}$. Columns (1) to (3) show that, even with R&D productivity controlled for, *ICM Intensity* variables are negatively related to value, with the relationship being more pronounced when the divisions of the conglomerate operate in innovative industries.[29] Interestingly, the negative effect for *Compete* is entirely confined to innovative industries. This is not surprising, given that this variable measures the intensity of the ICM with respect to R&D. The negative effect for *Diversity* and *Reallocate*, though considerably lower in economic magnitude, does remain significant in conglomerates that operate in non-innovative industries. This is consistent with other studies that suggest that ICMs may have other non-R&D related costs as well (e.g., power struggles, RSZ [2000]; over-investment, Stulz [1990]).

2.8 Robustness Tests

In this section, in addition to examining the robustness of my results to alternative specifications and sub-samples, I also examine whether other agency alternatives that have

[29]The results are economically meaningful. A 1 SD increase in these variables is associated with about a 3-4% decrease in EV.

been investigated in the literature might be able to explain some of my findings. In most of this section, I will employ models similar to (2.3) with additional interaction terms.

2.8.1 Alternative Agency Interpretations

First, to examine whether internal power struggles might be influencing the results, I test my predictions in conglomerates where investment opportunities are similar and in firms where CEO power is high–both scenarios where the cost of diversity identified in RSZ [2000] is expected to be low (Stein [2003]). As can be seen from Columns (1) and (2) in Panel A of Table B.8, novelty of innovation is negatively related to ICM intensity even in conglomerates with divisions with similar investment opportunities (indicated by dummy variable D^{Q_L}). In Columns (3) and (4), I examine whether the results are also found in firms where CEO has power. I follow the literature (Adams et al. [2005]) and define a CEO as being powerful if she is the chairman and president of the board (indicated by dummy variable D^{CEO_H}). I find evidence in line with my conjecture. This suggests that power struggles might not be the reason for observed R&D productivity inside conglomerates with active ICMs.[30]

Second, I examine whether the results are affected by the inefficiency of allocations in ICMs on account of biasing of information by large divisions (Wulf [2002]). Specifically, in Columns (5) and (6), I examine whether lower novelty of innovations is confined to conglomerates with large dispersion in the size of its divisions (indicated by dummy variable D^{Size_H}). I find little evidence to support this hypothesis. Finally, I examine whether efficiency in allocation of investments of the conglomerate is related to its R&D productivity (Stulz [1990]). More concretely, I examine whether conglomerates that over-invest in low Q divisions and/or under-invest in high Q divisions are also the ones that innovate less. Following RSZ [2000], I use the relative value added by allocation (RVA) for my tests. This measure captures the Q weighted transfers made between segments of a diversified firm–relative to the average investment ratio of single-segment firms in the same industry. As indicated in Columns (7) and (8), I find no evidence for the conjecture.

[30]The rent-seeking argument of Scharfstein and Stein [2000] might also not be at play here. As per their hypothesis, one would expect powerful CEOs to mitigate agency problems in conglomerates whose divisions face similar investment opportunities. In unreported tests, I do not find evidence for this conjecture. Admittedly, this test is, at best, a weak test of their theory. Information on CEO incentives would be needed to do a better test of rent seeking.

2.8.2 Sub-sample Analysis and Alternative Specifications

Since the NBER patent sample is matched based on firms that publicly traded in 1989, I examine whether having more mature firms in later years in the sample induces a survivorship bias. In principle, this can introduce a bias if mature conglomerates present in the later years do most of the incremental innovation and also have a high ICM intensity. To alleviate concerns, besides including age of the firm in all the regressions, I also re-estimate the relationship between the innovations and the intensity of the ICM for two sample periods: 1980 to 1989 and 1990 to 1998. The results show a similar negative relationship in both sample periods, thus dispelling any survivorship concerns.

Next, to ensure that the results are not driven by a significant number of firms that do not patent, the following two strategies are used: (i) tests are conducted only on sub-samples of innovative industries and firms and (ii) alternative specifications are employed. First, I restrict the analysis to only highly innovative industries. I follow Hall et al. [2005] and classify industries into 6 sectors: Drugs and Medical Instrumentation (henceforth just "Drugs"); Chemicals; Computers and Communications (henceforth just "Computers"); Electrical; Metals and Machinery; and miscellaneous ("low-tech industries"). The first four industry sectors are the source for most of the patents in the U.S. As reported in Column (9) of Table B.8, I find similar results even when I restrict the analysis to firms in the four innovative sectors. I also conduct all my tests on firms that have at least one patent in prior years and find that results are unaffected. Second, I employ zero-inflated Poisson and Negative Binomial specifications which control for the presence of many firms without patents and find similar results as those reported in the chapter.[31]

2.9 Conclusion

The central idea behind conglomeration is based on the notion that a well run internal capital market may be a better alternative to external capital market afflicted with agency conflicts and information asymmetries. The "visible hand" of a central headquarters may, therefore, be better able to exploit synergies across divisions and allocate capital optimally across them. However, the firm itself, as a nexus of contracts, also suffers from internal op-

[31] Alternative measures of R&D productivity are also employed to check the robustness of the results. These include measures that control for (i) the scale of R&D activity by constructing a portfolio of citations weighted patents (Trajtenberg [1990]) and (ii) self-cites besides industry, technology and time effects.

portunism, strategic information transmission and a host of other related problems. Could it be then, that there is a "dark side" to conglomeration that overwhelms its supposed advantages?

In this chapter, I have attempted to shed some light on the internal operations of conglomerates by focusing on the incentives to engage in novel R&D. I find that it is precisely those conglomerates that attempt to run active internal capital markets that show the signs of impaired innovativeness. I present a wealth of tests that bolster the notion that centralized control tends to act as a brake on the process of generating novel innovations. In an area of inquiry that is rife with problems of endogeneity and reverse causality, I am able to show, with the help of a novel adaptation of a case-control methodology, strong evidence in favor of the hypothesis that the diversified organizational form impedes the pursuit of novelty in innovation. Furthermore, such impediments seem to have significant value consequences. My research lends strong credence to the notion that value can be generated by focus.

I do not, however, claim that there is no benefit to conglomeration. In fact, it could very well be the case that the conglomerate form adds value in sectors where innovation is not particularly important. What these benefits are is left for future research.

CHAPTER 3

Organizational Design and Innovation

3.1 Introduction

In Chapter 2, I showed that organizational form may have an impact on its R&D productivity. These results should not be taken to imply that the relationship between internal capital market intensity and research output are hard-wired. Firms, possibly aware of consequent agency problems outlined in previous chapter, take steps to counteract diminished research incentives. This chapter works out of this argument.

I argue that the problems outlined earlier are due to lack of commitment form headquarters, asymmetric information and weak incentives. I then hypothesize that firms can take certain steps to counter each of these problems. First, decentralization of R&D budgets can be used by headquarters to commit to divisional managers that resources will not be moved based on expost performance reviews. Thus I expect conglomerates where a larger proportion of R&D budgets is left at the discretion of divisional managers (decentralized budgets) should produce more novel innovations. Next, long-term incentives to the divisional manager and CEOs with exposure to innovative divisions can ameliorate the negative impact that managerial self-interest and asymmetric information about the R&D project have on R&D productivity.

In my empirical tests, I find considerable evidence supporting these predictions. I find that decentralization of R&D budgets is significantly associated with more novel research output. This finding is in line with results in Aghion and Tirole [1997], who also argue that endowing managers with greater discretionary powers boosts incentives for producing creative output. Moreover, I also find improved research output to be associated with measures of incentive compensation granted to divisional managers and to the level of experience a CEO has with innovative divisions under his/her control. In addition, these mechanisms tend to ameliorate the negative impact that internal capital markets have on novelty of innovations.

Overall the findings in this chapter shed light on a few of the mechanisms that firms can use as a part of its organizational design to mitigate problems that can hinder creativity within the firm. The rest of the chapter is organized as follows. Section 3.2 presents the hypotheses and develops testable predictions. Section 3.3 presents the main empirical tests and Section 3.4 concludes.

3.2 Hypothesis Development and Predictions

In this section I discuss the characteristics of organizational design that might mitigate the problem that was outlined in Chapter 2

3.2.1 Alleviating the Agency Problem through Organizational Design

In developing the predictions in Chapter 2, I have implicitly assumed that conglomerates take as given the level of disincentives to R&D that came along with their organizational structure. However, most management realize the constraints their organizations impose and seek to lessen their impact through active organizational design. The problems that I have sketched above stem essentially from asymmetric information and incentives. Clearly, their impact may be lessened by enhanced attention to commitment mechanisms, a better alignment of incentives and a reduction in information asymmetries. The predictions below explore these possibilities.

First, the main agency problem may be alleviated if HQ can credibly commit to not redistribute resources midway from a division doing novel R&D. The proportion of R&D budgets that is left at the discretion of divisional managers can be thought of as an instrument that can be used to cement such a commitment. The reason to expect an improvement in R&D output with decentralization of R&D budgets is similar to that in Aghion and Tirole [1997] who argue that giving discretion to a manager can improve his incentives. With improved incentives, the divisional manager will (i) put in more effort and (ii) be more willing to shut down projects when interim information he obtains is bad. Therefore, one would expect improved R&D productivity in conglomerates where a large proportion of R&D budgets are decentralized.

Since the interests of HQ and the manager may not be perfectly aligned, the manager can use his informational advantage to make choices that are not in the best interest of HQ (e.g., invest in his pet projects). This trade-off between the superior knowledge of the manager and the agency costs of managerial delegation would determine the optimal degree of decentralization. In general, one would expect a decentralized structure to be optimally chosen when there are more novel projects opportunities faced by the conglomerate. More details on this argument can be found in the model presented in Section C.1. Thus:

Prediction 1: *Ceteris paribus, conglomerates with larger proportion of decentralized R&D budgets will produce innovations that are more novel.*

Second, long-term incentives to the divisional manager could also be used to mitigate the negative effects the ICM may have on R&D productivity. Specifically, if decisions on R&D projects are taken by HQ, proper incentives could align the managers towards providing the right effort and/or correct information (Wulf [2002]). In addition, even if the projects are chosen and conducted by divisions without HQ intervention, the managers will make project decisions that add to firm value if they are incentivized to do so. Note that this prediction is about the impact long-term incentives have on the negative effects of ICM activity on R&D productivity. This is different from Lerner and Wulf [2006] who show that firms where R&D managers are incentivized more tend to have novel innovations. Therefore:

Prediction 2: *Ceteris paribus, conglomerates with high-powered incentives for divisional managers will mitigate the negative effect ICMs have on R&D productivity.*

Finally, I also expect CEOs with experience in innovative divisions to be better at evaluating R&D projects proposed by divisional managers. Consequently, such CEOs may be able to ameliorate some of the agency problems that arise due to the difficulty of evaluating novel projects. This is consistent with the discussion in Stein [2003] as well as reports in the popular press. For instance, an article in Fortune Magazine in 1999 reports that "... Exposure to many disparate businesses give executives more ideas and confidence than most business people ever acquire ... Managerially, they've seen the world. They've built a greater fund of ideas and practices than managers who've spent a career in one industry". Thus:

Prediction 3: *Ceteris paribus, conglomerates where CEOs have exposure to innovative* *divisions will mitigate the negative effect ICMs have on R&D productivity.*[1]

3.3 Empirical Results

In the empirical analysis conducted in this chapter, I use the innovation and financial data that was described in Chapter 2. I elaborate on any additional data that is employed in this chapter along with the tests itself. In Section 3.3.1 I discuss the impact decentralization of R&D budgets can have on R&D productivity. I have also argued that agency problems and asymmetric information about projects are responsible for ICMs reducing the firm's R&D productivity. If so, there are two solutions. One is strengthening divisional manager incentives and the second is reducing information asymmetry between divisions and HQ. Sections 3.3.4 and 3.3.5 discuss these in turn.

3.3.1 R&D Productivity and Decentralization of R&D Budgets

The measures of ICM intensity used in Chapter 2 have the disadvantage that they are not fully focused on R&D activities *per se*. For testing the first prediction, I now turn to another measure that is directly concerned with the conduct of R&D: the proportion of R&D budget that is financed by divisions. The proportion of R&D budget left at the discretion of a division represents the degree of commitment by HQ to abstain from *ex post* reallocation contingent on performance reviews. Consequently, a higher degree of decentralization of budgets should lower the agency problems caused by reallocation incentives. However, it is impossible to determine the R&D budgeting policy for all the firms in the sample that conduct R&D. As a result, I use survey data from the Industrial Research Institute (IRI) which covers a wide range of industries. The firms surveyed by IRI are R&D intensive and account for over 25% of the total industrial research spending in the U.S. in 1994 (as reported by NSF in 1995). Most of these firms are members of the Fortune 500. The rest of the section discusses the sample before detailing out the analysis.

[1]Interestingly, consistent with these predictions, Business Week reports that " ... CEO skill is one of the critical determinants of the kind of innovation the organization conducts". CEO skill mattering for innovation is also consistent with the article in Fortune Magazine in 1999 which reports that: "Exposure to many disparate businesses give executives more ideas and confidence than most business people ever acquire ... Managerially, they've seen the world. They've built a greater fund of ideas and practices than managers who've spent a career in one industry."

3.3.2 Sample Construction

IRI, a non-profit organization with member firms active in industrial R&D, conducted two surveys amongst its member firms in 1994 and 2001. The surveys collected information on member firms' R&D organization structures as well as on the fractions of R&D budgets that came from corporate management, divisional management, and external sources (e.g., contract research). IRI received usable information from 120 of its approximately 180 members. Only a few of these 120 companies consented having their names printed on the published R&D policies, possibly due to secrecy concerns. I use information from 10-K filings, annual reports and other sources following the procedure outlined in Argyres and Silverman [2004] to determine the names of the remaining firms.[2] After eliminating single-segment firms, private firms and non-U.S. companies, I was able to identify a total of 54 diversified firms that I could match with Compustat data.

The survey data allow me to directly identify the proportion of R&D budgets that come from HQ. In addition, the survey also identifies firms that conduct R&D activities at the divisional level and firms which conduct R&D at a centralized location. From this information, I create two separate variables. First, $Divisional_{it}$ is a dummy variable equal to 1 if firm i has a divisional R&D structure, and 0 otherwise. This variable helps to isolate firms with centralized R&D and permits me to run tests of Prediction 1 for the remaining firms. The mean value of this variable in the sample is 0.87, suggesting that most of the firm-years in the sample have a divisional R&D structure. Second, and the key variable for the analysis, $\%H_qBudget_{it}$, is defined as the proportion of firm i's R&D budget provided by corporate headquarters. If a firm is classified as having a central R&D structure, and $\%H_qBudget$ is unavailable, I assume that for that time period, $\%H_qBudget_{it}$ is 100%. The mean value of this variable in the sample is 0.43, suggesting that an average multi-segment firm in the IRI sample has 43% of its R&D budgets decided by HQ. I use 817 observations for the tests using this sample.[3] Finally, IRI reports some structures as hybrid, i.e., doing R&D at both a divisional as well as a central level. These structures are

[2] I was immensely helped in the process of matching names to firms by Nick Argyres who graciously provided me with the results of his own matching exercise.

[3] Three issues related to $\%H_qBudget$ need mention. First, how effective is this measure at capturing the discretion of a division when HQ has effective control over these budgets in the future? If HQ reallocates resources even when a high proportion of R&D budgets are decided by the division, I would not find support for Prediction 1. Second, this variable is assumed to have the same value for years when no change to R&D policy is mentioned in the surveys. To account for concerns about serious correlation in standard errors due to this assumption, all the regressions in this section are estimated with standard errors clustered for time.

dealt with as follows. For identifying changes in the R&D structure, the question in the IRI survey where the respondents are asked when the organization structure last underwent a "significant change" is used. For the cases when the R&D structure is identified as being hybrid (R&D conducted both at a centralized location as well as in divisions), I used a methodology similar to that employed by Argyres and Silverman [2004] in categorizing the hybrid category as being divisional or central.

3.3.3 Empirical Analysis

Panel A of Table D.1 presents summary statistics of the key explanatory variables. The average values of Sales and R&D for the firms in the sample is \$13,315 million and \$499 million, respectively. Clearly, these firms are large and have R&D activity that is significantly higher than that of an average firm in the full sample (e.g., R&D intensity of 3.8% vs. 2.10%; Patents of 41 per year vs. 3 per year). To examine how decentralization of R&D budgets may affect the novelty of innovations produced by a conglomerate, I estimate the following model:

$$\mathrm{CPatent}^{d}_{it} = \left\{ \begin{array}{l} \alpha + \beta_1 \%\mathrm{H}_q\mathrm{Budget}_{it} + \beta_2 \mathrm{Divisional}_{it} + \beta_3 \%\mathrm{H}_q\mathrm{Budget}_{it} * \mathrm{Divisional}_{it} \\ + \; \delta \mathbf{Z}_{it} + \mathrm{Time\ F.E.} \end{array} \right\} \quad (3.1)$$

Panel B presents the results of the estimation. The coefficient estimate of interest β_1 in Column (1) is negative, suggesting that more centralized budgets are associated with less-novel innovations. In the next model, I condition on whether or not the firm has R&D at the divisional level by including the interaction term $\%H_q Budget^* Divisional$. The expectation is that most of the negative association in Column (1) should occur when the R&D is conducted in divisions. Consistent with this expectation, the coefficient estimate on the interaction term (β_3) is negative. Moreover, after including the interaction term, the estimate on $\%H_q Budget$ loses significance. In Column (3), I repeat the estimation including firm fixed effects and find similar results. This suggests that changes in control over R&D budgets in a firm is related to changes in novelty of its innovations. The coefficient estimates in Column (3) suggest that a 1 SD increase in the proportion of R&D funding by HQ (.12) in a fully divisional R&D conglomerate will decrease the citations per patent by 67% ($\frac{-.168*.12}{.3}$), as compared to an average patenting conglomerate.[4]

[4]Note that these findings are different from those in Argyres and Silverman [2004]. There could be several reasons for this. First, the identification in their study comes from the difference in R&D policies of

Since only large firms are surveyed in the IRI data, there could be a selection bias that results in a spurious correlation between $\%H_q Budget$ and novelty of innovations. To examine this, I use the Heckman [1979] model which accounts for the selection of the firms into IRI survey in the first stage. Specifically, for all the diversified firms in the base sample, a firm is treated as having been selected into the IRI survey if the information on R&D budgets and type of R&D organization is available. In the estimation of the first-stage regression (in Table D.2), the instruments I use are: whether or not the firm's age is in the top quartile of the sample in a given year ($Dummy^{HiAge=1}$), whether or not the firm's R&D is in the top quartile of the sample in a given year ($Dummy^{HiR\&D=1}$) and whether or not the firm is in the S&P 500 Index in a given year ($Dummy^{S\&P500=1}$). All these variables proxy for how well known or visible the firm is. The notion is that better known firms are the ones that are selected into the IRI survey. The selection model uses 12,090 observations, while the second-stage regression uses only the 817 observations. A highly significant estimate on Inverse Mills Ratio in the second stage (Column (4)) suggests that it is important to account for selection in this setting. Notably, however, the estimate on $\%H_q Budget$ is unchanged. Finally, in Columns (5) to (7), I employ the variables that proxy for the importance of ICMs along with $\%H_q Budget_{it}$.[5] I find that $\%H_q Budget$ remains significant in the presence of these variables. This is consistent with the earlier argument that degree of decentralization of R&D budgets captures aspects of ICM intensity that are not proxied by other indirect measures. Overall, the findings of this section support the prediction that decentralization of R&D budgets positively affects the novelty of innovations produced by a conglomerate.

3.3.4 Incentives

Incentives could align the managers towards providing the right effort and/or providing more reliable information. If these incentives are based on firm value, they would also have the additional benefit of reducing any lobbying motives that the divisional managers might otherwise have in order to increase the capital budgets of their divisions. I proxy for such

firms that have a central R&D laboratory with those that have divisional R&D laboratories. In contrast, my identification comes from the variation in R&D budgeting policies of firms all of whom have divisional laboratories. Moreover, the sample of firms in my study (diversified firms) is different from the sample employed in their study (single segment and diversified firms).

[5] It is instructive to note that $\%H_q Budget_{it}$ is positively correlated with *Diversity* (43%), *Reallocate* (31%) and *Compete* (29%); all significant at the 1% level.

incentives by options granted to non-executives with the expectation that non-executives are likely to include divisional managers. While these option grants may be small in absolute magnitude, they could proxy for other incentives that might be also given to the divisional managers.[6]

The data on options granted to non-executives is not readily available. However, the following data is available through SEC's EDGAR database: (i) the number of options that were granted in total and (ii) option holdings of top executives. The difference between these is attributed to non-executives. I randomly chose 600 multi-segment firms from the main sample and gathered information on the number of non-executive stock options issued in the fiscal years 1994-1998 (3000 observations). I then follow Oyer and Schafer [2005] and Core and Guay [2001] to construct indicator variables based on the estimates of the total number of options granted to non-executives. Specifically, I code the respective dummy variables to take a value of 1 if the methods used in these papers suggest that options are granted to non-executives as a matter of policy.

In particular, the two variables that capture whether the non-executives are granted options are constructed as follows. First, following Oyer and Schafer [2005], I assume that the highest 10% of employees at the firm receive an average grant one tenth as large as the average executive in the second through fifth compensation rank. I subtract these shares and shares granted to the top five executives from the total grants to employees, and assume the difference is the total shares granted to non-executives. If the difference is negative, then I assume there were no grants to non-executives. I set an indicator variable ($Options^{NE=1}_{Oyer}$) equal to one if the number of shares granted to non-executives represents at least 1% of the shares outstanding. Second, following Core and Guay [2001], I code a dummy variable ($Options^{NE=1}_{Core}$) if there are grants to employees that are not among the five highest paid workers at the firm.

It is instructive to note that approximately 24% of the firms in my sample had broad-based stock option plans during 1994 to 1998. This is significantly lower than what Oyer and Schafer [2005] report for their sample which includes many small single-segment firms. The average annual non-executive option grant at the median firm with $Options^{NE=1} = 1$ (for the dummy variable constructed following Oyer and Schafer [2005]) is around \$60,650.

[6]The obvious disadvantage of this data is that the non-executives might not include divisional managers. However, the information on incentives to divisional managers cannot be obtained from any other publicly available source of data that I am aware of.

Conglomerates that grant options to non-executives tended to be smaller and their stock returns were more volatile than the average conglomerate in the whole sample.

To examine how incentives are associated with novelty of innovations undertaken by the conglomerate, I estimate variants of the following model using *CPatent*^{d} as the dependent variable and present the results in Table D.3:

$$\text{CPatent}^d_{it} = \left\{ \begin{array}{l} \alpha + \beta_1 \text{ICM Intensity}_{it} + \beta_2 \text{Options}^{NE=1}_{it} + \delta \mathbf{Z}_{it} \\ + \beta_3 \text{ICM Intensity}_{it} * \text{Options}^{NE=1}_{it} + \text{Time F.E.} + \text{Firm F.E.} \end{array} \right\}, \quad (3.2)$$

The model in Column (1) shows that conglomerates that grant options to non-executives tend to produce more novel innovations on average (i.e., $\beta_2 > 0$). In particular, firms granting options to non-executives tend to produce 40% ($\frac{.12}{.3}$) more novel innovations. Similar results are found when unobserved firm heterogeneity is controlled for by employing a random effects model in Column (2). This finding is consistent with Lerner and Wulf [2006] who show that, in general, firms where R&D managers are paid more in options tend to be more productive.

Next, to examine if options can alleviate the deleterious effects of ICMs on the novelty of innovations, I include the interaction term *ICM Intensity* Options*$^{NE=1}$ in Columns (3) to (5). Consistent with Prediction 2, I find that granting options to non-executives ameliorates the negative impact an active ICM has on the novelty of innovations (i.e., $\beta_3 > 0$).[7] For robustness, I also use the dummy variable that takes a value 1 based on Core and Guay [2001] and find similar results. Overall, the evidence suggests that incentives (i) improve the novelty innovations a conglomerate produces and (ii) ameliorate the negative effect an ICM has on the novelty of innovations.

3.3.5 CEO Job History

In this section, I examine whether conglomerates with CEOs who have experience in innovative divisions have higher R&D productivity. The intuition is that CEOs with experience in innovative divisions may be better at evaluating R&D projects proposed by divisions. Consequently, these CEOs may be able to ameliorate some of the agency prob-

[7]The coefficient estimate in Column (3) suggests about a 20% ($\frac{.12*.24}{-.144}$) reduction in adverse impact of an active ICM on novelty of innovation. Note that tests in this section have not used a firm fixed effect specification to identify the level effect of option grants since there are not enough changes in the firm policy on option grants during the sample period. However, for Columns (3) to (5), the coefficients of interest are the interaction effects and a fixed-effects specification can be used. Results are found to be similar to those reported in the chapter when this was done.

lems that arise due to the difficulty of evaluating novel projects.

To build CEO job histories, I identify the appointment year of each CEO using news items. I then trace back the CEO's prior experience in the firms they come from (this procedure is similar to one employed in Xuan [2006]). The CEO job history sample is constructed by finding the CEO names for all companies included in my sample over the sample period. For this, I primarily rely on news items in Factiva news search, Lexis-Nexis, company annual reports, proxy statements, SEC filings, press releases and company websites. Not surprisingly, I am not able to find CEO names for all the firms in the sample. For the firms for whom CEO names are found, I search the news sources for age and education of CEO, the origin of CEO (internal candidate or outside hire), the nature of turnover (planned succession or forced turnover), and most importantly, CEO job history. In addition, I collect data on whether or not the CEO is also the chairman and president of the board. In some cases, I am able to augment and cross-check the CEO names from alternative sources (for years beyond 1990 from ExecuComp and for years from 1980 for the Forbes 500 CEOs).

I ultimately arrive at a final sample of 1,481 CEOs in 1,872 multi-segment firms between 1980 and 1998 (7,670 firm years). I code a dummy variable $CEO^{Innov=1}$ to be 1 if the CEO has advanced through the ranks from all the innovative divisions in their firms prior to CEO appointments. In my sample the mean value of $CEO^{Innov=1}$ across firm-years is 0.22.

