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Finance and Innovation: The Case of Publicly Traded Firms

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Finance and Innovation: The Case of Publicly Traded Firms

Abstract

We hypothesize that established firms with innovative projects and technologies will make relatively greater use of arm's length financing (such as public debt and equity); whereas less innovative firms will tend to use relationship based borrowing (such as bank borrowing). The hypothesis is developed using a simple model in which firms with more innovative projects give greater discretion to managers by relying on arm's length financing. When a firm has less innovative projects that are easier for a relationship lender to evaluate, the manager is given less discretion and bank borrowing is more prevalent. 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 receive a larger number of patents and these patents are more significant in terms of influencing subsequent patents. We confirm our results by demonstrating that firms that issue public debt for the first time and firms that issue equity through an SEO exhibit a significant increase in innovative activity for two years after the issue. Our results are robust to conditioning on financial constraints faced by the firm, firm size, R&D expenditure, market to book, firm maturity and the choice of a firm's decision to go to the public debt market. Firms producing more novel patents tend to have a higher firm value, operating performance and abnormal stock returns for upto two years subsequent to the innovation.

Finance and Innovation: The Case of Publicly Traded Firms

"...leading economic historians have noted that much of the U.S. economy's productive growth is attributable to innovations by pre-existing corporations..." William Baumol (2001)

I. Introduction

In this paper, we focus on financing and innovation activity of established publicly traded firms. As Baumol (2001, p.34) observes, much of the innovation that contributes to economic growth is done by such firms. However, despite their importance, the literature is virtually silent on the relationship between financing choices and the creation of successful and significant innovations in publicly traded firms.[1] We develop a simple model and empirically test its prediction that arm's length financing mechanisms are associated with a greater intensity and a higher quality of technological innovation. The importance of technological innovation for economic growth in the US and other industrialized economies is well established by the work of Solow (1957), Romer (1987; 1990) and others. Therefore, empirical support for our prediction would be consistent with some financing mechanisms being more conducive to technological progress and, hence, to economic growth.

We present a simple model of the financing of innovative investments by a firm with ongoing projects. The model allows us to develop testable predictions about the financing pattern of firms that are innovative but well beyond the start-up stage. In our set up the firm's capital structure and financing arrangements are used by the board to improve investment decisions. The underlying concern for the board is that the firm's manager is prone to agency problems – and is never inclined to terminate innovative projects. In particular, we show that the financial arrangements can be used to enhance firm value by determining whether the firm's manager has complete discretion over the innovative project or whether an imperfectly informed agent, such as a bank, has some control rights as well.

Three common types of financing are considered: arm's length financing in the form of public debt and equity, and relationship based financing in the form of bank loans. In the choice between debt and equity, it is optimal to use the highest debt level to reduce agency costs caused by "free cash flow" (Jensen, 1986), while keeping debt risk-free to avoid bankruptcy, assumed to be prohibitively costly. In the choice between bank and public debt, bank borrowing is preferred

[1]The relation between financing and innovation in young, start-up companies has been investigated more closely. In particular, the evidence 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...".

when the information the bank produces is of sufficiently high quality – because the bank refuses refinancing and terminates the project when its information is negative. The bank's information, we argue, is more likely to be reliable when the innovation is incremental; and less reliable for more radical discoveries (Scherer, 1984; Rajan and Zingales, 2003).[2] Hence, for novel projects, the board prefers a capital structure that consists of equity and public debt, and that does not involve the monitoring and information gathering costs associated with bank borrowing. We also show that, for a given level of novelty, firms that anticipate a larger number of innovations are more likely to pay the fixed costs associated with accessing public debt markets for the first time.

Our model demonstrates that more innovative firms will rely on arm's length financing – both public debt and equity – and thus give managers greater discretion over innovative projects. For firms with less innovative projects, those that can be evaluated by banks, it is optimal for some decisions to be made contingent on the bank's information. We also show that the debt to equity ratio is higher when debt financing is relationship based. Intuitively, the bank can terminate the project when it has negative information and can capture the project's liquidation value. As a result, the bank is willing to provide more loans ex-ante. Thus, for more novel projects and for a higher number of anticipated innovations, since the optimal capital structure shifts from relationship debt to arm's length debt, there is a reduction in the proportion of debt to equity in the capital structure.

The model generates two testable predictions. We expect firms with predominantly arm's length financing to have more innovations. We also expect these firms to generate radical innovations – those with significant influence on subsequent innovations. 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. We also use a dummy variable to indicate if a firm has access to public debt markets, since access may be established in anticipation of innovative activity and future rounds of financing. We measure a firm's innovative activity in two ways. One is by the number of patents the firm is granted in a year which proxies for the innovative intensity of the firm. The other measure focuses on the novelty and importance of a firm's patents. We infer a patent's novelty by a count of the times it is cited by subsequent patents because it has been argued that more cited patents have a greater influence on technological advances (see Trajtenberg, 1990; Hall et al., 2005). It has also been showed by Hall et al. (2005) and Harhoff et al. (1999) among others, that highly cited patents are valuable for the firm that creates them. In particular, Hall et al. (2005) show that a firm producing a patent with just 1 more citation above the mean of its cohort has almost a 3% higher market to book value than the average of the cohort. Thus, to take account

[2] Throughout the paper 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 products – by the innovating firm as well as other firms in its industry and elsewhere (Hall et al., 2005).

of the significance of a firm's innovations, we weight its patents by the number of their subsequent citations, following the methodology outlined by Hall et al. (2001; 2005). As an alternative, we also construct measures that identify patents as being drastic when, for a given year and technology class, they are in the top 1 percent of most cited patents.

For our empirical analysis, we use a panel of 11,125 US firms from 1974 to 2000 to estimate the relationship between innovation and financing choice. The sample is constructed by combining patent information from the NBER patent dataset (described in Hall, Jaffe, and Trajtenberg, 2001) with financial data from Compustat and SDC databases. We test our first prediction by using a simple count of patents that a firm creates as a dependent variable and our second prediction by using citation weighted patents variable and other indicators of drastic patents. We control for firm specific characteristics such as size, R&D expenditures, age, operating cash, financial constraints, profitability, industry concentration, market to book ratio, and time, state and industry fixed effects. The major findings are consistent with our predictions. We show that firms which choose arm's length financing create more citation weighted and drastic patents. The effect is economically large and suggests that firms, which have an equity to assets ratio that is 1 standard deviation higher than the industry mean, have almost 50% more citation weighted patents. Similarly, firms that have public debt to assets ratio that is 1 standard deviation above the industry mean, are associated with almost 20% more citation weighted patents. Furthermore, we find that access to public debt markets (i.e., using an indicator for outstanding debt) is associated with 13% more citation weighted patents as compared to firms that do not access the public debt market. We find that similar but economically weaker results hold for the simple count of patents.

We conduct a variety of additional tests that, taken together, provide strong support for the robustness of our findings. First, we show that our results are robust to using firm fixed effects, indicating that the results hold even after controlling for any unobserved time-invariant firm characteristics. In particular, this suggests that an increase in arm's length financing over time is positively associated with increase in the number and quality of innovations. Second, 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 (as measured by Kaplan Zingales, 1997 index; the criterion of Korajczyk and Levy, 2003 and Whited and Wu, 2005 index). While the relation between arm's length financing and innovation is not affected, we find that the lack of internal cash can hinder innovation for financially constrained firms, consistent with the evidence in Himmelberg and Peteresen (1994). We also find that our results are unaffected when we repeat the analysis in quintiles formed on other firms characteristics – age, market to book, sales, R&D, profitability, and internal cash. Third, we examine whether there are changes in the innovative activity of firms following a large infusion of arm's length financing; specifically, a first time issue of public debt or an issue of seasoned equity. We find strong evidence of an increase in innovative activity in a two year period following offerings of this type, suggesting that firms raise arm's length capital in anticipation of an increase in their innovative activity.

Fourth, we find that our results are similar when we use an instrumental variable approach to control for possible biases due to omitted variables related to the choice of some firms to access public debt markets. The approach addresses the concern that firms that borrow from public debt markets are fundamentally different – differences not being captured by our main model specification. We find that our estimates relating type of financing to innovation are similar to those found in our main analysis. Fifth, among the firms that don't have public debt in our sample, we distinguish between those that rely on a single bank and those that use multiple banks. The notion is that a multiple bank arrangement is somewhere between the relationship based nature of loans from a single bank and the arm's length nature of public debt. Consistent with our hypothesis, we find that the intensity and quality of innovation in firms with multiple banking relationships is higher than in firms that rely on a single bank, after controlling for other factors, including financial constraints. Sixth, we examine the value of firms that own patents and citation weighted patents. Similar to existing studies (Hall et al., 2005), we find that firms with more significant patents, measured by the number of citations received from other patents, experience a greater increase in future firm value (40%), operating performance (31.5%) and exhibit higher future abnormal returns (1.8%). The increase in value is gradual, however, suggesting that the market may be slow in recognizing the significance of an innovation. Finally, our results are robust to different model specifications (e.g., negative binomial, Poisson, first differences), variable definitions, subperiod analysis and are valid across a wide range of industries.

We believe that our paper makes several contributions to the literature. First, the paper offers a fairly novel approach to looking at the relationship between financing arrangements and innovation. It develops a theoretical model and provides convincing and robust evidence of an economically (and statistically) significant relationship between arm's length financing and the intensity and quality of innovation in publicly traded firms. Second, we use a more sophisticated approach to capture financing arrangements and demonstrate that arm's length financing through public debt and equity, rather than only the simple choice between debt and equity, is positively related to innovation. Third, in contrast to previous studies that relate the investment side of innovation to firm financing, we use the NBER patent dataset to measure the number and quality of successful innovations measured by patents and patent citations. All our results using these measures are obtained after controlling for the investment side of innovation using R&D expenditures. 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 influence development of innovative technologies and, possibly, economic growth.

Our predictions and findings are largely consistent with the theoretical arguments advanced in the literature. In general, these arguments suggest that, for radical innovations, the costs of relationship based financing outweigh its benefits. For instance, Rajan and Zingales (2003) argue that in relationship financing, the lender may not have the necessary skills to properly evaluate investments in an innovative technology. Therefore, since relationship lenders closely monitor investment decisions, their presence is likely to discourage such investments. Similarly, Allen and Gale (1999) argue that when there are differences of opinion among investors, projects are more likely to be financed using arm's length financing. Such differences of opinion are more probable for innovative technologies. Our paper is also related to the existing literature on the relationship between finance and economic growth (Rajan and Zingales, 1998a; Beck and Levine, 2002) since it indicates that institutions supporting arm's length financing may facilitate the innovation process and, hence, economic growth.[3] Since the paper focuses on association between specific financing arrangements and innovative activity, the paper closest to ours may be Kortum and Lerner (2000) which finds that firms that receive venture capital financing innovate more.

The paper is organized as follows. Section II discusses the model and develops the hypothesis and testable predictions. Section III describes the empirical methodology, the variables used in the empirical analysis and provides a description of the data sources and the construction of the sample. Section IV presents the empirical results that establish an association between innovation and the choice of financing arrangements. Section V presents further tests and section VI concludes.

II. Model and Hypothesis Development

We develop a simple model of financing of an innovative project by an established firm with existing investments and cash flows. The model allows us to develop testable predictions about the financing pattern of firms that are innovative but are well beyond the start up stage. In particular, the model suggests that firms that are more innovative will give their managers greater discretion by relying predominantly on arm's length financing – equity and public debt. For firms with less innovative projects, those that are more easily evaluated by banks, it is optimal for some decisions to be made contingent on the bank's information. We start by describing the agents, project and the contract possibilities.

II.A. Model Set-Up

We consider a publicly traded firm with on-going investments and the potential for developing innovative products. The firm's board of directors, denoted by ($\mathcal{B}$), is independent of managerial influence and seeks to maximize shareholder wealth.[4] The board may, for instance, insist on certain capital structure and financing choices if it believes them to be value enhancing. However,

[3] King and Levine (1993) and Demirgüç-Kunt and Maksimovic (1998) analyze differences in economic growth across countries and document a positive influence of financial development on economic growth. In general, cross-country studies provide evidence that institutions exert a profound influence on economic development (e.g., see survey by Djankov et al., 2003).

[4] The board members may, for instance, be motivated to act in shareholder interest out of concern for their reputation or shareholder lawsuits. While we have modelled the board as pushing for an optimal capital structure, there may be other players, such as large shareholders, that may potentially exercise similar influence.

the manager, denoted by ($\mathcal{M}$), is less devoted to shareholder value than $\mathcal{B}$ and tends to consume perquisites and divert firm resources. For decisions that are observable by the board, such as the choice of capital structure, we assume that the manager is obliged to follow the board's recommendations. For unobservable decisions, such as the consumption of private benefits, the manager follows her own interests. The manager is initially wealth constrained and, in the model's set-up, is not easily incentivized to act in shareholder interest. We show, however, that by its choice of capital structure and financing decisions, $\mathcal{B}$ can improve investment decisions about the innovative project and, thereby, enhance firm value.

All agents are risk neutral and the risk free interest rate is 0. There are three relevant dates: 0, 1 and 2. The firm has existing investments that are expected to produce a non-stochastic cash-flow of Y_2 at date 2. The firm receives a new opportunity to develop an innovative project that requires an investment of I_0 at $t = 0$. Market participants are fully aware of the firm's new opportunity and, at $t = 0$, have the same information about the project as the firm's board and manager. The development effort, which requires involvement of the existing manager, is expected to be successful with probability μ. If successful, the innovation is worth v at date 2, where v is drawn from a distribution with support $[v_l, v_h]$, with $v_h > v_l$. We denote the expected value of the innovation, if successful, as $\bar{v}$. If unsuccessful, the payoff at date 2 is 0. *Ex-ante,* at $t = 0$, the innovation project is assumed to have a positive NPV, i.e., $\mu\bar{v} > I_0$.

At the intermediate date, $t = 1$, costly new information about the project's likelihood of success may be acquired by some agents, as we describe below. If the new information causes the project to be terminated early i.e., at $t = 1$, the project's depreciated assets can be liquidated for a value of $0 < \beta\bar{v} < I_0$, where β may depend on characteristics of the project. By date $t = 2$, the assets are assumed to be fully depreciated.

For expositional ease, the firm is assumed to have no internal funds at $t = 0$ and is forced to access external capital markets to fund the new investment. In the analysis, we focus on three financing sources commonly used by established, publicly traded US firms: public equity, public debt and bank debt. The first two financing arrangements are usually regarded as being arm's length, while bank financing is considered to be more relationship based. The investors in public markets (both debt and equity) are taken to be relatively small and to have no particular skill or economic stake to bear the costs of privately acquiring the new information available at $t = 1$. Hence, in our set-up, only a bank is regarded as having the skills, familiarity with the client and economic stake to potentially develop new information at the intermediate date.

In terms of transaction costs, we abstract away from taxes and underwriting costs in the model. If the bank decides to collect information at $t = 1$, it pays a cost denoted by c. Such a cost would be anticipated and reflected in the cost of bank borrowing borne by the firm. The other transaction cost that plays an important role in our discussion is bankruptcy cost. For simplicity, bankruptcy costs are assumed to be large, both in terms of damaging firm value and in terms of personal costs such as a loss of reputation suffered by the board and management. As a consequence, we make the simplifying assumption, that it is always efficient for the firm to have only risk-free debt outstanding. The introduction of risky debt, while complicating the analysis, should not affect our main results as we briefly discuss later in the section (footnote 11). We assume that the legal system ensures that the debt contracts are strictly enforced and a default results in an immediate loss of the manager's control over the firm's assets including cash flows. This loss of control assumption is similar to the one made in the property rights literature (e.g., Hart and Moore, 1995). As a consequence, it is never optimal for the manager to default (and to trigger a loss of control), while there are firm assets that can be paid out.

II.B. Financial Structure Trade-offs: Equity, Public Debt and Bank Loans

Financial structure matters in the model because it can improve decision making regarding the innovative project – since the firm's manager may not seek to maximize shareholder value. As we will elaborate, the capital structure choice can be used to accomplish one of two outcomes: one is to leave the project decision making entirely to the firm's manager, while the other is to rely on a third party such as a bank to collect information and influence project decisions. We now provide details about the manager's agency problem, the information structure and the costs and benefits of the financial choices.

II.B.1. Information Acquisition at $t = 1$

At the intermediate date $t = 1$, while the firm's manager and the intermediary can obtain new information about the project, the board has no independent access to the new information. Our results suggest, however, that $\mathcal{B}$ may be able to induce its desired outcome i.e., whether to proceed or terminate the project at date 1, by choosing a capital structure that elicits appropriate actions by a bank that has collected the new information.

