Management Science

Publication details, including instructions for authors and subscription information:
http://pubsonline.informs.org

Arm's Length Financing and Innovation: Evidence from Publicly Traded Firms

Julian Atanassov

MANAGEMENT SCIENCE
Vol. 62, No. 1, January 2016, pp. 128–155
ISSN 0025-1909 (print) | ISSN 1526-5501 (online)

http://dx.doi.org/10.1287/mnsc.2014.2097

Arm's Length Financing and Innovation: Evidence from Publicly Traded Firms

Julian Atanassov
Department of Finance, Lundquist College of Business, University of Oregon, Eugene, Oregon 97403,
julian@unl.edu

Using a large panel of U.S. companies, I document that firms that rely more on arm's length financing, such as public debt and equity, innovate more and have higher-quality innovations than firms that use other sources, such as relationship-based bank financing. I hypothesize that one possible reason for this finding is the greater flexibility and tolerance to experimentation associated with arm's length financing. I find support for this hypothesis by showing that firms with more arm's length financing have greater volatility of innovative output, and are more likely to innovate in new technological areas. Furthermore, focusing only on bank financing, I demonstrate that firms have more novel innovations if they borrow from multiple banks, use predominantly credit lines, and have less intense covenants. I address potential endogeneity concerns by using instrumental variable analysis, and by showing that innovation increases significantly after new public debt offerings and seasoned equity offerings, but does not change after new bank loans.

Keywords: innovation; productivity; patents; patent citations; growth; capital structure; arm's length; public debt; banks; firm value
History: Received October 17, 2013; accepted June 24, 2014, by Gustavo Manso, finance. Published online in *Articles in Advance* April 17, 2015.

1. Introduction

Recent research in finance and economics documents a positive relation between financial development and economic growth (e.g., Levine and Zervos 1998, Bekaert et al. 2005). Less well established are the reasons for this relation and the direction of causality. This paper explores the gap in the literature by investigating the possible microlevel channels. One important channel through which financial development can affect economic growth is through technological innovation.[1] Financial markets can affect innovation in at least two ways—by relieving financial constraints, and by shaping the incentives of firms to pursue novel rather than routine projects.

The extant literature has already documented that financial market development relaxes financial constraints and makes it easier for firms to fund investments, including innovative projects (Brown et al. 2012, 2013; Cornaggia et al. 2015). This paper focuses on the second possibility and argues that different types of financial arrangements can affect the incentives of firms to innovate, even when financing is readily available. It empirically investigates two opposing theoretical views. On the one hand, Rajan and Zingales (2003) suggest that arm's length financing, such as public debt and equity, is more conducive to creating novel innovations, whereas relationship-based bank financing may be better suited to funding less innovative projects or incremental innovations. On the other hand, Holmstrom (1989) argues that arm's length capital markets hinder innovation because they pressure management to focus on short-term routine projects at the expense of longer-term innovative projects.

The existing literature has focused predominantly on the availability of finance, or the simple choice between equity and debt (Titman and Wessels 1988, Brown et al. 2013, Cornaggia et al. 2015). There is little evidence, however, about what types of debt financing, if any, are more conducive to innovation. Many of the previous studies also focus mainly on the input side of innovation (i.e., research and development (R&D) expenses), and do not relate the choice of financing to innovative output. Griliches (1990) and Hall et al. (2001, 2005), however, argue that most of the value and growth creation come from a small number of radical innovations. More recent studies (e.g., Acharya and Subramanian 2009, Hsu et al. 2014) have looked at the determinants of innovative output, but none of them examines the choice between arm's length and relationship-based bank financing.