To test the prediction formally, I use variants of the following specification:

$$\text{CPatent}_{it}^{d} = \left\{ \begin{array}{l} \alpha + \beta_1 \text{ICM Intensity}_{it} + \beta_2 \text{CEO}_{it}^{Innov=1} + \delta \mathbf{Z}_{it} \\ + \beta_3 \text{ICM Intensity}_{it} * \text{CEO}_{it}^{Innov=1} + \text{Time F.E.} + \text{Firm F.E.} \end{array} \right\}, \quad (3.3)$$

I also control for age and education of the CEO, the origin of the CEO (internal candidate or outside hire) and the nature of turnover (planned succession or forced turnover) when the CEO joined. Table D.4 presents the results of the estimation. The results in Column (1) show that $\beta_2 > 0$, suggesting that conglomerates with CEOs who have had experience in all innovative divisions tend to produce more novel innovations. In particular, firms with such CEOs tend to produce 57% ($\frac{.17}{.3}$) more novel innovations. In Column (2), I estimate the regression with firm and CEO fixed effects and find similar results. Intuitively, this shows that a conglomerate produces more novel innovations if a CEO with no exposure to innovative divisions is replaced by a CEO with skills to evaluate innovative technologies.[8]

[8] In unreported tests, I find strong evidence of a change in the nature of innovations around CEO turnover,

It is reasonable to ask whether CEO exposure matters more or less when innovations being produced across divisions are quite diverse. To test for this, I construct the measure of diversity in type of innovations across divisions using claims of the patents–classifying patents as either product based or process based.[9] Specifically, I calculate the standard deviation of the average type of innovation across segments (*Dispersion*) and use it in Column (3). I find that the coefficient estimate on $CEO^{Innov=1}$*Dispersion* is positive and significant, suggesting that CEO skill matters more when innovations across divisions are more diverse. The results thus far suggest that CEO exposure tends to matter significantly for the novelty of innovations produced by the conglomerate. This is consistent with arguments made by Rotemberg and Saloner [2000], where CEO vision and strategy have bearing on the incentives of employees to generate creative ideas.

Finally, I examine whether consistent with my prediction, CEO skill can ameliorate the impact the ICM has on novelty of innovations. Specifically, I include the interaction term *ICM Intensity**$CEO^{Innov=1}$ in Columns (4), (5) and (6). Consistent with the Prediction 3, I find that CEOs with a diverse background tend to alleviate the negative impact ICM has on the novelty of innovations (i.e., $\beta_3 > 0$). More specifically, multi-divisional firms where CEOs have had exposure to innovative divisions tend to have a reduction of about 20-25% in the negative impact the ICM intensity has on the novelty of innovations.

Overall, the results suggest that skilled CEOs (i) improve the novelty innovations a conglomerate produces and (ii) ameliorate the negative effect an ICM has on the novelty of innovations. These results are consistent with more innovative firms promoting or hiring CEOs with diverse experience to mitigate agency issues related to ICMs. The findings are also consistent with the notion that multi-segment firms that for totally unrelated reasons, appoint a CEO with exposure to innovative divisions, see an improvement in their R&D productivity.

with the innovations becoming more radical if a CEO with experience in all innovative divisions is promoted.

[9]To construct *Dispersion* the following procedure is used. An invention is classified as a process (*type*=1) if the claims of a patent have the following words: 'process', 'method' or 'approach'. Similarly, an invention is classified as product (*type*=2) if the claims have the following words: 'product', 'apparatus', 'device', 'invention', 'composition', 'compound', 'system', 'software', 'assembly' or 'machine'. I assign innovations as part process and part product if both product and process related words are found in the claims of the patent (*type*=1.5). *Dispersion* is then constructed as the standard deviation of average type of inventions across divisions of the conglomerate for a given year. The mean value of *Dispersion* in the sample is 0.35.

3.4 Conclusion

In this chapter, I show that there are avenues through which central managers may be better able to exert proper control over innovation incentives. After all, firms like General Electric have shown they can both "bring good things to life' (by innovating) and add value through a judicious mix of central coordination and decentralization. Of course, the mechanisms I consider in this chapter are far from exhaustive. Strategic alliances, joint ventures, centralized R&D centers are clearly some other mechanisms that come to mind. I leave it for future research to understand conditions under which each of these mechanisms are optimal and are employed.

CHAPTER 4

Finance and Innovation: The Case of Publicly Traded Firms

4.1 Introduction

The importance of technological innovations for economic growth has been well established by the work of Solow [1957] and others. Among the firms in the US that are responsible for the vast majority of technological innovations, a significant proportion is produced by mature corporations (Baumol [2001]).[1] The importance of innovations for creating shareholder value is also well recognized within publicly traded firms. For instance, a recent issue of *Business Week* (July 2005) surveys CEOs and reports that managing innovation and creativity inside the firm is the most important challenge facing CEOs of the large publicly traded US corporations. Though researchers have argued theoretically that there is a link between financing and innovation (Aghion and Tirole [1994]), there is little in the extant literature about the relationship between financing decisions and the creation of significant innovations by publicly traded firms.[2] In this chapter we fill this gap by asking whether the innovative activity of firms that are well beyond the start-up stage is related to their financial arrangements.

In the context of the dissertation, this chapter departs from Chapters 2 and 3 that were focused on internal organization of the firm keeping external financing fixed. In this chapter, the basic hypothesis is that certain external financing arrangements are more conducive to

[1] Baumol [2001] notes that much of the U.S. economy's productive growth can be attributed to significant innovations by established corporations.

[2] The relation between financing and innovation in young, start-up companies suggests that venture capital funding is positively related to the number of innovations. Interestingly, Kortum and Lerner [2000] in their study of young start up firms document that only *"...about 8% of industrial innovations from 1980-1992 were done by venture capital backed small firms..."*.

innovative activity than others. Specifically, we hypothesize that for publicly traded firms, arm's length financing such as public debt and equity will be associated with significantly more innovative activity than relationship based financing, such as bank loans. The hypothesis is developed by examining the implications two types of financing may have on managerial incentives to produce novel innovations as well as the preferences of financiers to lend to firms that produce novel innovations.

More specifically, in relationship based financing, by its very nature, the investor or lender acquires significant information about the firm – which reduces information asymmetry and allows for closer monitoring of firm management. The downside, however, is that the decision to provide and sustain financing depends on the lender's ability to value the firm's projects. The lender *e.g.,* a bank loan officer may, however, lack the necessary skills to evaluate investments in an innovative technology (Scherer [1984]). As a consequence, relationship based lenders will discourage managers from investing in innovative projects and be more ready to shut down ones that are ongoing (Rajan and Zingales [2003]). In comparison, arm's length financing such as public debt and equity gives managers more discretion to invest in innovative technologies. Managers have greater incentive to pursue uncertain but potentially breakthrough innovations – since they are less concerned about being denied refinancing and shut down, as they might with bank loans. Consequently, innovative firms would optimally choose arm's length financing while firms with innovative projects that are easier to evaluate would prefer bank borrowing.[3]

In addition to this, preferences of financiers towards firms that produce novel innovations could also make relationship financiers averse towards funding novel projects. More specifically, banks are averse to fund novel projects since they are aware that they suffer from soft budget constraints (Dewatripont and Maksin [1995]). In other words banks are concerned about not being able to shut down a project that turns out to be bad at a later date. Since there is more ex-ante uncertainty about quality of novel projects, banks will shy away from funding such projects in the first place. Moreover, banks being the primary deposit holders are subject to substantial reserve requirements and restrictions in lending (Stulz [2001]). This also makes them conservative in the choice of projects they select to fund.

[3]We develop a simple model to develop this argument more formally. The model is unreported in the chapter for brevity and is available upon request from the authors.

The arguments above generate two testable predictions. First, we expect firms that produce more novel innovations to have a higher proportion of equity and public debt financing in their capital structure. Second, since we expect this relationship to hold both in cross-section as well as over time, infusion of arm's length financing in the form of a seasoned equity or public debt offering should be associated with an increase in innovative activity; no such pattern is expected after an infusion of bank loans. We test our predictions by comparing the innovative activity of publicly traded firms that differ in their financing choices. Specifically, our proxies for arm's length financing are the proportion of equity and public debt in the firm's capital structure. For some of analysis we also employ a dummy variable to indicate if a firm has access to public debt markets at all – since access may be established in anticipation of innovative activity and future rounds of financing.

Though it has been a common practice in the finance literature to use R&D expenditures as a proxy for the innovative activity of the firm (e.g., Titman and Wessels [1988]), these combine the expenses incurred in both the research as well as the development phase. Since our predictions are on the productivity of the research that is undertaken by the publicly traded firm, rather than on the expenses incurred in developing the product/process, we focus on patent-based metrics. We are led to this choice by Trajtenberg [1990] and Griliches [1990] who show that patent-based metrics are better at measuring research productivity than R&D investments. Specifically, we measure the quantitative and qualitative aspect of innovative activity by two patent based variables. The first variable is the number of patents the firm is granted in a year and proxies for the innovative intensity of the firm. The other variable proxies for the novelty and importance of a firm's patents by accounting for the forward citations each patent receives, i.e., the citation of a patent by subsequent patents. We infer a patent's novelty by a count of the times it is cited by subsequent patents because it has been shown that more cited patents have a greater influence on technological advances and have a higher impact on firm value than less cited patents (Trajtenberg [1990]; Harhoff et al. [1999]; Hall et al. [2005]).

Our empirical analysis uses a panel of $11,125$ US firms from 1974 to 2000. The sample is constructed by combining patent information from the NBER patent dataset with financial data from Compustat and SDC databases. Our main sample consists of all the firms that operate in the industries where one or more firms produce a patent over the sample period. This alleviates sample selection concerns since the sampling procedure is independent of whether or not the firms patent or not. To explore the relationship between arm's length financing and innovation, we employ an empirical specification that, for the most part, takes innovative output as the dependent variable and type of financing as the explanatory variables. The specification, besides being consistent with our hypothesis that type of financing should be systematically associated with the firms' choice of financing, has an additional benefit. Specifically, it allows us to examine the association between innovative activity and all the financing variables simultaneously. We do, however, report some regression results with each of the financing variables as a dependent variable (separately) and the innovative output as the independent variable. In the empirical analysis we control for firm specific characteristics (e.g., size, R&D expenditures, age, financial constraints, profitability, industry concentration, market to book ratio) as well as time, state and industry fixed effects since past work has shown these factors to be systematically related to production of innovations.

Consistent with the first prediction, we find that firms that choose arm's length financing have more patents and more novel patents. Notably, since we control for R&D expenditures, our results on patent activity can be interpreted in terms of firm research productivity. The magnitude of our estimates is economically large. In particular, firms which have an equity to assets ratio that is one standard deviation higher than the industry mean, have almost 20% more citations per patent than an average patenting firm in the industry. Similarly, firms that have public debt to assets ratio that is one standard deviation above the industry mean, are associated with 7% more novel patents than an average patenting firm in the industry. Furthermore, access to public debt markets (i.e., using an indicator for outstanding public debt) is also associated with more citations per patent as compared to an average patenting firm in the industry. Similar, though economically smaller results hold for number of patents as well. Our main results are robust to alternative specifications (e.g. Poisson, zero-inflated Poisson, negative binomial, and Tobit) that specifically alleviate concerns that the sample has a large number of firms who do not patent.

Our hypothesis suggests that the relationship between type of financing and innovation should be stronger for firms for whom innovative activity is important. To test this, we confine ourselves to industries and firms with high innovative intensities. We find that our main results are stronger when we consider a sub-sample of highly innovative industries. In particular, the magnitude of results is significantly larger for firms operating in Drugs and Medical Instrumentation, Chemicals, Computers and Communications and Electrical industry sectors. Nevertheless, even for a sub-sample of low tech industries with low patenting intensity we find support for our main hypothesis. In addition, we also find the main results to be stronger when we focus on a sub-sample of firms that have at least one patent over the sample period.

Next, we examine whether, consistent with our second prediction, there are changes in the innovative activity of firms following a large infusion of arm's length financing. We find strong evidence of an increase in innovative activity for two years after a first time issue of public debt or an issue of seasoned equity. The estimates are also economically significant and indicate that firms, which issue public debt for the first time (do an SEO) experience a *43%* (*54%*) increase in the citations per patent two years after the issue of public debt (public equity). Importantly, there is no evidence that a similar infusion of funds in the form of bank loans is followed by an increase in patenting activity. This evidence is consistent with the notion that firms raise arm's length capital in anticipation of an increase in their innovative activity.

We also provide evidence that novel innovations have a large value impact for the firm that produces them. Specifically, we find that two years subsequent to the innovation, firms with more significant patents experience a large increase in their market value as compared to those firms who produce less novel innovations. In particular, when we sort the patenting firms annually into quintiles based on their citations per patent, firms in the quintile with the most significant patents (citations per patent of 16.8) experience a 17% increase in market value two years subsequent to the innovation when compared to innovating firms in the third quintile (citations per patent of 7.3). Our results are broadly in line with the "patent market premium" reported in Hall et al. [2005]. The magnitude of these findings suggests that, consistent with our hypothesis, firms should rationally make financing choice decisions taking their innovative activity into account.

We conduct several robustness tests to account for possible bias in our results due to omitted variables. First, we show that our results are robust to using firm fixed effects to control for any unobserved time-invariant factor that might be positively related to both innovative output and arm's length financing. Second, we find that our main results remain unchanged if we control for financial constraints faced by the firm in various ways. This addresses the concern that lower financial constraints may be driving the firm to both produce innovations and choose arm's length financing. In particular, we find that our results remain unchanged if we estimate our regression models separately in each of the quintiles constructed by sorting our sample of firms by financial constraints faced by the firm. We also find that our results are economically and statistically similar when we repeat the analysis in quintiles formed on firm characteristics to account for size, investment opportunities (market to book) and life cycle effects (age). Finally, our results are robust to controlling for any industry-level strategic patenting that might affect the propensity of a firm to innovate.

We conclude our analysis by providing insights on how to interpret the relationship we find between type of financing and innovative activity of the firm. In particular, as mentioned earlier, our findings could be driven by either the financing preferences of innovative firms ("demand side") and/or by the preferences of financiers towards firms that produce novel innovations ("supply side"). To investigate this issue we use an instrumental variable analysis to shift the supply side equation. Our results indicate that both effects are present – though demand side seems to be driving a large part of the main results. Specifically, we find an economically large relationship between arm's length financing instrumented by variables that do not affect the financing preferences of the firm (e.g., higher visibility) and more novel patents. We also provide additional support for this interpretation by showing that the estimates on type of financing variables remain similar when we restrict the analysis to firms for whom supply side effects might be argued to be small. Overall, the analysis suggests that our main results should be interpreted largely as coming from innovative firms choosing a particular financing structure (i.e., from the demand side).

Our chapter makes several contributions to the literature. First, the chapter offers a novel approach to look at the relationship between financing arrangements and research productivity for firms that are well beyond the start up stage. In contrast to previous studies that relate the input side of innovation (R&D expenditures) to firm financing, it uses patent based metrics to show that R&D output is an important determinant of the capital structure for publicly traded firms in the U.S. Importantly, these results are obtained after controlling for the investment side of innovation using R&D expenditures. Second, the chapter uses a more sophisticated approach to capture financing arrangements and demonstrates that arm's length financing through public debt and equity, rather than only the simple choice between debt and equity, is positively related to research productivity of the firm. Previous studies have argued that higher proportions of debt decrease R&D because it financially constrains the company from obtaining future financing for its R&D projects (e.g., Titman and Wessels [1988]). We emphasize a different aspect of capital structure and its relationship with R&D: arm's length financing allows firm managers a greater flexibility to experiment with new technologies, and as a result is preferred by firms which rely on innovation to generate value. Moreover, we show that our main findings hold even after we account for financial constraints faced by the firms. Finally, and most importantly, our findings are supportive of the view that financing institutions – in our case, the markets for arm's length financing – may be more conducive than banks to development of novel technologies and thereby, to economic growth.

The chapter is organized as follows. Section 4.2 discusses the theoretical motivation, and develops the hypothesis and testable predictions. Section 4.3 provides a description of the data sources and the construction of the sample, the variables used in the empirical analysis, and describes the empirical methodology. Section 4.4 presents the empirical results that establish an association between innovation and the choice of financing arrangements. Section 4.5 discusses the value impact of producing novel innovations while Section 4.6 provides further tests. Section 4.7 discusses endogeneity bias and Section 4.8 concludes.

4.2 Hypothesis and Empirical Predictions

In this section we develop the hypothesis that firms that produce novel innovations prefer arm's length financing. The hypothesis is developed by examining the differences between the two types of financing and their implications for managerial incentives to produce novel innovations (Aghion and Tirole [1994]; Baumol [2001]).[4] We also delineate the empirical predictions that are explored in the chapter.

The first difference between relationship and arm's length financing that may have consequences on the managerial incentives to pursue innovative investments is the role of information acquired by the lender or investor. More specifically, in the process of

[4]While a manager may not have identical incentives as an entrepreneur to pursue innovation, we will assume that managerial contracts provide sufficient incentives for the manager to pursue innovative activity. For example, as Baumol [2001] explains, though top managers are responsible for creating and approving the R&D agenda and budget, if they are closely monitored by relationship lenders, they will tend to do the same with their subordinates involved in creating innovations. On the other hand, if managers enjoy a relative freedom that comes with arm's length financing, they will be more inclined to allow similar freedom to their R&D subordinates.

making loans, banks acquire significant non-public information about the firm's financial condition and investment plans. This is done when the bank investigates the firm at the time of lending and subsequently through its monitoring of the firm. In contrast, arm's length financing investors do not usually acquire significant private information about the borrower. The upside in relationship financing is that the bank's information acquisition will reduce the usual information problems between the firm and its capital provider (e.g., Diamond [1984]). However, the role of information in relationship financing may make it less desirable for funding innovative projects. The reason is that when it comes to more innovative technologies, banks may lack the ability to assess its value and to deny financing (Scherer [1984]). As a consequence, relationship based lenders will discourage managers from investing in innovative projects and be more ready to shut down ones that are ongoing.[5]

Using this argument, Rajan and Zingales [2003] suggest that relationship financing may be a optimal choice for firms with projects that are not novel — as is the case with incremental rather than drastic innovations.[6] With arm's length financing, managers have greater incentive to pursue uncertain but potentially breakthrough innovations – since they are less concerned about being denied refinancing and shut down, as they might with relationship based financing in the form of bank loans. In a similar spirit, Aghion and Tirole [1994] argue that if the lender doesn't have much knowledge about the firm's projects, it is optimal to give more discretion to the firm's manager to encourage her initiative.

The second difference between the two types of financing that might impact the managerial incentives to pursue innovative investments is that in relationship financing, unlike arm's length financing, the lender may be more willing to renegotiate the terms of a loan due to his private information about the firm's future profitability. It may be hard to renegotiate the terms when there are a large number of small investors, as is the case with public debt or equity. While renegotiation can have benefits for the firm in certain situations (e.g., restructuring), Cremer [1995] argues that the possibility of renegotiation with the relation-

[5]Note that for start-up companies, some forms of relationship financing such as venture capital can be conducive to innovative activity (footnote 2). While banks are similar to venture capitalists in that they monitor the activities of firms they finance, as Hellmann and Puri [2000] argue, venture capitalists differ from banks since they also extensively provide valuable governance and technical support. The authors note *"Venture capitalists are said to benefit their companies through a variety of activities such as mentoring, strategic advice, monitoring, certification to outside investors, corporate governance..."*.

[6]Throughout the chapter we will interchangeably use drastic, radical and breakthrough to refer to novel innovations. A successful novel technology is one that is different from current existing technologies and is more likely to influence the development of future innovations – by the innovating firm as well as by other firms in its industry and elsewhere.

ship financier at a later date weakens the ex-ante effort exerted by the manager. This is more of a problem when the ex-ante uncertainty about success of the projects is high, as is the case with radical R&D projects (Rajan and Zingales [2003]).[7]

Both the arguments above suggest that firms with more innovative activity would optimally choose arm's length financing in the form of public debt and equity.[8] Thus our main hypothesis is that firms with more novel innovations will have a predominantly arm's length capital structure. Our first empirical prediction is:

Prediction 1: *Ceteris paribus, firms with relatively more arm's length financing such as equity and public debt in their capital structure will have more novel innovations.*

We expect the relationship between type of financing and novelty of innovations to hold both in cross-section as well as over time. Consequently, infusion of arm's length financing in the form of a seasoned equity or public debt offering – possibly acquired in anticipation of innovative activity – should be associated with an increase in innovative activity. Moreover we expect no such pattern after infusion of bank loans. Thus:

Prediction 2: *Ceteris paribus, firms that raise arm's length financing in the form of a seasoned equity or public debt offering will be associated with a significant increase in their innovative activity. Such an increase in innovative activity will not follow the raising of new bank loans.*

Note that the discussion so far has focussed on innovative firms optimally choosing arm's length financing. However, the relationship between type of financing and innovative activity of the firm could also be due to the preferences of relationship financiers towards firms that produce novel innovations. There are two broad reasons for the banks to be averse towards funding novel projects. First, banks are averse to fund novel projects since they are aware that they suffer from soft budget constraints (Dewatripont and Maksin [1995]). In particular, banks are concerned about not being able to shut down a project that turns out to be bad at a later date. Since there is more ex-ante uncertainty about quality of

[7]In addition there is another argument by Allen and Gale [1999] that suggests that arm's length financing will be preferred by firms which have novel projects. They argue that novel projects are more likely to obtain financing if there is a diversity of opinion among investors. Thus it is more likely that such projects will get funding from arm's length financing characterized by many diverse investors than from a relatively limited number of relationship financiers.

[8]In addition, equity financing also lowers bankruptcy risk. This may be valuable when the salvage value of the R&D project is low and bankruptcy can result in the dissipation of intellectual capital. This is consistent with Titman and Wessels [1988] who argue that companies with more unique products (like novel innovations) will use less debt because their customers, supplies and employees will fear bankruptcy and will not commit to the long term future of the firm.

novel projects, banks will shy away from funding such projects in the first place.[9] Second, being the primary deposit holders they are subject to substantial reserve requirements and restrictions in lending (Stulz [2001]). This also makes them conservative in the choice of projects they select to fund.

The discussion above suggests that an association between innovative activity and arm's length financing could also result from preferences of financiers towards firms that produce novel innovations. In our empirical analysis, we will investigate whether our results are consistent with the financing preferences of innovative firms ("demand side") and/or with the preferences of financiers towards firms that produce novel innovations ("supply side").

4.3 Data, Variable Construction and Model Specification

4.3.1 Measuring Innovation

Similar to motivation in Chapter 2 and 3, our predictions are on the productivity of the research that is undertaken by the publicly traded firm, rather than on the expenses incurred in developing the product/process. As a result, we focus on patents and patent citations to measure innovation. These measures have two important advantages over R&D expenditures used in the extant finance literature. First, patents measure innovative output. Using R&D expenditures instead of patents is akin to using total expenditures instead of net sales or profits to measure accounting performance. Second, patent citations allow us to measure the novelty of innovations, which is not possible if we use R&D expenditures. As Griliches [1990] notes, although patents provide an imperfect measure of innovation, there is no other widely accepted method that has been applied empirically to capture technological advances by firms.[10]

Our innovation variables are constructed from the NBER patent data set created by Hall, Jaffe, and Trajtenberg [2001] following the procedure outlined in Chapter 2. Note that Hall, Jaffe, and Trajtenberg [2001] match the assignees of the patents in the NBER

[9] Huang and Xu [1999] use a similar notion to make the argument that under some situations arm's length financing results in ex-ante better project selection. This result holds when the uncertainty of the projects is high, as is the case with radical discoveries.

[10] Using patents has its drawbacks (refer to footnote 13 in Chapter 2). We attempt to control for these factors in a variety of ways. In our analysis we will control for industry specific trends by using industry fixed effects. Furthermore, we also examine our predictions only in a sub-sample of industries selected based on their patenting intensities to address these concerns. To the extent that these tests cannot alleviate the concerns fully, our results are subject to the same criticisms as previous studies that use patents to measure innovation (e.g., Cockburn and Henderson [1998]).

dataset, by name, to manufacturing firms from Compustat, as of 1989. The fact that the matching occurs for firms that existed on or before 1989 might introduce a survivorship bias; with older firms dominating the latter half of our sample. As discussed in our empirical section, we control for this bias in a variety of ways and conclude that it does not affect our results.

For our analysis, we augment the sample of firms with patents by including all the firms in Compustat which operate in the same 4-digit SIC industries as the firms in the patent database, but don't have patents. We take the patent count to be zero for these firms. Including these firms alleviates some of the sample selection concerns since our sampling procedure is independent of whether the firms patent or not.[11] Since, the primary SIC code of firms changes over time, we include services and transportation companies in addition to manufacturing firms. We exclude industries such as financial services and utilities that operate under different regulatory rules and have financing arrangements that are unlike those of manufacturing firms (e.g., financial firms such as banks have legal reserve requirements and their financing arrangements include deposits). We restrict our tests to 1974-2000 since information on citations received by patents, a key variable in our analysis, is reliable over this time period.

We use two broad metrics to measure a firm's innovative activity. The first measure we employ is simply the patent count for a firm each year. Specifically, this variable counts the number of patent applications filed that year that were eventually granted. For the simple patent count we create two variables. The first variable, *Patent*, counts the number of patents for each firm in the same application year. The delay between the application and granting of patents, however, introduces a truncation bias and we construct a second variable, $Patent^c$ that adjusts patent counts to correct for the bias (discussed in the appendix).

The second metric measures the importance of each patent by accounting for the number of citations each patent receives in subsequent years. As mentioned in Chapter 2, this

[11] Inclusion of firms with no patents results in a large number of zeros for innovative output in our sample. To alleviate concerns that the presence of many firms without patents can bias our results, for robustness, we conduct our main analysis on: (i) a sub-sample of highly innovative industries, and (ii) on a sub-sample of firms that have at least one patent (in a year t or alternatively in the time period till year t). Furthermore, in our empirical analysis, we check for the robustness of our results by employing Poisson, Negative Binomial and Tobit specifications which control for presence of many firms with zero patents. We also find that our estimates are similar when we use a zero-inflated Poisson regression which is used to model count data that have many zero counts.

measure is motivated by the recognition that a simple count of patents to measure the level of innovative activity does not distinguish breakthrough innovations from less significant or incremental technological discoveries.[12] Therefore, we use patent citations to account for the significance of innovations.

Like patents, citations also suffer from a truncation bias since citations arrive over time. Another potential concern about citations is that different industries might have different propensities to cite patents.[13] We correct for these biases by using two methods suggested by Hall, Jaffe and Trajtenberg [2001] – the "fixed effects" method and the "quasi-structural" method (explained in appendix). Using these methods, we construct three dependent variables that measure the number of citations per patent for each firm in every year. The variable $CitedPatent^{Time}$ corrects for year fixed-effects, $CitedPatent^{Time-Tech}$ corrects both for time and technology class fixed effects, and $CitedPatent^{Quasi}$ uses the "quasi-structural" method to correct for the truncation bias. Although we primarily report the results with the $CitedPatent^{Time}$ variable, our findings throughout are statistically and economically similar when we use the other two variables instead.