At this stage, it is worth pointing out that the role of banks in acquiring client information is in the spirit of a wealth of research in the banking literature. It is claimed in the literature that a central function, if not the very *raison d'aitre*, of banks is their ability to monitor clients and develop information about their operations and quality (see e.g., Diamond, 1984; Rajan, 1992). Banks are regarded as having certain advantages in collecting information: For instance, in the process of making loans banks acquire information, which can lower the cost of making additional loans or collecting new information.[5] Aside from skills developed in certain types of loans or industries,

[5]As has been discussed in the literature, the benefit of relationship financing lies in its ability to solve asymmetric information problems (e.g., see Diamond, 1984) and, therefore, to finance profitable projects that would not be financed otherwise. The downside, of course, is that firms may fear a hold-up problem with the relationship financiers (Rajan, 1992) – i.e., these lenders may exploit their unique informational advantage and extract rents from the firm after a successful project. Such hold-up would ex-ante lead to reduced incentives to invest time, effort and human

banks are strongly motivated to engage in monitoring and information collection when they have substantial exposure to particular clients, especially since bank loans are usually illiquid. Clients may also be willing to provide banks with access to information they would not disclose publicly for competitive and other reasons (Bhattacharya and Chiesa, 1995). Hence, the incentives, skills and access of banks to monitor and acquire new information are likely to be much stronger than those of small investors in public equity or debt markets.

Information acquisition by the bank at $t = 1$ takes the following form: For a cost of c, the bank receives a noisy signal s of the project's success. Specifically, at $t = 1$, for a project that if continued would be successful at $t = 2$, the bank receives a positive signal (s^+) with a probability $\phi < 1$ i.e., $\Pr(s = s^+ \mid \text{successful project}) = \phi$. The rest of the time the bank receives a negative signal (s^-).[6] The parameter ϕ can be interpreted as a measure of the bank's information precision for identifying good projects. Note that with the positive signal the bank expects a minimum payoff of v_l from continuing the project.

The ability of a bank to uncover information about the project's success is, however, likely to depend on its familiarity with the innovative project's technology and its potential for generating value. We assume that the quality of the signal (ϕ) is based on how novel the innovative project is, with the noise-to-signal ratio increasing in the novelty of the project. The notion is that banks are able to obtain more reliable information when the projects are somewhat similar to those they have evaluated before and have expertise in. On the other hand, a fundamentally new technology or discovery, by definition, is not within their area of expertise and, thereby, generates a less precise signal. Our assumption is consistent with the evidence provided in Scherer (1984, p.72) who summarizes the findings of a survey of innovative firms on their experience with bank loans: *"...banks did not understand the nature of the technology involved in the product that was new to them."*.[7] In our analysis, we characterize project 'novelty' by a continuous measure $n \in [0, 1]$ and the effect of novelty on the quality of bank's information by $\phi\,'(n) < 0$. Novelty may have other effects as well and another assumption we make is that the liquidation values for more novel projects are lower, i.e., $\beta\,'(n) < 0$, because there may be little demand for assets associated with a more radical, but potentially unsuccessful (given the liquidation) investment. This notion of novelty is consistent with 'product uniqueness' noted in Titman and Wessels (1988). More generally, a successful novel technology is one that is different from current existing technologies and is more likely to influence the development of future products – by the innovating firm as well as other firms in its industry and elsewhere (Hall et al., 2005). Hence a natural way of identifying novel innovations in our empirical analysis is to examine the influence of an innovation on subsequent

capital into developing novel projects.

[6] Hence, while a positive signal implies a successful project, a negative signal can arise when the project is unsuccessful or when the bank is unable to evaluate a successful project.

[7] There are notable exceptions, such as the Silicon Valley Bank, which specializes in financing innovative firms. However, its focus and expertise makes it more like a venture capitalist than like a bank.

innovations.

II.B.2. The Manager's Agency Problem and Debt Financing

The manager's agency problem in our model has the flavor of the 'free cash-flow' problem (Jensen, 1986). Specifically, we assume that at the terminal date $t = 2$, the final cashflows and costs are difficult to verify. This allows $\mathcal{M}$ to divert for her own perquisite consumption or other personal uses a fraction $\theta > 0$ of any free cash flows at $t = 2$. The manager, therefore, will always want to continue any ongoing project that has the possibility of producing free cash flow at date 2. As Jensen (1986) argues, the agency problem can be potentially controlled by the use of debt – which is also the case in our model.

As we have mentioned, the manager has no incentives to default per se in our setting; since it only results in a loss of control over the firm's assets including any cash flows. As long as the debt is risk free, higher debt levels lead to lower levels of free cash flow from which the manager can divert funds. Hence, if the total cash-flow generated by the firm at date $t = 2$ is $Y_2 + \tilde{v}$, the amount that is available for investors (after diversion by the manager) is only $(1 - \theta)(Y_2 + \tilde{v})$. If the firm has a level of debt $D < Y_2 + \tilde{v}$, then total amount that creditors and shareholders can expect to receive is:

$$D + (1 - \theta)(Y_2 + \tilde{v} - D) = \theta D + (1 - \theta)(Y_2 + \tilde{v}).$$

In other words, since the manager is forced to fully pay debt-holders, this reduces the available resources that she can divert for her own purposes. Hence, in terms of a debt strategy, it is optimal for $\mathcal{B}$ to maximize the use of debt, subject to the debt being risk-free.

We can now summarize the trade-offs involved in using the three sources of financing: Equity allows for managerial discretion, does not cause liquidation of projects that are headed for success and does not lead to bankruptcy. The downside is that equity fails to shut down unprofitable projects and cannot deal with agency problems. Public debt limits the free cash problem and does not cause good projects to be liquidated. However, since no information is collected at $t = 1$, it does not stop bad projects. Moreover, it can lead to bankruptcy. Finally, bank debt limits the free cash flow problems, can cause bad projects to be liquidated, but can also result in good projects being terminated as well. Bank debt is associated with an additional cost of c to acquire new information and it can lead to bankruptcy.

II.C. The Choice between Arm's Length and Relationship Financing

We determine the conditions under which shareholders benefit from letting a bank's information determine whether the project is terminated or continued at date $t = 1$. We discuss later (in connection with Proposition 2) the details of the financing arrangement that makes it incentive compatible for the bank to force project liquidation at date $t = 1$, when it receives a negative signal. For now we will ignore θ, the cash flow diverted by the manager. If the bank's information is not to be used then, from earlier discussion, the project is never terminated and the expected payoff from the project at $t = 0$ is:

$$\mu\bar{v} \tag{E-1}$$

On the other hand, if the bank is the lender, the expected payoff at $t = 0$ can be expressed as:

$$\phi(n)\mu\bar{v} + \beta(n)(1 - \phi(n)\mu)\bar{v} - c\ , \qquad \text{where} \quad n \in [0, 1] \tag{E-2}$$

The first term in the expression above is the probability of a positive signal times the expected payoff from a successful project. The second term is the probability of a negative signal times the payoff from early liquidation. The last term is the cost of acquiring information. Hence, it is optimal for the decision to be made by the bank when expression (E-1)≤(E-2). Simplifying, this condition can be expressed as:

$$\frac{c}{\bar{v}} \leq \phi(n)\mu(1 - \beta(n)) + \beta(n) - \mu \tag{E-3}$$

To ensure that there are some conditions under which it is optimal for the bank to affect the outcome at date $t = 1$, a sufficient condition is that $\frac{c}{\bar{v}} < 1 - \mu$. We will assume this in the subsequent analysis. We can now state our first proposition:

Proposition 1 *It is optimal for the bank to have control rights and affect project decision making iff:*

$$\frac{c}{\bar{v}} \leq \phi(n)\mu(1 - \beta(n)) + \beta(n) - \mu$$

Furthermore,

(a) For a project with novelty n, there always exists a recovery rate from project liquidation, β^*, and a level of bank information quality, ϕ^*, such that when $\phi \geq \phi^*$ and $\beta \geq \beta^*$, it is optimal to give control to the bank.

(b) The more novel the project (i.e., higher n), the less likely it is that the bank will be given control.

Proof: See **Appendix D**.

The intuition behind this proposition is as follows. It is optimal to give the decision rights to the bank (i.e., RHS of (E-3) is increasing) when the quality of the bank's information is better ($\phi(n)$ is larger) and there are greater benefits from early liquidation (β is larger). Furthermore, since the precision of bank's information and the liquidation value of the project is falling in project novelty (n is larger), the likelihood that the bank will be given control of the project is falling in n (i.e., RHS of (E-3) is falling).

In our analysis we have abstracted from the costs of accessing public debt markets. As an extension, we now consider the fact that the initial issue of public debt may have a significant fixed cost as a firm's bonds are evaluated for the first time by rating agencies, underwriters and investors.[8] We argue that in the presence of fixed costs, firms that seek access to public debt markets will tend to be those that expect to issue bonds in the future as well. To illustrate the issue, let us modify the model to include a one time fixed cost of issuing public debt, say, F. Consider a firm which anticipates having to raise debt financing a number of times, say m, in the foreseeable future to finance innovative investments over time. In other words, consider a more dynamic version of the current one period model in which financing decisions are repeated a multiple number of times.[9] A firm without current access to the public debt market will, therefore, choose between issuing bonds and bank borrowing as indicated by (E-3), with the cost term $\frac{c}{\bar{v}}$ replaced by $\frac{c-f(m)}{\bar{v}}$. Here, $f(m)$ (with $f\,'(m) < 0$) represents the average fixed cost of entering the public debt market, i.e., the fixed cost allocated over the amount of capital anticipated to be raised in the future offerings. This suggests that if we keep the novelty (n) of projects fixed, a higher number of anticipated innovations can have an independent effect on making the use of public debt financing more likely. We state this as a corollary.

Corollary 1 *For a given level of novelty (n), the greater the anticipated number of innovations in the future, the less likely it is that the bank will be given control.*

To summarize, based on Proposition 1 and Corollary 1, we would expect firms to access the public debt market when they anticipate both a larger number of innovations and more novel innovations. Since gaining access to the public debt may be a precursor for later rounds of debt financing, in our empirical analysis, we will consider the access to public debt financing as one of our measures of arm's length financing.

With regard to the capital structure choice by the board, we note that if it is optimal for the bank to be given the decision rights over the project, then the bank debt must be of short term (1-period) maturity. The reason is that the bank can exercise control only when the firm has an obligation to repay its debt at $t = 1$ and the bank decides whether or not to refinance the debt. As mentioned, if it is not optimal to use the bank's information, public debt, which does not involve the investigation costs c, will be preferred by the board. Note that in our setup we can allow for the use of both public debt and bank debt in certain cases, though this is never an advantage and may be a disadvantage (if, for instance, the bank engages in costly information acquisition that is not utilized). Hence, for simplicity we will assume that the debt that is used is either all bank or all public debt. We now discuss how the firm's capital structure will be chosen by the board in order to maximize firm value.

[8] For instance, James and Smith (2000) suggest that with the high fixed floatation cost of public debt, a minimum economic size of a debt offering is close to $ 100 mill.

[9] With free cash flow problem, the board will want the firm to raise capital when the investments are made rather than making a huge offering and carrying excess cash.

II.D. Optimal Capital Structure Decision at t=0

Based on our discussion above and taking note of the manager's diversion (θ fraction of the cash flow), we characterize the board's optimal capital structure decision at $t = 0$ as follows:

Proposition 2 *The board optimally chooses the following capital structure for the innovative firm at* $t = 0$*:*

(a) If it is optimal for the bank to be given control over the project termination (i.e., (E-3) is true), then it is optimal for the face value of the firm's first period loan to be $L_1 = \beta(n)\bar{v} + Y_2$*, which is the largest risk-free debt obligation the firm can assume. The rest of the capital structure is equity and has a value* $(1 - \theta)\mu\bar{v}\phi(n)$ *.*

(b) If it is optimal not to give decision rights to the bank, then the capital structure consists of public debt P_2 *maturing at* $t = 2$*, where* $P_2 = Y_2$*. The equity has a value of* $(1 - \theta)\mu\bar{v}$*.*

Proof: See **Appendix D**.

The intuition behind this proposition is simple. In the first statement, the largest risk obligation (face value) that the firm can take at date 1 is L_1. This consists of the two parts Y_2 and $\beta\bar{v}$. The amount Y_2 is the non-stochastic cash-flow at date $t = 2$ and its presence always allows the firm to borrow an amount Y_2. The other part $\beta\bar{v}$ represents the amount obtained by liquidating the project's assets. The liquidation is forced only when it is incentive compatible for the bank to not refinance L_1 after receiving a negative signal s^-.[10] With the negative signal, the maximum 1-period loan that the bank would provide at $t = 1$ is Y_2, thereby causing liquidation of the ongoing project (since the firm must liquidate the project to avoid default). On the other hand, when the bank receives a positive signal, the 1-period risk free loan it is willing to provide at $t = 1$ is greater than the firm's existing obligation L_1 and the liquidation of the project. The rest of the firm's capital structure consists of equity. The second statement (b) implies that when it is not optimal to give decision rights to the bank, public debt is chosen to reduce any discretionary cash with the manager. The debt is set to the maximal amount of cash expected (for certain) at $t = 0$ (Y_2) and the rest of the capital structure is again equity.[11]

[10] As we have observed earlier, the firm is unable to raise alternative funds if it is denied refinancing by the bank – this can be either because the information is negative or because the board will want project liquidation and not allow recourse to other forms of financing. Note that if the bank's information is not sufficiently reliable, the capital structure is designed so it does not give control to the bank in our setup.

[11] For simplicity of exposition and analysis, we have assumed that the bankruptcy costs are sufficiently severe to deter the use of risky debt. The possibility of risky debt should not, however, affect our results. In the case of public debt: If it is optimal for the public debt to be risky, the only effect will be to increase its face value. None of the conclusions regarding the change of control are affected. In the case of bank debt: There is no effect on the control decisions as well. Risky debt will be issued by the bank only if the debt is issued on receipt of s^- at date 1. This implies that the total funding that the bank is willing to provide in a negative state increases from $Y_2 + \beta\bar{v}$ to $Y_2 + \beta\bar{v}$ plus an additional amount that the bank finds optimal to lend (traded off at the margin with bankruptcy costs).

Finally, based on Proposition 1 and 2 and Corollary 1, we can analyze how the proportion of equity to debt of the firm varies with the novelty of the innovative project at $t = 0$. We summarize this in the next proposition:

Proposition 3 *The more novel the innovative project (higher the n) or the greater the anticipated number of innovations in the future, the higher the equity to debt ratio ($\frac{Equity}{Debt}$) in the optimal capital structure of the firm.*

Proof: See **Appendix D**.

The first part of this proposition combines the insights from Propositions 1 and 2. In particular, from Proposition 1, it follows that for a less novel project, the bank is likely to get control. Furthermore, from Proposition 2, it is clear that with bank financing the amount of debt (L_1) that can be taken at $t = 0$ is higher than the amount of public debt (P_2) at $t = 0$; since the bank takes into account the potential liquidation value of the project at $t = 1$. Moreover, the equity value at $t = 0$ with bank control is lower than when the firm borrows from the public debt market since with a probability $(1 - \phi\mu)$ the bank liquidates the firm when it gets a negative signal. Thus, for a given n, bank control leads to a smaller equity to debt ratio. As projects become more novel, the optimal capital structure shifts from bank debt to public debt, thereby increasing the proportion of equity to debt. Combining the intuition above with Corollary 1, it follows that with fixed costs of entering the public debt market, a greater number of anticipated innovations is more likely to be associated with public debt financing – and hence a higher equity to debt ratio.

As mentioned before, in our setup there is no advantage to having a mixture of bank and public debt and the debt is assumed to be either all bank debt or all public debt. However, over time, as a firm gets both novel and incremental innovative projects, we expect a firm with more novel innovations to borrow predominantly from the public debt market (Proposition 1) – and thereby to have a high proportion of public debt in its capital structure. Thus, in our empirical analysis, we will use the proportion of public debt financing in addition to proportion of equity (Proposition 3) and the access to public debt markets (Corollary 1) as a measure of arm's length financing.