I address this gap in the literature by investigating whether the innovative activity of publicly

[1] Solow (1957) and Scherer (1984), among many others, have argued and documented that technological innovation is the primary determinant of economic growth.

traded firms is related to the source of their external financing. Using a panel of 12,271 U.S. firms from 1974 to 2000[2] and patents and patent citations to measure the quantity and quality of innovation, I find that firms with a greater proportion of arm's length financing, such as public debt and equity, have more patents and citations per patent. The magnitude of the estimates is economically large. Firms that have a proportion of public debt that is one standard deviation above the industry mean have 7% more citations per patent than the average firm in the industry. Even the mere access to public debt markets (i.e., using an indicator for outstanding public debt) is strongly and positively related to the number of citations per patent. Finally, I find that firms with a proportion of equity that is a standard deviation higher than the industry mean have 20% more citations per patent than the average firm in the industry. The findings show that, somewhat contrary to the results in the previous literature, debt can play a positive role in firm innovation if it is in the form of arm's length public debt.[3]

Next, I explore the mechanism behind these findings and hypothesize that arm's length financing allows greater flexibility and tolerance to experimentation with novel ideas. According to Manso (2011), greater tolerance to experimentation is key to innovation. I provide two major tests for this hypothesis. First, I predict that firms that have more arm's length financing will experience more volatile innovative output and will create more innovations in new technological fields. Consistent with this prediction, I find that firms that have public debt financing and that have a greater proportion of equity financing in their capital structure have more volatile patents and citations per patent. Such firms also have a higher score on two indices of originality and generality, indicating that those firms have more patents that cite and are cited by patents from a wider variety of technological fields than firms that rely more on other types of financing.

As a second test of whether flexibility of financing can influence innovation, I focus only on bank financing, and I investigate in greater detail the association of different types of banking relationships and innovation. I first argue that borrowing from multiple banks is more of an arm's length relationship than borrowing from a single bank. It would be easier for a single bank to shut down or refuse to finance novel projects that it does not understand, whereas if firms borrow from multiple banks, there is a greater probability that at least one bank will fund the project (Rajan and Zingales 2003). Using bank loan data from DealScan, I show strong support for this hypothesis. I find that if a firm borrows from multiple banks, it has more citations per patent.

I also test whether bank loan types or banking relationship that allow greater flexibility to experiment are associated with more novel patents. Following Sufi (2009), I argue that credit lines are more flexible than term loans. I also argue that firms that have less stringent covenants have more flexibility and tolerance to experimentation. Consistent with this hypothesis, I find that firms with credit lines are more innovative, whereas firms with term loans are less innovative than otherwise similar firms. I also find that firms with more intense covenants (Bradley and Roberts 2004), and firms that are more likely to violate their financial covenant agreements (Nini and Smith 2012) create less citations per patent. These results also support the findings of Gu et al. (2014) and Tian and Wang (2014).

I conduct several tests to control for potential endogeneity. Endogeneity can stem from simultaneity—innovative firms are more likely to use arm's length financing because, for example, arm's length investors prefer to invest in firms with novel and potentially riskier projects. I provide evidence that the direction of causality can go from the source of financing to innovation by employing different tests. First, I use an instrumental variables approach. The instruments are variables that influence the supply of financing, but do not affect innovative activity directly. I use two instruments suggested by Faulkender and Petersen (2006), and used by Aghion et al. (2013), to measure visibility and familiarity, and thus the level of informational asymmetry: an indicator for whether the firm belongs to the S&P 500 (*S&P* 500), and the percentage of firms in the industry of a given firm in a given year that have public debt ($\text{Log}(1 + \%\textit{Public})$).[4] The results are still statistically significant and similar in magnitude to the main results, mitigating endogeneity concerns and suggesting a causal influence of arm's length financing on innovation.

I further explore the causal link by examining what happens to innovation after a change in the source of financing. I find strong evidence of an increase in innovative activity between two and four years after a first-time issue of public debt, or after an issue of seasoned equity (SEO).[5] In contrast, I find no evidence

[2] The sample period is determined by the availability of patent data from the National Bureau of Economic Research (NBER) patent data set. Even though the data are available until 2006, I use 2000 as the cutoff year, because the truncation problem of patent citations described in §3 becomes particularly severe in later years.

[3] For robustness, I use several alternative definitions of the main explanatory and dependent variables and find similar results.

[4] The instruments are explained and motivated in greater detail in §6.

[5] In addition to providing a causal link, this test also alleviates the concern that the variable measuring the proportion of equity that I use in the main analysis may also include retained earnings or private equity.

that a similar infusion of funds in the form of bank loans is followed by an increase in innovative activity.