4.3.2 Measuring Type of Financing

The key explanatory variables of interest in our analysis are the proxies for arm's length financing. The first variable that proxies for arm's length financing is equity. We measure this variable as $\frac{Equity}{Assets}$ where *Equity* is the firm's book equity and *Assets* are the total assets of the firm. We also repeat all our analysis replacing book equity by market equity and find qualitatively similar results. The second variable used to proxy for arm's length financing is the amount of the firm's public debt. To collect information on public debt issues, we use SDC Platinum. We merge the public debt issuers sample (from 1970) with Compustat

[12]The distribution of patent value has been found to be extremely skewed (Pakes and Schankerman [1984]; Griliches, Pakes, and Hall [1987]) and Trajtenberg [1990] and Hall et al. [2005] among others have shown that patent citations provide a good measure of innovation value. Additionally, Harhoff et al. [1999], in a study of German patent holders of US patents, find that the most highly cited patents are very valuable, with a single citation worth about $1 million. Notably, the importance of patent citations is not only appreciated in the academic world, but is also considered an important measure of firm value by real word financiers. An article in Forbes magazine in 2002 states that "... determining technological relevance is the holy grail of intellectual property. Old metrics of R&D spending left us short on context. Counting patents would be irrelevant. But tracking forward citations to a company's patents can give investors a better idea of how well a company is spending its R&D money."

[13]For example, the computer industry tends to have a lower number of citations on average than the pharmaceutical industry. Therefore, a patent in the computer industry, which was applied for in 1985 and which received 15 citations by 2000 might not be directly comparable to a patent in the pharmaceutical industry applied for in 1995 and received 13 citations by 2000.

by matching cusips. Using the information on public debt issue and maturity of the debt, we wrote a program to construct the amount of public debt outstanding for each firm in a given year. We measure this variable as $\frac{Public}{Assets}$ where *Public* is the amount of public debt of the firm.[14]

Our third proxy measures access to the public market. Our expectation is that access may be established in anticipation of innovative activity and future rounds of financing. We construct two alternative variables that proxy for the access to public debt markets, closely following Houston and James [1996; 2001] and Hadlock and James [2002] who argue that if a firm has public debt, its borrowing is arm's length. First, we construct a dummy variable $Public^s$ that takes the value of *1*, if the firm has public debt outstanding in the current year t or any year before that, as reported in SDC, and *0* otherwise. We also follow Faulkender and Petersen [2004] and use the debt rating reported in Compustat as a proxy for whether the firm has access to public debt markets. Compustat reports whether the firm has a bond rating or a commercial paper rating. If the firm has either of them, we code the firm as having access to public debt financing. Therefore, we create an indicator variable $Public^c$, which takes value of *1*, if the firm has a public debt rating in the current year t or any year before that, and *0* otherwise. In our sample, $Public^c$ and $Public^s$ observations overlap to the extent of 90.9%.

4.3.3 Other Explanatory Variables

The data on assets (*Assets*), sales (*Sales*), industry SIC, R&D expenditures (*RD*), book equity (*Equity*), debt (*Debt*), net property plant and equipment (*PPE*), cash (*Cash*), operating profits (*EBIDTA*), market to book (Q) and retained earnings (*RetEarn*) comes from Compustat. We require that firms in our sample have information on sales. Note that many firms do not separately report R&D expenses and thus the variable is missing on Compustat for many firms. Following the literature (e.g., Lerner [2004]), we assume that any firm that reports total assets but not R&D expenses had no R&D expenses in

[14]Note that to the extent that some firms might be buying back or retiring their public debt, our measure $\frac{Public}{Assets}$ might over-report public debt in their capital structure. On the other hand since SDC reports debt issues from 1970 onwards, there might be cases where we under-report public debt in the capital structure as well. To examine if the noise might be serious, we take a random sample of 25 firms with public debt outstanding in 1980, 1985, 1990 and 1995. We collect the information on the proportion of public debt for these firms by looking in their proxy filings, 10Ks and annual report filings. We find that the amount reported in these statements is close to the information we collected from SDC (margin of error was less than 7%).

that year. The final sample includes *11,125* firms that have publicly traded stock (*109,500* firm years), *1,777* of which have registered a patent in one or more years during the sample period (*16,980* firm years).

In our empirical specification, we follow Hall and Ziedonis [2001] among others and include the log of R&D expenditures (*Log(RD)*) and firm size (*Log(Sales)*) as control variables. For robustness, we use the number of employees in the firm as an alternative proxy for firm size. We also control for industry competition using an industry sales Herfindahl index (*HI*) constructed at the 4 digit SIC level and, for robustness, at the Fama and French [1997] *48* industry level. The data used to construct the market and firm stock returns comes from the Center for Research in Security Prices (CRSP). We also use CRSP to construct the variable that measures the age of the firm (*Age*). We construct this measure based on the years from a firm's IPO as reported in CRSP. All the variables in our analysis are winsorized at the 1^{st} and 99^{th} percentiles to protect the results from the influence of extreme outliers.

4.3.4 Empirical Specification

In our empirical tests, we focus on the demand side and estimate the following equation:

$$\text{Innovation}_{it} = \gamma_1 + \gamma_2 \text{Financing}_{it} + \gamma_3 \text{X}_{it} + \mu_i + \delta_t, \tag{4.1}$$

where *Financing* are the financing variables, X are the firm characteristics which affect a firm's R&D output, μ_i captures time-invariant firm specific effects and δ_t captures time specific effects. There are a number of reasons why we chose this specification. First, this specification allows us to examine the association between innovative activity and the multiple measures of a firm's arm's length financing at the same time. In our analysis we will check the robustness of our findings by using alternative specifications with each of the financing variables as a dependent variable (separately) and the innovative output as the independent variable. Second, and more importantly, this specification is consistent with the demand side discussion – since we expect that type of financing should be systematically associated with the firms' choice of financing. Of course, as discussed in the hypothesis section, in equilibrium a positive coefficient on *Financing* could be either the demand effect we are testing for, or financing supply factors that are correlated with the a firm's innovative activity. To isolate how much our findings are affected by demand and supply side, we use three separate approaches.

First, we control for firm characteristics that might explain any variation in the supply of type of financing based on the innovation a firm produces. Towards this end, our specification controls for firm specific characteristics (e.g., size, R&D expenditures, age, financial constraints, profitability, industry concentration, market to book ratio) as well as time, state, industry (and in some cases firm) fixed effects. Our second approach is to examine the variation in demand side directly. We do this by estimating an instrumental variables version of the model. The instruments are variables that are related to supply of financing but do not affect the demand for financing directly. By first predicting the type of financing with instruments and then using the predicted values in equation(4.1), we ensure that we are capturing a demand side effect rather than an unmeasured supply factor. Finally, we conduct our analysis for firms for whom supply effects might be considered to be less important. The hope is to shed light on the magnitude of supply effects by comparing the impact of *Financing* variables on innovation for these firms relative to the entire sample.

4.4 Empirical Results

In this section, we present the summary statistics of our sample and test our main predictions. Sections 4.4.1 and 4.4.2 discuss the descriptive statistics while Sections 4.4.3 to 4.4.6 examine the relationship between arm's length financing and innovation.

4.4.1 Descriptive Statistics: Distribution of Patents and Citations Per Patent

Panel A in Table F.1 reports the distribution of firms by patent grants for every year from 1974 to 2000. As the table shows, the distribution of firms by patent grants is very right-skewed, with the 75^{th} percentile of the distribution is zero. The proportion of patenting firms has decreased over the sample period. In 1974, 25% of the sample firms had at least one patent application, as compared to only 11% in 1995. Furthermore, the proportion of patenting firms has decreased over the sample period, but conditional on patenting, the number of patent grants per firm has increased. These trends are consistent with those reported in Hall, Jaffe and Trajtenberg [2001].

In Panel B of the table, we divide the sample into patent classes, and reports the number of firms for each patent class each year. The first class consists of firms with 0 patent awards, the second of one or two patents, the third of three to ten, the fourth of eleven to one hundred, and the fifth of more than one hundred. Firms with zero patents represent roughly 84% of the sample, firms with one or two patents and three to ten patents about 6% and 5%, respectively, and firms with eleven to one hundred patents about 4%. The remaining one percent of the sample comprises firms with more than one hundred patent applications. The fact that large number of firms have zero patents may create a bias when these variables are used as dependent variables in an OLS framework (Cameron and Trivedi [1998]; Griliches [1990]). Consequently, throughout the chapter, we employ Poisson, Negative Binomial and zero-inflated Poisson specifications that address this concern.

Panel C of the table shows the distribution of patenting firm years by industry, excluding financials and utilities. Although all industries are represented, two important issues need to be highlighted. First, there is a large variation across industries, and that the largest patenting activity takes place in Chemicals, Pharmaceuticals, Machinery, Aircraft and Automobiles. In particular, more than 55% of aircraft and chemical firms are awarded at least one patent, as opposed to less than 2% in Agriculture and precious metals. Second, there is large variation within industries, in that even in the most innovative industries (e.g., Chemicals) up to 70% of the firm-years are without patents.

Panels D and E report the distribution of citations per patent in our sample (*Cited-Patent*^{Time}). As is indicated, the distribution is left skewed with only about 20% patents reporting more than 1 cite. This suggests that most of the total number of citations in our sample are received from a small number of highly cited patents. As argued in the previous literature, these are the more novel and more valuable patents Hall et al. [2005].

4.4.2 Descriptive Statistics: Patents, Citations Per Patent and Firm Characteristics

Table F.2 provides preliminary evidence that firms with more arm's length financing tend to be more innovative. In Panel A we present descriptive statistics for firms with one or more patent grants over the sample period compared to firms that did not receive any patents (the median number of patents per firm in our the sample is 0). As indicated by the mean values reported in the table, firms with patents are larger (sales of \$*2.7* billion vs. \$*0.9* billion per year), have higher R&D expenditure (\$*111* million vs. \$*38* million per year), have a higher market to book ratio (*1.86* vs. *1.60*) and belong to more concentrated industries (Herfindahl index of *0.49* vs. *0.43*) than firms without patents. Firms with patents over the sample period have a higher mean public debt to asset ratio (*0.05* vs. *0.02* per year) and have a higher mean equity to asset ratio (*0.54* vs. *0.49* per year) than firms without patents. Moreover, on average a larger proportion firms with patents access the public debt market than firms without patents (*0.35* vs. *0.12* per year). The differences in various statistics between the two groups of firms are significant at the 1% level. These univariate comparisons are in line with our predictions that firms with patents should have a higher equity to asset ratio and a higher public debt to asset ratio. Interestingly, the differences in the two samples are not on account of differences in R&D intensity ($\frac{RD}{Sales}$), which is approximately the same in both samples.

In Panel B of Table F.2 we compare, among the firms that have patents in a given year, the characteristics of the firms with above and below the median number of citations per patent (median is 6.6). Firms with above median citations per patent are, on average, larger, have higher R&D expenditure, have more tangible assets, have a higher market to book ratio, have a higher public debt to asset and equity to asset ratio and have a larger proportion of firms accessing the public debt market. The differences in capital structure are again in line with our expectations. Finally, in Panel C, we present the pairwise correlations between our key explanatory variables. As is indicated in the table, there is little evidence of collinearity among our variables. Since these are only summary statistics, for more meaningful comparisons, we next turn to multivariate analysis.

4.4.3 Number of Patents and Arm's Length Financing

In Table F.3, we report our first set of regression results. We use a fixed effects Poisson panel regression to relate the type of financing to the number of innovations, controlling for various firm and industry characteristics. Specifically, we estimate the following model using the truncation bias adjusted patent count *Patent*^{c} as a dependent variable:

$$\text{Patent}^c_{it} = \lambda_{it} = \exp\left\{ \begin{array}{l} \alpha\text{Financing}_{it} + \ \gamma_1\text{Log(RD)}_{it} + \gamma_2\text{Log(Sales)}_{it} \\ + \ \delta\mathbf{Z}_{it} + \text{Time F.E.} + \text{Industry F.E.} + \text{State F.E.} \end{array} \right\}. \tag{4.2}$$

To ensure that our inferences are not affected by the non-integer values, we round each non-zero observation to its nearest integer. In Column (7) we use a negative binomial model which accounts for the possible over-dispersion of the count dependent variable. To examine if the effects are stronger for industries where patenting might be considered more important, in Column (8) we restrict attention to innovative industries.[15] The explanatory variables we are most interested in are different proxies for arm's length financing and are captured in *Financing*. In models (1) and (2) we use only $\frac{Equity}{Assets}$ to proxy for arm's length financing. In models (3) and (4) we *also* include public debt dummy ($Public^c$ and $Public^s$, respectively), while in models (5) to (8) we use the proportion of public debt ($\frac{Public}{Assets}$) in addition to the public debt dummy ($Public^s$). As indicated in the data section, both access to the public debt market and extent of public debt financing may be associated with greater innovative activity.

Following the literature (e.g., Aghion et al. [2005]), the matrix of control variables $\boldsymbol{Z}$ includes industry concentration measured by the Herfindahl index (HI) and the squared term of the Herfindahl index to capture a possible non-linear relationship between competition and innovation. $\boldsymbol{Z}$ also includes firm age (Age) and age square (Age^2), where the age is measured by years since the IPO to control for life-cycle effects. In the estimation, we also control for size, measured by sales (*Log(Sales)*) and investments in innovative projects measured by R&D expenditures (*Log(RD)*).[16] Finally, we also include as control variables, market to book ratio of the firm (Q) to capture the investment opportunities faced by the firm and controls for financial constraints faced by the firm (profitability of the firm ($\frac{EBIDTA}{Assets}$), operating cash ($\frac{Cash}{Assets}$), retained earnings ($\frac{RetEarn}{Assets}$) and asset tangibility ($Tangible$)). All regressions in this table are estimated with time, state and industry fixed effects and the reported standard errors are heteroskedastic consistent to control for over dispersion, and are also corrected for the panel.

Our results demonstrate that arm's length financing is positively associated with innovation. Consistent with *Prediction 1*, we find that the estimated coefficient on $\frac{Equity}{Assets}$ is positive and significant at the 1% level in models (1) to (8). This finding is different from the studies that find a positive association between equity and R&D expenditure (e.g., Titman and Wessels [1988]; Hall [1990]) since we find a positive relationship between innovative *output* of the firm while controlling for its investments in R&D. Similarly, the estimated

[15]We take all the industries from the list of industries in Panel C of Table F.1 where more than 20% of the firms are granted a patent in a given year to be innovative. We tried alternative cut-offs of 15% to 40% but our results are unaffected.

[16]Note that the use of *Log(Sales)* and *Log(RD)* as explanatory variables, together with a Poisson specification is equivalent to scaling the dependent variable by dividing it by $Sales^{\gamma_2}$ or by RD^{γ_1}., and this allows us to further control for non-linear differences in size.

coefficient on the public debt dummy ($Public^c$ or $Public^s$) in models (3) and (4) and on the proportion of public debt ($\frac{Public}{Assets}$) in models (5) to (8) is positive and significant at the 1% level.[17]

Note that in model (6), we repeat our estimation with firm fixed effects. Using firm fixed effects alleviates concerns that unobservable firm specific differences (such as time invariant characteristics related to size or asymmetric information) in the cross-section might be affecting our estimates.[18] The qualitative nature of our results is unchanged. This indicates that the effect of arm's length financing on innovation is evident in a time series form as well. Intuitively, on average an increase in the equity or public debt in a firm's capital structure is associated with the firm creating more innovations. Our results are robust to an alternative model specification (negative binomial) in Column (7). Following Cameron and Trivedi [1998], we also perform a Lagrange multiplier (LM) test for overdispersion of the negative binomial type in all our tests. We find that in all regression models the negative binomial model is rejected in the favor of a model where the variance is proportional to the mean. Finally, in model (8) we restrict attention only to innovative industries and find qualitatively similar though stronger results (e.g., coefficient estimate on $\frac{Equity}{Assets}$ in Column (5) with entire sample is 0.398 vs. 0.593 in Column (8)). This suggests that the relationship might be more important for industries where patenting is more important.

The results in Table F.3 are economically significant. Specifically, in Column (5) of Table F.3, controlling for other factors at their mean levels, a one standard deviation (henceforth SD) increase in $\frac{Equity}{Assets}$ is associated with a 8.4% increase (exp{0.398*0.20}-1) in the number of patents produced by the firm as compared to the mean patenting firm in its industry (mean number of patent counts in the whole sample is 4.65).[19] Similarly a one SD increase in $\frac{Public}{Assets}$ is associated with a 4.4% increase (exp{0.425*0.10}-1) in patents pro-

[17]It is worth noting that the proportion of public debt is not just another proxy for leverage. If that was the case we would expect to find a *negative* relationship between public debt and innovation because the existing empirical evidence demonstrates a positive relationship between the presence of public debt and leverage (Faulkender and Petersen [2004]) and a negative relationship between leverage and R&D (Titman and Wessels [1988]).

[18]Note that we lose observations when we use firm fixed effects. This occurs because observations where the dependent variable does not change for a firm over the sample period get dropped in a non-linear panel model (Cameron and Trivedi [1998]). In our sample this amounts to dropping firms who do not patent at all during the sample period.

[19]To be conservative, we report the economic significance based on estimates of the Poisson model through out the chapter. As mentioned before, the Poisson model corrects for the bias in the estimates on account of a large number of zeros in the dependent variable. The economic magnitude of our results is significantly higher when we use estimates from an OLS specification.

duced by the firm as compared to the mean patenting firm in its industry. Moreover, access to public debt markets is associated with 6% more patents as compared to firms that do not have access to the public debt market. Though the change in the absolute number of patents may seem small, we will show that even small changes in number of patents can have significant value implications for the firm in Section 4.5.

In all the regression models, the coefficients on *HI* are positive while the coefficients on HI^2 are negative. Both estimates are highly significant. This finding has been interpreted as evidence that while some monopoly power encourages innovation, too much does not (Aghion et al. [2005]). Consistent with the findings in the literature (e.g., Griliches [1990]), our estimates indicate that firms with more R&D expenditures create more patents. The elasticity of innovations to R&D expenditure is *.40* in Column (5) which is similar to previous findings (e.g., Hall and Ziedonis [2001]; Lerner [2004]). The estimated elasticity is between *0* and *1*, indicating no increasing returns to scale. This coefficient implies that a doubling of R&D expenditures is associated with a *40%* increase in the number of patents created by the firm. The coefficient on *Log(Sales)* is positive indicating that larger firms develop more innovations in our sample. More mature firms (*Age*) have more patents, though the economic significance of the estimate is small. We also find that the coefficient on Age^2 (unreported for brevity) is negative but insignificant. The results also indicate that firms with higher market to book, more tangible assets and higher profitability create more innovations.

Overall, these results strongly support our first prediction. We now turn to testing the first prediction using citations per patent to proxy for R&D output of the firm. As mentioned earlier, since a lot of patents are incremental in nature, accounting for citations a patent receives makes citations per patent a better proxy of novelty of innovations than a simple count of patents. Consequently, we expect the relationship between citations per patent and arm's length financing to be stronger than the relationship between arm's length financing and a simple patent count.

4.4.4 Citations Per Patent and Arm's Length Financing

We follow the established literature and measure the novelty of a patent by the number of forward citations that it receives (e.g., Trajtenberg [1990]). The two alternative measures used in this section are $CitedPatent^{Time}$ and $CitedPatent^{Time-Tech}$ which measure the citations per patent applied for by each firm in a given year corrected for time, and time and technology class respectively. To use the Poisson specification, we round each non-zero observation of citations per patent to the nearest integer to make it a count variable.

We start our analysis with Table F.4, where we use a fixed effects panel regression to study the relationship between $CitedPatent^{Time}$ and financing arrangements. Specifically, we estimate:

$$\text{CitedPatent}_{it}^{Time} = \lambda_{it} = \exp\left\{\begin{array}{l} \alpha_0 + \alpha\text{Financing}_{it} + \ \gamma_1\text{Log(RD)}_{it} + \gamma_2\text{Log(Sales)}_{it} \\ + \ \delta\mathbf{Z}_{it} + \text{Time F.E.} + \text{Industry F.E.} + \text{State F.E.} \end{array}\right\} \quad (4.3)$$

The control variables ($\boldsymbol{Z}$) are the same as the ones used in Table F.2. Consistent with our first prediction, the *Financing* variables are statistically significant and positively associated with more novel innovations in models (1) to (5). In model (6) of the table, to examine if the main results are stronger for industries where patenting might be considered more important, we estimate the regression only for innovative industries. We also include firm fixed effects to alleviate concerns that unobservable firm specific differences might be affecting our estimates. We find qualitatively similar but stronger results (e.g., coefficient estimate on $\frac{Equity}{Assets}$ in Column (4) with entire sample is 0.801 vs. 0.952 in Column (6)). We discuss this issue further when we conduct a more detailed industry by industry analysis in the subsequent sub-section. For robustness, we use $CitedPatent^{Time-Tech}$ as a dependent variable instead of $CitedPatent^{Time}$ in model (7) to control for any cohort effects within a technology class. The results from this model are statistically and economically significant and similar to the findings from the other models in Table F.4.

Consistent with our expectation, the relationship between citations per patent and arm's length financing to be stronger than the relationship between arm's length financing and a simple patent count. This can be best seen if one notes that estimated coefficients of the variables that proxy for arm's length financing are larger in model (5) of Table F.4 than in model (5) of Table F.3. Specifically, controlling for other factors at their mean levels, a one SD increase in $\frac{Equity}{Assets}$ is associated with 19.5% more (exp{0.89*0.2}-1) citations per patent by the firm as compared to the mean patenting firm in its industry (mean citations per patent in the whole sample is 0.7). Similarly a one SD increase in $\frac{Public}{Assets}$ is accompanied by 6.8% more (exp{0.66*0.10}-1) citations per patent by the firm as compared to the mean patenting firm in its industry. We also find that access to public debt markets is associated with 7% more citations per patent. For robustness, we employ other dependent variables

($CitedPatents^{Quasi}$) that measure the quality of innovations and other specifications that address the concern that the sample has many firms with zero citations per patent (e.g., zero-inflated Poisson specification) and find similar results (unreported). For brevity, most of the remaining results in the chapter are presented using citations per patent to measure the novelty of innovations.

4.4.5 Sub-sample Analysis: Innovating Firms and Innovating Industries

The arguments used to develop our hypothesis suggest that the relationship between type of financing and innovation should be stronger for firms for whom innovative activity is important. In this subsection, we conduct three tests on sub-samples to establish whether our results are stronger when we confine ourselves to firms and industries where innovation is more important.

In Columns (1) and (2) of Panel A of Table F.5, our sample includes only firms that have at least one patent (*Patent>0*) during a given year. Since all firms innovate, restricting the sample in this way can help establish if the impact of the type of financing is greater on more cited innovations than on innovations in general. Specifically, we re-estimate (4.3) on this sample. In model (3), we employ firm fixed effects as well. The coefficients on $\frac{Equity}{Assets}$, $Public^s$ and $\frac{Public}{Assets}$ are positive and significant at *1%* level. The coefficients on the financing variables in these equations have a larger economic impact than those when the full sample of firms was used (Table F.4). For instance, estimates in model (3) of Table F.5 suggest that, *among patenting firms*, a one SD increase in $\frac{Equity}{Assets}$ is associated with 28.4% more (exp{0.962*.26}-1) citations per patent and a one SD increase in $\frac{Public}{Assets}$ is associated with 12.4% more (exp{.785*.15}-1) citations per patent (mean citations per patent is 7.31 among patenting firms).[20] This is consistent with the notion that the form of financing has a significantly greater influence on novel innovations among patenting firms. The results also assure us that our previous findings in the full sample of firms are not biased by the inclusion of firms that don't have any patents. For robustness, in model (4) we conduct our analysis restricting the sample to firms with at least one patent in that year or any year before it and find similar results.

In models (5) and (6) of Panel A, we construct an alternative variable to confirm that

[20]Similarly, *among the firms that innovate*, access to public debt markets is associated with 11.1% more citations per patent.

among patenting firms those with arm's length financing are more likely to be drastic innovators than incremental innovators. To compare firms with novel innovations to firms with patents that are incremental, we construct an indicator variable called *DrasticIncrem*. The variable equals *1* if a firm is in the top *1%* of firms ranked by the number of citations per patent received per year in a given *technology class*, and *0* if a firm is ranked among the bottom *30%*. Restricting the comparison within the technology class controls for any cohort effect. We estimate the following panel fixed effects logit regression:

$$\text{DrasticIncrem}_{it} = \Phi \left\{ \begin{array}{c} \alpha_0 + \alpha \text{Financing}_{it} + \gamma_1 \text{Log(RD)}_{it} + \gamma_2 \text{Log(Sales)}_{it} \\ +\delta \mathbf{Z}_{it} + \text{Time F.E.} + \text{Industry F.E.} + \text{State F.E.} \end{array} \right\}. \tag{4.4}$$

As reported, the coefficient estimates on $\frac{Equity}{Assets}$, $Public^s$ and $\frac{Public}{Assets}$ are positive and significant (economically as well as statistically) and confirm that among patenting firms, those with arm's length financing are more likely to have novel innovations than incremental ones. To address the concerns that the cutoffs chosen are arbitrary and might affect the results, for robustness, we examine alternative cutoffs of *2%*, *5%* and *10%* for classifying the drastic innovators and *15%*, *20%*, *25%* and *40%* for classifying the incremental innovators and find that the results are unaffected by these alternative cutoffs.

Finally, since there is a significant variation in the distribution of patents both *across* and *within* various industries (Panel C of Table F.2), we examine whether our results are stronger in industries with more patenting activity. To conduct our analysis, we follow Hall et al. [2005] and classify industries into 6 sectors. The industry sectors are: Drugs and Medical Instrumentation (henceforth just "Drugs"); Chemicals; Computers and Communications (henceforth just "Computers"); Electrical; Metals and Machinery; and miscellaneous ("low-tech industries"). The first five industry sectors are the source of most of the patents in the manufacturing sector in the US. The last miscellaneous group includes everyone else. Subsequently, we estimate (4.3) for each of these industry sectors. The estimates are reported in Panel B of Table F.5. AAs can be observed, the estimates are statistically significant and larger in industries where patenting might be considered to be important. In particular, the economic significance of the estimated coefficients (the impact of taking a one standard deviation increase in the financing variables on innovative output) in the Low-tech and Metals and Machinery sectors is smaller than those in the other industry sectors for which patenting is considered more important (e.g., a 1 SD increase in $\frac{Equity}{Assets}$ is associated with 30% increase in citations weighted patents for firms in the Drugs sector while it is associated with only 7% increase for firms in the Metals sector). Moreover, the financing variables are significant in each of these sectors at the 5% level indicating that our predictions hold across industry groups. This suggests that even for industries where patenting is not considered to be important, there may still be a connection between R&D output and arm's length financing.