II.E. Hypothesis and Empirical Predictions

We conclude the section by outlining our main hypothesis and empirical predictions. Drawing upon the model presented above, our main hypothesis is that innovative firms will have a predominantly arm's length capital structure. To test this hypothesis, we need measures of a firm's innovative activity. As we detail in the next section (Section III), we will rely on patent data to obtain information on innovations. We do this in two ways. First, following Corollary 1, we simply count the number of innovations a company has created as a proxy of the firm's current and future innovative intensity. Based on this, 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 innovations.*

Second, although a simple innovation count captures to an extent the innovative activity of a firm, the count is likely to contain both incremental and drastic innovations. As discussed in the model section (Proposition 1), we expect the association between arm's length financing and innovation to be stronger for firms with more novel or drastic innovations. To measure novelty, we rely on the extent to which a patent has been cited by subsequent patents. Based on this, our second empirical prediction is:

Prediction 2: *Ceteris paribus, firms with relatively more arm's length financing in their capital structure will have more novel innovations.*

Our main predictions are generally consistent with arguments made elsewhere in the literature. Aghion and Tirole (1997), for example, argue that if the principal (in our case the relationship financier) doesn't have much knowledge about the firm's projects, it is optimal to give more authority to the agent (in our case the manager of the firm) to encourage her initiative.[12] On a different note, Rajan and Zingales (2003) argue that arm's length financing is more likely to be associated with drastic innovation since public markets, with more publicly available information, give firms that experiment with new technologies a better chance of obtaining financing from outside investors. In a similar spirit Allen and Gale (1999) show that for novel projects, investors often differ in their opinion about the likelihood of success. A relationship based financier shuts down a project if he disagrees with the manager. Thus, the probability of approval is low since the firm's innovative idea has only one shot at being approved. In contrast, with arm's length financing, there are a large number of investors, each with her own prior about the project's success. Therefore, the probability that the project is approved is higher than in relationship financing since it is related to the probability that at least one or more investor agrees to finance it.

From a different perspective, Dewatripont and Maskin (1995) reach a similar conclusion. They argue that relationship financiers provide the firms with "soft budget constraints" because they cannot commit *ex-ante* not to refinance unprofitable projects *ex-post*. That makes such financiers inherently conservative ex-ante, particularly for projects that they cannot evaluate. Another drawback of bank financing, especially valid for our sample of US firms, is that banks might be forced to terminate projects early due to the legal prudential reserve requirements (Stulz, 2001). Our predictions are also consistent with the literature on capital structure, which finds that firms with higher R&D expenditures choose less debt and more equity financing (e.g., Titman and Wessels, 1988).

[12]In their model, unlike ours, the beneficial role of arm's length financing is through inducement of more effort on part of the manager.

III. Data, Variable Construction and Model Specification

In subsection A we describe the data sources and variables (dependent and explanatory) used in our empirical analysis and in subsection B we discuss the model specification. **Appendix A** provides detailed definition of all the variables used in our analysis. We start by describing the data sources used to construct the dependent variable.

III.A. Data and Variable Construction

Dependent Variable

The variables that measure innovation are constructed by using data from the NBER patent data set created by Hall, Jaffe, and Trajtenberg (2001). The patent data set provides among other items, annual information on patent assignee names, on the number of patents, on the number of citations received by each patent, on the technology class of the patent and on the year that the patent application was filed. The application year is important because it is closer to the time of the actual innovation than the grant year (Griliches, Pakes, and Hall, 1987). 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.

Hall, Jaffe, and Trajtenberg (2001) match the assignees of the patents in the NBER dataset, by name, to approximately 6000 manufacturing firms from Compustat, as of 1989.[13] As they indicate, the match is not perfect because assignees obtain patents under a variety of names and the USPTO (US Patent and Trademark Office) does not keep a unique identifier for each patenting organization from year to year. Hall, Jaffe, and Trajtenberg perform a cumbersome procedure to account for these idiosyncrasies and the matched firms in the patent dataset are identified by the six-digit cusip number if the assignee is a public corporation or is a subsidiary of a public corporation covered in the Compustat Industrial Annual database. Using these cusip numbers, we merge the financial data in Compustat with the NBER patent dataset.

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. We include only manufacturing firms because the matching between the patent dataset and Compustat by Hall et al. (2001) is done only for manufacturing firms. In addition, non-manufacturing firms usually operate under different regulatory rules and their financing arrangements are unlike those of manufacturing firms (e.g., financial firms such as

[13] 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.

banks have legal reserve requirements and their financing arrangements include deposits).[14] We start from 1974 since we have information on patent forward citations, a key variable in our analysis, from that date onward. Though our data ends in 2002, we restrict our tests to 1974-2000 since the truncation bias in patents granted and citations received by a patent (discussed below and in **Appendix B**) is especially severe in the last three years of the patent sample (Hall et al., 2005).

As Griliches (1990) indicates, patents have been widely used in the empirical literature to measure innovation. Although patents provide an imperfect measure of innovation, there is no other widely accepted method which can be applied to capture technological advances by individual firms. Nevertheless, we are aware that using patents has its drawbacks. 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. To that extent, our results are subject to the same criticisms as previous studies that use patents to measure innovation (e.g., Griliches, 1990; Cockburn and Henderson, 1998).

We use two broad metrics to measure how innovative a firm is. The first is a simple patent count for each firm per year and measures the firm's current and future innovative intensity. The second metric measures the importance and drastic nature of each patent by weighing the patent by the number of citations it receives in subsequent years. 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, while the second variable, $Patent^c$ is the same as the first but is adjusted to correct for the truncation bias in patent grants (explained in **Appendix B**).

Our second metric of innovative activity is motivated by the recognition that a simple count of patents to measure the level of innovative activity has its limitations. One of the biggest problems is that it does not distinguish breakthrough innovations from less significant or incremental technological discoveries. Pakes and Shankerman (1984) and Griliches, Pakes, and Hall (1987) show that the distribution of the importance of patents is extremely skewed, i.e., most of the value is concentrated in a small number of patents. Trajtenberg (1990), Albert et al. (1991), and Hall et al. (2005) among others have demonstrated that patent citations are a good measure of the value of innovations.[15] Intuitively, the rationale behind using patent citations to identify important innovations is that if firms are willing to further invest in a project that is building upon a previous patent, it implies that the cited patent is influential and economically significant. In addition, patent citations tend to arrive over time, suggesting that the importance of a patent may be revealed over a period of time and may be difficult to evaluate by financiers at the time it is

[14] Specifically, we exclude financial firms (SIC codes starting with *6*) and government firms (SIC codes starting with *9*).

[15] 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. We provide additional evidence of the link between citations and firm value later in the paper.

discovered. Therefore, we use patent citations to account for the significance of innovations and to test our prediction that firms with arm's length financing have more novel and technologically influential innovations.

Patent citations, however, suffer from a severe truncation bias, which arises because patent citations are received many years after the patent was applied for and granted. Another potential concern is that different industries might have different propensities to cite patents.[16] 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. While the fixed effects method corrects for these biases by dividing the number of patent citations by the average amount of patent citations in the same group (year, technology class or year-technology class) to which the patent belongs, the quasi-structural method corrects for these biases by weighting the patents by an econometrically estimated distribution of the citation lag. Details on the two methods and their advantages and drawbacks are explained in **Appendix B**. 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[17], and $CitedPatent^{Quasi}$ uses the "quasi-structural" method to correct for the truncation bias.

In another attempt to measure important or drastic innovations we use the procedure suggested by Ahuja and Lampert (2001) to construct a variable (*Drastic*) by ranking all the patents in the same application year by the number of times they are cited in all subsequent years in our sample period. Thus, we ensure that each patent is compared only to its cohort, since patent citation data suffers from the truncation bias explained above. Based on this ranking, we select the top *1*% of patents in each year and label them drastic innovations. Finally, we count the number of drastic patents per firm per year. This count represents the variable *Drastic*. For robustness we rank the patents in the same technological class and in the same year by the number of all subsequent citations received. We name this variable $Drastic^{Tech}$. While for the variable *Drastic* the relevant cohort is the same year, for the variable $Drastic^{Tech}$, the relevant cohort is the same year and technological class. For robustness we also use *2*% and *5*% cutoff rates to identify the drastic innovations. In contrast to *Drastic*, which is a count variable, $CitedPatents^{Time}$, $CitedPatent^{Time-Tech}$ and $CitedPatent^{Quasi}$ are continuous variables. More importantly, since both citation weighted patents and drastic patents account for both the significance as well as the number of patents, we expect a stronger association between arm's length financing and innovations when innovations are measured by these variables

[16]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 2002 might not be directly comparable to a patent in the pharmaceutical industry applied for in 1995 and received 13 citations by 2002.

[17]As Hall, Jaffe and Trajtenberg (2001) explain, the "fixed effects" method described here is not equivalent to using fixed effects in our regressions because the unit of the analysis in the construction of the dependent variables is the patent and the unit of analysis in the regressions is the firm. For more details refer to Hall, Jaffe and Trajtenberg (2001).

as compared to a simple count of patents.

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. 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). We now describe the construction of the main explanatory variables used in our empirical analysis.

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.[18] 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 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.[19] Our third proxy measures access to the public market. 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%.

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,

[18]We also repeat all our analysis replacing book equity by market equity and find qualitatively similar results.

[19]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 1985 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 5%).

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.

III.B. Model Specification

To test our empirical predictions, we will use two main specifications. Whenever the dependent variable is a count variable (*Patent*, *Drastic*, $Drastic^{Tech}$) we follow the literature (e.g., Griliches et al., 1984; Cockburn and Henderson, 1998) and use a Poisson regression model. Following Griliches and Pakes (1980), we assume that the innovation counts (defined below in terms of patents) are generated by a production function $Y = f(\mathbf{X}, \gamma)$, where Y is the number of innovations, $\mathbf{X}$ is a vector of explanatory variables and γ is a vector of parameters. The single parameter of the Poisson distribution function is λ, which is an exponential function of the explanatory variables and is related to Y and X in the following way:

$$E[Y_{it}] = \lambda_{it} = exp\left[X_{it}^{'}\gamma + \beta_t + \beta_I + \beta_s\right]. \tag{E-4}$$

Here i indexes the firm, t indexes the year, s indexes the state, and I indexes the industry. β_t, β_I and β_s capture the year, industry and state fixed effects. Using time fixed effects controls for any time trends (Hall and Ziedonis, 2001), changes in patenting patterns over time (Kortum and Lerner, 2000) and prevailing market conditions. Using industry and state fixed effects control for any industry and state wide differences in firm R&D and innovative intensity (Kortum and Lerner, 2000; Hall et al., 2005). For constructing industry dummies, we classify industries at a 4 digit SIC level and check for robustness using the *48* industry classification used in Fama and French (1997). We estimate this model by maximum likelihood for the Poisson distribution. Gouriéroux, Montfort, and Trognon (1984) show that since the Poisson model is in the linear exponential class, the Poisson coefficient estimates are consistent if the mean specification is correct and the robust standard errors are consistent even under a misspecification of the distribution. Hence we report robust standard errors.

Two of the control variables, Sales and R&D expenditure, which proxy for size, are log transformed, while the other explanatory variables ($\mathbf{Z}_{it}$) are in levels. $\mathbf{Z}_{it}$ includes our main variable that proxies for arm's length financing and other explanatory variables such as operating earnings, market to book ratio, asset tangibility, cash, retained earnings, age of the firm and industry concentration. As a result our basic specification is:

$$E[Y_{it}] = \lambda_{it} = exp\left[\gamma_1 \text{Log(RD)}_{it} + \gamma_2 \text{Log(Sales)}_{it} + \delta \mathbf{Z}_{it}\right]. \tag{E-5}$$

In our model, coefficients on Sales and R&D have a constant elasticity interpretation, which implies that a 1% increase in these variables increases the dependent variable by $\gamma_1\%$ (or $\gamma_2\%$). All other coefficients in model (E-5) have the elasticity interpretation,

$$\left[\frac{1}{\lambda_{it}}\frac{\partial \lambda_{it}}{\partial Z_{it}}\right] = \delta, \tag{E-6}$$

which implies that a unit increase in the explanatory variable increases the dependent variable by $\delta\%$.

Whenever the dependent variable is not a count variable ($Patent^c$, $CitedPatents^{Time}$, $CitedPatents^{Time-Tech}$ or $CitedPatents^{Quasi}$), we use a PCSE (panel corrected standard error) specification. This specification adjusts for contemporaneous correlation and heteroskedasticity among the firm patents as well as for the autocorrelation in each firm's patents (Beck and Katz, 1995). Our specification is of the form:

$$E[Y_{it}] = \left[X'_{it}\gamma + \beta_t + \beta_I + \beta_s\right], \tag{E-7}$$

where the variables are as defined above. We would like to point out that R&D expenditure enters contemporaneously in our production function. We don't include lags since past literature (Griliches et al., 1986; Montalvo, 1997) concludes that the lag R&D structure is poorly identified due to high within-firm correlation of R&D spending over time.

IV. Empirical Results

IV.A. Descriptive Statistics

Sample properties of the main variables involved in our analysis are briefly described in Table I. 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*). 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) compared to firms without patents. Moreover, on average, as compared to firms that did not receive any patents, firms with patents have a larger proportion of firms accessing the public debt market (*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.[20]

[20]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 I 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 citation weighted patents (Median=7; Mean=5). Firms with above median citation weighted patents 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.

IV.B. Multivariate Analysis: Patents

In Table II 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 in Columns (1) to (6) using the simple patent count *Patent* as a dependent variable:

$$\text{Patent}_{it} = \lambda_{it} = \exp\left\{ \begin{array}{l} \alpha\text{Financing}_{it} + \ \gamma_1\text{Log(RD)}_{it} + \gamma_2\text{Log(Sales)}_{it} \\ + \delta\mathbf{Z}_{it} + \text{Time F.E.} + \text{Industry F.E.} + \text{State F.E.} \end{array} \right\}. \tag{E-8}$$

In Column (7) we use a negative binomial model which accounts for the possible over-dispersion of the count dependent variable. In Column (8) we use OLS with an alternative definition of our dependent variable ($Patent^c$) which, as mentioned earlier, accounts for the truncation of the patent grants in the later years of the sample. 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 hypothesis 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), $\boldsymbol{Z}$ is the matrix of control variables which 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 the possibility that maturity of the firm might be related to its innovativeness. 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)*). Finally, we also include as control variables, the market to book ratio of the firm (Q), profitability of the firm ($\frac{EBIDTA}{Assets}$), operating cash ($\frac{Cash}{Assets}$), retained earnings ($\frac{RetEarn}{Assets}$) and asset tangibility (*Tangible*). Since Rajan and Zingales (1995) and others have shown that profitability, size, tangibility and market to book are associated with $\frac{Equity}{Assets}$, inclusion of these variables in our model alleviates concerns about omitted variables. All regressions in this table are estimated with time, state and industry fixed effects and the reported standard errors are heteroskedastic consistent and also corrected for the panel.[21]

Our results are strongly supportive of our first prediction 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 is consistent with the literature that finds a positive association between equity and R&D expenditure (Titman and Wessels 1988; Hall, 1990; Greenwald, Salinger, and Stiglitz, 1992). Our finding is different, however, since we find a positive relationship between innovative output of the firm, while controlling for its R&D expenditure. Similarly, consistent with the first prediction, the estimated 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.[22] Note that both the amount of public debt and the public debt dummy are significant suggesting that, consistent with the discussion in the model section, both the access to public debt market and the proportion of public debt may be important for the firm's innovative activity.

In all the regression models, the coefficients on *HI* are positive while the coefficients on HI^2 are negative. Both estimates are highly significant. Such a non-monotonic relationship is in line with Aghion et al. (2005) that reports a non-monotonic relationship between R&D expenditure and industry concentration. This finding has been interpreted as suggesting that while some monopoly power encourages innovation, too much does not. Other firm specific control variables are significant as well. Consistent with the findings in the literature (e.g., Griliches, 1990; Caves, 1998), our estimates indicate that firms with more R&D expenditures create more patents. The coefficient on *Log(Sales)* is positive indicating that larger firms develop more innovations in our sample. More mature firms (*Age*) are found to create more innovations, though the economic significance of the estimate is small. We also find that the coefficient on Age^2 is negative but insignificant. Our results also indicate that firms with higher market to book, more tangible assets and higher profitability create more innovations.

In model (6), we repeat our estimation after inclusion of firm fixed effects. Inclusion of firm fixed effects alleviates concerns that unobservable firm specific differences in the cross-section might be affecting our estimates. 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,

[21] Standard errors in the Poisson models throughout the paper are heteroskedastic consistent to control for over dispersion and are corrected for the panel.

[22] 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 Table IX in this paper), and a negative relationship between leverage and R&D (Titman and Wessels, 1988).

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).[23] Finally, in model (8) we use the alternative definition of our dependent variable ($Patent^c$) with OLS specification. The results in Table II are economically significant. Specifically, in Column (8) of Table II, controlling for other factors at their mean levels, a 1 standard deviation (henceforth, SD) increase in $\frac{Equity}{Assets}$ is associated with a 47% increase in patents produced. Similarly a 1 SD increase in $\frac{Public}{Assets}$ is associated with a 12% increase in patents produced. 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. Note that the elasticity of innovations to R&D expenditure is *.40* in Column (5) which is similar to previous findings (e.g., Griliches et al., 1984; Cockburn and Henderson, 1996; Hall and Ziedonis, 2001; Lerner, 2005). 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. Overall, the results in this section strongly support our first prediction.