I show next that the relation between the source of financing and innovation is stronger for firms and industries where patenting is more important. In particular, the magnitude of results is significantly larger for firms operating in drugs and medical instrumentation, chemicals, computers and communications, and electrical industry sectors. For firms that have patents, I show that arm's length financing leads to more radical rather than incremental patents. Finally, I provide evidence that novel innovations are important for firm value. Specifically, I find that two years after a patent application, firms with more heavily cited patents experience a larger increase in their market value. These results are broadly in line with the "patent market premium" reported in Hall et al. (2005), and suggest a possible channel through which arm's length financing can influence firm value—through the increase of high-quality innovations.

This paper is organized as follows. Section 2 presents the theoretical motivation. Section 3 provides a description of the data sources and construction of the sample, the variables used in the empirical analysis, and describes the empirical methodology. Sections 4–7 present the empirical results. Section 8 concludes.

2. Theoretical Motivation

Why does the choice between arm's length and bank financing influence the innovative output of the firm? Rajan and Zingales (2003) argue that with arm's length financing there is more public information, and it allows investors from many different backgrounds to evaluate independently the portfolio of innovative projects of the firm. Therefore, the firm can appeal to a wide range of investors and persuade at least some of them that the new technology will be successful. Allen and Gale (1999) argue that novel projects are more likely to obtain financing if there is a diversity of opinion among investors. Therefore, if the firm's projects are fairly novel, approaching investors with sufficiently diverse views could improve the odds of receiving financing for its projects.

In relationship-based bank financing there is little public information and there are a small number of well-informed lenders that acquire significant private information about the firm. The advantage of bank financing is that it reduces informational asymmetries (Diamond 1984, Hadlock and James 2002), allows for closer monitoring of the firm's managers, and reduces the likelihood of financing bad projects. The disadvantage is that financing is often provided in tranches, which allows the bank to constantly monitor the development of projects. Because novel projects may take longer to become successful, and may need greater tolerance to experimentation and failure (Manso 2011, Azoulay et al. 2011), banks may be ill suited to finance novel innovations. The decision to provide and sustain financing depends on the lender's ability to value the firm's projects. The lender, represented for instance by a bank loan officer, may have the knowledge to evaluate projects that are in his line of expertise and previous experience, but lack the necessary skills to evaluate novel technologies (Scherer 1984). Moreover, banks are subject to substantial reserve requirements and restrictions in lending (Stulz 2004). This may make them inherently conservative in the choice of the projects they select to fund.

Public debt investors may also be better positioned than banks to benefit from the upside of novel and risky projects because of the warrants and the options to convert to equity that are often attached to public debt. Hence, other things equal, firms that have a higher proportion of public debt financing in their capital structure will create more novel technologies. Finally, publicly traded debt and equity securities also differ from private debt in terms of the feedback they can provide management, especially if these markets are sufficiently liquid. The argument is that, in the process of trading in the secondary market, security prices can aggregate diverse pieces of investor information and ultimately reflect an accurate (investor) assessment of firm value. Such learning may be especially valuable when the investments are of a radical nature and managers and capital providers can improve decisions as a result of input from a wide range of investors (see Baumol 1965, Bond et al. 2012). Having a greater volume and value of public securities outstanding can increase trading volumes, enhance liquidity, and improve the informativeness of the securities. A similar argument is made in Holmstrom and Tirole (1993), where it is suggested that actions such as the issuance of more public securities can enhance market liquidity and induce better decision making.

Following the arguments presented in this section, I present two testable hypotheses. First, firms that have a higher proportion of arm's length financing, such as public debt and equity, in their capital structure will have a greater quantity and higher quality of innovative output. Second, I hypothesize that arm's length financing will allow for greater flexibility and tolerance to experimentation with novel projects. Following this hypothesis, I predict that arm's length financing will be positively related to innovative volatility. I also predict that firms that rely to a greater extent on arm's length financing will influence and be influenced by innovations in a wider spectrum of technological fields than firms that rely on other types of financing. Finally, I predict that among firms that rely only bank financing, those firms that have more arm's length and more flexible banking relationships will have more novel innovations.