Summarizing, we find support for the first prediction when we confine ourselves to firms and industries where innovation is more important. This suggests that the findings in the full sample of firms are not biased by the inclusion of firms that don't have any patents. Consistent with our expectation, we also find that the relationship between arm's length financing and innovation is stronger in these sub-samples than when we conduct the tests on the entire sample.

4.4.6 Innovations Subsequent to Changes in Financing

Our second prediction is that infusion of arm's length financing in the form of a seasoned equity or public debt offering should be associated with an increase in innovative activity and that no such pattern should be observed after infusion of a bank loan. In this subsection we investigate the relationship between the type of financing and innovation by examining changes in innovative activity following significant changes in type of financing by the firm. More specifically, we analyze the change in innovative activity of firms that issue public debt for the first time or issue public equity through a seasoned equity offering (SEO).[21] Moreover, in a smaller sample where we have information on bank loans taken by the firms, we examine the change in innovative activity of firms who finance investments through a bank loan.

We examine the change in the innovative activity of firms subsequent to the event by constructing the dummy variable, $Post^D_{0-2}$ ($Post^E_{0-2}$; $Post^B_{0-2}$), that takes a value *1* if it is the first or the second year since the firm issued public debt for the first time (issued equity through an SEO; took new bank loan) over the sample period, and *0* otherwise. To measure whether the innovative activity is affected over longer time periods, we also construct the dummy variable $Post^D_{2-4}$ ($Post^E_{2-4}$; $Post^B_{2-4}$), if it is the third and fourth year since the

[21]The reason we focus on the first issue of public debt is that it is likely to represent a substantial change in the arm's length financing available to the firm. Not only is arm's length capital raised, but the offering also establishes access to and likelihood of future offerings in the public debt market. Also, though we would like to assess the change in innovative activity of firms subsequent to an IPO, we are unable to do so since we do not have detailed financial data before the firm goes public.

firm issued public debt for the first time (issued equity through an SEO; took a new bank loan). For the construction of these variables, we collect data on *all* public debt issues and SEOs available in SDC database. After matching the firms (by cusip) with our patent and financial data, we find that we have *1,239* firms that issued public debt for the first time and *2,845* firms (*4,166* issues) that had an SEO during the sample period. Information on bank loans comes from the Loan Pricing Corporation's DealScan database (see Dahiya et al. [2003] for detailed discussion on the DealScan database). We match the data from Dealscan to financial data from Compustat using tickers where available. However, Dealscan does not provide tickers for all public companies that it covers and when it does, they are sometimes unreliable. Therefore, we increase our sample after manually matching by company names. In terms of sample size for tests with bank loans, there are two caveats. First, since the coverage of firms in DealScan is relatively limited, the number of observations used in the tests is smaller than in other tests. Second, the coverage of DealScan begins from 1985 and therefore our tests are run only for the 1985-2000 period. In our tests we have *2,896* firms and *10,540* firm years with *645* firms taking new bank loans over this period.

For our analysis, we estimate the following model on various explanatory variables:

$$\text{CitedPatent}_{it}^{Time} = \exp\left\{\begin{array}{l} \alpha_0 + \alpha\text{Financing}_{it} + \beta_0\text{Post}_{0-2it}^{k} + \beta_1\text{Post}_{2-4it}^{k} + \ \gamma_1\text{Log(RD)}_{it} \\ + \ \gamma_2\text{Log(Sales)}_{it} + \delta\mathbf{Z}_{it} + \text{Time F.E.} + \text{Industry F.E.} \\ + \ \text{State F.E.} \end{array}\right\} \quad (4.5)$$

where $k \in \{D, E, B\}$ corresponds to the first time public debt issue, SEO and a new bank loan respectively. More precisely, in Columns (1) and (2) of Table F.6 we analyze the change in innovation two to four years after the initial offering of public debt and in Columns (3) and (4) two to four years after an seasoned equity offering. Finally, Columns (5) and (6) examine the change in innovation two to four years after a new bank loan. Based on our hypothesis, we expect the coefficient estimate on $Post_{0-2}^{k}(\beta_0)$ to be positive for arm's length financing variables. Controls in each case include all the variables used in the model in Table F.3. We also estimate these regressions with time, state and industry fixed effects and correct the standard errors for the panel.

As is evident from the table, the results are consistent with our second prediction: firms which issue public debt for the first time (do an SEO) have more valuable innovations as measured by citations per patent in the years subsequent to the first time issue of public debt (SEO). The coefficient estimates on $Post_{0-2}^{D}(Post_{0-2}^{E})$ are positive and significant at

1% level. The estimates are also economically significant and indicate that firms, which issue public debt for the first time (do an SEO) experience a *43%* (*54%*) increase in the citations per patent two years after the issue of public debt (public equity). Moreover, the coefficients which measure innovations subsequent to a bank loan are insignificant.

Note that the estimate on $Post^k_{2-4}$ for three and four years after the initial issue of public debt (after an SEO) in model (2) (model (4)) are small in magnitude (about 5-7%) compared to the estimate for the first two years after the public debt issue (after the SEO). This suggests that the increase in innovative activity is relatively short-lived and that firms may be issuing public debt (issuing equity) in anticipation of a burst of innovative activity. Our results are robust to alternative dependent variable definitions and model specifications.[22]

Overall, our findings provide substantial evidence that obtaining additional arm's length financing is followed by at least two years of increase in innovative activity and that such a pattern is not observed after new bank loans.[23] This evidence is consistent with both the arguments discussed in the hypothesis section: firms that anticipate an increase in their innovative activity might be choosing more arm's length financing as well as relationship financiers might be averse to lend to firms that produce novel innovations. In Section 4.7, we will examine which of these arguments can explain our results in more detail.

4.5 Innovation and Firm Value

Our hypothesis relies on arguments that implicitly assume that producing novel innovations has value implications that are large enough for the firms (financiers) to take into account when taking decisions related to capital structure (funding of projects). In this section we examine whether consistent with these arguments producing novel innovations impacts the value of the firm that produces them. Doing so will also help us infer whether

[22] In particular, we also conducted the estimation using $CitedPatent^{Time}$ and a Tobit random effects regression. Using Tobit alleviates concerns that our results in this section are partly driven by a significant number of firms with zero patents. Specifically, since the number of citations per patent per firm is a non-negative number, it can either remain at zero or increase for these firms. Thus, when we examine the innovative activity of firms after an event, there may be an upward bias on the coefficient estimate on $Post^k_{0-2}$.

[23] Note that, our estimation in this section, though similar to a firm fixed effects estimation, differs in an important dimension. As can be seen from our earlier results, a fixed effects estimation, while affecting our results modestly, results in a loss of data during the estimation. To the extent that there is some information contained in the *between* panel estimator, our procedure results in better estimates than what we would have obtained by employing firm fixed effects and losing observations.

the impact of increasing the financing variables on the number of citations per patent (in absolute numbers) is economically meaningful in value terms. Another objective of our analysis is to investigate the lag with which the market recognizes the value of a novel innovation after the patent protection is sought. To the extent that patent applications may not be announced and, even when announced, may be difficult for financial intermediaries and other market participants to evaluate – we expect that information about the value of the innovation would only gradually get incorporated into the firm's market value.

In Table F.7, we examine the impact of significant patents on the firm's subsequent stock market valuation by investigating the relationship between future market to book value (Q) of firms sorted into quintiles based on the quality of their innovations. We do our analysis in quintiles since, as noted earlier, the distribution of citations is very skewed and thus the effect of citations on firm value may not be fully revealed by estimating value regressions with citations per patent as an explanatory variable. To conduct our analysis, we first sort all the firms which have at least one patent during the sample period each year into quintiles based on $CitedPatent^{Time}$. In the second step, for each of the quintiles, we estimate the following model for firms in each quintile for each *year*:

$$y_{it+j} = \left\{ \gamma_t + \delta \mathbf{Z}_{it} + \text{Industry F.E.} + \text{State F.E.} \right\}. \tag{4.6}$$

Our dependent variable y is equal to the future market-to-book ratio – one year forward in the future in Column (1), two years in the future in Column (2) and three years in Column (3). We continue to conduct our analysis relative to the application year of patents since the work surveyed in Griliches [1990] finds that patent counts by application date are closer to the actual innovation and are more tightly linked to market value than counts by granting date. Other explanatory variables used are firm specific characteristics such as size (*Size*), maturity of the firm (*Age*) and firm profitability. Since Daines [2001] finds that Q is different for Delaware and non-Delaware firms, we include state dummies in our regression. Morck and Yang [2001] show that inclusion in the S&P 500 index has a positive impact on Q. Thus, as a control we use a dummy variable equal to one if a firm is in the S&P 500. Industry fixed effects are also included to control for cross-industry differences in value.

For our inferences, we are interested in the difference in coefficient estimates γ between various quintiles – since that can be interpreted as the difference in value between firms in the innovative quintiles after controlling for other factors that explain future Q. To conduct our analysis we use an estimation technique that is a variant of the methods of Fama and MacBeth [1973]. In particular, we estimate annual cross-sectional regressions of (4.6) with statistical significance assessed within each year (by cross-sectional standard errors) and across all years (with the time-series standard error of the mean coefficient). Table F.7 summarizes the results for each quintile. Each row gives the Fama-MacBeth coefficient estimates of γ and standard errors averaged across years of the sample.

The difference in the estimates of γ (26 in each quintile) between the third (Q_3: mean citation per patent of 7.3) and the last quintile (Q_5: median citation per patent of 16.8) in the last row of the table suggests that firms in the highest citations per patent quintile have a 17% higher ($\{Q_5 - Q_3\}/Q_3$=.29/1.68) market to book value two years after the innovation than firms in the median citations per patent quintile. Our results suggest that novel innovations have a significant impact on firm value even after controlling for other factors that might explain differences in value. Our results are broadly in line with the "patent market premium" reported in Hall et al. [2005] (about 1.8% for an increase of 1 citation per patent for highly cited firms). Similar effects are also prevalent for firms who produce below average citations per patent.[24] The findings in the table also show that the value differences persist for upto two years subsequent to the sorting year – suggesting the time period over which the value of the innovation is incorporated in the stock price.[25]

For robustness, besides employing alternative measures of novelty, we also replicate the analysis in this section after pooling all the patenting firms together. In particular, we estimate (4.6) on all the patenting firms after including measures that capture the novelty of innovation. To account for skewness in citations per patent, we break the citations per patent variable into five groups and include dummy variables for each group. The groups are: 0-0.69, 0.70-1.97, 1.98-7.31, 7.31-10.33, >10.33. Our results on value implications for the five groups are qualitatively similar to those reported in the chapter. Finally, we

[24]For instance the difference between firms in the highest and the lowest quintile suggests that firms in the highest citations per patent quintile have a 58% higher ($\{Q_5 - Q_1\}/Q_1$=.73/1.24) market to book value two years after the innovation than firms in the lowest citations per patent quintile.

[25]We also find difference in estimate of abnormal stock returns between the third and the fifth quintile. Specifically, firms in the highest citations per patent quintile have a 1.44% higher annual market adjusted return and a 1.08% higher annual three factor adjusted return two years after the innovation than firms in the median citations per patent quintile. While we advocate slow information revelation for novel innovations as the reason for this gradual value recognition by the market, another reason why we might find persistent abnormal return differences between the various citations per patent quintiles could be an omitted risk factor in the factor model. In particular, one can think of a risk factor on the lines of Pastor and Veronesi [2005] who argue that a firm's fundamental value increases with uncertainty about average future profitability (in our case uncertainty about the average productivity of a new innovation).

find qualitatively similar results when we examine the future operating performance (ROA) of firms across the most and the least innovative quintiles. More precisely, in unreported tests, we find that firms in the highest citations per patent quintile have about 31.5% higher operating performance two years after the innovation than firms in the median citations per patent quintile.

Overall our analysis in this section in conjunction with analysis in Section 4.4 suggests that producing novel innovations has significant value impact for the firm that produces it. The magnitude of these findings suggests that, consistent with our hypothesis, firms (financiers) would make decisions on capital structure (funding of projects) taking the innovative activity into account.

4.6 Omitted Variables and Other Robustness Tests

One concern with our analysis is that variables like financial constraints, size, investment opportunities, and maturity of the firm could influence both the type of financing the firm chooses as well as the innovations that it produces. In the first three subsections we address the problem of omitted variables in detail. The last subsection reports additional miscellaneous robustness tests. For brevity, we discuss our findings in many instances without reporting the detailed results. All these results can be obtained upon request from the authors.

4.6.1 Impact of Financial Constraints

A question that has received attention in the literature is the extent to which the availability of financial resources affects a firm's ability to invest. Within the context of investments in R&D, Himmelberg and Petersen [1994] show that, due to capital market imperfections, internal cash is the primary source of financing of R&D expenditures for a panel of small high-tech firms. To the extent that access to arm's length markets might suggest smaller financial constraints, this might offer an alternative explanation for our findings – financially unconstrained firms innovate and financially constrained firms don't. Note that our main regression results (Table F.3 to Table F.5) suggest that, although important, internal finance accounts for only some part of the relationship between the choice of financing and innovation. Specifically, despite the fact that we had included three measures of internal finance, namely operating cash ($\frac{Cash}{Assets}$), operating income ($\frac{EBIDTA}{Assets}$) and retained earnings ($\frac{RetEarn}{Assets}$), our measures of arm's length financing are statistically and economically significant. In this sub-section we examine in greater detail the importance of financial constraints in explaining our results.

We follow Lamont, Polk and Saa-Requejo [2001] and Baker, Stein and Wurgler [2003] and construct the five-variable Kaplan Zingales index (KZ index) for each firm-year to measure the strength of financial constraints faced by the firm. Underlying the KZ index is the work by Kaplan and Zingales [1997], who undertake an in-depth study of the financial constraints faced by a sample of 49 low-dividend manufacturing firms. Using both subjective and objective criteria, they rank these firms on an ordinal scale, from the least to most financially constrained. Most useful for our purposes, they then estimate an ordered logit regression which relates their qualitative ranking (mapped into a 1-to-5 scale, where 1 indicates *no constraint* and 5 a *certain constraint*) to five Compustat variables. This regression attaches positive weight to market to book and leverage, and negative weight to operating cash flow, cash balances, and dividends. The KZ index is constructed as:

$$KZ = -1.002\frac{CF}{Assets} - 39.368\frac{Div}{Assets} - 1.315\frac{Cash}{Assets} + 3.139\frac{Debt}{Assets} + 0.283Q, \qquad (4.7)$$

where $\frac{CF}{Assets}$ is cash flow over lagged assets; $\frac{Div}{Assets}$ is cash dividends over assets; $\frac{Cash}{Assets}$ is cash balances over assets; $\frac{Debt}{Assets}$ is the leverage ; and Q is the market value of equity over assets.

For each year, we rank firms into quintiles according to their KZ index, and test the significance of the external and internal financing variables in each KZ quintile. The quintile ranking procedure is similar to the one used by Baker, Stein and Wurgler [2003]. For each KZ quintile, we estimate (4.3) using the dependent variable $CitedPatent^{Time}$. Controls in each case include all the variables used in Table IV. In each case, we estimate regressions with time, state and industry fixed effects. It is worth noting that the average sales of firms in 1987 in the Himmelberg and Petersen [1994] sample was \$39 mill. As compared to that, the average sales of firms in each of the quintiles (from the least to most financially constrained in terms of 1987 dollars) are (\$1094 mill), (\$1050 mill), (\$753 mill), (\$397 mill) and (\$310 mill). Thus, intuitively, we might expect the effects found by Himmelberg and Petersen [1994] to be mainly present in the quintile consisting of most financially constrained firms.

The results reported in Panel A of Table F.8 demonstrate a positive and significant association between arm's length financing variables ($\frac{Equity}{Assets}$ and $\frac{Public}{Assets}$) and citations per patent for each of the KZ quintiles.[26] Notably, our results are economically significant and the effects are similar to those reported earlier. The fact that we find a positive association between arm's length financing and innovation in all KZ quintiles implies that arm's length financing is not a simple proxy for the presence of financial constraints. Consistent with Himmelberg and Petersen (1994), we find that internal cash ($\frac{Cash}{Assets}$) is positively related to patents for the most financially constrained companies in quintile (Q_5). However, for the other qunitiles (Q_1 to Q_4), we find an insignificant or even a negative relationship between innovation and internal cash. The finding of a negative association in less constrained quintiles is somewhat surprising and suggests that the presence of excess internal cash (relative to the industry mean)[27] is potentially associated with greater agency costs – which in turn hinder innovation. The presence of excess internal cash proxying for agency problems has been documented, for instance, in Harford [1999] who shows that firms with large cash reserves make poor acquisition decisions.

For robustness, in Panels B and C we conduct the analysis using operating cash ($\frac{Cash}{Assets}$) and operating income ($\frac{EBIDTA}{Assets}$) as the sorting variables instead of *KZ* and find qualitatively similar results. In addition, we also use alternative methods to measure financial constraints. Specifically, we repeat the analysis in this subsection following the methodology of Korajczyk and Levy [2003] and Whited and Wu [2005] for classifying firms as constrained. While Korajczyk and Levy use dividends and market to book of the firm as the criterion for classifying constrained firms ($Div = 0$ and $Q > 1$), Whited and Wu construct an index based on a structural model as: $-0.091\frac{CF}{Assets} - 0.062\ DIVPOS + 0.021\ TLTD - 0.044\ Size + 0.102\ ISG - 0.035\ SG$, where *TLTD* is the ratio of the long term debt to total assets; *DIVPOS* is an indicator that takes the value of one if the firm pays cash dividends; *SG* is firm sales growth and *ISG* is the firm's three-digit industry sales growth. A higher value of this index represents a financially constrained firm. We again find support for our predictions in both the constrained and unconstrained set of firms classified based on these two measures. Our results also hold when other alternative measures of innovativeness are employed.

[26] For conciseness, we do not report the coefficients of the other control variables (including $Public^s$) in the table. The estimates of these control variables are similar in sign and magnitude to those reported in our main regressions.

[27] Note that we estimate our regressions with industry fixed effects. Thus, the interpretation of a firm's $\frac{Cash}{Assets}$ on innovation in the regression is relative to the industry mean $\frac{Cash}{Assets}$.

Overall the evidence in this section suggests that financial constraints and internal financing do play an important role in explaining the innovative activity of a firm. These results are consistent with numerous studies in the literature that show that financial constraints can affect the investment decisions of a firm (e.g., Guedj and Scharfstein [2005]). However, financial constraints and internal financing alone cannot explain the relationship we find between type of financing and novelty of innovations.

4.6.2 Impact of Other Firm Characteristics

In this subsection, we conduct further tests to examine whether other firm characteristics could be influencing both the type of financing the firm chooses as well as the innovations that it produces. We follow the same empirical strategy as the last subsection and conduct the analysis in each of the quintiles formed on the basis of sales to control for size, market-to-book ratio to control for investment opportunities and age to control for maturity of the firm. Sorting firms into quintiles helps allay the concern that the positive relationship between arm's length financing and innovation may be the result of fundamental non-linear differences in size, investment opportunities and maturity of the firm.

The analysis comprises of two steps. In the first step, for each year we sort all firms into quintiles based on one of the firm characteristics mentioned above. In the second step, for each quintile, we estimate (4.3) where the dependent variable is $CitedPatent^{Time}$. Controls in each estimation include all the variables used in the model in Table F.4. Specifically, in Table F.9, we sort firms into quintiles based on *Sales* in Panel A, Q in Panel B and *Age* in Panel C. In each case, we estimate regressions with time, state and industry fixed effects. Our results indicate that even after grouping firms by their firm characteristics, for every quintile, firms with more equity and more public debt tend to innovate more. In particular, our results hold for a range of sales quintiles ($4 mill to $1848 mill), market to book quintiles (0.7 to 4.6) and age quintiles (1.99 yrs to 31.9 yrs). The results also hold in the range of R&D quintiles ($0.3 mill to $92 mill) – again suggesting that our results are obtained after controlling for the investment side of innovation using R&D expenditures. We do not report the results for R&D quintiles in the table since the estimates are very similar to those reported for the sales quintiles in Panel A. Importantly, the economic significance of the estimates (unreported) in quintiles formed on various firm characteristics is large and comparable to our findings in the entire sample.[28]

For robustness, we also sort on firm specific characteristics that measure a firm's asymmetric information and agency problem within the firm since they could affect both the type of financing and innovation. Specifically, we construct quintiles based on analyst forecast dispersion and firm specific stock variance (asymmetric information) and Gompers, Ishi Metrick governance index and outside block holdings (agency problem). We find that our main results are similar in each of the quintiles formed based on these characteristics.[29] Our findings are also robust to using other alternative measures of innovation (e.g., $Patent^c$) as well as alternative specifications (e.g., Negative binomial). This section provides additional evidence that our results are not being unduly driven by a few specific firms or firm characteristics.

4.6.3 Impact of Industry-Level Strategic Patenting

The literature in industrial organization argues that patent portfolio and the extent of fragmentation of property rights among the rivals may affect the firms propensity to innovate (Ziedonis [2004] and Noel and Schankerman [2006]). Omission of these variables could potentially bias the coefficient estimates on type of financing when we run (4.3). In this subsection, we alleviate any omitted variable concerns by including variables that capture the industry-level strategic patenting variables in our main specification.

The first variable we construct captures the 'patent portfolio' effect of strategic patenting through patent propensity of a firm's rivals (*Patprop*). Following Noel and Schankerman [2006], the notion behind this variable is that, given the stock of own R&D and technology spillovers, firms facing rivals with higher patent propensities will find themselves at a disadvantage in bargaining over patent disputes. As a result firms facing higher *Patprop* should have lower propensity to patent This variable is computed by taking the weighted average of the patent to R&D ratio of all other firms that are in the same industry as firm i.[30]

[28] To save on space, we report only the coefficients of our main explanatory variables. The coefficients of the control variables (including $Public^s$) are similar in sign and magnitude to those reported in our main regressions.

[29] Note that we have data on Gompers, Ishi Metrick governance index and outside block holdings. Thus, our tests with these variables are restricted to the period 1990-2000.

[30] More formally, let $Z_{it} = \frac{PS_{it}}{G_{it}}$ denote the patent to R&D ratio of firm i;where PS is the stock of patents and G is the stock of R&D. The stock variables are constructed following the procedure in Hall et al. [2005] by initializing the stock at the beginning of the sample period and using a 15% depreciation rate. We calculate $Patprop_{it} = \sum_{j \neq i} \frac{\tau_{ij}}{\sum_{j \neq i} \tau_{ij}} Z_{jt}$ where τ_{ij} is the technological proximity between firms and is measured as the un-centered correlation coefficient between the patent distributions of firm i and j across patent technology

The second variable (*Citecon*) captures patent thicketing. Following Ziedonis [2004], the idea here is that a 'thicket' of fragmented property rights among rival firms impedes R&D activity of a firm by constraining its ability to operate without extensive licensing of complementary technologies. To capture the patent thicket effect of strategic patenting, we want a measure of how many rivals a firm must negotiate with in order to preserve freedom of operation in its R&D activity. For this purpose, we use a concentration index of a firms patent citations that is, the degree to which patents cited by firm i (called 'backward citations') are held by relatively few firms. The notion is that when a firm's backward patent citations are more concentrated among a few technology rivals, that will affect the firm's transaction costs in dealing with any patent disputes that may arise and thus, it's willingness to invest in innovative technologies. To construct this concentration index, we first identify the firm which owns each patent that firm i cites in any of the patents it holds as of year t: From this information, we compute the share of firm i's backward citations that is accounted for by each of its cited firms. Self-cites are excluded. We then compute *Citecon* as the sum of the shares of the four firms that firm i cites the most (this varies over time as patents are accumulated).[31]

In unreported tests, we find evidence that firms produce less patents as well as less novel patents, conditional on their R&D, when they face rivals with higher patent propensities and when there is a greater concentration of the backward citations among rivals. More specifically, the point estimate on *Patprop* is negative and strongly significant (-1.01). This finding is consistent with that in Noel and Schankerman [2006] who argue that firms are in a worse bargaining position in resolving patent disputes with rivals that have large patent portfolios, which thereby reduces the profitability of patenting. The effect is substantial – the estimate implies that a 1 SD increase in the average patent propensity (.08) of technology rivals is associated with a reduction in citations per patent of the firm of 11.50%. Moreover, there is strong evidence that greater concentration of citations (*Citecon*) among the rivals is associated with a statistically significant reduction in novel patents by the firm. This finding is consistent with the evidence for semiconductors from Ziedonis [2004], who finds that greater fragmentation (lower concentration) of patent rights increases patenting, conditional

classes (Hall et al. [2001]). In our sample, the mean *Patprop* is 0.08.

[31] More formally, let s_{ijt} $(i \neq j)$ denote the share of the total number of citations by firm i that refer to patents held by firm j; cumulated up to year t and arranged in descending order. The 4 firm concentration measure is $Citecon_{it} = \sum_{j=1}^{4} s_{ijt}$. In the sample, mean value of *Citecon* is 0.67

on R&D. The point estimates (-.62) implies that a 1 SD increase in citations concentration (.25) reduces novel patents by around 22.14%.

Importantly for us, inclusion of these variables does not effect the magnitude or significance of the coefficient estimates on the financing variables. In particular, similar to the estimates in Column (5) of Table F.4, the estimates on $\frac{Equity}{Assets}$, $\frac{Public}{Assets}$ and $Public^s$ are .813, .648 and .065 respectively. This section provides evidence that our results are not being biased due to omission of any industry-level strategic patenting variables.

4.6.4 Other Robustness Tests

We end this section by conducting several additional tests to verify the robustness of our main regression results. First, since the NBER patent sample is primarily composed of firms that were publicly traded in 1989, we examine if having more mature firms in later years in the sample induces a survivorship bias. In principle, this can introduce a bias in the estimates if the mature firms present in the latter years do most of the innovation and also have a predominantly arm's length financed capital structure. In Section 4.6.2, we already demonstrated that this bias might not be substantial in our sample since our results are valid in each of the quintiles sorted by firm age. To further allay these concerns, we follow the approach in Schoar [2002] and re-estimate the relationship between the innovations and the type of financing for two sample periods: 1974 to 1987 and 1988 to 2000. The results of this sub-period analysis suggest that a similar positive relation between innovation and arm's length financing exists in both sample periods. We also re-estimate all our regressions with age dummies and find that our results are not affected.