IV.C. Multivariate Analysis: Citation Weighted Patents

We next investigate the relationship between the financing variables and patents that are more significant. Based on *Prediction 2*, we expect a positive association between arm's length financing and more novel patents. Moreover, as mentioned earlier, we expect this relationship to be stronger than the relationship between arm's length financing and a simple patent count since, by construction, novel patents account for both the significance as well as the number of patents.

As discussed in the data section, we follow the established literature and measure the novelty of a patent by the number of forward citations that a certain patent receives (e.g., Trajtenberg, 1990). The three alternative measures used in this section are: (i) $CitedPatent^{Time}$ which measures the citation weighted patents produced by a firm per year (Table III); (ii) *Drastic* which is a count of the number of breakthrough or novel patents produced by the firm in a given year (Table IV) and (iii) An indicator variable which measures whether a firm is in the top 1 percent of all citations per patent received per year in a given technology class or not (Table V). Other alternative dependent variables that we employed are discussed in the robustness section. The model specifications and the results are described below.

We start our analysis in Table III, where we use the fixed effect panel regression to study the relationship between a firm's $CitedPatent^{Time}$ and its financing arrangements. Specifically, we

[23] 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 for all our tests the negative binomial model is rejected in the favor of a model where the variance is proportional to the mean.

estimate:

$$\text{CitedPatent}_{it}^{Time} = \left\{ \begin{array}{l} \alpha_0 + \alpha\text{Financing}_{it} + \ \gamma_1\text{Log(RD)}_{it} + \gamma_2\text{Log(Sales)}_{it} \\ + \ \delta\mathbf{Z}_{it} + \text{Time F.E.} + \text{Industry F.E.} + \text{State F.E.} \end{array} \right\}. \tag{E-9}$$

The control variables ($\boldsymbol{Z}$) are the same as the ones used in Table II. Consistent with our second prediction, the *Financing* variables are statistically significant and positively associated with more novel innovations. Since citation weighting of patents accounts for both the number and significance of patents done by the firm, we expect that the association between arm's length financing and innovation to be stronger for citation weighted patents compared to number of patents alone. Comparing estimates on the *Financing* variables in model (8) of Table II, where we used a similar specification, with estimates in model (4) of Table III, we see that the economic significance of the variables that proxy for arm's length financing is larger in magnitude. Specifically, controlling for other factors at their mean levels, a 1 SD increase in $\frac{Equity}{Assets}$ is associated with 57% more citation weighted patents. Similarly a 1 SD increase in $\frac{Public}{Assets}$ is accompanied by 20% more citation weighted patents. We also find that access to public debt markets is associated with 13% more citation weighted patents as compared to firms that do not have access to the public debt market.

We next analyze whether the type of financing is related to a count of breakthrough (*Drastic*) patents. Specifically, we estimate the following Poisson model in Columns (1) to (4) of Table IV:

$$\text{Drastic}_{it} = \lambda_{it} = \exp \left\{ \begin{array}{l} \alpha\text{Financing}_{it} + \ \gamma_1\text{Log(RD)}_{it} + \gamma_2\text{Log(Sales)}_{it} \\ + \ \delta\mathbf{Z}_{it} + \text{Time F.E.} + \text{Industry F.E.} + \text{State F.E.} \end{array} \right\}. \tag{E-10}$$

The dependent variable is *Drastic* and the control variables are the same as used in Table II. Comparing estimates in model (5) of Table II, where we used a similar specification, with estimates in model (3) of Table IV, it is clear that the economic significance of the variables that proxy for arm's length financing is larger for the breakthrough patents. Specifically, controlling for other factors at their mean levels, a 1 SD increase in $\frac{Equity}{Assets}$ is associated with 60% more drastic patents produced and a 1 SD increase in $\frac{Public}{Assets}$ is associated with 33% more drastic patents produced. Furthermore, access to public debt markets is associated with 12% more drastic patents as compared to firms that do not have access to the public debt market. In model (4), we re-estimate our model with firm fixed effects and find similar results. This reconfirms that our results hold both in time-series as well as in the cross-section. We also use a negative binomial specification in model (5) and find that our results are qualitatively similar. Finally, in model (6), we use an alternative definition of our dependent variable ($CitedPatents^{Quasi}$) and use an OLS specification. Again as shown in the table our results are robust to this alternative definition of novel innovation.

Next, we conduct two additional tests to confirm that arm's length financing is more strongly associated with drastic innovations than with the simple count of patents – many of which may be incremental. To do this, we first investigate the relationship between arm's length financing and more cited patents, restricting the sample to only include firms that have patents in a given year.

Then we conduct a second test where we compare firms that create novel innovations to firms with patents that are likely to be only incremental.

For the first test, 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 (E-9) on this sample. The results are reported in Column (1) and (2) of Table V. The coefficients on $\frac{Equity}{Assets}$, $Public^s$ and $\frac{Public}{Assets}$ are positive and significant at *1%* level. These results are consistent with the notion that the form of financing has a significantly greater influence on novel innovations than on a simple count of patents. The results also assure us that our previous findings in the full sample of firms are not biased in some manner by the inclusion of firms that don't have any patents. Note that the coefficients on the *Financing* variables in these equations are as economically meaningful as the coefficients we obtained earlier.[24] For robustness, we re-estimate our model restricting the sample to firms with at least one patent over the entire sample period and find similar results.

In models (3) and (4) of Table V, we compare firms with novel innovations to firms with patents that are likely to be only incremental. Specifically, we construct an indicator variable called *DrasticIncrem* which 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:

$$\text{DrasticIncrem}_{it} = \Phi \left\{ \begin{array}{l} \alpha_0 + \alpha \text{Financing}_{it} + \gamma_1 \text{Log(RD)}_{it} + \gamma_2 \text{Log(Sales)}_{it} \\ +\delta \mathbf{Z}_{it} + \text{Time F.E.} + \text{Industry F.E.} + \text{State F.E.} \end{array} \right\}. \quad \text{(E-11)}$$

As reported, the coefficient estimates on $\frac{Equity}{Assets}$, $Public^s$ and $\frac{Public}{Assets}$ are positive and significant and confirm that firms with arm's length financing are more likely to be drastic innovators than incremental innovators. For robustness, we try alternative cutoffs of *2%* and *5%* for the drastic innovators and *40%* and *50%* for the incremental innovators and find that the results are unaffected by these alternative cutoffs. Our results in this subsection strongly support our second prediction.

V. Further Tests and Robustness

In this section, we test some extensions of our predictions and investigate the robustness of our main results by examining alternative explanations. In subsection A, we analyze the impact of a

[24]From estimates in models (2) and (3) of Table V, firms with 1 SD increase in $\frac{Equity}{Assets}$ is associated with 25% more citation weighted patents and a 1 SD increase in $\frac{Public}{Assets}$ is associated with 10% more citation weighted patents when compared to firms that produce mean citation weighted patents *among the firms that innovate*. Furthermore, access to public debt markets is associated with 4.5% more citation weighted patents as compared to firms that do not have access the public debt market, *among the firms that innovate*.

firm's financial constraints on its innovative activity and on our main findings. Specifically, we are interested in investigating the extent to which the results on arm's length financing are a reflection of financial constraints. In subsection B, we examine whether our main results are affected because of inadequate controls for differences in firm characteristics in our earlier tests. In subsection C, we analyze the innovation output of firms after they issue public debt for the first time or issue public equity through a seasoned equity offering (SEO). In subsection D, we conduct instrumental variable analysis to control for possible coefficient bias due to omitted variables. In subsection E, we focus on firms that do not access the public debt market during our sample period, and examine whether borrowing from multiple banks vs. borrowing from a single bank is positively associated with innovation. The notion is that borrowing from multiple banks results in financing with attributes similar to arm's length financing. In subsection F, we explore the relationship between the quality of innovations created by a firm and its subsequent market valuation, operating performance and abnormal stock returns. Finally, in subsection G, we conduct additional miscellaneous robustness tests. For brevity, we discuss the results without reporting them in many instances in this section. All these results can be obtained by requesting the authors.

V.A. 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 lower financial constraints, this offers an alternative explanation for our findings – financially unconstrained firms innovate and financially constrained firms don't. In this sub-section we examine how such financial constraints might be affecting the estimates in our analysis. Note that our main regression results (Table II to Table V) suggest that, although important, internal finance accounts for only some part of the relationship between the choice of financing and innovation.[25] Below, we analyze in greater detail the importance of financial constraints.

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-obviously financially constrained.

[25]Specifically, despite the fact that we had included three measures of internal finance, namely operating income ($\frac{EBIDTA}{Assets}$), operating cash ($\frac{Cash}{Assets}$) and retained earnings ($\frac{RetEarn}{Assets}$), our measures of arm's length financing are statistically and economically significant.

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:

$$KZ = -1.002\frac{CF}{Assets} - 39.368\frac{Div}{Assets} - 1.315\frac{Cash}{Assets} + 3.139\frac{Debt}{Assets} + 0.283Q, \tag{E-12}$$

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). Specifically, for each KZ quintile, we estimate the following panel regression:

$$\text{Patent}_{it} = \left\{ \begin{array}{l} \alpha_0 + \alpha\text{Financing}_{it} + \ \gamma_1\text{Log(RD)}_{it} + \gamma_2\text{Log(Sales)}_{it} \\ + \ \delta\mathbf{Z}_{it} + \text{Time F.E.} + \text{Industry F.E.} + \text{State F.E.} \end{array} \right\}. \tag{E-13}$$

Controls in each case include all the variables used in Table III. 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 mil. 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 VI demonstrate a positive and significant association between arm's length financing variables ($\frac{Equity}{Assets}$ and $\frac{Public}{Assets}$) and patents for each of the KZ quintiles.[26] 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.[28]

[26]For conciseness, we do not report the coefficients of the other control variables (including $Public^s$) in the table. The estimates of the 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 $\frac{Cash}{Assets}$.

[28]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.

We repeat the analysis using the dependent variable $CitedPatent^{Time}$ to examine if our second prediction holds in each of the KZ quintiles. Our results are reported in Panel B. Comparing the estimates on $\frac{Equity}{Assets}$ and $\frac{Public}{Assets}$ in each KZ quintile in Panel B with the corresponding estimates in Panel A, it is clear that the positive and significant association between arm's length financing variables and innovation is stronger, when innovation is measured by citation weighted patents, rather than by a simple patent count. This finding is again consistent with our second prediction. Note that internal cash is also positively associated with novel innovation only for firms in the most financially constrained quintile.

For robustness we 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.[29] We again find support for our predictions in both the constrained and unconstrained set of firms. Overall the evidence in this section suggests that financial constraints and internal financing alone cannot explain our main findings, although they may have a role to play in explaining innovative activity.

V.B. Quintile Analysis

In this subsection, we conduct stricter tests to account for the effect of firm characteristics on our results. We divide the sample into quintiles formed on the basis of various firm characteristics such as sales, market-to-book ratio, age, operating income and operating cash. 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 differences in size, R&D expenditure, market to book, age, internal cash or profitability of firms that are not adequately captured by our control variables or by the KZ analysis in the previous section.

We conduct our analysis in two steps. Specifically, 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 (E-13) where the dependent variable is $CitedPatent^{Time}$. Controls in each estimation include all the variables used in the model in Table III. Specifically, we match firms into quintiles based on *Sales* in Panel A, Q in Panel B, *Age* in Panel C, $\frac{Cash}{Assets}$ in Panel D and $\frac{EBIDTA}{Assets}$ in Panel E. In each case, we estimate regressions with time, state and industry fixed effects.

Our results are reported in Panels A to E of Table VII and indicate that even after grouping firms by their firm characteristics, for every quintile, firms with more equity and more public debt

[29] Korajczyk and Levy use the criterion for classifying constrained firms as: $Div = 0$ and $Q > 1$; Whited and Wu construct an index based on a structural model as: $-0.091\frac{CF}{Assets} - 0.062\ DIVPOS + 0.021\ TLTD - 0.044\ Size + 0.102\ ISGit - 0.035\ SG$, 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.

tend to innovate more. In particular, note that 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). Most importantly, 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.[30] This section provides additional robust evidence that our results are not being unduly driven by a few specific firms or firm characteristics.

V.C. Innovations Subsequent to a First Time Public Debt Offering or a Seasoned Equity Offering (SEO)

In this subsection we investigate the relationship between arm's length financing and innovation by examining changes in innovative activity following significant changes in arm's length financing by the firm. More specifically, we analyze the innovative activity of firms that issue public debt for the first time or issue public equity through a seasoned equity offering (SEO).[31] Consistent with our model, we expect firms to issue equity or public debt if they anticipate an increase in their innovative activity. Since we examine the same firm before and after the issue, we have a substantially direct test of whether financing from arm's length markets is associated with a subsequent increase in innovative activity.

We examine the change in the innovative activity of firms subsequent to the two types of events, by constructing the dummy variable, $Post_2^D$ ($Post_2^E$), that takes a value *1* for the two years since the firm issued public debt for the first time (issued equity through an SEO) over the sample period, and *0* otherwise. To measure whether the innovative activity is affected over longer time periods, we also construct dummy variables, $Post_{2-3}^D$ ($Post_{2-3}^E$) and $Post_{2-4}^D$ ($Post_{2-4}^E$) that take a value *1* in the third and third and fourth years since the firm issued public debt for the first time (issued equity through an SEO) over the sample period and *0* otherwise. For 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 issued SEOs during the sample period. For our analysis, we use this sample and estimate the following model

[30] 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. Notably, consistent with Himmelberg and Petersen (1994), we find that $\frac{Cash}{Assets}$ is positive in the lowest sales and age quintiles (Q_1 and Q_2). 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. We also find that the results hold when we use *Patent* as the dependent variable instead.

[31] 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.

on various explanatory variables:

$$\text{CitedPatent}_{it}^{Time} = \left\{ \begin{array}{l} \alpha_0 + \alpha\text{Financing}_{it} + \beta_0\text{Post}_{2it}^k + \beta_1\text{Post}_{lit}^k + \ \gamma_1\text{Log(RD)}_{it} \\ + \gamma_2\text{Log(Sales)}_{it} + \delta\mathbf{Z}_{it} + \text{Time F.E.} + \text{Industry F.E.} \\ + \text{State F.E.} \end{array} \right\}, \quad \text{(E-14)}$$

where $k \in \{D, E\}$ corresponds to the first time public debt issue and the SEO respectively and $l \in \{2-3, 2-4\}$ corresponds to third and third and fourth year subsequent to the first time public debt issue or a SEO. More precisely, in Columns (1), (2) and (3) of Table VIII we estimate the model using variables that capture two, three and four years subsequent to the first time issue of public debt and in Columns (4), (5) and (6) we estimate the model using variables that capture two, three and four years subsequent to the SEO. Based on our hypothesis, we expect the coefficient estimate on $Post_2^k(\beta_0)$ to be positive. Controls in each case include all the variables used in the model in Table III.[32] 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 hypothesis – firms which issue public debt for the first time (do an SEO) have more valuable innovations as measured by citation weighted patents in the years subsequent to the first time issue of public debt (SEO). In particular, the coefficient estimates on $Post_2^D(Post_2^E)$ are positive and significant at *1%* level. The estimates are economically significant and indicate that firms which issue public debt for the first time (do an SEO) experienced a *26%* (*39%*) increase in the citation weighted patents two years after the issue of public debt (public equity), other things equal.

Note that the estimates on $Post_{2-3}^k$ and $Post_{2-4}^k$ for three and four years after the initial issue of public debt (after an SEO) in models (2) and (3) (models (5) and (6)) 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.[33] Overall, our findings in this section provide substantial evidence that obtaining additional arm's length financing is followed by at least two years of increase in innovative activity.[34]

[32]Note that to enable us to make proper inferences about the estimate on $Post_2^D$, $Post_{2-3}^D$ and $Post_{2-4}^D$ we define a modified financing variables $Public^{\#s}$ which like $Public^s$ takes a value 0 for all the years when the firm does not have public debt. However, to avoid overlap with $Post_2^D$, $Post_{2-3}^D$ and $Post_{2-4}^D$, it takes a value of 0 for 2, 3 and 4 years respectively after a firm issues public debt for the first time. After the first 2, 3 and 4 years this dummy takes a value 1.

[33]In particular, besides using *Drastic* as a dependent variable with a Poisson estimation specification, we also conducted the estimation using $CitedPatent^{Time}$ and a Tobit 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 citation weighted patents 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 $Post_2^k$.

[34]Note that, our estimation in this section, though similar to a firm fixed effects estimation, differs in an important

V.D. Instrumental Variable Estimation

In this subsection we examine if the economic impact of public debt on innovation might be due to the omission of unobserved variables in our specification – specifically related to public debt financing. In particular, an alternative hypothesis is that a positive and strongly significant association between public debt and innovation exists since there is something fundamentally different about firms that borrow from public debt markets – differences not being captured by our current model specification. To address this issue, we employ a two equation instrumental variable (IV) model.[35] We estimate this IV model with two alternative techniques – the control function approach (with $CitedPatent^{Time}$ as dependent variable and OLS specification in second stage) and the Generalized Method of Moments (with *Drastic* as dependent variable and Poisson specification in second stage). The first equation of the model explains firm's choice of public debt financing and the second equation estimates the creation of novel innovations. **Appendix C** briefly discusses the methodology that we use to obtain the results that we discuss below.

We start by estimating a first stage equation that explains whether or not the firm chooses to borrow from the public debt market. Specifically, in the first stage we estimate a logit regression of the form:

$$\text{Public}^{s}{}_{it} = \Phi \left\{ \begin{array}{l} \beta_0 + \beta_1\{\frac{Equity}{Assets}\}_{it} + \beta_2\text{Size}_{it} + \beta_3 Q_{it} + \beta_4\text{Tangible}_{it} \\ +\beta_5\sigma_{\text{firm,it}} + \beta_6\text{Age}_{it} + \beta_7\{\frac{EBIDTA}{Assets}\}_{it} + \beta_8\text{KZ}_{it} \\ +\ \gamma^{'}\text{Instruments}_{it} + \text{Time F.E.} + \text{Industry F.E.} \end{array} \right\}. \tag{E-15}$$

Our dependent variable is $Public^s$.[36] Following the literature that explains the choice of public debt financing (e.g., Hadlock and James (2002)), we include firm level control variables *Size*, $\frac{Equity}{Assets}$, *Q*, *Age*, $\frac{EBIDTA}{Assets}$ and *Tangible*. We decompose firm's stock return variance into firm specific, industry specific and market specific components and include the firm specific component of the stock return variance ($\sigma_{\text{firm,it}}$) as an additional control.[37] We follow the procedure in Campbell et al. (2001)

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.

[35]There is also a possibility of simultaneity bias due to the fact that once the public debt is in place it might have an independent effect on innovation. Using an IV model also ensures that the estimates of our model are not affected by this type of bias.

[36]Note that the choice of public debt – the endogenous variable we need to instrument in the second stage equation – appears both directly ($Public^s$) and indirectly in the proportion of public debt ($\frac{Public}{Assets}$). Therefore, when we instrument, we perform two first stage estimations - one for $Public^s$ and another for the ratio $\frac{Public}{Assets}$ (unreported).

[37]We also estimate the first stage using the overall stock return variance instead of the three decomposed terms and find results similar to Hadlock and James (2002) who include this variable to capture information asymmetry. Since the literature (e.g., Campbell et al., 2001) interprets the firm specific component of stock return volatility as capturing information asymmetry, we include this as a control rather than as an instrument. This addresses the concern that firm's information asymmetry may be related to its innovation, independent of public debt.

for this decomposition (discussed in **Appendix E**). We estimate the regressions with time and industry fixed effects and report the results in Table IX.

For estimating the second stage equation (innovation equation), we require at least one of the explanatory variables in the first stage equation to be an instrument in the second stage, i.e., it has to be uncorrelated to innovation except through public debt. To this end, we use several alternative instruments in our analysis. In model (1), we use the industry component of the firm's stock return variance ($\sigma_{\text{ind,t}}$) as an instrument. We take industry related stock return volatility of the firm as an instrument since, for instance, Cantillo and Wright (2000) argue that industry volatility can influence the choice of public debt financing. In models (2) and (3), we follow Faulkender and Petersen (2004) and include two more instruments. The first one is based on how well known or visible the firm is. The notion is that better known firms will find it easier to access public bond markets. As a measure of whether the firm is widely known 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. In model (3), we use the Log of one plus the percentage of firms in the industry of a given firm in a year (*Log(1+%Public)*) that have public debt as an instrument. The notion here is that the probability of a firm having public debt is also related to how unique the firm is. For instance, a new firm which manufactures autos may be able to issue bonds more easily, since the bond market already knows the industry and the competitors, as most auto manufacturers have outstanding public debt. We believe that the instruments we have picked are not directly affecting the nature of the firm's innovative activity (we are not aware of any suggestion or evidence to the contrary in the literature). In model (4), for robustness, we include all the instruments together.

As indicated in the table, our instruments are significant predictors of whether or not a firm borrows from the public market. In particular, the probability of a firm choosing public debt financing is negatively related to the industry specific variance of its stock returns and 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. The coefficient estimates on the other variables in all the columns indicate that the probability of a firm having public debt is positively related to *Size*, *Tangible* and *Age* and negatively related to $\frac{EBIDTA}{Assets}$, Q, $\frac{Equity}{Assets}$ and σ_{firm}. The signs and significance of coefficient estimates on these explanatory variables are similar to the results reported in Hadlock and James (2002) and Faulkender and Petersen (2004).

We now discuss the results of our second stage regression. As discussed in the methodology section, the second stage in CFA and GMM is different in that CFA uses an OLS specification while the second stage in GMM uses a Poisson specification. Specifically, we estimate the second stage after including the control function of residuals (CFA) and $\Phi(Z'\beta)$ (for GMM) from the first stage. We construct three control functions and three $\Phi(Z'\beta)$'s corresponding to models (1), (2) and (3) of Table IX (first stage). These models correspond to σ_{ind}, *S&P 500* and (*Log(1+%Public)*) being used as instruments in the first stage. Subsequently, in models (1), (2) and (3) of Table X, we use

CFA and in models (4), (5) and (6) we use GMM. The other explanatory variables are the same as the ones used in the basic regression in Table III. Our results using both CFA and GMM show that the estimates of arm's length financing variables are qualitatively similar to those in Table III and Table IV respectively. However, a Hausman test (reported in notes to Table X) comparing the estimates in Table IV with estimates in Table X suggests that controlling for a firm's public debt choice decision does have a small but statistically significant effect on the coefficient estimates.[38]

The economic significance indicated by the estimated coefficients on $\frac{Public}{Assets}$ is close to those reported in our initial estimations without instruments. In particular, firms with 1 SD more public debt than average produce 18% more citation weighted patents. In unreported regressions, we re-estimated the models in Table II using the control function approach ($Patent^c$ as dependent variable) and GMM (*Patent* as dependent variable). Our coefficient estimates on the financing variables are smaller than those reported in Table X. This suggests that the finding that financing arrangements have a stronger influence on novel innovations than on innovations in general is robust to IV estimation and again confirms our second prediction. The evidence in this section suggests that our main results are largely unaffected even after controlling for a possible omitted variable bias.

V.E. Another Proxy for Arm's Length Financing

As an extension of our empirical analysis, we examine if among firms with no public debt access in our sample, those with multiple banks display an innovation pattern closer to firms with public debt access. Within the context of our model, having multiple banks resembles more arm's length financing than borrowing from a single bank, since for a given size of the initial investment, the exposure of each bank is small. Therefore banks may not have the incentives to diligently investigate the investment opportunity of the firm. Moreover, it might be more difficult for multiple banks to act in a coordinated manner when they need to terminate the project. This notion also finds support in the literature (e.g., Rajan, 1992; Houston and James, 1996; Thakor 1996). Therefore, empirically, we expect a positive association between borrowing from multiple banks and the number of citation weighted patents (and for patents in general).

To test this prediction, we start with firms that *do not* have public debt during the sample period. For these firms, we create a variable *Multiple*, which takes a value of *0*, if the firm borrows from a single bank in the current year t or in any year before that, and *1* if the firm borrows from multiple banks. To construct this variable, we gather data from the Loan Pricing Corporation's DealScan database, on the number of lead banks that a firm uses when it receives a bank loan

[38]In the CFA, we find that the residuals from the first stage are significant in the second stage regression. This suggests that the choice of a firm to go to the public debt market has a discernable effect on the estimates in the second stage. However, the difference in magnitude of the estimates on the relevant variables suggests that this effect is small.

(see Dahiya et al., 2003 for more detailed discussion on the DealScan database and identification of lead banks). Consistent with Dahiya et al. (2003), we choose only lead banks to count the number of lenders. Supporting banks, named by DealScan as Participants, are excluded from the count since they only provide assistance and follow the direction of the lead banks. 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 often unreliable. Therefore, we increase our matched sample by hand after carefully checking company names. In terms of sample size we would like to note two caveats. First, since the coverage of firms in DealScan is relatively limited, the number of observations used in the tests that involve the variable *Multiple* is much 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 *7,190* firm years when we use *Multiple*. In our sample we find that, as compared to firms that borrow from a single bank, firms that borrow from multiple banks are, on average, larger in terms of sales ($3,137 mill vs. $410 mill), more profitable in terms of $\frac{EBIDTA}{Assets}$ (0.13 vs. 0.09) and have lower cash to assets ratio (0.06 vs. 0.12). The characteristics of firms borrowing from multiple vs. single banks in our sample are similar to those reported in Houston and James (2001).

We use fixed effect panel regression to study again the relationship between the number of citation weighted patents a firm produces in a given year and its financing arrangements. Specifically, in Table XI we estimate (E-9) with *Financing* proxied by *Multiple*. The control variables are the same as used in Table III. Houston and James (2001) show that, as compared to firms that borrow from multiple banks, firms borrowing from a single bank face 'cash flow constraints' for large projects. We control for the size of investments for innovative projects by including $Log(RD)$ and include KZ as a control for financial constraints faced by the firm in model (3). As is reported in the table, *Multiple* is statistically significant and positively associated with more novel innovations in all the specifications used in the table. The estimates on the other arm's length proxy $\frac{Equity}{Assets}$ are also statistically significant. Our estimates are economically meaningful. Specifically, controlling for other factors at their mean levels, among firms without public debt access, those which borrow from multiple banks are likely to produce 5% more citation weighted patents than those borrowing from a single bank. Despite the smaller sample size as compared to other tests, these results are robust to using different specifications (negative binomial and Poisson) in models (4) and (5) and alternative dependent variable definitions ($Patent^c$ in model (1), $CitedPatent^{Time}$ in models (2) and (3) and *Drastic* in models (4) and (5)). Note that we already control for financial constraints and therefore our variable captures something more than the lack of resources to finance innovation. As an additional test to ensure that our results are not affected by financial constraints, we conducted the analysis in KZ quintiles following the methodology in Section V.A. Our results are similar to those reported in Table XI.

To address concerns about a possible selection bias due to the imperfect matching from DealScan to Compustat, we treat all the firms with cited innovations that do not borrow from public markets and for which we don't have banking information, as having a single bank relationship (i.e., *Multiple* = 0). This biases our sample against finding any support for our corollary (i.e., against finding support that firms with multiple bank relationship produce more novel innovations). We find that our results remain significant, though the magnitude of the coefficients is marginally smaller. Overall the evidence indicates that firms that borrow from multiple banks create more novel innovations (and innovations in general) as compared to firms that borrow from a single bank.

V.F. Innovation, Firm Value, Firm Performance and Stock Returns

In this subsection we investigate the impact of a firm's innovative activity on its subsequent stock market valuation. Our first objective is to establish an association between the quality of a firm's innovations as measured by citations weighted patents (revealed over time), and its future value and operating performance. Based on previous work (Hall et al., 2005), we expect a positive association between quality of a firm's innovation and its future value. Another objective of our analysis is to investigate the type of 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 price. As a consequence, the firms with more novel and significant innovations should have higher future abnormal returns – as the value of the innovation is gradually recognized by the market – than firms that have no or only incremental innovations.

In Panel A of Table XII, we first examine the relationship between future market to book value (Q) of firms sorted into quintiles based on the quality of their innovations. In particular, 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*:

$$\mathrm{y}_{it+j} = \left\{ \gamma_t + \delta \mathbf{Z}_{it} + \text{Industry F.E.} + \text{State F.E.} \right\}. \tag{E-16}$$

Our dependent variable y is one, two and three year future Q in Columns (1) to (3). Following Hall et al. (2005), we continue to conduct our analysis relative to the application year of patents since the work surveyed in Griliches, Pakes, and Hall (1987) finds that patent counts by application date are more tightly linked to market value than counts by granting date. We include the firm's *Size* and *Age* as control variables (Shin and Stulz, 2000). Since Daines (2001) finds that Q is different for Delaware and non-Delaware firms, we include state dummies in our regression. Morck and Yeung (2001) show that inclusion in the S&P 500 index has a positive impact on Q. Thus, we include a dummy variable for S&P 500 inclusion as a control. We also control for other firm specific characteristics like cash and operating profits. Finally, we include industry fixed effects to control for cross industry differences in value and performance. For our inferences, we are interested in the difference in coefficient estimates γ between the first and the fifth quintile – since that can be interpreted as the difference in value or performance between firms in the most and the least innovative quintiles after controlling for other factors that explain future Q.

For 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 (E-16) 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). Panel A 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. Specifically, the difference in the estimates of γ (26 in each quintile) between the first and the last quintile in the last row of Panel A suggests that firms in the highest citation weighted patent quintile have a 40% higher market to book value two years after the innovation than firms in the lowest citation weighted 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. This finding is consistent with Hall et al. (2005) who find that firms having above median number of citations per patent display a significant value premium. As shown in the table, these differences persist for upto two years subsequent to the sorting year – suggesting the time period over which the value of the innovation is fully recognized. We find qualitatively similar results when we examine the future operating performance (ROA) of firms across the most and the least innovative quintiles. More precisely, we find that firms in the highest citation weighted patent quintile have about 31.5% higher operating performance two years after the innovation than firms in the lowest citation weighted patent quintile.

In Panel B of Table XII, we examine the relationship between future excess stock returns (R) of firms sorted into quintiles based on the quality of their innovation. In particular, for each of the quintiles formed as in Panel A, we estimate the following model for each *year*:

$$\mathrm{R}_{it+j} = \left\{ \ \alpha_t + \beta_1 \mathrm{R}_t^m + \beta_2 \mathrm{SMB}_t + \beta_3 \mathrm{HML}_t \ \right\}. \tag{E-17}$$

Our dependent variable is one year future stock returns (R_{t+1}) in Columns (1) and (4), two year future stock returns (R_{t+2}) in Columns (2) and (5) and three year future stock returns (R_{t+3}) in Columns (3) and (6). We follow prior research and estimate a 1-factor model for each quintile in models (1) to (3) and use the Fama-French 3-factor model in models (4) to (6). In particular, we control for excess value weighted market returns (R^m) in all the models. We also include *SMB* (small minus big) and *HML* (high minus low) factors in models (4) to (6). Our interest is in the difference of the coefficient estimate α between the first and the fifth quintile – since that can be interpreted as the difference in excess returns between firms in the two quintiles after controlling for appropriate risk factors.

As in Panel A, each row in Panel B gives the Fama-MacBeth coefficient estimate on α and standard errors averaged across years of the sample. Specifically, the difference in estimate of α between the first and the last quintile in the last row of Panel B suggests that firms in the highest citation weighted patent quintile have a 1.68% higher annual market adjusted return and a 1.80% higher annual three factor adjusted return two years after the innovation than firms in the lowest citation weighted patent quintile.[39] Our results are consistent with the notion that the firm value increases in response to creation of novel innovations – those that have a greater influence on subsequent innovations. Again, it takes about two years for the information to be incorporated into stock prices.[40]

V.G. Other Robustness Tests

We conduct several additional tests to verify the robustness of our main regression results that are reported in Tables II and III. For conciseness, we discuss the results without reporting them. 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 V.B., 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 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 the innovations and arm's length financing exists in both sample periods. We also re-estimate all our regressions with age dummies in line with Oyer (2005) who argues that this approach alleviates survivorship bias of the type we are concerned about. We find that our results are not affected.

Second, since Hall et al. (2005) show that the R&D and patenting intensity varies across industries, we examine how this might impact our results. To do this, 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 "Com-

[39] 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 lowest and highest citation weighted patent quintiles could be an omitted risk factor in the factor model. In unreported analysis, we repeat the regressions with a 4-factor model (including momentum factor) and find that our results are similar. Also note that the standard errors in the Fama-MacBeth regressions in this section are corrected for autocorrelation up to four lags using the Newey and West procedure.