Second, we check the robustness of our results by employing the alternative dependent variable definitions that we described earlier ($CitedPatent^{Time-Tech}$ and $CitedPatent^{Quasi}$) mainly to control for any cohort effects within technology class, besides industry, time and state effects. We find that our regression results are essentially unchanged.[32] We also construct all our measures after excluding self citations (a firm citing its own patents in subsequent patents that it obtains) and find that it has little effect on our results. Third,

[32] Additionally, we also find similar results with three alternative ranking procedures to measure the overall significance of the firm's patents. We rank firms by the total number of citations received by the firm for all its patents in a given year and by the ratio of forward to backward citations for a firm for all its patents in a year. We refer the reader to Hall, Jaffe and Trajtenberg [2001] where it is discussed in detail why the ratio of forward to backward citations gives an indication of the significance of a patent. Finally, we also construct a variable for each firm in a year as the sum of all patents whose citations are two standard deviations above the mean citations of all the patents in a technology class in a year.

we re-estimate our basic model using aggregate data over three and five year time intervals, instead of one year periods. The rationale is that our explanatory variables (such as R&D expenditure) may take longer than one year to fully impact innovation. For this purpose, we also estimate all our models with one and two year lags of the main explanatory variables. The results are similar to our findings in Tables F.3 and F.4.

Fourth, since our sample is over a long time period, we adjust our measures like sales and R&D expenditures for inflation and repeat our analysis. We find that our results are unaffected. Moreover, our results remain unchanged if we apply the cross-sectional regression tests, conducted each year, with standard errors calculated using the method of Fama-MacBeth. Next, we use the first difference transformation instead of firm fixed effects transformation for testing our predictions. This addresses the concern that the fixed effects estimator might be biased due to serial correlation of firm characteristics. Our results are robust to using this specification as well.

Finally, we also estimate our specification using the three financing variables as the dependent variable and report the results in Table F.10. Our specification is of the following form:

$$\mathrm{y}_{it} = \left\{ \begin{array}{l} \beta_1 + \beta_2 \mathrm{Size}_{it} + \beta_3 Q_{it} + \beta_4 \mathrm{Tangible}_{it} + \beta_5 \sigma_{\mathrm{firm,it}} + \beta_6 \mathrm{Age}_{it} \\ +\beta_7 \{\frac{EBIDTA}{Assets}\}_{it} + \beta_8 \mathrm{KZ}_{it} \\ + \gamma' \, CitedPatent^{Time}{}_{it} + \text{Industry F.E.} + \text{Time F.E.} \end{array} \right\}, \tag{4.8}$$

where the dependent variables in Column (1) and (2) are the financing variables – $\frac{Equity}{Assets}$ and $\frac{Public}{Assets}$ respectively. In Column (3), we employ a logit model that is similar to (4.8) with $Public^s$ as the dependent variable. The explanatory variables in this equation are motivated by the previous literature on capital structure. Specifically, it is argued in the prior work that firm level control variables such as size (*Size*), investment opportunities (Q), maturity (*Age*), profitability ($\frac{EBIDTA}{Assets}$), financial constraints (KZ), tangibility of assets (*Tangible*) and firm specific variance ($\sigma_{\mathrm{firm,it}}$), influence the financiers decisions to lend to firms (e.g., Faulkender and Petersen [2004]). Following these papers we also estimate the regressions with time and industry fixed effects. Our results again indicate a positive association between citations per patent and arm's length financing variables in all the specifications.[33]

[33]The coefficient estimates are economically meaningful: a 1 SD increase in innovativeness of the firm is associated with about 5.3% increase in $\frac{Equity}{Assets}$ and about 3.7% increase in $\frac{Public}{Assets}$. Similarly a 1 SD increase in innovativeness of the firm is associated with about 2.8% higher probability of the firm accessing capital from the public debt market.

4.7 Interpreting the Results: Endogeneity Concerns

Our main results (Tables F.3 to F.5) point to a relationship between the type of financing and the innovative activity of the firm. How should we interpret this relationship? Should we think of this as firms – possibly anticipating a burst of innovative activity – choosing arm's length financing ("demand side" effect) and/or should we interpret the findings as type of financiers choosing firms to lend to based on the innovative activity in the firm ("supply side" effect). As explained in Section 4.3.4, we employ an instrumental variable analysis to identify the demand side effect by shifting the supply side using appropriate instruments. In particular, we identify the demand side effect using variables that influence the willingness of arm's length financiers to provide financing and are exogenous to the type of financing choice of innovative firms.

4.7.1 Estimating Demand Effect: Instrumenting Type Of Financing

To assess whether there is any evidence of "demand side" effect: firms – possibly anticipating a burst of innovative activity – choosing arm's length financing, we use a base specification that is similar to (4.3) with novelty of innovations as the dependent variable:

$$\text{CitedPatent}_{it}^{Time} = \lambda_{it} = \exp\left\{\begin{array}{l} \alpha_0 + \alpha\text{Financing}_{Instrumented\ it} + \ \gamma_1\text{Log(RD)}_{it} \\ + \ \gamma_2\text{Log(Sales)}_{it}\delta + \mathbf{Z}_{it} + \text{Time F.E.} \\ +\text{Industry F.E.} + \text{State F.E.} \end{array}\right\}. \quad (4.9)$$

To ensure that we identify the demand side equation rather than the supply side one, we require instruments for type of financing. These variables should explain the supply of financing to firms and should be exogenous to the demand side equation. We construct two such variables based on the literature (Faulkender and Petersen [2004]) that argues that these variables affect the supply of financing to firms. The first is based on how well known or visible the firm is. The notion is that financiers are more likely to lend to firms (through equity (SEO) or public debt) that are better known. As a measure of whether the firm is visible to the markets we construct a dummy variable, *S&P 500*, which takes a value 1 if the firm is in the S&P 500 Index in a given year and 0 otherwise. The second variable is based on the percentage of firms in the industry of a given firm in a year that have public debt (*Log(1+%Public)*). The notion here is that the public markets are likely to provide funds to firms that are not too unique. For instance, a new firm which manufactures autos may be able to issue more stocks or bonds more easily, since the market already knows the industry and the competitors, as most auto manufacturers have outstanding shares and public debt. Both these variables are discussed in detail in Faulkender and Petersen [2004]. We choose these variables as instruments to demand side equation since we do not believe there is any obvious reason for the firms to directly take these variables into consideration when making their decisions on what capital structure to choose.

For the first stage we employ a specification that takes the three financing variables as the dependent variable and is of the following form:

$$\mathrm{y}_{it} = \left\{ \begin{array}{l} \beta_1 + \beta_2 \mathrm{Size}_{it} + \beta_3 Q_{it} + \beta_4 \mathrm{Tangible}_{it} + \beta_5 \sigma_{\mathrm{firm,it}} + \beta_6 \mathrm{Age}_{it} \\ +\beta_7 \{\frac{EBIDTA}{Assets}\}_{it} + \beta_8 \mathrm{KZ}_{it} + \beta_9 \mathrm{S\&P\ 500}_{it} + \beta_{10} \mathrm{Log(1+\%Public)}_{it} \\ +\mathrm{Industry\ F.E.} + \mathrm{Time\ F.E.} \end{array} \right\}, \tag{4.10}$$

where the equation uses $\frac{Equity}{Assets}$ and $\frac{Public}{Assets}$ with an OLS model and $Public^s$ with a logit model. The explanatory variables in this equation are motivated by the previous literature on capital structure (Faulkender and Petersen [2004]). Following these papers we also estimate the regressions with time and industry fixed effects.

We find that both the instruments are significant predictors of whether or not a firm obtains capital from arm's length financiers (unreported for brevity). In particular, the amount of equity and public debt financing is positively related to whether or not the firm is in the S&P 500 Index and to the proportion of firms in its industry that have public debt. Moreover, the instruments also are positively related to the probability of a firm having public debt. The point estimates on the instruments are economically significant – for instance a firm in S&P 500 index has about 15% more equity and 14% more public debt in its capital structure.[34] Importantly, we find that the instruments explain significant variation in the type of innovation done by the firm. In particular, the F-test rejects the null that the coefficients on both instruments are jointly zero. Moreover, the test of over-identifying restrictions fails to reject the joint null hypothesis that our instruments are uncorrelated with the error term and are correctly excluded from the second-stage regression.

To estimate the demand side equation, we employ (4.9) after instrumenting financing variables by *S&P 500* and *Log(1+%Public)*. Importantly, we use Generalized Methods

[34] As reported in Panel A of Table F.11, the coefficient estimates on the other variables are consistent with the literature (e.g., Rajan and Zingales [1995]): the proportion of equity and public debt in the capital structure is positively related to *Size*, *Tangible* and *Age* and negatively related to $\frac{EBIDTA}{Assets}$, Q and σ_{firm}.

of Moments (GMM) to model (4.9) since this equation employs a non-linear specification (Poisson) with instrumented financing variables. More details on the technique can be found in Mullahy [1996]. More specifically, in Table F.11, we estimate GMM using the specification discussed above. In the first two models we use $CitedPatent^{Time}$ as the dependent variable. Comparing results between Column (1) and (2) suggest that the estimates of arm's length financing variables are statistically significant though slightly smaller in magnitudes when the financing variables are instrumented. A Hausman test (unreported) comparing the estimates in Column (1) and (2) suggests that controlling for supply side effects does have a significant effect on the coefficient estimates. In particular, the point estimates suggest that, a one SD increase in $\frac{Equity}{Assets}$ is associated with 14.4% more (exp{0.67*0.2}-1) citations per patent by the firm as compared to the mean patenting firm in its industry. Similarly a one SD increase in $\frac{Public}{Assets}$ is accompanied by 6.0% more (exp{0.58*0.10}-1) citations per patent by the firm as compared to the mean patenting firm in its industry. We also find that access to public debt markets is associated with 6.3% more citations per patent.

We find similar results across Columns (3) to (6) when we compare the estimates using $CitedPatent^{Time-Tech}$ and $CitedPatents^{Quasi}$ as alternative dependent variables. More specifically, the estimates on financing variables are smaller once they are instrumented by variables which we argue shift the supply side equation.

4.7.2 Putting It All Together

The result in the previous subsection clarifies the interpretation of our main results. Comparing the magnitude of results reported in Section 4.4.4 with those where we estimate the demand side effects suggests that the relationship between type of financing and innovation is largely a demand side effect. For instance, a one SD increase in $\frac{Equity}{Assets}$ was shown to be associated with 19.6% more citations per patent by a firm relative to the mean patenting firm in its industry in Table F.4. In comparison, we find this effect to be relatively similar (14.4%) when we estimated the demand side equation with instruments. In other words, this suggests that our results are largely on account of a firm optimally deciding on arm's length financing whenever it envisages that it is going to take up innovative projects – though, given the reduction in magnitude of estimates, there is some evidence that preference of financiers also accounts for a part of the relationship between type of financing and innovation.

In addition to the instrumental variable analysis, we also conduct three additional tests which also support our conjecture that the demand side effects might be primarily driving our findings. The basic idea behind these tests is to estimate the relationship between type of financing and innovation for firms for whom the supply side effects might be less important. The notion is that for these firms any relationship between innovation and type of financing is likely to be driven primarily due to demand side considerations. Note that we have already provided some preliminary evidence towards this in Section 4.6.2 where we showed that the estimates on type of financing variables are similar in firms belonging to the medium to large *Sales* quintiles. Following this spirit, in Columns (1) to (3) of Panel B of Table F.11, we conduct analysis only on firms with public debt, firms with public debt and a credit rating of and firms with public debt and multiple banking relationships respectively. As shown in the table, our results are similar in all the three columns. Note that these estimates are similar to those reported for the whole sample (e.g., Table F.4). This suggests that relationship between innovation and type of financing is likely to be driven primarily due to demand side considerations.

Overall the results of this section have important implications for capital structure literature since the analysis suggests that the capital structure decisions of a firm are influenced significantly by its innovative strategy.

4.8 Conclusion

In this chapter, we hypothesize that established firms with more novel projects give greater discretion to managers by relying on arm's length financing, while firms with innovative projects that are easier to evaluate have more bank borrowing. Using a large panel of US companies from 1974-2000, we find that consistent with our predictions, firms that rely more on arm's length financing are associated with a larger number of patents and these patents are more significant in terms of influencing subsequent patents. We confirm our findings by showing a significant increase in innovative activity of firms following a large infusion of arm's length financing and no such pattern after infusion of bank financing. Producing novel innovations leads to a significantly higher firm value and suggests that firms would rationally make financing choice decisions taking their innovative activity into account. Finally, we use an IV approach to ameliorate endogeneity concerns and demonstrate that our correlations are driven primarily by innovative firms choosing their capital structure. Our findings show that R&D output is an important determinant of the capital structure for publicly traded firms in the U.S.

We believe that the results of the chapter may have broader implications. At a micro level, the results suggest that we should also observe other firm policies directed toward giving discretion to firm managers. One such policy that innovative firms can use is incentive based compensation for managers. Interestingly, evidence to this extent has been provided in a recent study by Lerner and Wulf [2006]. At a macro level, the findings suggest that financial development or, at least, the establishment of arm's length financing institutions, may affect the innovation process and economic growth. Hence, changes in regulation and taxes that affect the choice of financing arrangements by firms, may have consequences for technological advances and, possibly, for longer term economic growth.

CHAPTER 5

Conclusion and Future Work

Technological innovations have long been regarded as being central to building shareholder value. Introducing a significant innovation allows a firm to simultaneously lower cost and enhance differentiation, thereby increasing its competitive advantage. Though theoretical literature in organizational economics suggests that differences in internal organization may have substantial implications for a firm's innovative behavior, empirical evidence on this relationship remains scant. In Chapters 2 and 3, I show how R&D productivity is influenced by differences in organizational structure of a firm. At a broader level, the answers I provide in these chapters extend our understanding of what sets the boundaries of the firm. In these chapters I show that there is a clear cost (lower R&D productivity) to combining firms in a particular fashion. Of course, more empirical research needs to be done to understand the benefits involved when firms combine before any conclusion can be drawn on what determines the boundaries of various organizational forms.

In Chapter 4, I turn to one of the most important questions in corporate finance: What factors affect capital structure decisions of a firm? In this chapter I show that firms with higher R&D productivity rely more on arm's length financing as compared to bank borrowing. This suggests that R&D strategy of a firm may be an important determinant of its capital structure. At a more broader level, the findings suggest that financial development or, at least, the establishment of arm's length financing institutions, may affect the innovation process. Hence, it would be interesting to investigate how changes in regulation and taxes that affect the choice of financing arrangements by firms have consequences for technological advances and, possibly, for longer term economic growth.

APPENDICES

APPENDIX A

Simple Model in Chapter 2

A.1 Simple Model: Baseline Case

I sketch a simple model to illustrate the intuition behind the discussion in Chapter 2. To fix ideas, consider a conglomerate with two divisions A and B with divisional managers M_A and M_B respectively, and a corporate headquarter, HQ. I begin by investigating an organization in which HQ has all the decision rights and must approve any new investments. It is assumed that HQ will act to maximize firm value (Stein [1997]). There are three dates in the model $t = 0$, 1 and 2. At $t = 0$, HQ approves or declines investment projects proposed by the two divisions. The projects by two divisions are different in ways that will be elaborated below. At $t = 1$ information about the profitability of the projects may be received and funds may be reallocated among the divisions. Final payoffs are received at $t = 2$. The discount rate is taken to be zero and all participants are risk-neutral. Managers are assumed to receive private benefits that are increasing in the investments and final cash flows of their division. For now, I assume that there is no compensation contract.

Division A is engaged in R&D projects that are less radical and are based on well established technologies that are understood by HQ. I assume that investments in A result in low, but non-negative returns. Consequently, if there are funds available in B that are being invested in zero or negative NPV investments, they will be optimally reallocated to A by HQ.

Projects in B are innovative and there is considerable uncertainty about their eventual outcome. As elaborated below, the project novelty or uncertainty is parameterized by θ. For simplicity, it is assumed that the division receives only a single innovative project that needs to be funded at date $t = 0$. Once the project arrives, HQ evaluates the project and decides whether or not to fund it. Investment in the project is made in two stages: a preliminary research and development phase which reveals information about the NPV of the project followed by an additional investment in implementation phase. More specifically, if the project is initiated at $t = 0$, then depending on the signal $s \in \{s_c$: signal to continue, s_t: signal to terminate$\}$ received about the project at $t = 1$, HQ may continue with a second round of investment. I assume that the second round of investment is denoted by x and that the total investment over two periods is given by I_0. At $t = 0$ the M_B and HQ are symmetrically informed with respect to the project, and the project is *ex ante* expected to be successful with a probability π and produce a payoff of r if successful. However, by $t = 1$, M_B receives precise information on whether or not the project is going to be successful. On the other hand, HQ, receives a precise signal with probability $1 - \theta$ and an equiprobable continue/terminate signal with probability θ. The likelihood with which a precise signal is received is independent of whether the project is successful or not. Note that one is assuming that noise in HQ's information is increasing with the novelty of the innovative project, θ. The intuition behind this assumption has been discussed in the text.

The following additional assumptions are made about projects in B. To ensure that information is consequential, it is assumed that: (1) if no information is received about the innovative project at $t = 1$ and it is never stopped, the NPV is negative: *i.e.,* $v_n \equiv \pi r - I_0 < 0$ and (2) if the project is continued or terminated based on the information available to M_B, it is always positive NPV: *i.e.,* $v_i \equiv \pi r + (1 - \pi)x - I_0 > 0$. Finally, to make the setup interesting, it is assumed that other than the innovative project, investments in B yield zero or slightly negative NPV. Thus, in the absence of a novel project in B, HQ would optimally reallocate funds to A. This issue is central to the agency problem between HQ and M_B. The private benefits received by the divisional managers are affected by the resources available and are taken to be $\overline{b}$ ($\underline{b}$) when the project is funded at $t = 1$ and the project is successful (unsuccessful). When the investment is made in a zero NPV project in B, they are assumed to be b, while the benefits are normalized to 0 when there is no funding of the project. Since I assume that private benefits are increasing in resources (investments and final cash flows) available to a division, I take $\overline{b} > b > \underline{b} > 0$.

A.1.1 Optimal R&D Investment for HQ

The assumptions regarding the nature of the $R\&D$ investment in B imply that it is profitable to invest at $t = 0$ only when the decision on whether to continue or terminate the project at date $t = 1$ is, at least with some probability, contingent on the information revealed about the project. The quality of the project becomes noisily known to HQ with probability θ and based on the information revealed, the project can be continued or terminated. HQ also asks M_B to report his signal $s \in \{s_c,\ s_t\}$ to his since the divisional manager receives a more accurate signal. The question is whether M_B will have the incentive to truthfully reveal negative information about the project.

Since HQ is free to reallocate the saving x from project termination at $t = 1$, M_B, given his private benefits, will have no incentive to truthfully reveal information about the project at $t = 1$ if it results in the project not being funded. In other words, M_B always reports $s = s_c$. As discussed earlier, in the absence of an innovative project, it is optimal for HQ to reallocate available resources to A. The assumptions about reallocation are made for simplicity. More generally, all I need is that there be sufficient competition for R&D resources inside the firm with projects not perfectly correlated with B.

In this scenario, if the R&D project is started in B, the optimal strategy for HQ is to continue when it gets positive information about the project and terminate only when negative information about the project becomes available at $t = 1$. Moreover given M_B's strategy, HQ ignores the divisional manager's report. Therefore the expected payoff to HQ, $V_c(\theta)$, from initially approving the project can be expressed as:

$$V_c(\theta) = (1-\theta)\{\pi r + (1-\pi)x - I_0\} + \frac{\theta}{2}\{(\pi r - I_0) - (I_0 - x)\}. \tag{A.1}$$

The payoff is a sum of two parts: with a probability of $(1-\theta)$, HQ optimally terminates the project while with (θ), HQ is able to do so only $\frac{1}{2}$ the time. It is easy to see that so long as $\{\frac{v_i}{v_i - \frac{1}{2}[v_n - (I_0 - x)]}\} < 1$, $\exists$ a θ^* such that for $\theta > \theta^*$, the project will not be approved by HQ. More formally:

Lemma: *HQ optimally only takes projects at* $t = 0$ *that have novelty* $\theta \leq \theta^*$, *where* $\theta^* = \{\frac{v_i}{v_i - \frac{1}{2}[v_n - (I_0 - x)]}\}$. *Any project with* $\theta > \theta^*$ *will not be approved at* $t = 0$. *At* $t = 1$, *it is optimal for* M_B *to report* $s = s_c$, *irrespective of the information he receives.*

The lemma is obtained by equating (A.1) to zero. The intuition behind this result is that HQ will tend to reject the projects that are significantly novel since it will not be able to evaluate the project and decide when it is appropriate to shut down the project at a later date. The agency problem is that the M_B, who has the information, has little incentive to provide HQ with information since it expects that the resources will be reallocated.

APPENDIX B

Tables and Figures for Chapter 2

Panel A: Distribution of Patent Counts

Median	75%	80%	90%	95%	99%	Max	Mean	Std. Dev	Observations
0	0	1	4	15	84	2,302	3.66	32.70	44,108

Panel B: Patenting Firm-years over Time

	Number of Patents					
Year	0	1-2	3-10	11-100	>100	Observations
1980 - 1985	8,448	1,025	848	699	133	11,011
1985 - 1990	8,905	999	906	636	130	11,483
1990 - 1995	9,545	903	770	573	136	11,976
1995 - 1998	7,940	452	483	440	136	9,638
All Firms	34,838	3,379	3,008	2,349	534	44,108
Multi-segment Firms	7,954	1,250	1,344	1,251	291	12,090
Single-segment Firms	26,884	2,129	1,664	1,098	243	32,018

Panel C: Single-segment vs. Multi-segment Firms

	Single-segment			Multi-segment			All Firms
	Mean	Max	Min	Mean	Max	Min	Mean
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Sales ($ million)	1,020	17,410	10	2,016	23,512	11	1,293
RD ($ million)	22	479	0	43	878	0	28
Q	1.21	9.35	.39	.87	8.49	.55	1.11
HI	.23	.86	.05	.28	.89	.06	.24
Patents[a]	5	2,302	0	3	1,016	0	4.5
CPatents[a]	1.06	5.43	0	.84	3.55	0	.99
$\frac{RD}{Sales}$ (%)	2.15	4.90	0	2.13	3.72	0	2.15
Observations		32,018			12,090		44,108

Panel D: Patenting Multi-segment Firms

	CPatent≤ Mean (=.84)			*CPatent*> Mean (=.84)			Patenting Firms
	Mean	Max	Min	Mean	Max	Min	Mean
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Sales ($ million)	3,397	12,636	16	3,774	23,512	19	3,567
RD ($ million)	87	818	.58	111	878	1.02	98
Reallocate	1.55	3.91	0	1.11	3.80	0	1.35
Diversity	.24	.75	.03	.18	.62	.02	.21
Diversification Index	1.73	5.33	1.18	1.48	4.12	1.11	1.61
EV (excess value)	-.04	1.90	-2.20	.08	2.14	-1.82	.02
Observations		2,494			2,060		4,554

Note:
This table reports the summary statistics of the key variables used in the analysis. Patent information comes from the NBER patent data set, significantly augmented with patent specific details for 423,640 patents from the United States Patent and Trademark Office website. Information includes the number of patents by each firm, the number of citations received by each patent, assignee name, inventor name and location and details on claims in the patent. I select all public firms from the NBER patent file that have financial data available in the S&P's Compustat database and include all the firms in Compustat that operate in the same industries as the firms in the patent database but which do not have patents. Then I apply the same screens as Berger and Ofek [1995]. Data on Sales, R&D expenditures, SIC codes and other financials comes from Compustat. Panel A and B provide details on distribution and descriptive statistics of patents across years. Panel C corresponds to firm years for single and multi-segment firms. Among the multi-segment firms that patent, Panel D corresponds to firm years with above and below mean citations per patent in the sample period. All differences between Column (1) and Column (4) in Panels C and D are statistically significant at the 1% level. [a] signifies that data is only for firms that produce at least one patent during a given year. Data in this table is for the period 1980 to 1998.

Table B.1: Summary Statistics

	$Patent_t$: All Firms			$CPatent_t$: All Firms		
	Poisson	Poisson	NegBin	Poisson	Poisson	NegBin
	(1)	(2)	(3)	(4)	(5)	(6)
$\text{Dummy}^{mseg=1}$	-.643 (.024)***	-.684 (.024)***	-.621 (.110)***	-2.609 (.021)***	-2.386 (.023)***	-2.028 (.149)***
Sales	.571 (.006)***	.571 (.006)***	.551 (.028)***	.398 (.046)***	.402 (.046)***	.405 (.048)***
RD	.713 (.008)***	.711 (.008)***	.790 (.057)***	4.435 (.557)***	4.497 (.557)***	4.453 (.558)***
Leverage	-1.477 (.069)***	-.777 (.069)***	-.685 (.211)***	-.302 (.133)***	-.253 (.133)**	-.298 (.133)***
$\frac{Capx}{Assets}$	-.842 (.144)***	-.832 (.144)***	-1.553 (.552)***	-1.283 (1.139)	-1.260 (1.138)	-1.323 (1.141)
$\frac{Cash}{Assets}$	-.210 (.260)	-.200 (.292)	-.191 (.311)	-.293 (.364)	-.301 (.332)	-.284 (.807)
$\frac{NPPE}{Assets}$	1.060 (.617)*	.994 (.617)*	.890 (.619)*	.371 (.123)***	.374 (.124)***	.253 (.133)*
$\frac{EBIDTA}{Assets}$	1.842 (.056)***	1.541 (.056)***	3.099 (.360)***	3.285 (.839)***	3.239 (.839)***	3.283 (.839)***
Age	.049 (.022)**	.053 (.022)**	.052 (.022)**	.043 (.023)**	.046 (.022)**	.045 (.022)**
Q	.018 (.009)**	.016 (.009)*	.017 (.010)*	.010 (.005)**	.013 (.007)*	.015 (.008)*
HI	2.190 (.090)***	2.124 (.090)***	1.912 (.111)***	1.514 (.090)***	1.517 (.089)***	1.566 (.110)***
HI^2	-2.031 (1.072)**	-2.016 (1.071)*	-2.331 (1.055)**	-1.430 (.732)*	-1.345 (.759)*	-1.280 (.682)*
Observations	44,108	44,108	44,108	44,108	44,108	44,108
p-value, χ^2 test	0.00	0.00	0.00	0.00	0.00	0.00
Other Controls	Yes	Yes	Yes	Yes	Yes	Yes
Time Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
State Fixed Effects	Yes			Yes		
Firm Fixed Effects		Yes	Yes		Yes	Yes

Note:
This table reports the results of regressions that relate patents and citations per patent produced to firm characteristics. Specifically, I estimate the following model: $y_{it} = \exp\left(\beta_1 \text{Dummy}_{it}^{mseg=1} + \delta \mathbf{Z}_{it} + \text{Time F.E.} + \text{State F.E.}\right)$. Here, y is the dependent variable that measures either the patents or the citations per patent. Both measures of R&D productivity are corrected for truncation in grants and citations as well as for technology class. $\text{Dummy}^{mseg=1}$ is an indicator variable that takes a value 1 for multi-segment firms and is 0 otherwise. $\mathbf{Z}$ includes Sales, RD, Leverage, $\frac{EBIDTA}{Assets}$, $\frac{Capx}{Assets}$, $\frac{Cash}{Assets}$ and $\frac{NPPE}{Assets}$ and Q. All regressions are estimated with time and state fixed effects and the standard errors reported in parentheses are heteroskedastic consistent to account for over dispersion in Poisson models. Data is for the period 1980 to 1998. ***, ** and * denote significance at 1%, 5% and 10%, respectively.