[40] We repeat the analysis by sorting firms into groups based on whether or not they patent. Since the median firm in the sample does not patent, we are left with two groups. The results presented in this section (in both the Panels) are qualitatively similar if we repeat the analysis focussing on the differences between these two groups instead of the top and bottom quintile of firms sorted based on the quality of their innovation. We also conducted the entire analysis in this section (for firms with patents) sorting firms based on simple patent count (*Patent*). Consistent with Hall et al. (2005) our results are economically weaker than those reported in this section – suggesting the importance of novelty of patents rather than a simple patent count.

puters"); Electrical; Metals and Machinery; and miscellaneous (low-tech industries). The first five industry sectors are the source for most of the patents in the manufacturing sector in the US. The last miscellaneous group includes everyone else (for details on the industry sector definitions, see Hall et al., 2005). Subsequently, we estimate (E-9) for each of these industry sectors. Our results are significant across each of these sectors with economically weakest results being for the Metals and Machinery and the low-tech sectors. In particular, the estimates on $\frac{Equity}{Assets}$ (α_1) and $\frac{Public}{Assets}$ (α_2) for the six sectors are as follows: (i) *Drugs*: $\alpha_1 = 1.3$ (z=3.49), $\alpha_2 = 1.9$ (z=1.99); (ii) *Chemicals*: $\alpha_1 = 1.9$ (z=3.24), $\alpha_2 = 1.69$ (z=4.02); (iii) *Computers*: $\alpha_1 = 1.9$ (z=6.23), $\alpha_2 = 1.5$ (z=8.41); (iv) *Electrical*: $\alpha_1 = .84$ (z=6.19), $\alpha_2 = .99$ (z=3.29); (v) *Metals*: $\alpha_1 = .08$ (z=1.68), $\alpha_2 = .45$ (z=1.77) and (vi) *Others*: $\alpha_1 = .52$ (z=4.10), $\alpha_2 = .20$ (z=3.06). These estimates indicate that our predictions hold across these industry sectors.

Third, we address the concern that a firm's asymmetric information and agency problem might be omitted variables in our specification, affecting both the type of financing and innovation. Though the use of firm fixed effects controls for time invariant unobserved variables (which possibly include asymmetric information and agency problems within a firm), we also include in our specification various proxies that have been linked to asymmetric information (market to book, analyst forecast dispersion and firm specific stock variance) and agency problems (Gompers, Ishi Metrick governance index, outside block holdings and public pension fund oversight). We find that our main results are unaffected.[41]

Fourth, 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. The results are similar to our findings in Tables II and III. Fifth, we check the robustness of our results by employing the alternative dependent variable definitions that we described earlier ($CitedPatent^{Time-Tech}$, $Drastic^{Tech}$); 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.[42] 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. Finally, 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 first difference transformation.

[41]Note that we have data on Gompers, Ishi Metrick governance index, outside block holdings and public pension fund oversight only from 1990 onwards. Thus, our tests with these variables are restricted to the period 1990-2000.

[42]Additionally, we also try two 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 ($Drastic^{\mathrm{All}}$) and by the ratio of forward to backward citations for a firm for all its patents in a year ($Drastic^{\mathrm{Ratio}}$). 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.

VI. Conclusion

In the paper we offer a simple model to show that the financing arrangements of an innovative firm can matter for the innovation process and the firm's market value. It is shown that arm's length financing, that gives greater discretion to the firm's manager, may be optimal when the innovation is drastic and difficult for a financial intermediary to value. On the other hand, when the innovation is more incremental, it may be optimal to rely on a relationship based financing arrangement that yields some control to an informed financial intermediary. Hence, the empirical prediction that we test is that firms that rely predominantly on arm's length financing, such as equity and public debt, will innovate more and have more novel innovations than those with relationship based financing, such as bank debt.

The empirical analysis relies on patents developed by publicly traded US corporations over the 1974-2000 period as a measure of a firm's innovative activity. Patents are rated as being more or less drastic based on the citations in subsequent patents. Our empirical findings are consistent with our hypothesis: there is strong evidence that firms with arm's length borrowing receive more patents and these patents tend to be more drastic. The results are economically meaningful – a firm with a 1 standard deviation above the mean equity to asset ratio (public debt to asset ratio) has 57% (20%) more citation weighted patents. Moreover, access to public debt markets is associated with 13% more citation weighted patents as compared to firms that do not access the public debt market.

We extend the empirical analysis of the hypothesis in a variety of ways. A notable finding is that in the two years following a large infusion of arm's length financing – specifically, the first time issue of public debt or a seasoned equity offering – firms tend to have a burst of innovative activity, suggesting that arm's length financing may be taking place in anticipation of the innovative activity. Our results are robust to conditioning on financial constraints faced by the firm, firm size, R&D expenditure, market to book, firm maturity, the choice of a firm's decision to go to the public debt market and a variety of model specifications and variable definitions.

We believe that the results of the paper may have broader implications. The results 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.

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Appendix A: 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. *Drastic*$_{it}$: Count of the drastic patents applied for in year t by firm i. A patent is classified as drastic by first ranking all the patents in the application year t by the number of times they are cited in all subsequent years in our sample period. Second, based on this ranking, we select the top *1*% patents among all the patents in year t and label them drastic innovations. Finally, we count the number of drastic patents by firm i in year t (Source: NBER Patent Data).

10. $Drastic_{it}^{Tech}$: Count of the drastic patents in application year t by firm i where the procedure is the same as *Drastic* except that the ranking is based on all the patents in the same technological class (Source: NBER Patent Data).

11. *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*% (Source: NBER Patent Data).

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

13. $(\frac{Equity}{Assets})_{it}$: 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.

14. *Factors*: R_t^m is the excess value weighted market returns in year t, SMB_t is small minus big factor in year t and HML_t is the high minus low factor in year t (Source: Kenneth French's web site).

15. *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).

16. *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 26 (Source: Compustat).

17. *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).

18. *Multiple*$_{it}$: A dummy variable takes a value of *1* if firm i borrows from multiple banks in year t or in any year before that, and *0* if the firm borrows from a single bank (Source: Deal Scan Database).

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

20. $Patent_{it}^c$: 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).

21. $Post_2^k$: A dummy variable that takes a value *1* in year t if 2 years have passed since firm i issued public debt (superscripted D) for the first time (issued SEO; superscripted E) over the sample period and *0* otherwise where $k \in \{D, E\}$ (Source: SDC Platinum Database).

22. *PPE*$_{it}$: Net property plant and equipment of firm i in year t (Source: Compustat Data 8).

23. *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).

24. $Public_{it}^s$: 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).

25. $Public_{it}^c$: 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).

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

27. R_{it}: Excess stock returns of firm i in year t (Source: CRSP).

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

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

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

31. $S\&P\ 500_{it}$: 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).

32. $\sigma_{\text{firm,it}}$, $\sigma_{\text{ind,it}}$, $\sigma_{\text{mkt,it}}$: 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. More details on the procedure used are provided in Appendix E. The stock returns are based on CRSP (Source: CRSP).

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

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

Appendix B: Construction of Dependent Variable

The 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. As we would expect, patents applied for in later years have higher weight factors. In contrast to $Patent$ which is a count variable, $Patent^c$ is a continuous variable.

The 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 C: Control Function Approach and GMM

The basic idea in the control function approach is to use the residuals from the first stage (the choice of financing equation) as an additional control in the second stage (innovation production equation). In our case, the first stage regression is a logit of the form:

$$\text{Financing}_{it} = \Phi(\delta z_{it} + \beta' \mathbf{x}_{it}) + u_{it}, \tag{E-18}$$

where *Financing*$_{it}$ is a binary variable representing whether or not the firm borrows from public debt market, x_{it} are control variables, z_{it} are instruments and u_{it} is the residual. The second stage regression uses OLS specification with *CitedPatent* as the dependent variable:

$$\text{CitedPatents}_{it} = [\alpha_0 + \alpha \text{Financing}_{it} + \gamma^{'} \mathbf{w}_{it}] + \epsilon_{it}. \tag{E-19}$$

Note that some of the elements of $\mathbf{x}$ and $\mathbf{w}$ can be the same. The control function assumption (Newey, Powell and Vella, 1999) can be expressed by the following equation:

$$E[\epsilon_{it} | \text{Financing}_{it}, \mathbf{w}_{it}, u_{it}] = 0. \tag{E-20}$$

Under this assumption, controlling for u_{it} in the second stage is sufficient to retrieve the unbiased estimates. In our estimation we use maximum likelihood to recover the parameters of interest. Specifically, our first stage involves estimating a logit regression of the form described in (E-15). The second stage then takes the following form:

$$E[Y_{it}] = [\gamma_1 \text{Log(RD)}_{it} + \gamma_2 \text{Log(Sales)}_{it} + \alpha \text{Financing}_{it} + \delta \mathbf{Z}_{it}], \tag{E-21}$$

where $\mathbf{Z}_{it}$ is a vector which besides the other explanatory variables used in our main regressions also includes the control function of residuals constructed from the first stage

Generalized Method of Moments (GMM)

The second technique that we use in our estimation is GMM since the dependent variable is a count variable (*Drastic*) and both the first stage and the second stage are non-linear. In our setting, we consider the following equations:

$$\begin{aligned} \text{Drastic}_i &= \exp\{[\alpha \text{Financing}_i + \gamma' \mathbf{x}_{1i}] + u_{1i}\} && \text{(E-22)} \\ \text{Financing}_i &= \Phi[\alpha_1 \text{Drastic}_i + \beta^{'} \mathbf{x}_{2i}] + u_{2i}. && \text{(E-23)} \end{aligned}$$

Note that some of the elements of $\mathbf{x}_{1i}$ and $\mathbf{x}_{2i}$ can be same. We drop the t subscript in the discussion for notational convenience. A consistent estimator of (δ_1, γ) in this simultaneous equation framework is the GMM estimator, and a natural choice of instrument for Financing$_{it}$ is $\Phi(\mathbf{x}_{2i}^{'}\hat{\beta})$, where $\hat{\beta}$ is the logit estimator of β (Mullahy, 1996; Montalvo, 1997). In our analysis, we first construct the instrument for the GMM ($\Phi(\mathbf{x}_{2i}^{'}\hat{\beta})$) by running the first stage (E-15) and then use the approach outlined below to find the two step efficient GMM estimator.[43] We now describe briefly the econometrics behind our two step GMM estimator. We first present the standard Poisson model for count data. Let y_i, $i = 1, ..., N$ denote the dependent count variable, which is independently Poisson distributed, with conditional mean specified as:

$$E[\mathbf{y}_{it} | \mathbf{x}_{it}] = \lambda_{it} = exp(\beta' \mathbf{x}_{it}), \tag{E-24}$$

where $\mathbf{x}_i$ is a k vector of explanatory variables and β is a k-vector of parameters. The maximum likelihood estimator, denoted β_{ML} solves the first order condition $\mathbf{X}'(y - \lambda) = 0$, where $\mathbf{X}$ is an $N \times K$ matrix, and $\mathbf{y}$ and λ are N vectors, and $\sqrt{N}(\beta_{ML} - \beta)$ has a limiting distribution with mean 0 and variance the limit of $(N^{-1}\mathbf{X}^{'}\mathbf{M}\mathbf{X})^{-1}$, where M=diag(λ). In practice, the standard errors are often biased due to the presence of over or under dispersion. Correct standard errors are computed from the estimated variance of the Poisson pseudo likelihood (PL) estimator (See Gouriéroux, Monfort, and Trognon (1984)):

$$Var(\hat{\beta_{PL}}) = (\mathbf{X}^{'}\hat{\mathbf{M}}\mathbf{X})^{-1}(\sum(y_i - \hat{\lambda_i})^2 x_i x_i^{'})(\mathbf{X}^{'}\hat{\mathbf{M}}\mathbf{X})^{-1},$$

where $\hat{M}$= diag($\hat{\lambda_i}$) and $\hat{\lambda_i} = exp(\mathbf{x}_i^{'}\beta_{PL}^{'}) = exp(\mathbf{x}_i^{'}\beta_{ML}^{'})$.

[43] Note that for the GMM model in our setting, the logical consistency or coherence is an issue. It is easily established that the model is only coherent when it is triangular i.e., $\alpha = 0$ or $\alpha_1 = 0$ (Blundell and Smith, 1994): $P(Financing_i = 1) + P(Financing_i = 0) = \Phi[\alpha_1 \exp\{\{\alpha + \gamma^{'}\mathbf{x}_{1i}\}\} + \beta^{'}\mathbf{x}_{2i}] + (1 - \Phi[\alpha_1 \exp\{\{\gamma^{'}\mathbf{x}_{1i}\}\} + \beta^{'}\mathbf{x}_{2i}])$. This expression is equal to 1 if α_1=0 or α=0. Assuming that $\alpha \neq 0$, i.e. a binary variable is included as regressor in the model for the count variable, we have that for coherency $\alpha = 0$. We will assume these conditions hold in our tests.

The conditional mean specification (E-24) implicitly defines a regression model

$$y_i = \lambda_i + u_i = exp(\beta' x_i) + u_i$$

with $E[u_i|x_i] = 0$. The GMM estimator (Hansen 1982), based on this moment condition only, minimizes:

$$(y-\lambda)^{'} X W_N^{-1} X^{'}(y-\lambda) \tag{E-25}$$

where W_N is a weight matrix. As the minimum of the function is obtained at $X^{'}(y-\lambda) = 0$, the GMM estimator for β will be the same as the Poisson maximum likelihood estimator, irrespective of the weight matrix (for more details see Mullahy 1996). When some elements of x_i are endogenous (as is the case in our paper), implying that $E[u_i|x_i] \neq 0$, λ_i is no longer the conditional mean of y_i and the Poisson ML estimator will no longer be consistent. If there are instruments z_i available such that $E(u_i|z_i) = 0$, then the consistent nonlinear instrumental variables (NLIV) estimator is given by the minimization of:

$$(y-\lambda)^{'} Z(Z^{'}Z)^{-1}Z^{'}(y-\lambda)$$

This is a one step GMM estimator. However, the efficient two step GMM estimator, given the instruments is found by minimization of:

$$(y-\lambda)^{'} Z(Z^{'}\tilde{\Omega}Z)^{-1}Z^{'}(y-\lambda)$$

where $Z^{'}\tilde{\Omega}Z = \Sigma_1^N (y_i - \tilde{\lambda_i})^2 z_i z_i^{'}$.

Appendix D: Proofs

Proof of Proposition 1: The proof of when the bank will be given control follows from conditions described in the text. For proof of part (a), note that the condition (E-3) can be rewritten as: $\phi(n) \geq \frac{\frac{c}{\bar{v}}+\mu-\beta(n)}{\mu(1-\beta(n))}$. Given the parametric assumptions in the text, $\beta(n) \in (\frac{\frac{c}{\bar{v}}}{1-\mu}, \frac{I_0}{\bar{v}})$. Moreover, $\frac{\frac{c}{\bar{v}}+\mu-\beta(n)}{\mu(1-\beta(n))}$ is decreasing in $\beta(n)$. Thus, for the maximum possible value of $\beta(n)$ in this range, say $\hat{\beta}$, $\exists$ a ϕ^* such that $\phi* = \{\frac{\frac{c}{\bar{v}}+\mu-\hat{\beta}}{\mu(1-\hat{\beta})}\}$ and $\phi(n) \geq \phi*$. Similarly, (E-3) can be rewritten as: $\beta(n) \geq \frac{\frac{c}{\bar{v}}+\mu(1-\phi(n))}{(1-\phi(n)\mu)}$. Given the parametric assumptions in the text, $\phi(n) \in (\frac{\frac{c}{\bar{v}}+\mu-\frac{I_0}{\bar{v}}}{1-\mu}, 1)$. Again, $\frac{\frac{c}{\bar{v}}+\mu(1-\phi(n))}{(1-\phi(n)\mu)}$ is decreasing in $\phi(n)$. Thus, for the maximum possible value of $\phi(n)$ in this range, say $\hat{\phi}$, $\exists$ a β^* such that $\beta* = \frac{\frac{c}{\bar{v}}+\mu(1-\hat{\phi})}{(1-\hat{\phi}\mu)}$ and $\beta(n) \geq \beta*$.

To prove that for novel projects, bank is less likely to get control, it is enough to show that the partial derivative of left hand side of (E-3) w.r.t. n is decreasing in n. The derivative is: $\phi'(n)\mu(1-\beta(n)) + \beta'(n)(1-\mu\phi(n)) < 0$. ■

Proof of Proposition 2: For proof of part (a), recall that the bank loans have to be of short maturity and the loans have to be structured so that it is optimal for the bank to terminate the project when it receives a negative signal. Denote by L_1 and L_2 the 1-period loans that are made by the bank, where L_1 is the loan at $t = 0$ to be repaid at date $t = 1$ and L_2 is the refinancing loan at $t = 1$ and is to be paid at $t = 2$. L_1 is chosen before the bank receives its signal at $t = 1$; however since L_2 is determined at $t = 1$ it can be affected by whether the bank's signal is positive or negative. Let us denote by L_2^+ & L_2^- the second period loans from the bank depending on whether it receives a positive or negative signal. We set L_2 to be the largest financing that would be feasible without bankruptcy risk at date 1 to ensure that debt will be risk-free. First let us consider when the signal s is negative. Under this scenario, the project is to be terminated and we require that:

$$\begin{aligned} L_2^- < L_1 \leq \beta(n)\bar{v} + L_2^- \\ L_2^- = Y_2 \end{aligned} \tag{E-26}$$

The intuition behind these conditions is as follows. First, if there is to be liquidation on receiving a negative signal, then $L_1 > L_2^-$ ensures that the first period loan L_1 is large enough not to be paid by refinancing loan L_2^- when the bank receives a negative signal. Second, with $L_1 \leq \beta\bar{v} + L_2^-$, the maximum second period loan after a negative signal plus liquidation of the project $(\beta(n)\bar{v} + L_2^-)$ is sufficient to pay off L_1. These two conditions ensure that the bank terminates the project when it receives a negative signal. Finally, we set L_2^- to Y_2 since this keeps the debt risk-free. Besides the reputational costs imposed on the $\mathcal{B}$ if the firm defaults, it is also never in the interest of $\mathcal{M}$ to let the firm default since she loses the associated private benefits. Note that since the board is interested in setting the debt to the maximal amount without imposing bankruptcy risk, they would set $L_1 = \beta(n)\bar{v} + Y_2$. Ex-ante value of the innovative project with the bank control is $\mu\bar{v}\phi(n)$. Since the manager diverts θ of this value, ex-ante equity value is the remainder: $(1-\theta)\mu\bar{v}\phi(n)$.

Note that if s is positive, the bank will be able to provide a second period loan (L_2^+) that is sufficient to pay off the first period loan. Since the project is successful, the board would force any additional cash-flow out of the firm in the form of a dividend. Therefore we require:

$$L_2^+ \geq L_1 = \beta(n)\bar{v} + Y_2$$
$$L_2^+ = Y_2 + \min\{v\} = Y_2 + v_l \tag{E-27}$$

The intuition behind these conditions is as follows. First, with a positive signal the maximum second period loan L_2^+ should be large enough to allow L_1 to be refinanced without liquidation of the project. The second condition sets the debt L_2^+ to the maximum amount of cash flow that is expected at t=1 after a positive signal ($Y_2 + v_l$). Note that if $v_l > \beta(n)\bar{v}$, with bank debt, there may be extra free cash with the firm at $t = 1$. $\mathcal{B}$ forces $\mathcal{M}$ to distribute any such excess cash as dividends.

For part (b), note that the public debt is set equal to the maximal amount of cash expected (for certain) at $t = 0$ (Y_2) and the rest of the capital structure is again equity $(1 - \theta)\mu\bar{v}$. ■

Proof of Proposition 3: The $\frac{Equity}{Debt}$ ratio with bank control is given by $\frac{(1-\theta)\mu\bar{v}}{\beta(n)\bar{v}+Y_2}$ while this ratio is $\frac{(1-\theta)\mu\bar{v}}{Y_2}$ when the firm chooses to borrow from the public debt market. Comparing the two terms, the proportion of equity to debt is higher when the firm borrows from the public debt markets. Since the control shifts from the bank to public debt as the project becomes novel (Proposition 1) and with greater number of anticipated innovations (Corollary 1), the conclusion follows. ■

Appendix E: Campbell Variance Decomposition

We compute the variance of the past 36 months of stock returns of the firm preceding the year t, and use it as a proxy for the overall risk. CRSP data provides the value-weighted return, the variance of which we use as the market specific risk. To compute the industry specific return, we form a market-value weighted portfolio of all the firms in that industry (based on Fama French 48 industries). To get the industry and firm specific risk, we regress the value weighted industry return on the market return and get the residual. The variance of this residual is treated as the industry-specific risk. Similarly, we regress firm return on industry residual return and market return and get the residual, the variance of which is treated as firm-specific risk. For details please refer to Campbell et al. (2001).

Table I:
Summary Statistics

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 financial firms (SIC codes starting with 6) and government firms (SIC codes starting with 9). 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 citation weighted patents ($CitedPatent^{Time}$) 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.

Panel A: Firm Characteristics and Patents

	$Patent \leq$ 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 Citation Weighted Patents for Patenting Firms

	$CitedPatent^{Time} \leq$ Median (=7)			$CitedPatent^{Time} >$ Median (=7)			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

Table II:
Patents and Financing Arrangements

This table reports the results relating patents produced in a firm to the type of its financing. Specifically we estimate poisson models in Columns (1) to (6), a negative binomial model in Column (7) and OLS in Column (8). All variable definitions are provided in Appendix A. The dependent variable is *Patent* in Column (1) to (7) and $Patent^c$ in Column (8). Other controls (not reported in the table) include 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.

	Dependent Variable Model Specification							
	Patent	*Patent*	*Patent*	*Patent*	*Patent*	*Patent*	*Patent*	$Patent^c$
	Poisson	Poisson	Poisson	Poisson	Poisson	Poisson	NegBin	OLS
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log(Sales)	.597	.561	.540	.418	.563	.770	.277	.10
	(.002)***	(.003)***	(.003)***	(.003)***	(.003)***	(.006)***	(.009)***	(.001)***
Log(RD)	.394	.407	.406	.408	.409	.140	.061	.15
	(.002)***	(.002)***	(.002)***	(.002)***	(.002)***	(.004)***	(.006)***	(.001)***
Hi	2.197	3.024	2.912	1.634	2.867	.766	.766	1.2
	(.093)***	(.093)***	(.093)***	(.094)***	(.093)***	(.100)***	(.310)**	(.14)***
Hi^2	-2.553	-3.406	-3.331	-2.410	-3.254	-1.881	-.859	-.22
	(.072)***	(.072)***	(.072)***	(.073)***	(.072)***	(.078)***	(.264)***	(.12)*
$\frac{Equity}{Assets}$	.184	.227	.211	.243	.298	.105	.092	.11
	(.014)***	(.014)***	(.014)***	(.015)***	(.014)***	(.019)***	(.026)***	(.005)***
$Public^c$			.192					
			(.005)***					
$Public^s$				.199	.075	.069	.073	.066
				(.004)***	(.009)***	(.008)***	(.008)***	(.007)***
$\frac{Public}{Assets}$					.320	.733	.344	.14
					(.002)***	(.023)***	(.040)***	(.01)***
Q		.067	.063	.051	.070	.044	.034	.05
		(.002)***	(.002)***	(.002)***	(.002)***	(.002)***	(.008)***	(.02)**
Tangible		1.060	.994	.990	1.071	.374	.253	.11
		(.017)***	(.017)***	(.017)***	(.017)***	(.024)***	(.073)***	(.01)***
$\frac{EBIDTA}{Assets}$		.823	.786	.768	.754	1.291	.848	.512
		(.026)***	(.026)***	(.026)***	(.026)***	(.033)***	(.080)***	(.02)***
Age		.049	.051	.050	.045	.047	.044	.048
		(.002)***	(.002)***	(.003)***	(.002)***	(.002)***	(.003)***	(.002)***
$\frac{Cash}{Assets}$		-.21	-.20	-.19	-.29	-.30	-.28	-.22
		(.26)	(.29)	(.31)	(.36)	(.33)	(.80)	(.29)
$\frac{RetEarn}{Assets}$		-.03	-.02	-.03	-.03	-.03	-.02	-.02
		(.01)*	(.03)	(.03)	(.02)	(.03)	(.02)	(.03)
Observations	109,003	109,003	109,003	109,003	109,003	57,330	57,330	109,003
Adjusted R^2								0.22
Log-likelihood	-33,644.7	-33,841.0	-33,843.4	-33,851.6	-33,855.1	-19,840.3	-19,680.8	
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	Yes
Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes			Yes
State Fixed Effects	Yes	Yes	Yes	Yes	Yes			Yes
Firm Fixed Effects						Yes	Yes	

Table III:
Citation Weighted Patents and Financing Arrangements

This table reports the results relating cited patents produced in a firm to the type of its financing. Specifically we estimate panel OLS models in all the columns. All variable definitions are provided in Appendix A. The dependent variable is citation weighted patents, $CitedPatent^{Time}$. Other controls (not reported in the table) include Age^2. All regressions are estimated with time, state and industry fixed effects and the standard errors reported in the parenthesis are corrected for the panel. Data is for the period 1974 to 2000. ***, ** and * denote significance at 1%, 5% and 10% respectively.

	Dependent Variable: $CitedPatent^{Time}$				
	OLS	OLS	OLS	OLS	OLS
	(1)	(2)	(3)	(4)	(5)
Log(Sales)	.216 (.008)***	.203 (.008)***	.159 (.008)***	.212 (.008)***	.209 (.021)***
Log(RD)	.367 (.009)***	.367 (.009)***	.353 (.009)***	.366 (.009)***	.162 (.019)***
Hi	2.389 (.662)***	2.373 (.663)***	2.300 (.661)***	2.380 (.661)***	.94 (.476)**
Hi^2	-1.549 (.562)***	-1.546 (.564)***	-1.510 (.562)***	-1.546 (.562)***	-.276 (.145)**
$\frac{Equity}{Assets}$	.801 (.073)***	.555 (.095)***	.714 (.095)***	.843 (.074)***	.342 (.114)***
$Public^c$		.081 (.022)***			
$Public^s$			.092 (.024)***	.088 (.20)***	.076 (.19)***
$\frac{Public}{Assets}$				.537 (.079)***	.405 (.117)***
Q	.005 (.002)**	.007 (.003)***	.006 (.003)**	.005 (.002)**	.015 (.007)**
Tangible	.740 (.085)***	.713 (.086)***	.714 (.086)***	.747 (.085)***	.385 (.159)**
$\frac{EBIDTA}{Assets}$	.004 (.003)*	.014 (.005)**	.003 (.001)**	.003 (.002)**	.100 (.045)**
Age	.041 (.003)***	.043 (.002)***	.049 (.002)***	.043 (.003)***	.049 (.004)***
$\frac{Cash}{Assets}$	-.14 (.11)	-.13 (.12)	-.13 (.11)	-.21 (.1)	-.19 (.15)
$\frac{RetEarn}{Assets}$	-.07 (.06)	-.08 (.07)	-.07 (.09)	-.07 (.07)	-.09 (.08)
Observations	109,003	109,003	109,003	109,003	97,990
Adjusted R^2	.16	.17	.17	.19	.22
Time Fixed Effects	Yes	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes	Yes	
State Fixed Effects	Yes	Yes	Yes	Yes	
Firm Fixed Effects					Yes

Table IV: Alternative Measures of Novel Patents and Financing Arrangements

This table reports the results relating novel patents produced in a firm to the type of its financing. Specifically we estimate Poisson models in Columns (1) to (4), a negative binomial model in Column (5) and OLS in Column (6). Other controls (not reported in the table) include $\frac{Cash}{Assets}$, $\frac{RetEarn}{Assets}$, Age and Age^2. All variable definitions are provided in Appendix A. The dependent variable is *Drastic* in Column (1) to (5) and $CitedPatent^{Quasi}$ in Column (6). 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.

	Dependent Variable Model Specification					
	Drastic	*Drastic*	*Drastic*	*Drastic*	*Drastic*	$CitedPatent^{Quasi}$
	Poisson	Poisson	Poisson	Poisson	NegBin	OLS
	(1)	(2)	(3)	(4)	(5)	(6)
Log(Sales)	.179	.228	.111	.270	.147	.209
	(.029)***	(.029)***	(.029)***	(.055)***	(.050)***	(.008)***
Log(RD)	.619	.656	.648	.301	.265	.365
	(.026)***	(.027)***	(.027)***	(.047)***	(.045)***	(.006)***
Hi	1.171	1.377	.214	-1.553	.074	2.374
	(.855)	(.860)	(.863)	(.934)*	(1.312)	(.661)***
Hi^2	-2.804	-2.999	-1.925	-.692	-.511	-1.550
	(.639)***	(.642)***	(.647)***	(.700)	(1.049)	(.562)***
$\frac{Equity}{Assets}$	.832	.834	.890	.647	.660	.802
	(.159)***	(.157)***	(.158)***	(.198)***	(.261)**	(.073)***
$Public^c$	.153					
	(.012)***					
$Public^s$		.136	.137	.138	.133	.121
		(.013)***	(.009)***	(.010)***	(.012)***	(.006)***
$\frac{Public}{Assets}$			.748	.504	.896	.549
			(.066)***	(.234)**	(.344)***	(.079)***
Q	.009	.007	.005	.005	.001	.007
	(.014)	(.007)	(.014)	(.019)	(.024)	(.003)***
Tangible	2.076	2.277	2.148	.515	.197	.712
	(.163)***	(.161)***	(.162)***	(.213)**	(.280)	(.080)***
$\frac{EBIDTA}{Assets}$	.319	.355	.408	1.331	1.375	.014
	(.186)*	(.194)**	(.249)***	(.347)***	(.023)***	(.021)
Observations	109,003	109,003	109,003	49,040	49,040	109,003
Adjusted R^2						.20
Log-likelihood	-28,754.4	-29,168.4	-29,172.2	-19,120.1	-20,198.3	
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
State Fixed Effects	Yes	Yes	Yes			Yes
Firm Fixed Effects				Yes	Yes	

Table V:
Drastic vs. Incremental Patents and Financing Arrangements

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) and (2), we estimate the panel regression of $CitedPatent^{Time}$ on various explanatory variables for firms which have at least one patent in a given year during our sample. In Columns (3) and (4) 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%. 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 corrected for the panel. Data is for the period 1974 to 2000. ***, ** and * denote significance at 1%, 5% and 10% respectively.

	$CitedPatent^{Time}_{P>0}$		$DrasticIncrem$=1	
	OLS	OLS	Logit	Logit
Log(Sales)	.643 (.077)***	.652 (.077)***	.214 (.032)***	.281 (.029)***
Log(RD)	.310 (.053)***	.308 (.053)***	.366 (.024)***	.380 (.023)**
Hi	6.786 (3.490)**	6.609 (3.491)***	4.331 (1.636)***	4.322 (1.682)**
Hi^2	-3.217 (3.771)	-3.076 (3.772)	-4.088 (1.392)***	-3.929 (1.088)**
$\frac{Equity}{Assets}$	.971 (.479)**	.962 (.493)**	.363 (.169)**	.395 (.148)**
$\frac{Public}{Assets}$		.785 (.358)**		.772 (.240)***
$Public^s$		.325 (.110)***		.305 (.141)***
Q	.443 (.061)***	.445 (.061)***	.099 (.023)***	.086 (.019)***
Tangible	.427 (.755)	.455 (.755)	.878 (.277)***	.895 (.312)***
$\frac{EBIDTA}{Assets}$	.343 (.774)	.374 (.774)	.555 (.283)*	.595 (.287)*
Observations	15,085	15,085	10,200	10,200
Adjusted R^2	.14	.15		
Log-likelihood			-4,529.4	-4,547.3
p-value, χ^2 test			0.00	0.00
Time Fixed Effects	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes	Yes
State Fixed Effects	Yes	Yes	Yes	Yes

Table VI:
Innovation and Financial Constraints : KZ Quintiles

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 their KZ index. In the second stage, for each quintile, we estimate a panel regression of $CitedPatent^{Time}$ or *Patent* on various explanatory variables. Panel A presents coefficient estimates with *Patent* as the dependent variable while Panel B presents estimates with $CitedPatent^{Time}$ as the dependent variable. Other controls (not reported in the table) include $Public^s$, *Log(Sales)*, *Log(RD)*, *Q*, *Tangible*, *Age*, Age^2, *HI* and HI^2. All variable definitions are provided in Appendix A. 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.