Table B.2: R&D Productivity in Single and Multi-segment Firms

Panel A: *Patent* and *CPatent*

	$Patent_t$: Multi-segment Firms			$CPatent_t$: Multi-segment Firms		
	Poisson	Poisson	Poisson	Poisson	Poisson	Poisson
	(1)	(2)	(3)	(4)	(5)	(6)
Reallocate	-.233 (.110)**			-.764 (.301)***		
Diversity		-1.791 (.401)***			-2.37 (.860)***	
Diversification Index			-.285 (.141)**			-.320 (.162)**
Observations	12,090	12,090	12,090	12,090	12,090	12,090
p-value, χ^2 test	0.00	0.00	0.00	0.00	0.00	0.00
Other Controls	Yes	Yes	Yes	Yes	Yes	Yes
Time Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes

Panel B: Variation of $Patent^d$ and $CPatent^d$

	$Patent^d_t$: Multi-segment Firms			$CPatent^d_t$: Multi-segment Firms		
	OLS	OLS	OLS	OLS	OLS	OLS
	(1)	(2)	(3)	(4)	(5)	(6)
Reallocate	-.042 (.021)**			-.112 (.053)**		
Diversity		-.409 (.191)***			-.734 (.096)***	
Diversification Index			-.055 (.028)**			-.099 (.040)**
Observations	12,090	12,090	12,090	12,090	12,090	12,090
R^2 (%)	34	34	34	37	37	37
Other Controls	Yes	Yes	Yes	Yes	Yes	Yes
Time Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes

Note:
This table reports the results of regressions that relate patents and citations per patent produced in a multi-segment firm to its ICM intensity. Specifically, in Panel A, I estimate: $y_{it} = \exp\{\ \beta_1 \text{ICM Intensity}_{it} + \delta \mathbf{Z}_{it} + \text{Time F.E.} + \text{Firm F.E.}\ \}$. y is the dependent variable that measures either the patents or the citations per patent. Both measures of R&D productivity are corrected for truncation in grants and citations as well as for technology class. In Panel B, I estimate $y_{it} = \{\ \alpha + \beta_1 \text{ICM Intensity}_{it} + \delta \mathbf{Z}_{it} + \text{Time F.E.} + \text{Firm F.E.}\ \}$. Here, the dependent variables measure either the patents or the citations per patent, additionally adjusted for industry effects following the approach of Berger and Ofek [1995]. I proxy for ICM intensity in all models by *Reallocate*, *Diversity* and *Diversification Index.* Control variables ($\mathbf{Z}$) included in the estimation but unreported for brevity are Sales, RD, Leverage, $\frac{EBIDTA}{Assets}$, $\frac{Capx}{Assets}$, $\frac{Cash}{Assets}$, $\frac{NPPE}{Assets}$, *HI*, HI^2, *Q*. All regressions are estimated with time and firm fixed effects and the standard errors reported in parentheses are heteroskedastic consistent. Data is for the period 1980 to 1998. ***, ** and * denote significance at 1%, 5% and 10%, respectively.

Table B.3: Variation of R&D Productivity with ICM Intensity

	$CPatent^d_t$: Multi-segment Firms					
	OLS					
	(1)	(2)	(3)	(4)	(5)	(6)
Compete	-.173 (.032)***	-.144 (.020)***	-.191 (.019)***	-.188 (.020)***	-.190 (.021)***	-.188 (.026)***
Reallocate			-.116 (.055)**			
Diversity				-.709 (.095)***		
Diversification Index					-.080 (.069)	
$\text{Dummy}^{Patent=0}$						-.007 (.009)
Observations	12,090	12,090	12,090	12,090	12,090	12,090
R^2 (%)	36	37	38	37	38	39
Other Controls	Yes	Yes	Yes	Yes	Yes	Yes
Time Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Firm Fixed Effects		Yes	Yes	Yes	Yes	Yes

Note:
This table reports the results of regressions that relate citations per patent ($CPatent^d$) produced in a multi-segment firm to its divisional R&D competition. Specifically, I estimate the regression of the following form:
$\text{CPatent}^d_{it} = \{\ \alpha + \beta_1 \text{ICM Size}_{it} + \beta_2 \text{Compete}_{it} + \ \delta \mathbf{Z}_{it} + \text{Time F.E.} + \text{Firm F.E.}\ \}$, where the measure of innovation is corrected for truncation in grants and citations, for the technology class and additionally adjusted for industry effects following the approach of Berger and Ofek [1995]. I capture the competition for R&D resources inside the conglomerate by *Compete*. I proxy for ICM intensity in all models by *Reallocate*, *Diversity* and *Diversification Index*. Control variables ($\mathbf{Z}$) included in the estimation but unreported for brevity are Sales, RD, Leverage, $\frac{EBIDTA}{Assets}$, $\frac{Capx}{Assets}$, $\frac{Cash}{Assets}$, $\frac{NPPE}{Assets}$, *HI*, HI^2, *Q*. All regressions are estimated with time and firm fixed effects and the standard errors reported in parentheses are heteroskedastic consistent. Data is for the period 1980 to 1998. ***, ** and * denote significance at 1%, 5% and 10%, respectively.

Table B.4: Variation of R&D Productivity with R&D Competition

	Deals which failed for reasons exogenous to R&D of the Target or Bidder
422	All unsuccessful merger bids
-64	Difference in corporate philosophy over growth strategy
-45	Other competing bids emerged and the acquisition with the competitor went through
-32	Valuation issues/due diligence revelation about target's operations
-29	Target refusal of offer based on disagreement over valuation
-28	Target and bidder management disagreement over restructuring and strategy
-19	Market/analysts expected the deal to fail
-16	Problem in bidder's operations (was not clear if R&D was involved) revealed over the course of negotiations
-14	Not enough information/negotiations not completed
175	*Final Control Group*

Note:
The sample of friendly deals from SDC is selected with the following restrictions: (i) the announcement date falls between 1980 and 1998 and the bidder and target are U.S public firms; the sample ends in 1998 so that I can track innovation at least 4 years after the merger bid (relevant data on patents is available in NBER dataset till 2002); (ii) the bidder's market capitalization is exceeds that of firms in the bottom decile using NYSE size breakpoints and (iii) the mode of payment is all-cash or all-equity. To construct the control group, I start with the sample containing all failed bids and employ the information from Lexis-Nexis and Factiva to exclude any deal whose failure was related to R&D of either the target or the bidder. To focus on deals which are *ex ante* not too different, I drop deals that the media/analysts/markets expect to fail. To track the innovation of targets once they have been acquired, I search for the name of the subsidiary by examining the assignee name on an invention. In cases when it is reported and matches with the name of the acquired target, patent information is used directly. When a subsidiary name is not reported, using the state of location of the inventors of the patent, I track the location of subsidiaries before they were acquired and match it with locations of subsidiaries of the conglomerate after the merger. Information on location of the subsidiaries of a conglomerate is obtained from *Directory of Corporate Affiliations*. In cases when the state of location is same for different subsidiaries in a conglomerate after the merger, I follow the approach in Section 2.3.2.

Table B.5: Sample Construction for Case-Control Test

Panel A: Failed and Successful Targets Before the Event

	Treatment (Successful)	Control (Failed)	Difference
	Mean	Mean	Mean
	(1)	(2)	(3)
Sales ($ million)	771	776	5
RD ($ million)	16	14	2
$\frac{EBIDTA}{Assets}$	.12	.11	.01
CPatents[a]	.70	.77	-.07
Observations	13,460	1,130	

Panel B: Probability of Deal Succeeding

	Prob(Success=1)$_t$				
	(1)	(2)	(3)	(4)	(5)
Size	-.166 (.30)	-.163 (.30)	-.164 (.30)	-.166 (.33)	-.165 (.33)
$\frac{EBIDTA}{Assets}$	.30 (.24)	.31 (.23)	.32 (.23)	.29 (.21)	.28 (.21)
RD	-.009 (.008)	-.009 (.008)	-.009 (.007)	-.010 (.008)	-.011 (.007)
Leverage	-.132 (.075)*	-.133 (.075)*	-.128 (.075)*	-.134 (.075)*	-.130 (.075)*
$\frac{Capx}{Assets}$	-4.15 (3.90)	-4.13 (3.91)	-4.11 (3.89)	-3.93 (3.93)	-3.91 (3.92)
Dummy$^{A_{dind}}$			.31 (.18)*	.30 (.18)*	.31 (.19)*
Dummy$^{A_{mseg}}$			.004 (.002)*	.004 (.002)*	.004 (.002)*
Patent$^{3yr_{avg}}$				-.93 (.88)	
CPatent$^{3yr_{avg}}$					.23 (.56)
Observations	14,590	9,010	14,590	14,590	14,590
p-value, χ^2 test	0.00	0.00	0.00	0.00	0.00
F-test (Joint Significance[b] p-values)	.383	.384	.384	.384	.383
Other Controls	Yes	Yes	Yes	Yes	Yes
Time Fixed Effects	Yes	Yes	Yes	Yes	Yes
Firm Fixed Effects		Yes			

Panel C: Difference in Difference Specification

	$CPatent_t$						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
After	-.110 (.016)***	-.052 (.059)	-.051 (.059)	-.051 (.060)	-.050 (.061)	-.050 (.061)	-.049 (.060)
After*Treat		-.222 (.062)***	-.071 (.032)**	-.010 (.030)	-.011 (.031)	-.011 (.031)	-.010 (.028)
After*Treat*Dummy$^{A_{mseg}}$			-.451 (.149)***	-.420 (.149)***	-.173 (.078)**	-.122 (.078)*	-.185 (.070)**
After*Treat*Dummy$^{A_{dind}}$				-.092 (.043)**	-.091 (.042)**	-.091 (.042)**	-.089 (.040)**
After*Treat*Dummy$^{A_{mseg}}$*Diversity					-.604 (.230)***		
After*Treat*Dummy$^{A_{mseg}}$*Reallocate						-.166 (.081)**	
After*Treat*Dummy$^{A_{mseg}}$*Compete							-.140 (.068)**
Observations	25,320	25,320	25,320	25,320	25,320	25,320	25,320
R^2 (%)	21	22	24	24	26	26	26
Other Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note:
In Panel A, I provide summary statistics of the control and treatment sample. [a] signifies that data is only for firms that produce at least one patent during a given year. Panel B presents the logit regression relating the probability of a deal succeeding for a target to the characteristics of the target and the potential acquirer. Joint significance[b] is for coefficients on *Size*, RD, $\frac{EBIDTA}{Assets}$ and $\frac{Capx}{Assets}$. Panel C presents the results of a difference in difference regression, where the measure of innovation is corrected for truncation in grants and citations and for the technology class. *Treat* is an indicator variable that takes a value 1 for targets in the treatment group. $Dummy^{A_{dind}}$ and $Dummy^{A_{mseg}}$ take a value 1 if the potential acquirer is in the same SIC as the target and when the potential acquirer is a multi-segment firm, respectively. $Patent^{3yr_{avg}}$ and $CPatent^{3yr_{avg}}$ measure the previous three-year average R&D productivity of the target. Other control variables included in the estimation in Panel C (unreported for brevity) are as in earlier tables. All regressions are estimated with time fixed effects and the standard errors reported in parentheses are heteroskedastic consistent. Merger dates in the sample correspond to the period 1980 to 1998. ***, ** and * denote significance at 1%, 5% and 10%, respectively.

Table B.6: Establishing Causality: R&D Productivity of Targets in Unrelated Mergers

Panel A: Excess Value (EV_t)

	(1)	(2)	(3)
CPatent	.079		
	(.011)***		
CPatent^d		.047	.031
		(.014)***	(.011)***
CPatent^d*$\text{Dummy}^{P>0}$			.052
			(.014)***
Size	-.058	-.057	-.040
	(.004)***	(.004)***	(.004)***
$\frac{Capx}{Assets}$	1.371	1.366	.937
	(.142)***	(.141)***	(.141)***
$\frac{EBIDTA}{Assets}$	1.827	1.826	1.826
	(.127)***	(.127)***	(.127)***
Leverage	-1.213	-1.209	-.921
	(.061)***	(.061)***	(.061)***
Observations	12,090	12,090	12,090
R^2 (%)	19	23	24
Other Controls	Yes	Yes	Yes
Time Fixed Effects	Yes	Yes	Yes
Firm Fixed Effects		Yes	Yes

Panel B: Excess Value (EV_t) in Innovative Industries

	(1)	(2)	(3)
CPatent^d	.031	.030	.031
	(.012)***	(.012)***	(.012)***
CPatent^d*$\text{Dummy}^{P>0}$	.051	.049	.046
	(.014)***	(.015)***	(.014)***
Diversity * $\text{Dummy}^{P>0}$	-.241		
	(.024)***		
Reallocate * $\text{Dummy}^{P>0}$		-.029	
		(.007)***	
Compete * $\text{Dummy}^{P>0}$			-.026
			(.011)**
Diversity	-.251		
	(.052)***		
Reallocate		-.002	
		(.001)**	
Compete			-.001
			(.001)
Observations	12,090	12,090	12,090
R^2 (%)	24	24	25
Other Controls	Yes	Yes	Yes
Time Fixed Effects	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes

Note:
This table reports the results of regressions that relate excess value (EV) to innovation and ICM related characteristics. Specifically, in Panel A I estimate: $\text{EV}_{it} = \{\ \alpha + \beta_1 \text{CPatent}_{it} + \delta \mathbf{Z}_{it} + \text{Time F.E.} + \text{Firm F.E.}\ \}$, where EV is constructed following Berger and Ofek [1995]. Following these authors, control variables ($\mathbf{Z}$) included in the estimation are Size (*Log (Assets)*), *Leverage*, $\frac{Capx}{Assets}$, $\frac{EBIDTA}{Assets}$ and $\frac{Cash}{Assets}$ (some of which are unreported for brevity). In Panel B I examine how the relationship in Panel A varies when the divisions of a conglomerate operate in innovative industries. I also include *ICM intensity* in these models as proxied by *Reallocate*, *Diversity* and *Compete*. All regressions are estimated with time and firm fixed effects and the standard errors reported in parentheses are heteroskedastic consistent. Data is for the period 1980 to 1998. ***, ** and * denote significance at 1%, 5% and 10%, respectively.

Table B.7: R&D Productivity and Excess Value

	$CPatent^d_t$: Multi-segment Firms								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Di	-.581 (.066)***		-.609 (.067)***		-.710 (.084)***		-.714 (.085)***		-.724 (.087)***
Di*D^{Q_L}	-.212 (.039)***								
Di*D^{CEO_H}			-.113 (.053)**						
Di*D^{Size_H}					.019 (.031)				
Re		-.101 (.049)**		-.109 (.052)**		-.143 (.048)**		-.113 (.051)**	
Re*D^{Q_L}		-.127 (.043)***							
Re*D^{CEO_H}				-.155 (.061)**					
Re*D^{Size_H}						.002 (.011)			
RVA							.034 (.020)*	.052 (.022)**	
Observations	12,090	12,090	7,670	7,670	12,090	12,090	12,090	12,090	7,430
R^2 (%)	37	37	54	54	37	37	37	37	42
Other Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note:
This table reports the results of regressions that test for robustness of the relationship between citations per patent produced in a multi-segment firm to its ICM intensity. Specifically, I estimate regressions of the form: $y_{it} = \{\ \alpha + \beta_1 \text{ICM Intensity}_{it} + \ \delta \mathbf{Z}_{it} + \text{Time F.E.} + \text{Firm F.E.}\ \}$, where the dependent variables measure either the patents or the citations per patent, additionally adjusted for industry effects following the approach of Berger and Ofek [1995]. I proxy for ICM intensity in all models by *Reallocate* and *Diversity.* These variables are referred to as *Re* and *Di* in the table for brevity. D^{Q_L} is an indicator variable that takes a value 1 if the standard deviation of Q across the divisions in a multi-segment firm is in the lowest quintile of the sample of multi-segment firms for that year and 0 otherwise. D^{CEO_H} is an indicator variable that takes a value 1 if the CEO of the conglomerate is the chairman and president of the board in that year and 0 otherwise. D^{Size_H} is an indicator variable that takes a value 1 if the standard deviation of *Size* across the divisions in a multi-segment firm is in the highest quintile of the sample of multi-segment firms for that year and 0 otherwise. *RVA* is the relative value added by allocation measure of RSZ [2000]. Control variables ($\mathbf{Z}$) included in the estimation but unreported for brevity are Sales, RD, Leverage, $\frac{EBIDTA}{Assets}$, $\frac{Capx}{Assets}$, $\frac{Cash}{Assets}$ and $\frac{NPPE}{Assets}$. All regressions are estimated with time and firm fixed effects and the standard errors reported parentheses are robust and are corrected for the panel in all models. Data is for the period 1980 to 1998. ***, ** and * denote significance at 1%, 5% and 10%, respectively.

Table B.8: Robustness Checks

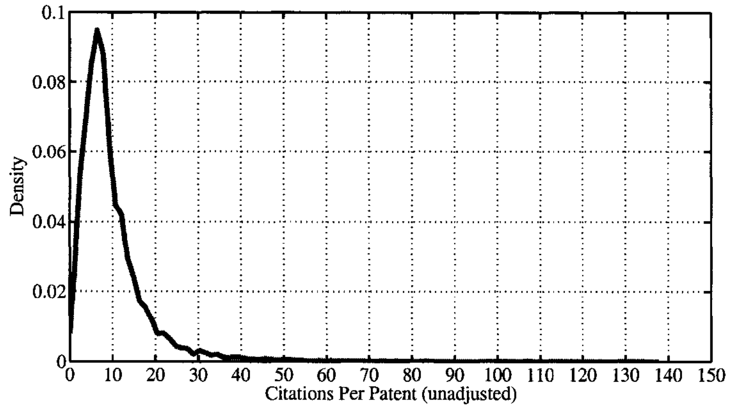

Figure B.1: Distribution of citations per patent (unadjusted) in the sample.

This figure presents the citations per patent for the multi-segment and single-segment firms in the sample that patent. These citations have not yet been adjusted for time or technology class effects. The bandwidth for the density estimation is selected using the plug-in formula of Sheather and Jones (1991). As can be observed, the citations are extremely left skewed, with a large mass of the distribution centered around 8-9 citations. Data is for the period 1980 to 1998.

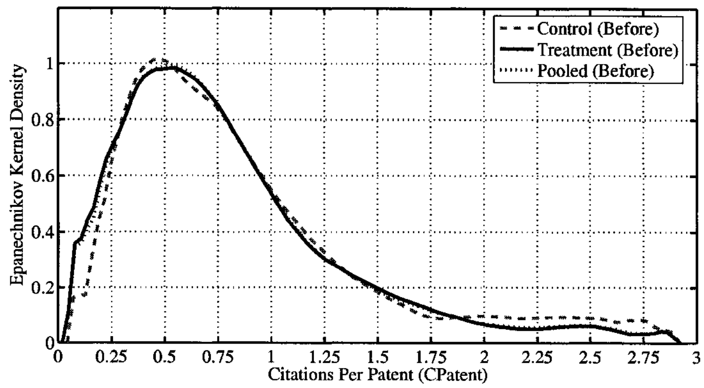

Figure B.2: Distribution of citations per patent in the quasi-experiment.

This figure depicts the Epanechnikov kernel density of citations per patent corrected for technology and time effects (*CPatent*), before the intended merger date for *treatment* (targets that successfully merged) and *control* (targets that fail to merge for reasons exogenous to innovation) groups. Also shown is the density of pooled data. The bandwidth for the density estimation is selected using the plug-in formula of Sheather and Jones (1991). The figure shows that the density of citations per patent is similar for both the control and treatment groups before the intended merger date. A Kolmogorov-Smirnov test for equality of distribution functions cannot be rejected at the 1% level. Data is for the period 1980 to 1998.

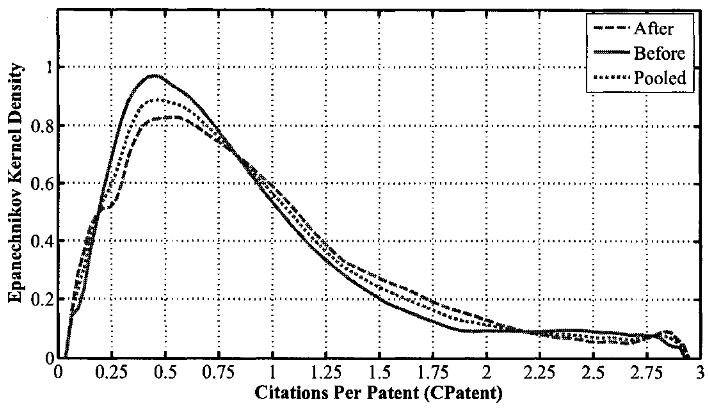

Figure B.3: Control Group Before and After Event Date.

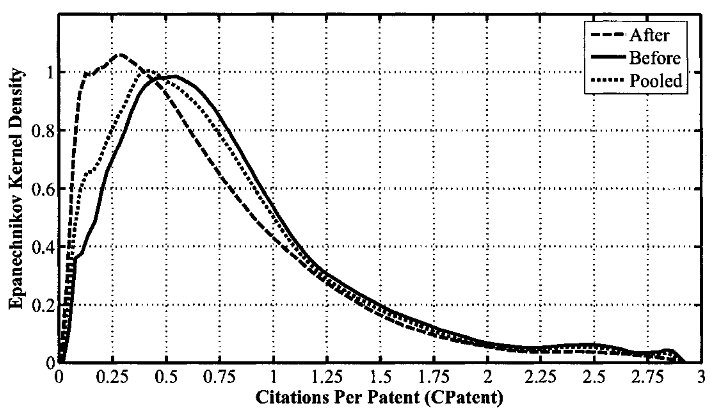

Figure B.4: Treatment Group Before and After Event Date.

These figures depict the Epanechnikov kernel density of citations per patent corrected for technology and time effects (*CPatent*), before and after the intended merger date for treatment and control groups. The bandwidth for the density estimation is selected using the plug-in formula of Sheather and Jones (1991). Figure B.3 shows that for the control group, the density of citations per patent is similar before and after the intended merger date. A Kolmogorov-Smirnov test for equality of distribution functions cannot be rejected for Figure B.3 at the 1% level. In contrast, Figure B.4 shows that after the intended merger date, the treatment group suffers a fall in R&D productivity. The leftward shift of the density in Figure B.4 is significant since a Kolmogorov-Smirnov test for equality of distribution functions is rejected at the 1% level.

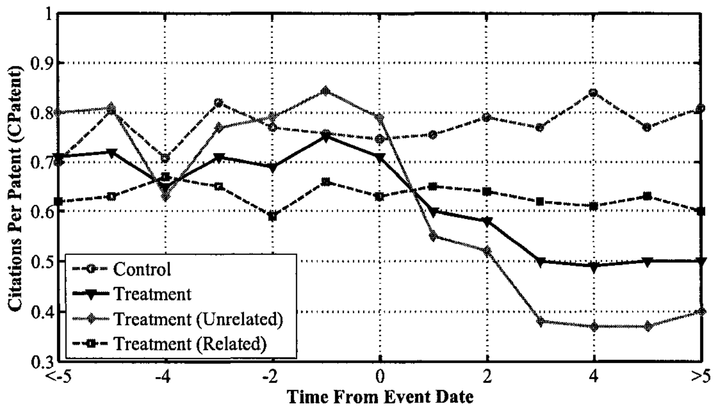

Figure B.5: Trend of Citations Per Patent in Control and Treatment Groups.

This figure shows the trend of citations per patent corrected for technology and time effects (*CPatent*), for years before and after the event. While *CPatent* of the control group remains at about an average of 0.77 before and after the merger, it falls for the treatment group after the merger date (by an average of about 0.20). Moreover, the drop in *CPatent* in the treatment group occurs primarily in those targets that are engaged in unrelated mergers (mergers where the primary SIC code of the bidder is different from the SIC code of the target).

APPENDIX C

Simple Model in Chapter 3

C.1 Simple Model: Credible Commitment by HQ

Continuing from model from Section A.1, I now illustrate that commitment by HQ to keep funds with M_B, in some situations, can elicit the right report from M_B. More formally, consider a structure (decentralized) where HQ leaves the funds with M_B with probability of p, if a negative signal is reported. Given the earlier assumptions on private benefits, it is easy to see that M_B truthfully reveals negative information as long as $pb > \underline{b}$. In other words, it is incentive compatible for M_B to report truthfully about the project at $t = 1$ if the probability p is large enough, i.e., $p \in (\frac{\underline{b}}{b}, 1]$. Thus p can be interpreted as degree of decentralization or the extent to which control rights are with the divisional manager.

The benefit of decentralized structure is that innovative projects can be taken efficiently, while the cost is the loss in NPV due to investments in division B by M_B, which as per assumptions earlier, yield zero or negative NPV. The expected payoff of a decentralized structure for the HQ is: $V_d = v_i - (1-\pi)px$. Clearly whether the conglomerate decides to adopt a decentralized structure will depend on the loss in value to the HQ by allowing M_B to invest in projects of lower value vs. choosing a centralized structure where projects with lower NPV are not taken in B but innovative projects with $\theta > \theta^*$ are declined. In general, one would expect the decision of choosing a decentralized structure to depend on the probability distribution of the types of projects that are expected to arrive at B. In particular, decentralization will be desirable so long as: $(1-\pi)\{px\} \leq \{v_i - \frac{1}{2}\{v_n - (I_0 - x)\}E[\theta|\theta \leq \theta^*]$, where E[.] is the expectation w.r.t θ. Here L.H.S represents the expected loss in value in a decentralized structure while R.H.S is the expected loss due to noise in decision making when the structure is centralized.