Panel A: Financial Constraints, Patents and Type of Financing

	Q1 Low Constraint	Q2	Q3	Q4	Q5 High Constraint
$\frac{Equity}{Assets}$	.017 (.004)***	.018 (.005)***	.032 (.003)***	.024 (.004)***	.015 (.003)***
$\frac{Public}{Assets}$	.474 (.117)***	.271 (.054)***	.491 (.071)***	.108 (.044)**	.014 (.008)*
$\frac{RetEarn}{Assets}$	-.026 (.007)***	-.042 (.010)***	-.017 (.009)*	-.015 (.009)	.00008 (.0007)
$\frac{Cash}{Assets}$	-.086 (.073)	-.188 (.073)**	-.229 (.069)***	-.363 (.085)***	.170 (.045)***
$\frac{EBIDTA}{Assets}$	.01 (.055)	.07 (.061)	.03 (.051)	.04 (.063)	.008 (.011)
Mean Quintile KZ	-.73	.45	1.00	1.64	3.08
Observations	22,716	23,112	23,125	23,139	23,076
Adjusted R^2	.13	.11	.16	.17	.15
Time Fixed Effects	Yes	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes
State Fixed Effects	Yes	Yes	Yes	Yes	Yes

Panel B: Financial Constraints, Citation Weighted Patents and Type of Financing

	Q1 Low Constraint	Q2	Q3	Q4	Q5 High Constraint
$\frac{Equity}{Assets}$	.244 (.120)**	.676 (.194)***	.203 (.126)	.479 (.155)***	.141 (.040)***
$\frac{Public}{Assets}$	.850 (.319)***	.556 (.180)***	1.351 (.283)***	.445 (.142)***	.329 (.116)***
$\frac{RetEarn}{Assets}$	-.033 (.019)*	-.075 (.034)**	-.008 (.035)	-.031 (.029)	-.003 (.003)
$\frac{Cash}{Assets}$	-1.221 (.199)***	-.275 (.242)	-.212 (.273)	-.295 (.276)	.151 (.042)***
$\frac{EBIDTA}{Assets}$	.091 (.14)	.19 (.22)	.073 (.21)	.23 (.20)	.02 (.043)
Mean Quintile KZ	-.73	.45	1.00	1.64	3.08
Observations	22,716	23,112	23,125	23,139	23,076
Adjusted R^2	.12	.18	.16	.17	.18
Time Fixed Effects	Yes	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes
State Fixed Effects	Yes	Yes	Yes	Yes	Yes

Table VII: Citation Weighted Patents and Financing Arrangements: Quintile Analysis

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 panel regression of $CitedPatent^{Time}$ on various explanatory variables. Panel A, B, C, D and E present coefficient estimates with firms sorted into quintiles based on *Sales*, *Q*, *Age*, $\frac{Cash}{Assets}$ and $\frac{EBIDTA}{Assets}$ respectively. Other controls (not reported in the table) include $Public^s$, *Log(Sales)*, *Log(RD)*, *Q*, *Tangible*, *Age*, Age^2, $\frac{Cash}{Assets}$, $\frac{RetEarn}{Assets}$, $\frac{EBIDTA}{Assets}$, *HI* and HI^2. All variable definitions are provided in Appendix A. 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.

	Q1 Low	Q2	Q3	Q4	Q5 High
			Panel A: *Sales* Quintiles		
$\frac{Equity}{Assets}$	.232 (.019)***	.264 (.079)***	.165 (.066)**	.735 (.153)***	.171 (.201)***
$\frac{Public}{Assets}$	.103 (.015)***	.115 (.018)***	.186 (.014)***	.158 (.208)***	.278 (.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)***	.90 (.065)***
$\frac{Public}{Assets}$	.551 (.128)***	.787 (.166)***	.310 (.021)***	.390 (.162)**	.329 (.201)*
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		
$\frac{Equity}{Assets}$	.245 (.057)***	.263 (.052)***	.212 (.029)***	.388 (.088)***	.195 (.072)***
$\frac{Public}{Assets}$	.205 (.018)***	.276 (.118)**	.458 (.173)***	.421 (.154)***	.455 (.205)**
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
			Panel D: $\frac{Cash}{Assets}$ Quintiles		
$\frac{Equity}{Assets}$	.126 (.040)***	.373 (.070)***	.233 (.053)***	.431 (.039)***	.126 (.057)**
$\frac{Public}{Assets}$	.698 (.158)***	.340 (.136)**	.792 (.165)***	.112 (.021)***	.269 (.142)*
Mean Quintile Value	.005	.02	.05	.12	.37
Observations	30,030	28,860	28,009	28,657	29,538
			Panel E: $\frac{EBIDTA}{Assets}$ Quintiles		
$\frac{Equity}{Assets}$	.170 (.028)***	.107 (.053)**	.809 (.102)***	.663 (.097)***	.244 (.061)***
$\frac{Public}{Assets}$	.101 (.035)***	.690 (.224)***	.750 (.148)***	.504 (.195)***	.893 (.283)***
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

Table VIII: Citation Weighted Patents after Seasoned Equity Offering and First Time Public Debt Issue

This table reports the results relating novel patents produced in a firm to the type of its financing subsequent to a public debt offering and a seasoned equity offering. We estimate an OLS model in all the columns with the dependent variable $CitedPatent^{Time}$. 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 variable definitions are provided in Appendix A. 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.

	Dependent Variable: $CitedPatent^{Time}$					
	Post First Time Public Debt Issue			Post Seasoned Equity Offering		
	(1)	(2)	(3)	(4)	(5)	(6)
Log(Sales)	.135	.135	.135	.134	.132	.130
	(.006)***	(.006)***	(.006)***	(.006)***	(.006)***	(.006)***
Log(RD)	.349	.349	.349	.349	.349	.349
	(.007)***	(.007)***	(.007)***	(.007)***	(.007)***	(.007)***
Hi	1.800	1.793	1.792	1.785	1.781	1.777
	(.491)***	(.491)***	(.491)***	(.491)***	(.490)***	(.490)***
Hi^2	-1.011	-1.007	-1.006	-.982	-.975	-.969
	(.421)**	(.421)**	(.421)**	(.421)**	(.421)**	(.421)**
$\frac{Equity}{Assets}$	.793	.791	.790	.777	.770	.766
	(.053)***	(.053)***	(.053)***	(.053)***	(.053)***	(.053)***
$\frac{Public}{Assets}$	.448	.511	.508	.704	.796	.749
	(.061)***	(.060)***	(.063)***	(.071)***	(.077)***	(.079)***
$Post_2^D$	.301	.300	.302			
	(.075)***	(.075)***	(.074)***			
$Post_{2-3}^D$		.019				
		(.009)**				
$Post_4^D$			.030			
			(.017)**			
$Post_2^E$				.448	.449	.448
				(.041)***	(.040)***	(.040)***
$Post_{2-3}^E$					.009	
					(.005)*	
$Post_{2-4}^E$						.021
						(.012)**
$Public^{\#s}$	.060	.063	.064			
	(.024)***	(.025)***	(.025)***			
$Public^s$				.073	.072	.071
				(.032)**	(.032)**	(.032)**
Observations	109,003	109,003	109,003	109,003	109,003	109,003
Adjusted R^2	.17	.17	.17	.18	.18	.18
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

Table IX:
Determinants of Choice of Public Debt Financing (First Stage)

This table reports the results of regressions relating the choice of public debt financing to key explanatory variables used in the prior literature. Specifically, we estimate the panel logit regression where the dependent variable is a dummy variable $Public^s$. Other controls (not reported in the table) include σ_{mkt} and $\frac{Cash}{Assets}$. All variable definitions are provided in Appendix A. All regressions are estimated with time 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.

	Dependent Variable: $Public^s$			
	(1)	(2)	(3)	(4)
σ_{ind}	-8.689			-10.400
	(1.243)***			(2.431)***
S&P 500		.973		.996
		(.051)***		(.052)***
Log(1+%Public)			.965	1.153
			(.157)***	(.162)***
Size	.701	.626	.689	.611
	(.013)***	(.013)***	(.013)***	(.013)***
Tangible	.601	.583	.375	.316
	(.078)***	(.079)***	(.084)***	(.085)***
Q	-.035	-.127	-.023	-.112
	(.015)**	(.020)***	(.014)	(.019)***
$\frac{EBIDTA}{Assets}$	-.790	-.903	-.706	-.809
	(.109)***	(.116)***	(.111)***	(.117)***
$\frac{Equity}{Assets}$	-2.625	-2.571	-2.523	-2.450
	(.134)***	(.135)***	(.134)***	(.135)***
Age	.021	.021	.021	.021
	(.001)***	(.001)***	(.001)***	(.001)***
σ_{firm}	-3.590	-3.952	-3.262	-3.545
	(1.529)**	(1.558)**	(1.441)**	(1.460)**
Observations	109,003	109,003	109,003	109,003
Log-likelihood	-36,300.8	-36,317.4	-36,359.6	-36,599.9
p-value, χ^2 test	0.00	0.00	0.00	0.00
Time Fixed Effects	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes	Yes

Table X:
Citation Weighted Patents and Financing Arrangements: Instrumental Variables (Second Stage) – Control Function Approach and GMM

This table reports the results of regressions relating innovations produced in a firm to its type of financing while addressing the choice of firms to take on public debt. In Columns (1), (2) and (3) we follow the control function (CFA) approach (Newey, Powell and Vella, 1999) and include control function constructed from the determinants of financing equation (Table X). Specifically, we estimate the panel regression of $CitedPatent^{Time}$ on various explanatory variables including the control function of residuals. In Columns (4), (5) and (6), we estimate the GMM estimator (Mullahy, 1996) with $Public^s$ being instrumented by the predicted value ($\Phi(Z'\beta)$) constructed based on Table IX and the dependent variable being *Drastic*. A more detailed description of the control function approach and GMM is provided in the text and in Appendix B. Other controls (not reported in the table) include *HI*, HI^2, *Q*, *Tangible*, $\frac{Cash}{Assets}$, $\frac{RetEarn}{Assets}$, $\frac{EBIDTA}{Assets}$, *Age* and Age^2. All variable definitions are provided in Appendix A. 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.

	Dependent Variable: $CitedPatent^{Time}$			Dependent Variable: *Drastic*		
	CFA	CFA	CFA	GMM	GMM	GMM
	σ_{ind}	*S&P 500*	*Log(1+%Public)*	σ_{ind}	*S&P 500*	*Log(1+%Public)*
	(1)	(2)	(3)	(4)	(5)	(6)
Log(Sales)	.159	.158	.263	.121	.119	.115
	(.008)***	(.006)***	(.007)***	(.004)***	(.005)***	(.005)***
Log(RD)	.303	.301	.303	.554	.552	.553
	(.008)***	(.008)***	(.008)***	(.009)***	(.009)***	(.009)***
$\frac{Equity}{Assets}$	.642	.655	.641	.814	.811	.812
	(.095)***	(.093)***	(.093)***	(.159)***	(.155)***	(.152)***
$Public^s$	.082	.071	.077	.112	.118	.116
	(.022)***	(.020)***	(.021)***	(.010)***	(.009)***	(.008)***
$\frac{Public}{Assets}$	.437	.443	.441	.409	.402	.401
	(.077)***	(.079)***	(.078)***	(.201)***	(.202)***	(.209)***
Observations	109,003	109,003	109,003	109,003	109,003	109,003
Adjusted R^2	.17	.18	.18			
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

Hausman endogeneity test based on estimates in Table III and GMM in Table IX
$Public_s$ (Column(4) in Table X - Column(3) in Table IV): $(-0.025)^{***}$; p-value (0.001)

Table XI:
Innovation and Multiple Bank Relationships

This table reports the results relating innovations produced in a firm to its type of banking relationship for firms who do not have access to public debt markets in our sample. Specifically we estimate OLS in Columns (1) to (4), poisson model in Column (5) and negative binomial model in Column (6). The dependent variable is $Patent^c$ in Column (1), $CitedPatent^{Time}$ in Column (2) to (4) and *Drastic* in Columns (5) and (6). Other controls (not reported in the table) include $\frac{Cash}{Assets}$, $\frac{RetEarn}{Assets}$, *Age* and Age^2. All variable definitions are provided in Appendix A. 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 1985 to 2000. ***, ** and * denote significance at 1%, 5% and 10% respectively.

	Dependent Variable					
	Model Specification					
	$Patent^c$	$CitedPatent^{Time}$	$CitedPatent^{Time}$	$CitedPatent^{Time}$	*Drastic*	*Drastic*
	OLS	OLS	OLS	OLS	Poisson	NegBin
	(1)	(2)	(3)	(4)	(5)	(6)
Log(Sales)	.338	.282	.281	.225	.559	.294
	(.029)***	(.047)***	(.047)***	(.172)	(.058)***	(.105)***
Log(RD)	.388	.346	.346	.389	.407	.488
	(.021)***	(.034)***	(.035)***	(.098)***	(.042)***	(.080)***
HI	1.710	-5.185	-5.183	-.506	4.983	6.290
	(2.543)	(4.097)	(4.104)	(5.302)	(3.595)	(3.475)*
HI^2	-1.024	4.945	4.939	.351	-4.297	-3.790
	(2.161)	(3.482)	(3.488)	(4.441)	(2.778)	(3.268)
$\frac{Equity}{Assets}$	.102	.738	.685	.784	.358	.855
	(.051)**	(.343)**	(.331)**	(.324)**	(.196)**	(.442)**
Multiple	.308	.383	.384	.314	.812	.620
	(.093)***	(.150)**	(.150)**	(.20)*	(.178)***	(.261)**
KZ			-.011			
			(.056)			
Q	.046	.098	.096	.276	.259	.226
	(.022)**	(.036)***	(.037)***	(.096)***	(.051)***	(.085)***
Tangible	.991	.189	.187	.644	4.409	1.872
	(.258)***	(.416)	(.417)	(1.013)	(.416)***	(.737)**
$\frac{EBIDTA}{Assets}$	.790	.262	.247	1.664	.225	.777
	(.244)***	(.394)	(.403)	(.918)*	(.564)	(1.133)
Observations	6,493	6,493	6,480	5,671	2,185	2,185
Adjusted R^2	.15	.12	.12	.12		
Log-likelihood					-2,465.7	-2,168.8
p-value, χ^2 test					0.00	0.00
Time Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes			
State Fixed Effects	Yes	Yes	Yes			
Firm Fixed Effects				Yes	Yes	Yes

Table XII:
Citation Weighted Patents and Future Firm Value and Abnormal Returns

This table reports the results relating cited patents produced in a firm to the type of its financing. 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 $CitedPatent^{Time}$. In the second stage, for each quintile, we estimate a Fama-MacBeth (1973) regression of future market to book on various explanatory variables in Panel A and of future returns on various explanatory variables in Panel B. Control variables in Panel A include *Size*, *Age*, *S&P 500*, $\frac{Cash}{Assets}$, $\frac{EBIDTA}{Assets}$, state, industry and time dummies. In Panel B, control variables include excess value weighted market returns, *SMB* and *HML* factors. All variable definitions are provided in Appendix A. Data is for the period 1974 to 2000. ***, ** and * denote significance at 1%, 5% and 10% respectively.

Panel A: Value and Cited Patents (per annum)

	Q_{t+1}	Q_{t+2}	Q_{t+3}
	(1)	(2)	(3)
Quintile$_1$ (Q_1)	1.14	1.22	1.38
(Least Cited)	(.67)*	(.79)	(.91)
Quintile$_2$ (Q_2)	1.17	.98	1.32
	(.72)*	(.77)	(.92)
Quintile$_3$ (Q_3)	1.34	1.18	1.01
	(.62)**	(.61)*	(.77)
Quintile$_4$ (Q_4)	1.71	1.68	1.52
	(.37)***	(.69)**	(.97)
Quintile$_5$ (Q_5)	1.80	1.71	1.69
(Most Cited)	(.36)***	(.79)**	(1.08)
Difference Q_5- Q_1	.66	.49	.31
	(.22)***	(.28)*	(.37)

Panel B: Abnormal Returns and Cited Patents (per month)

	$\alpha^{R^m}_{t+1}$	$\alpha^{R^m}_{t+2}$	$\alpha^{R^m}_{t+3}$	$\alpha^{3Factor}_{t+1}$	$\alpha^{3Factor}_{t+2}$	$\alpha^{3Factor}_{t+3}$
	(1)	(2)	(3)	(4)	(5)	(6)
Quintile$_1$ (Q_1)	.12	.11	.06	-.03	-.03	-.005
	(.141)	(.142)	(.138)	(.106)	(.108)	(.108)
Quintile$_2$ (Q_2)	.11	.12	.08	-.02	-.02	-.06
	(.151)	(.120)	(.121)	(.07)	(.07)	(.07)
Quintile$_3$ (Q_3)	.20	.16	.13	.16	.15	.17
	(.110)*	(.991)*	(.104)	(.09)*	(.09)*	(.102)
Quintile$_4$ (Q_4)	.28	.27	.23	.14	.14	.13
	(.131)**	(.122)**	(.158)	(.081)*	(.077)*	(.098)
Quintile$_5$ (Q_5)	.30	.25	.24	.15	.12	.14
	(.150)**	(.148)**	(.182)	(.092)**	(.091)**	(.144)
Difference Q_5- Q_1	.17	.14	.18	.18	.15	.14
	(.07)**	(.10)*	(.13)	(.06)***	(.110)*	(.14)