APPENDIX D

Tables and Figures for Chapter 3

Panel A: Multi-segment Firms in IRI sample

	Mean (1)	Max (2)	Min (3)
Sales ($ million)	13,315	23,110	91
RD ($ million)	499	879	0
Patent[a]	41	982	0
CPatent[a]	.82	3.51	0

Panel B: *CPatent*^{d} and Decentralization of R&D Budgets

	CPatent^d_t: Multi-segment Firms						
				OLS			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
%H$_q$Budget	-1.60 (.288)***	.140 (.150)	.141 (.151)	.138 (.145)	.140 (.151)	.139 (.150)	.140 (.150)
%H$_q$Budget*Divisional		-1.69 (.51)***	-1.68 (.51)***	-1.54 (.52)***	-1.67 (.50)***	-1.68 (.50)***	-1.64 (.51)***
Diversity					-.695 (.076)***		
Reallocate						-.140 (.033)***	
Compete							-.241 (.119)**
Divisional		.43 (.78)					
λ				-.197 (.043)***			
Observations	817	817	817	817	817	817	817
R^2 (%)	45	45	46	47	47	47	47
Other Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Clustering For Time	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State Fixed Effects	Yes	Yes		Yes			
Firm Fixed Effects			Yes		Yes	Yes	Yes

Note:
This table reports the results of regressions that relate citations per patent (*CPatent*^{d}) produced in a multi-segment firm to the degree of decentralization of its R&D budgets. Panel A presents descriptive statistics of some key variables in the IRI sub-sample. In Panel B, I estimate: CPatent$^d_{it}$ = $\alpha + \beta_1\%\text{H}_q\text{Budget}_{it} + \beta_2\text{Divisional}_{it} + \beta_3\%\text{H}_q\text{Budget}_{it} * \text{Divisional}_{it} + \delta\mathbf{Z}_{it} + \text{Time F.E.} + \text{State F.E.}$, where the measure of innovation is corrected for truncation in grants and citations, for the technology class and additionally adjusted for industry effects following the approach of Berger and Ofek [1995]. *%H$_q$Budget* measures the proportion of R&D budget of a division that is contributed to by the headquarters. *Divisional* is an indicator variable that takes a value 1 if the R&D structure of the conglomerate is divisional and 0 otherwise. I proxy for ICM intensity in the models by *Reallocate*, and *Diversity*. Control variables ($\mathbf{Z}$) included in the estimation but unreported for brevity are Sales, RD, Leverage, $\frac{EBIDTA}{Assets}$, $\frac{Capx}{Assets}$, $\frac{Cash}{Assets}$, $\frac{NPPE}{Assets}$, *HI*, *HI*^{2}, *Q*. All regressions are estimated with time and state fixed effects and the standard errors reported in parentheses are heteroskedastic consistent. [a] signifies that data is only for firms that produce at least one patent during the sample period. Data is for the period 1980 to 1998. ***, ** and * denote significance at 1%, 5% and 10%, respectively.

Table D.1: Variation of R&D Productivity with Decentralization of R&D Budgets

	Prob(inIRIsurvey=1)$_t$
	(1)
Dummy$^{HiAge=1}$	.29 (.05)***
Dummy$^{HiR\&D=1}$	.58 (.043)***
Dummy$^{S\&P500=1}$	.34 (.048)***
Size	.27 (.02)***
$\frac{EBIDTA}{Assets}$	.59 (.18)***
Leverage	-.06 (.04)
$\frac{Capx}{Assets}$	-.08 (.27)
Observations	12,090
Pseudo-R^2 (%)	23
Other Controls	Yes
Time Fixed Effects	Yes

Note:
I use the Heckman [1979] selection model with two-step efficient estimates. Specifically, for all the diversified firms in the base sample, a firm is treated as having been selected into the IRI survey if the information on R&D budgets and type of R&D organization is available. In the estimation of the first-stage regression, the instruments I use are: whether or not the firm's age is in the top quartile of the sample in a given year ($Dummy^{HiAge=1}$), whether or not the firm's R&D is in the top quartile of the sample in a given year ($Dummy^{HiR\&D=1}$) and whether or not the firm is in the S&P 500 Index in a given year ($Dummy^{S\&P500=1}$). All these variables proxy for how well known or visible the firm is. The notion is that better known firms are the ones that are selected into the IRI survey. The selection model uses 12,090 observations, while the second-stage regression uses only the 817 observations.

Table D.2: Selection Model for IRI sub-sample

	CPatent$_t^d$: Multi-segment Firms				
			OLS		
	(1)	(2)	(3)	(4)	(5)
Options^{NE}	.120 (.031)***	.151 (.024)***	.012 (.006)**	.023 (.011)**	.011 (.005)**
Options^{NE}*Reallocate			.119 (.061)**		
Options^{NE}*Diversity				.647 (.315)**	
Options^{NE}*Compete					.186 (.080)**
Reallocate			-.144 (.038)***		
Diversity				-.819 (.102)***	
Compete					-.245 (.037)***
Observations	3,000	3,000	3,000	3,000	3,000
R^2 (%)	42	43	43	43	43
Other Controls	Yes	Yes	Yes	Yes	Yes
Time Fixed Effects	Yes	Yes	Yes	Yes	Yes
State Fixed Effects	Yes	Yes	Yes	Yes	Yes
Firm Random Effects		Yes	Yes	Yes	Yes

Note:
This table reports the results of regressions that relate citations per patent produced in a multi-segment firm to whether options are granted to its non-executive officers. Specifically, I estimate the following regression:
$\text{CPatent}_{it}^d = \alpha + \beta_1 \text{ICM Intensity}_{it} + \beta_2 \text{Options}_{it}^{NE=1} + \beta_3 \text{ICM Intensity}_{it} * \text{Options}_{it}^{NE=1} + \delta \mathbf{Z}_{it} + \text{Time F.E.} + \text{Firm F.E.}$, where the measure of innovation is corrected for truncation in grants and citations, for the technology class and additionally adjusted for industry effects following the approach of Berger and Ofek [1995]. *Options*$^{NE=1}$ is an indicator variable that takes a value 1 if the firm provides options to its non-executives following the procedure of Oyer and Schaefer [2005] and is 0 otherwise. I proxy for ICM intensity in the models by *Reallocate*, *Diversity* and *Compete*. Control variables (**Z**) included in the estimation but unreported for brevity are Sales, RD, Leverage, $\frac{EBIDTA}{Assets}$, $\frac{Capx}{Assets}$, $\frac{Cash}{Assets}$, $\frac{NPPE}{Assets}$, *HI*, HI^2, *Q*. All regressions are estimated with time and state fixed effects and the standard errors reported in parentheses are heteroskedastic consistent. Data is for the period 1980 to 1998. ***, ** and * denote significance at 1%, 5% and 10%, respectively.

Table D.3: Mitigating Effect of Divisional Manager Incentives

	CPatent^d_t: Multi-segment Firms					
	OLS					
	(1)	(2)	(3)	(4)	(5)	(6)
$\text{CEO}^{Innov=1}$	.179 (.066)***	.174 (.065)**	.099 (.052)**	.015 (.050)***	.013 (.051)***	.012 (.050)***
$\text{CEO}^{Innov=1}$ * Dispersion			.481 (.239)***			
$\text{CEO}^{Innov=1}$ * Reallocate				.213 (.108)**		
$\text{CEO}^{Innov=1}$ * Diversity					.573 (.161)***	
$\text{CEO}^{Innov=1}$ * Compete						.162 (.68)**
Dispersion			1.197 (.730)*			
Reallocate				-.224 (.047)***		
Diversity					-.797 (.320)***	
Compete						-.233 (.041)***
Observations	7,670	7,670	7,670	7,670	7,670	7,670
R^2 (%)	51	54	55	56	56	56
Other Controls	Yes	Yes	Yes	Yes	Yes	Yes
Time Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Firm Fixed Effects		Yes	Yes	Yes	Yes	Yes

Note:
This table reports the results of regressions that relate citations per patent produced in a multi-segment firm to the job history of its CEO. Specifically, I estimate the regression of the following form:

$$\text{CPatent}^d_{it} = \begin{array}{l}\alpha + \beta_1 \text{ICM Intensity}_{it} + \beta_2 \text{CEO}^{Innov=1}_{it} + \beta_3 \text{ICM Intensity}_{it} * \text{CEO}^{Innov=1}_{it} \\ + \delta \mathbf{Z}_{it} + \text{Time F.E.} + \text{Firm F.E.}\end{array}$$

, where the measure of innovation is corrected for truncation in grants and citations, for the technology class and additionally adjusted for industry effects following the approach of Berger and Ofek [1995]. $CEO^{Innov=1}$ is an indicator variable that takes a value 1 if the CEO has job experience in all the innovative divisions of the conglomerate and is 0 otherwise. I proxy for ICM intensity in the models by *Reallocate*, *Diversity* and *Compete*. Control variables (**Z**) included in the estimation but unreported for brevity are Sales, RD, Leverage, $\frac{EBIDTA}{Assets}$, $\frac{Capx}{Assets}$, $\frac{Cash}{Assets}$ $\frac{NPPE}{Assets}$, *HI*, HI^2, *Q*. All regressions are estimated with time and firm fixed effects and the standard errors reported in parentheses are heteroskedastic consistent. Data is for the period 1980 to 1998. ***, ** and * denote significance at 1%, 5% and 10%, respectively.

Table D.4: Mitigating Effect of CEO Skill

APPENDIX E

Variable Definitions for Chapter 4

E.1 Variable Definitions and Data Sources

1. Age_{it}: Age of firm i in year t based on the years from a firm's IPO as reported in CRSP (Source: CRSP).

2. $Assets_{it}$: Total assets of firm i in year t (Source: Compustat Data 6).

3. $(\frac{Cash}{Assets})_{it}$: Cash of firm i in year t divided by its $Assets$ (Source: Compustat Data 1).

4. $(\frac{CF}{Assets})_{it}$: Cash flow of firm i in year t divided by its $Assets$ (Source: Compustat Data 14+ Data 18).

5. $CitedPatent_{it}^{Time}$: Measures the number of citations per patent applied for in year t by firm i. The weight of each patent is the number of citations received by a patent applied for in year t divided by the total number of citations received by all patents applied for in year t (Source: NBER Patent Data).

6. $CitedPatent_{it}^{Time-Tech}$: Measures the number of citations per patent applied for in year t by firm i. The weight of each patent is the number of citations received by a patent applied for in year t divided by the total number of citations received by all patents applied for in year t, in the same technological class (Source: NBER Patent Data).

7. $CitedPatent_{it}^{Quasi}$: Measures the number of citations per patent applied for in year t by firm i. The number of citations of each patent in year t is multiplied by the weighting index and summed for all the patents by firm i in year t and then divided by the number of patents by firm i in year t (Source: NBER Patent Data).

8. $(\frac{Debt}{Assets})_{it}$: Total debt of firm i in year t divided by its $Assets$ (Source: Compustat Data 9+ Data 34) .

9. $DrasticIncrem_{it}$: An indicator variable which equals *1* if a firm i is in the top *1%* of firms ranked by the number of citations per patent received in year t in a given *technology class*, and *0* if a firm is ranked among the bottom *30%*. Alternative cutoffs as described in the text are also employed (Source: NBER Patent Data).

10. $EBIDTA_{it}$: Earnings before interest depreciation taxes and amortization of firm i in year t (Source: Compustat Data 13).

11. $(\frac{Equity}{Assets})_{it}$: Book equity of firm i in year t divided by its *Assets* (Source: Compustat Data 6 - Data 181 + Data 10 + Data 35 + Data 79). In case Data 10 (preferred stock) is missing the value is replaced by Data 56.

12. HI_{it}: Herfindahl index of firm i in year t constructed based on sales at both a 4 digit SIC and for robustness for the Fama and French (1997) *48* industries (Source: Compustat; Kenneth French's web site).

13. KZ_{it}: Measures the financial constraints faced by firm i in year t and is constructed as in (Baker, Wurgler and Stein, 2003). Specifically, $KZ_{it} = -1.002(\frac{CF}{Assets})_{it} - 39.368(\frac{Div}{Assets})_{it} - 1.315(\frac{Cash}{Assets})_{it} + 3.139(\frac{Debt}{Assets})_{it} + 0.283Q_{it}$, where $\frac{CF}{Assets}$ is cash flow over lagged assets; $\frac{Div}{Assets}$ is cash dividends over assets; $\frac{Cash}{Assets}$ is cash balances over assets; $\frac{Debt}{Assets}$ is the leverage; and Q is the market value of equity over assets constructed as explained in definition 20 (Source: Compustat).

14. *Log(1+%Public)*$_{it}$: Log of one plus the percentage of firms in the industry of firm i in year t that have public debt outstanding in year t (Source: Compustat; SDC Platinum).

15. $Patent_{it}$: Count of the number of patents in application year t by firm i (Source: NBER Patent Data).

16. $Patent^{c}_{it}$: Number of patents in application year t by firm i corrected for the truncation bias in patents granted towards the end of the sample using the methodology of Hall, Jaffe and Trajtenberg (2001, 2005) (Source: NBER Patent Data).

17. $Public_{it}$: Amount of public debt outstanding of firm i in year t. Collected from SDC using the information on public debt issue data and maturity of each debt issue (Source: SDC Platinum Database).

18. $Public^{s}_{it}$: A dummy variable that takes value of *1*, if firm i has public debt outstanding in current year t or any year before that, as reported in SDC, and *0* otherwise (Source: SDC Platinum Database).

19. $Public^c_{it}$: A dummy variable that takes value of *1*, if firm i has a bond rating or a commercial paper rating (or both) in current year t or any year before that, as reported in Compustat, and *0* otherwise (Source: Compustat).

20. Q_{it}: Market to book ratio of firm i in year t (Source: Compustat $\frac{\text{Assets} + \text{Data 199* Data 25-BookEquity}}{\text{Assets}}$; where Data 199 is the year end closing price and Data 25 is year end outstanding shares).

21. $(\frac{RetEarn}{Assets})_{it}$: Retained earnings of firm i in year t divided by its *Assets* (Source: Compustat Data 36).

22. RD_{it}: R&D Expenditure by firm i in year t (in \$ million) (Source: Compustat Data 46).

23. $Sales_{it}$: Sales by firm i in year t (in \$ million) (Source: Compustat Data 12).

24. $S\&P\ 500_{it}$: A dummy variable that takes a value 1 for firm i in year t if the firm is in the S&P 500 Index as reported in Compustat and 0 otherwise (Source: Compustat).

25. $\sigma_{\text{firm,it}}, \sigma_{\text{ind,it}}, \sigma_{\text{mkt,it}}$: Campbell et al. [2001] decomposition of stock return volatility of firm i in year t into firm specific risk, industry specific risk, and market specific risk respectively. The stock returns are based on CRSP (Source: CRSP).

26. $Size_{it}$: Log of *Assets* of firm i in year t (Source: Compustat).

27. $Tangible_{it}$: Measured as the ratio of *PPE* to *Assets* of firm i in year t (Source: Compustat).

E.2 Construction of Dependent Variable

- Truncation Bias in Patent Grants: The truncation bias in patent grants stems from the fact that there is an average lag of about two years between patent applications and patent grants. Thus, as one progresses towards the end of the sample, patents reported in the dataset might under-report the actual patenting propensity of a firm – since many of the patents, though applied for, might not have been granted. Note that although we use the application year as the relevant year for our analysis, the patents appear in the database only after they are granted. We follow Hall, Jaffe and Trajtenberg [2001; 2005] and correct for this bias by using the application-grant empirical distribution to compute "weight factors". Then we multiply each simple patent count (*Patent*) by the corresponding weight factor to get $Patent^c$. As we would expect, patents applied for in later years have higher weight factors.

- Truncation Bias in Patent Citations: The truncation bias in patent citations arises because patent citations are received many years after the innovation was created. We follow Hall, Jaffe, and Trajtenberg [2001] and use two methods to correct for the truncation bias. The first method is called "fixed effects". It consists of scaling patent citations by dividing them by the average amount of patent citations in the same group (year, technology class or year-technology class) to which the patent belongs. The advantage of the fixed effects approach is that we compare only patents that are in the same cohort and effectively purge the data from any effects due to truncation or other artificial differences in the propensity to receive citations among different groups. The drawback is that we also remove any real differences among the groups. Since the focus of this paper is not on estimating such differences we are not very concerned about this drawback. Using the fixed effects method, we create two dependent variables. The first one measures the number of citations per patent, where the number of citations received by a patent applied for in a given year is divided by the total number of citations received by all patents applied for in the same year ($CitedPatent^{Time}$). The second dependent variable is again citations per patent, where the number of citations received by a patent in a given year in a given technological class is divided by the total number of citations received by all firms in the same year, in the same technological class ($CitedPatent^{Time-Tech}$).

  As we mentioned, the fixed effects method has its drawbacks. Therefore, for robustness we use a second method called "quasi-structural". It attempts to econometrically estimate the distribution of the citation lag. The benefits of this approach is that it allows for real differences in the number of citations received in different time periods and technological classes. The drawback is that it requires two additional assumptions – the shape of the distribution over time is independent of the total number of citations received and the lag distribution does not change over time. Using the estimated distribution lag, we create a weighting index and multiply the number of citations by this index. As we would expect, the index is higher for later years. Our third dependent variable is created by first multiplying the number of citations for each patent by the weighting index, then calculating the sum of the result for each firm per year and dividing by the number of patents for the same year ($CitedPatent^{Quasi}$).

APPENDIX F

Tables and Figures for Chapter 4

Panel A: Distribution of Patent Counts

Median	75%	80%	90%	95%	99%	Max	Mean	Std. Dev	Observations
0	0	1	4	15	121	3,013	4.65	36.25	109,500

Panel B: Distribution of Patenting Firms

	Number of Patents					
Year	0	1-2	3-10	11-100	>100	Observations
1974	2,398	280	299	186	42	3,205
1975	2,475	293	292	179	45	3,284
1976	2,589	275	262	182	43	3,351
1977	2,614	289	251	186	37	3,377
1978	2,887	283	233	182	35	3,620
1979	2,896	259	197	183	22	3,557
1980	3,133	281	194	184	30	3,822
1981	3,230	234	218	189	31	3,902
1982	3,385	259	208	180	37	4,069
1983	3,455	251	207	163	36	4,112
1984	3,457	260	237	161	33	4,148
1985	3,452	229	233	163	37	4,114
1986	3,555	245	236	164	28	4,228
1987	3,538	253	230	163	33	4,217
1988	3,512	294	218	153	29	4,206
1989	3,505	232	219	155	36	4,147
1990	3,690	211	201	142	32	4,276
1991	3,787	272	206	143	35	4,443
1992	3,798	287	203	149	33	4,470
1993	3,747	183	186	142	32	4,290
1994	3,801	180	170	143	38	4,332
1995	3,825	150	172	149	37	4,333
1996	3,919	144	173	142	42	4,420
1997	3,933	153	132	132	40	4,390
1998	3,981	120	129	129	51	4,410
1999	3,970	97	121	135	50	4,373
2000	3,988	94	133	137	52	4,404
Total	92,520	6,108	5,560	4,316	996	109,500

Table F.1: Patent and Citations Per Patents Counts

Panel C: Distribution of Patenting Firms by Industry

Industry Name	Number of Patents: 0	1-2	3-10	11-100	>100	Firm-Years
Agriculture	358	4	0	0	0	362
Aircraft	286	86	164	144	54	734
Apparel	1,852	137	47	6	0	2,042
Automobiles and Trucks	1,209	189	234	271	103	2,006
Beer and Liquor	418	26	18	7	0	469
Business and Office Supplies	973	171	201	158	2	1,505
Candy and Soda	284	36	32	38	0	390
Chemicals	2,390	221	239	428	108	3,386
Communication	2,612	21	10	10	24	2,677
Computers	2,727	295	248	276	94	3,640
Construction and Related Materials	3,922	538	459	298	24	5,241
Consumer Goods	2,924	319	284	304	135	3,966
Defense	126	29	24	15	10	204
Electrical Equipment	2,886	206	208	131	24	3,455
Electronic Equipment	3,368	639	515	368	92	4,982
Entertainment	1,198	22	8	3	0	1,231
Fabricated Products	399	96	43	19	0	557
Food Products	1,705	187	190	112	0	2,194
Healthcare	1,498	19	7	0	0	1,524
Machinery	2,293	551	687	473	62	4,066
Measurement Equipment	2,974	276	239	132	11	3,632
Medical Equipment	2,911	237	272	135	36	3,591
Miscellaneous	3,689	279	153	58	3	4,182
Non-Metallic and Industrial Mining	760	28	57	39	0	884
Personal and Business Services	7,644	156	139	52	4	7,995
Petroleum and Natural Gas	8,514	138	99	146	65	8,962
Pharmaceutical Products	2,690	158	144	308	103	3,403
Precious Metals	834	6	2	0	0	842
Printing and Publishing	1,416	52	23	0	0	1,491
Recreation	1,125	158	73	71	24	1,451
Restaurants, Hotels and Motels	3,304	31	3	0	0	3,338
Retail	6,643	37	23	0	0	6,703
Rubber and Plastics	1,035	143	99	27	0	1,304
Shipbuilding and Railroad Equipment	139	14	24	39	0	216
Shipping Containers	489	135	184	71	10	889
Steel	2,433	209	215	131	6	2,994
Textiles	1,152	138	133	17	0	1,440
Tobacco Products	580	18	15	0	0	613
Transportation	4,468	11	2	0	0	4,481
Wholesale	6,292	92	43	29	2	6,458
Total	92,520	6,108	5,560	4,316	996	109,500

Panel D: Distribution of Citations Per Patent (Whole Sample)

Median	75%	80%	90%	95%	99%	Max	Mean	Std. Dev	Observations
0	0	1	2.3	7.1	21.6	253	0.7	4.20	109,500

Panel E: Distribution of Citations Per Patent (Patenting Firms)

0-20%	21-40%	41-60%	61-80%	81-100%	Median	Mean	Std. Dev	Observations
0.68	1.85	6.60	10.21	16.86	6.60	7.31	9.17	16,980

Note:
This table reports the summary statistics of the distribution of number of patents granted in our sample. Patent information comes from the NBER patent data set provided by Hall, Jaffe, and Trajtenberg [2001]. This information includes the number of patents by each firm and the number of citations received by each patent. We select all public firms from the NBER patent file, which have financial data available in the S&P's Compustat database. We include all the firms in Compustat which operate in the same industries as the firms in the patent database, but don't have patents. Panel A gives information on the distribution of number of patents granted in the sample between 1974 and 2000. Panel B reports the number of firms by number of patents granted for each year during the sample period. Panel C reports the number of patenting firm years by industry and number of patents granted during the sample period. Panel D gives information on the distribution of citations per patent for each patent granted during the sample period. Finally, Panel E gives information on the distribution of citations per patent only among patenting firms during the sample period.

Table F.1: Patent and Citations Per Patents Counts (contd.)

Panel A: Firm Characteristics and Patents

	Patent ≤ Median (=0)			*Patent* > Median(=0)			All Firms
	Mean	Max	Min	Mean	Max	Min	Mean
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Sales ($ million)	931	15,610	0.11	2,799	40,993	4.03	1,118
RD ($ million)	38	820	.01	111	1998	.12	53
Tangible	.32	.92	.01	.33	.87	.04	.32
$\frac{Equity}{Assets}$	.49	.88	.05	.54	.91	.05	.50
$\frac{Public}{Assets}$	.02	.43	.00	.05	.47	.00	.03
$Public^s$	.12	1	0	.35	1	0	.13
HI	.43	.94	.13	.49	.95	.22	.44
Q	1.60	10.1	.43	1.86	8.82	.56	1.80
Observations		92,520			16,980		109,500

Panel B: Firm Characteristics and Citations Per Patent for Patenting Firms

	$CitedPatent^{Time}$ ≤ Median (=6.6)			$CitedPatent^{Time}$ > Median (=6.6)			All Firms
	Mean	Max	Min	Mean	Max	Min	Mean
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Sales ($ million)	2,594	38,236	4.03	2,994	40,993	2.53	2,799
RD ($ million)	107	2,018	.12	121	2,098	.62	111
Tangible	.32	.78	.04	.33	.87	.05	.32
$\frac{Equity}{Assets}$	.51	.89	.05	.58	.93	.06	.54
$\frac{Public}{Assets}$	.05	.42	.00	.07	.47	.00	.05
$Public^s$	.33	1	0	.37	1	0	.35
HI	.49	.94	.22	.50	.94	.22	.49
Q	1.49	6.6	.56	1.95	10.1	.59	1.86
Observations		7,524			9,456		16,980

Panel C: Correlation Matrix of Main Explanatory Variables

	Log(Sales)	Log(RD)	Tangible	$\frac{Equity}{Assets}$	$\frac{Public}{Assets}$	HI	Q	$\frac{EBIDTA}{Assets}$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log(Sales)	1.00							
Log(RD)	.29	1.00						
Tangible	.13	.03	1.00					
$\frac{Equity}{Assets}$	-.01	-.04	-.07	1.00				
$\frac{Public}{Assets}$	.06	.05	.05	-.04	1.00			
HI	-.05	-.03	.02	-.03	.02	1.00		
Q	-.03	-.001	-.10	-.05	-.03	-.06	1.00	
$\frac{EBIDTA}{Assets}$	.03	.02	.05	.32	.02	.03	-.20	1.00

Note:
This table reports the summary statistics of the key variables used in our analysis. Patent information comes from the NBER patent data set provided by Hall, Jaffe, and Trajtenberg [2001]. This information includes the number of patents by each firm and the number of citations received by each patent. We select all public firms from the NBER patent file, which have financial data available in the S&P's Compustat database. We include all the firms in Compustat which operate in the same industries as the firms in the patent database, but don't have patents. Data on Sales, R&D expenditures, the Herfindahl index, leverage and net property plant and equipment comes from Compustat. We exclude firms in financial sector and utilities. We collect data on public debt issues from SDC Platinum. Panel A corresponds to firm years for firms with above and below median *Patent* in the sample. Among the firms that patent, Panel B corresponds to firm years for firms with above and below median citations per patent ($CitedPatent^{Time}$) in the sample period. All differences between Column (1) and Column (4) in Panels A and B are statistically significant at 1% level. Panel C presents the correlation between key variables used in our analysis. Data in this table is for the period 1974 to 2000.

Table F.2: Summary Statistics

	Dependent Variable: $Patent^c$ Model Specification							
	Poisson (1)	Poisson (2)	Poisson (3)	Poisson (4)	Poisson (5)	Poisson (6)	NegBin (7)	Poisson (8)
Log(Sales)	.597 (.002)***	.561 (.003)***	.540 (.003)***	.418 (.003)***	.563 (.003)***	.770 (.006)***	.277 (.009)***	.562 (.003)***
Log(RD)	.394 (.002)***	.407 (.002)***	.406 (.002)***	.408 (.002)***	.409 (.002)***	.140 (.004)***	.061 (.006)***	.410 (.002)***
Hi	2.197 (.093)***	3.024 (.093)***	2.912 (.093)***	1.634 (.094)***	2.867 (.093)***	.766 (.100)***	.766 (.310)**	2.862 (.093)***
Hi^2	-2.553 (.072)***	-3.406 (.072)***	-3.331 (.072)***	-2.410 (.073)***	-3.254 (.072)***	-1.881 (.078)***	-.859 (.264)***	-3.250 (.072)***
$\frac{Equity}{Assets}$	.184 (.014)***	.227 (.014)***	.211 (.014)***	.243 (.015)***	.398 (.014)***	.305 (.019)***	.292 (.026)***	.593 (.013)***
$Public^c$			.192 (.005)***					
$Public^s$				.199 (.004)***	.075 (.009)***	.069 (.008)***	.073 (.008)***	.082 (.008)***
$\frac{Public}{Assets}$					.425 (.002)***	.733 (.023)***	.344 (.040)***	.640 (.003)***
Q		.067 (.002)***	.063 (.002)***	.051 (.002)***	.070 (.002)***	.044 (.002)***	.034 (.008)***	.053 (.021)***
Tangible		1.060 (.017)***	.994 (.017)***	.990 (.017)***	1.071 (.017)***	.374 (.024)***	.253 (.073)***	1.082 (.016)***
$\frac{EBIDTA}{Assets}$		.823 (.026)***	.786 (.026)***	.768 (.026)***	.754 (.026)***	1.291 (.033)***	.848 (.080)***	.712 (.026)***
Age		.049 (.002)***	.051 (.002)***	.050 (.003)***	.045 (.002)***	.047 (.002)***	.044 (.003)***	.048 (.002)***
$\frac{Cash}{Assets}$		-.21 (.26)	-.20 (.29)	-.19 (.31)	-.29 (.36)	-.30 (.33)	-.28 (.80)	-.21 (.29)
$\frac{RetEarn}{Assets}$		-.03 (.01)*	-.02 (.03)	-.03 (.03)	-.03 (.02)	-.03 (.03)	-.02 (.02)	-.05 (.04)
Observations	109,003	109,003	109,003	109,003	109,003	57,330	57,330	13,020
Log-likelihood	-33,644.7	-33,841.0	-33,843.4	-33,851.6	-33,855.1	-19,840.3	-19,680.8	-17,780.1
p-value, χ^2 test	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Time Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes			Yes
State Fixed Effects	Yes	Yes	Yes	Yes	Yes			Yes
Firm Fixed Effects						Yes	Yes	

Note:
This table reports the results relating patents produced in a firm to the type of its financing. Specifically we estimate poisson models in all the columns but one (Column (7)) where a negative binomial model is employed. The dependent variable is $Patent^c$ with each non-zero observation rounded to its nearest integer. Other controls (not reported in the table) include Age^2. In Column (8), we only restrict attention to innovative industries where we take all the industries where more than 20% of the firms are granted a patent in a given year to be innovative. All regressions are estimated with time, state and industry fixed effects and the standard errors reported in the parenthesis are heteroskedastic consistent to account for over dispersion in Poisson models and are corrected for the panel in all the models. Data is for the period 1974 to 2000. ***, ** and * denote significance at 1%, 5% and 10% respectively.

Table F.3: Patents and Financing Arrangements

	Dependent Variable Model Specification						
	Cited Patent^{Time}						*Cited Patent*$^{Time-Tech}$
	Poisson (1)	Poisson (2)	Poisson (3)	Poisson (4)	Poisson (5)	Poisson (6)	Poisson (7)
Log(Sales)	.208 (.008)***	.203 (.008)***	.199 (.008)***	.192 (.008)***	.190 (.008)***	.179 (.007)***	.167 (.005)***
Log(RD)	.267 (.009)***	.267 (.009)***	.253 (.009)***	.266 (.009)***	.262 (.008)***	.260 (.008)***	.161 (.003)***
Hi	2.381 (.662)***	2.371 (.663)***	2.369 (.661)***	2.366 (.661)***	2.365 (.660)**	2.011 (.617)***	.46 (.201)**
Hi^2	-1.549 (.562)***	-1.546 (.564)***	-1.510 (.562)***	-1.546 (.562)***	-1.542 (.556)**	-1.501 (.315)**	-.121 (.070)*
$\frac{Equity}{Assets}$	.801 (.043)***	.805 (.041)***	.804 (.045)***	.801 (.044)***	.809 (.044)***	.952 (.044)***	.748 (.022)***
$Public^c$		.081 (.022)***					
$Public^s$			.059 (.020)***	.058 (.020)***	.069 (.019)***	.089 (.017)***	.063 (.024)***
$\frac{Public}{Assets}$				.537 (.008)***	.662 (.007)***	.881 (.008)***	.590 (.010)***
Q	.015 (.002)***	.017 (.003)***	.016 (.003)***	.015 (.002)***	.012 (.004)***	.011 (.003)***	.027 (.001)***
Tangible	.740 (.085)***	.713 (.026)***	.714 (.026)***	.747 (.025)***	.685 (.029)**	.688 (.024)***	.384 (.027)***
$\frac{EBIDTA}{Assets}$	.054 (.023)**	.054 (.025)**	.053 (.024)**	.053 (.024)**	.050 (.025)**	.051 (.022)***	.044 (.014)***
Age	.041 (.003)***	.043 (.002)***	.049 (.002)***	.043 (.003)***	.049 (.004)***	.041 (.003)***	.036 (.005)***
$\frac{Cash}{Assets}$	-.14 (.11)	-.13 (.12)	-.13 (.11)	-.15 (.10)	-.16 (.15)	-.12 (.07)*	-.16 (.08)**
$\frac{RetEarn}{Assets}$	-.07 (.06)	-.08 (.07)	-.07 (.09)	-.07 (.07)	-.09 (.08)	-.08 (.05)*	-.06 (.06)
Observations	109,003	109,003	109,003	109,003	109,003	13,020	109,003
Log-likelihood	-20330.31	-20342.68	-20359.38	-20363.30	-20390.81	-14,789.38	-16,585.8
p-value, χ^2 test	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Time Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes		Yes
State Fixed Effects	Yes	Yes	Yes	Yes	Yes		Yes
Firm Fixed Effects						Yes	

Note:
This table reports the results relating cited patents produced in a firm to the type of its financing. Specifically we estimate poisson model in all the columns with the dependent variable as citations per patent, $CitedPatent^{Time}$ in Columns (1) to (6) and $CitedPatent^{Time-Tech}$ in Column (7). We round each non-zero observation to its nearest integer for the dependent variables that we employ. In Column (6), we only restrict attention to innovative industries where we take all the industries where more than 20% of the firms are granted a patent in a given year to be innovative (list of industries is provided in Panel C of Table I). All regressions are estimated with time, state and industry fixed effects and the standard errors reported in the parenthesis are heteroskedastic consistent to account for over dispersion in Poisson models and are corrected for the panel in all the models. Data is for the period 1974 to 2000. ***, ** and * denote significance at 1%, 5% and 10% respectively.

Table F.4: Citations Per Patent and Financing Arrangements

Panel A: Sub-sample of Patenting Firms

	$CitedPatent^{Time}$				$DrasticIncrem$=1	
	Patent in year t > 0			Patent in year t or any year before > 0	Patent in year t > 0	
	Poisson				Logit	
	(1)	(2)	(3)	(4)	(5)	(6)
$\frac{Equity}{Assets}$	.987 (.021)**	.981 (.023)**	.962 (.022)***	1.17 (.041)***	.363 (.169)**	.395 (.148)**
$\frac{Public}{Assets}$		.791 (.372)***	.785 (.358)**	.796 (.308)**		.772 (.240)***
Public^s		.119 (.039)***	.105 (.040)***	.113 (.051)**		.305 (.141)***
Observations	14,996	14,996	12,040	22,810	10,200	10,200
Log-likelihood	-16,342.2	-16,666.4	-13,387.3	-18,666.4	-4,529.4	-4,547.3
p-value, χ^2 test	0.00	0.00	0.00	0.00	0.00	0.00
Time Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes		Yes	Yes	Yes
State Fixed Effects	Yes	Yes		Yes	Yes	Yes
Firm Fixed Effects			Yes			

Panel B: Sub-sample of Innovative Industries

	$CitedPatent^{Time}$					
	Poisson					
	Drugs	*Chemicals*	*Computers*	*Electrical*	*Metals*	*Low-tech*
	(1)	(2)	(3)	(4)	(5)	(6)
$\frac{Equity}{Assets}$	1.32 (.020)***	1.88 (.022)***	1.92 (.026)***	.84 (.024)***	.38 (.18)**	.52 (.27)**
$\frac{Public}{Assets}$	1.90 (.421)***	1.69 (.410)***	1.51 (.553)***	.99 (.383)***	.45 (.25)*	.20 (.11)**
Public^s	.109 (.030)***	.101 (.031)***	.102 (.027)***	.079 (.029)***	.039 (.019)**	.019 (.010)*
Observations	12,312	10,477	26,548	23,876	10,051	26,236
Log-likelihood	-16,342.2	-16,666.4	-13,387.3	-18,666.4	-4,529.4	-4,547.3
p-value, χ^2 test	0.00	0.00	0.00	0.00	0.00	0.00
Time Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
State Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes

Note: This table reports the results of regressions relating innovations to the type of financing for a sub-sample of firms as defined below. In Columns (1) to (4) of Panel A, we estimate the poisson panel regression of $CitedPatent^{Time}$ on various explanatory variables for firms which have at least one patent in a given year during our sample. We round each non-zero observation to its nearest integer for the dependent variable that we employ. Columns (1) to (3) include all the firms that patent in a given year while in Column (4) the sample includes firms that have at least one patent in a given year or any year before it. In Columns (5) and (6) of Panel A, we estimate the panel logit regression of the modified innovation variable (*DrasticIncrem*) on various explanatory variables. *DrasticIncrem* is a dummy variable which equals 1 if a firm is in the top 1% in terms of the citations received for a given year in a given industry, and 0 if the citations received for a given year in a given industry are in the bottom 30%. In Panel B, we estimate (4.3) for each of the 6 industry sectors classified based on Hall et al. [2005] – Drugs and Medical Instrumentation; Chemicals; Computers and Communications; Electrical; Metals and Machinery; and miscellaneous low-tech industries. Other controls (not reported in the table) include $\frac{Cash}{Assets}$, $\frac{RetEarn}{Assets}$, Age and Age^2. All regressions are estimated with time, state and industry fixed effects and the standard errors reported in the parenthesis are heteroskedastic consistent to account for over dispersion in Poisson models and are corrected for the panel in all the models. Data is for the period 1974 to 2000. ***, ** and * denote significance at 1%, 5% and 10% respectively.

Table F.5: Sub-Sample Analysis: Patenting Firms and Innovative Industries

	Dependent Variable: $CitedPatent^{Time}$					
	First Time Public Debt Issue		Seasoned Equity Offering		Bank Loan	
	Poisson					
	(1)	(2)	(3)	(4)	(5)	(6)
Post^{D}_{0-2}	.301 (.075)***	.302 (.074)***				
Post^{D}_{2-4}		.049 (.023)**				
Post^{E}_{0-2}			.448 (.041)***	.449 (.040)***		
Post^{E}_{2-4}				.027 (.016)*		
Post^{B}_{0-2}					-.081 (.059)	-.084 (.058)
Post^{B}_{2-4}						.006 (.072)
$\frac{Equity}{Assets}$	.793 (.053)***	.791 (.053)***	.777 (.053)***	.770 (.053)***	.697 (.244)***	.699 (.242)***
$\frac{Public}{Assets}$	.448 (.061)***	.511 (.060)***	.704 (.071)***	.796 (.077)***	.551 (.048)***	.560 (.048)***
Public^{s}	.060 (.024)***	.063 (.025)***	.073 (.032)**	.072 (.032)**	.031 (.018)*	.030 (.018)*
Observations	109,003	109,003	109,003	109,003	10,540	10,540
p-value, χ^2 test	0.00	0.00	0.00	0.00	0.00	0.00
Time Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
State Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes

Note:
This table reports the results relating novel patents produced in a firm to the type of its financing subsequent to a public debt offering, a seasoned equity offering and a bank loan. We estimate a poisson model in all the columns with the dependent variable $CitedPatent^{Time}$. We round each non-zero observation to its nearest integer for the dependent variable that we employ. Other controls (not reported in the table) include *Q*, *Tangible*, *Age*, Age^2, $\frac{Cash}{Assets}$, $\frac{RetEarn}{Assets}$, $\frac{EBIDTA}{Assets}$, *HI* and HI^2. All regressions are estimated with time, state and industry fixed effects and the standard errors reported in the parenthesis are heteroskedastic consistent to account for over dispersion in Poisson models and are corrected for the panel in all the models. Data is for the period 1974 to 2000. ***, ** and * denote significance at 1%, 5% and 10% respectively.

Table F.6: Citations Per Patent Subsequent to First Time Public Debt Issue, a Seasoned Equity Offering and a Bank Loan

Future Value and Cited Patents

	Q_{t+1} (1)	Q_{t+2} (2)	Q_{t+3} (3)
Firms with No Patents (Cites per Patent: 0)	1.25 (.047)***	1.20 (.068)***	1.17 (.053)***
Quintile$_1$: Q$_1$ (Cites per Patent: 0.69)	1.31 (.145)***	1.24 (.063)***	1.22 (.19)***
Quintile$_2$: Q$_2$ (Cites per Patent: 1.97)	1.65 (.092)***	1.61 (.067)***	1.36 (.071)***
Quintile$_3$: Q$_3$ (Cites per Patent: 7.31)	1.73 (.073)***	1.68 (.088)***	1.53 (.087)***
Quintile$_4$: Q$_4$ (Cites per Patent: 10.33)	1.93 (.253)***	1.91 (.263)***	1.58 (.215)***
Quintile$_5$: Q$_5$ (Cites per Patent: 16.85)	2.01 (.142)***	1.97 (.112)***	1.61 (.123)***
Difference: Q$_5$- Q$_3$	.27 (.04)***	.29 (.14)**	.07 (.05)
Difference: Q$_5$- Q$_1$	.70 (.08)***	.73 (.36)**	.39 (.23)

Note:
This table reports the results relating cited patents produced in a firm to its subsequent market to book value. The coefficient estimate reported in the table is obtained using a two-stage procedure. In the first stage, we sort all the firms who have atleast one patent over the sample period year wise into quintiles according to their $CitedPatent^{Time}$. Mean citations per patent for each of the quintiles is also reported in the table. In the second stage, for each quintile, we estimate a Fama-MacBeth [1973] regression of future market to book on various explanatory variables. Control variables include *Size*, *Age*, *S&P 500*, $\frac{Cash}{Assets}$, $\frac{EBIDTA}{Assets}$, state, industry and time dummies. We also report the results for all the firms who do not have any patents in the first row. Data is for the period 1974 to 2000. ***, ** and * denote significance at 1%, 5% and 10% respectively.

Table F.7: Citations Per Patent and Future Firm Value

Financial Constraints, citations per patent and Type of Financing

	Q1	Q2	Q3	Q4	Q5
	Model: Poisson				
	Low				High
	Panel A: KZ Quintiles				
$\frac{Equity}{Assets}$	.544 (.120)***	.776 (.194)***	.903 (.123)***	.879 (.155)***	.941 (.040)***
$\frac{Public}{Assets}$	.650 (.319)***	.656 (.180)***	1.351 (.283)***	.545 (.142)***	.629 (.116)***
$\frac{Cash}{Assets}$	-1.111 (.190)***	-.257 (.249)	-.221 (.295)	-.205 (.279)	.153 (.040)***
$\frac{EBIDTA}{Assets}$	.083 (.13)	.177 (.20)	.071 (.38)	.203 (.26)	.028 (.040)
Mean Quintile Value	-.73	.45	1.00	1.64	3.08
Observations	22,716	23,112	23,125	23,139	23,076
	Panel B: $\frac{Cash}{Assets}$ Quintiles				
$\frac{Equity}{Assets}$	.826 (.040)***	.773 (.070)***	.933 (.053)***	.931 (.039)***	.726 (.057)***
$\frac{Public}{Assets}$	.698 (.183)***	.440 (.133)***	.792 (.156)***	.712 (.121)***	.569 (.142)***
Mean Quintile Value	.005	.02	.05	.12	.37
Observations	30,030	28,860	28,009	28,657	29,538
	Panel C: $\frac{EBIDTA}{Assets}$ Quintiles				
$\frac{Equity}{Assets}$	.370 (.028)***	.707 (.053)***	.909 (.102)***	.693 (.097)***	.944 (.061)***
$\frac{Public}{Assets}$	.401 (.038)***	.690 (.221)***	.750 (.144)***	.504 (.192)***	.893 (.280)***
Mean Quintile Value	.001	.05	.10	.15	.26
Observations	28,930	23,105	30,507	30,909	30,803
Time Fixed Effects	Yes	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes
State Fixed Effects	Yes	Yes	Yes	Yes	Yes

Note:
This table reports the results relating cited patents produced in a firm to the type of its financing. The coefficient estimates reported in the table are obtained using a two-stage procedure. In the first stage, we sort all the firms year wise into quintiles according to a firm characteristic. In the second stage, for each characteristic quintile, we estimate a poisson panel regression of $CitedPatent^{Time}$ on various explanatory variables. We round each non-zero observation to its nearest integer for the dependent variable that we employ. Panel A, B and C present coefficient estimates with firms sorted into quintiles based on KZ, $\frac{Cash}{Assets}$ and $\frac{EBIDTA}{Assets}$ respectively. Other controls (not reported in the table) include $Public^s$, *Log(Sales)*, *Log(RD)*, *Q*, *Tangible*, *Age*, Age^2, *HI* and HI^2. All regressions are estimated with time, state and industry fixed effects and the standard errors reported in the parenthesis are heteroskedastic consistent to account for over dispersion in Poisson models and are corrected for the panel in all the models. Data is for the period 1974 to 2000. ***, ** and * denote significance at 1%, 5% and 10% respectively.

Table F.8: Innovation, Financing Arrangements and Financial Constraints: Quintile Analysis

	Q1	Q2	Q3	Q4	Q5
	Model: Poisson				
	Low				High
	Panel A: *Sales* Quintiles				
$\frac{Equity}{Assets}$	.232 (.019)***	.668 (.079)***	.631 (.066)**	.935 (.153)***	1.171 (.201)***
$\frac{Public}{Assets}$	.603 (.015)***	.415 (.018)***	.586 (.014)***	.658 (.208)***	.478 (.221)***
Mean Quintile Value ($ mill)	4.2	25.11	87.95	336.45	1,848.87
Observations	30,606	28,796	29,165	28,222	28,305
	Panel B: *Q* Quintiles				
$\frac{Equity}{Assets}$	.194 (.115)*	.909 (.136)***	1.086 (.139)***	1.206 (.116)***	.990 (.065)***
$\frac{Public}{Assets}$	.551 (.128)***	.787 (.166)***	.310 (.021)***	.390 (.122)***	.529 (.191)***
Mean Quintile Value	.72	.96	1.19	1.63	4.67
Observations	23,144	23,188	23,170	23,188	23,179
	Panel C: *Age* Quintiles				
$\frac{Equity}{Assets}$	.645 (.057)***	.963 (.052)***	.912 (.029)***	.888 (.088)***	.795 (.072)***
$\frac{Public}{Assets}$	.705 (.017)***	.576 (.186)***	.658 (.170)***	.521 (.151)***	.455 (.250)**
Mean Quintile Value (yrs from IPO)	1.99	5.50	10.93	14.72	31.94
Observations	39,598	28,414	30,321	20,797	25,964
Time Fixed Effects	Yes	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes
State Fixed Effects	Yes	Yes	Yes	Yes	Yes

Note:
This table reports the results relating cited patents produced in a firm to the type of its financing. The coefficient estimates reported in the table are obtained using a two-stage procedure. In the first stage, we sort all the firms year wise into quintiles according to a firm characteristic. In the second stage, for each characteristic quintile, we estimate a poisson panel regression of $CitedPatent^{Time}$ on various explanatory variables. We round each non-zero observation to its nearest integer for the dependent variable that we employ. Panel A, B and C present coefficient estimates with firms sorted into quintiles based on *Sales*, *Q* and *Age*, respectively. Other controls (not reported in the table) include $Public^s$, *Log(Sales)*, *Log(RD)*, *Q*, *Tangible*, *Age*, Age^2, $\frac{Cash}{Assets}$, $\frac{RetEarn}{Assets}$, $\frac{EBIDTA}{Assets}$, *HI* and HI^2. All regressions are estimated with time, state and industry fixed effects and the standard errors reported in the parenthesis are heteroskedastic consistent to account for over dispersion in Poisson models and are corrected for the panel in all the models. Data is for the period 1974 to 2000. ***, ** and * denote significance at 1%, 5% and 10% respectively.

Table F.9: Innovation, Financing Arrangements and Firm Characteristics: Quintile Analysis

	Dependent Variable: *Financing*		
	OLS	OLS	Logit
	$\frac{Equity}{Assets}$	$\frac{Public}{Assets}$	$Public^s$
	(1)	(2)	(3)
CitedPatent^{Time}	.013 (.003)***	.0006 (.0001)***	.012 (.002)***
Log(Sales)	-.026 (.001)***	.005 (.001)***	.689 (.013)***
Tangible	-.059 (.004)***	.031 (.005)***	1.035 (.074)***
Q	.011 (.005)**	-.002 (.001)***	-.084 (.014)***
$\frac{EBIDTA}{Assets}$	.013 (.003)***	-.019 (.006)***	-.683 (.113)***
Observations	109,003	109,003	109,003
Other Controls	Yes	Yes	Yes
Adjusted R^2	.19	.28	
Log-likelihood			-36,587.5
p-value, χ^2 test			0.00
Time Fixed Effects	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes
State Fixed Effects	Yes	Yes	Yes

Note:
This table reports the results of regressions examining the relationship between type of financing and innovation using an alternative specification. The specification in this table uses financing variables as the dependent variable and innovation as the explanatory variable. Specifically, we estimate the OLS models with $\frac{Equity}{Assets}$ and $\frac{Public}{Assets}$ as Financing variables in Columns (1) and (2). In Column (3), we employ a logit model with $Public^s$ as the dependent variable. Other controls (not reported) include $\frac{Cash}{Assets}$, $\frac{RetEarn}{Assets}$, Age and $\sigma_{\text{firm},it}$. All regressions are estimated with time, state and industry fixed effects and the standard errors reported in the parenthesis are corrected for the panel in all the models. Data is for the period 1974 to 2000. ***, ** and * denote significance at 1%, 5% and 10% respectively.

Table F.10: Innovation, Financing Arrangements and Firm Characteristics: Alternative Specification

Panel A: Estimating the Demand Effect – Second Stage with Instrumented Financing Variables

	Model: Poisson					
	$CitedPatent^{Time}$		$CitedPatent^{Time-Tech}$		$CitedPatent^{Quasi}$	
	(1)	(2)	(3)	(4)	(5)	(6)
$\frac{Equity}{Assets}$	.810 (.065)***		.796 (.098)***		.849 (.093)***	
$\frac{Public}{Assets}$	.664 (.017)***		.683 (.032)***		.697 (.031)***	
$Public^s$	.068 (.020)***		.073 (.029)***		.074 (.027)***	
$\frac{Equity}{Assets}$ $Instrumented$		.672 (.152)***		.660 (.136)***		.624 (.193)***
$\frac{Public}{Assets}$ $Instrumented$		.586 (.137)***		.581 (.131)***		.570 (.135)***
$Public^{s\,Instrumented}$		.061 (.023)***		.057 (.021)***		.059 (.022)***
Observations	109,003	109,003	109,003	109,003	109,003	109,003
Other Controls	Yes	Yes	Yes	Yes	Yes	Yes
Log-likelihood	-20304.2	-20299.9	-16,707.1	-16,661.1	-18,390.2	-18,239.5
p-value, χ^2 test	0.00	0.00	0.00	0.00	0.00	0.00
Time Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
State Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes

Panel B: Sub-Sample of Firms with Public Debt, High Credit Ratings and Multiple Banks

	Dependent Variable: *CitedPatent*		
	$Public^s = 1$	$Public^s = 1$ and Credit Rating$\in$\{A,B\}	$Public^s = 1$ and Multiple Banks
		Poisson	
	(1)	(2)	(3)
$\frac{Equity}{Assets}$	.802 (.105)***	.817 (.106)***	.793 (.090)***
$\frac{Public}{Assets}$	.688 (.087)***	.681 (.081)***	.657 (.085)***
Observations	14,170	9,330	3,180
Other Controls	Yes	Yes	Yes
Log-likelihood	-7,102.9	-7,001.1	-5,290.1
p-value, χ^2 test	0.00	0.00	0.00
Time, Industry and State Fixed Effects	Yes	Yes	Yes

Note:
This table reports the results of regressions examining whether the main results (Table IV) can be interpreted as the "demand side" effect. The first stage instruments the financing variables by whether or not they are a part of the S&P 500 index (*S&P 500*) and by the percentage of firms in the industry of a given firm in a year that have public debt (*Log(1+%Public)*). The dependent variable in the second stage is $CitedPatent^{Time}$ in models (1) and (2) while in models (3) to (6) we use alternative dependent variables ($CitedPatent^{Time-Tech}$ and $CitedPatents^{Quasi}$). Other controls (not reported) include *HI*, *HI*^{2}, *Q*, *Tangible*, $\frac{Cash}{Assets}$, $\frac{RetEarn}{Assets}$, $\frac{EBIDTA}{Assets}$, *Age*, *Age*^{2}, *Patprop* and *Citecon*. Panel B uses the Poisson model with estimations restricted to sub-samples as defined in the panel. All regressions are estimated with time, state and industry fixed effects and the standard errors reported in the parenthesis are corrected for the panel in all the models. Data is for the period 1974 to 2000. ***, ** and * denote significance at 1%, 5% and 10% respectively.

Table F.11: Interpreting the Results: Instrumenting Type of Financing Variables and Sub-Sample Analysis

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