3. Data, Variable Construction, and Model Specification

3.1. Measuring Innovation

Because the main hypothesis is about the novelty of the research that is undertaken by publicly traded firms, rather than about the expenses incurred in developing the product, I focus on patents and patent citations to measure innovation. These measures have two important advantages over R&D expenditures used in the extant finance literature. First, patents measure research output. Using R&D expenditures instead of patents is akin to using total expenditures instead of net sales or profits to measure accounting performance. Second, patent citations allow us to measure the novelty of innovations that is not possible when using R&D expenditures. As Griliches (1990) notes, although patents provide an imperfect measure of innovation, there is no other widely accepted method that has been applied empirically to capture technological advances by firms.[6]

The innovation variables are constructed from the NBER patent data set created by Hall et al. (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 (starting in 1974), 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 et al. 1987).

For my analysis, I augment the sample of firms with patents by including all the firms in Compustat that operate in the same four-digit Standard Industrial Classification (SIC) industries as the firms in the patent database, but do not have patents. I take the patent count to be zero for these firms. Including these firms alleviates some of the sample selection concerns because the sampling procedure is independent of whether or not the firms patent (Cameron and Trivedi 1998).[7] I exclude industries such as financial services and utilities that operate under different regulatory rules and have financing arrangements that are unlike those of manufacturing firms (e.g., financial firms such as banks have legal reserve requirements and their financing arrangements include deposits). I restrict the tests to the period before 2000 because information on citations received by patents, a key variable in the analysis, is more reliable over this time period.

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

The second metric measures the importance of each patent by accounting for the number of citations each patent receives in subsequent years. This measure is motivated by the recognition that a simple count of patents to measure the level of innovative activity does not distinguish breakthrough innovations from less significant or incremental technological discoveries. Moreover, the distribution of patent value has been found to be extremely skewed (Pakes and Schankerman 1984, Griliches et al. 1987). Hall et al. (2005), Atanassov (2013), and Seru (2014), among others, have shown that patent citations provide a good measure of innovation value.

Like patents, citations also suffer from a truncation bias because citations arrive over time. Another potential concern about citations is that different industries might have different propensities to cite patents.[8] I correct for these biases by using two methods suggested by Hall et al. (2001)—the "fixed effects" method and the "quasi-structural" method

[6] Using patents has its drawbacks (Griliches 1990). Not all firms and industries patent their innovations because some inventions do not meet the patentability criteria and because the inventor might rely on secrecy or other means to protect its innovation. In addition, patents measure only successful innovations. Following Cockburn and Henderson (1998), I attempt to control for these factors in a variety of ways. In my analysis, I will control for industry specific trends by using industry fixed effects. Furthermore, I also examine the main hypothesis in a subsample of industries selected based on their patenting intensities to address these concerns.

[7] Inclusion of firms with no patents results in a large number of zeros for innovative output in the sample. To alleviate concerns that the presence of many firms without patents can bias the results, I (i) conduct the main analysis in §6.3 on a subsample of highly innovative industries and innovative firms and (ii) employ specifications that control for the presence of many firms with zero patents (Poisson (and zero-inflated Poisson), negative binomial, and Tobit).

[8] 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 that was applied for in 1985 and received 15 citations by 2000 might not be directly comparable to a patent in the pharmaceutical industry that was applied for in 1995 and received 13 citations by 2000.

(explained in detail in Hall et al. 2001). Using these methods, I construct three dependent variables that measure the number of citations per patent for each firm in every year. The variable $CitedPatent^{\text{Time}}$ corrects for year fixed effects, $CitedPatent^{\text{Time-Tech}}$ corrects both for time and technology class fixed effects, and $CitedPatent^{\text{Quasi}}$ uses the quasi-structural method to correct for the truncation bias. Although I primarily report the results with the $CitedPatent^{\text{Time}}$ variable, my findings throughout are statistically and economically similar when I use the other two variables instead.

3.2. Measuring the Type of Financing

Among the key variables of interest in the analysis are the proxies for arm's length financing. The first variable that proxies for arm's length financing is equity. I measure this variable as *Equity*/*Assets*, where *Equity* is the firm's book equity and *Assets* are the total assets of the firm (constructed from Compustat). I also repeat all the analysis replacing book equity by market equity and find qualitatively similar results. The second variable used to proxy for arm's length financing is the amount of the firm's public debt. To collect information on public debt issues, I use SDC Platinum. I merge the public debt issuer's sample (from 1970) with Compustat by matching cusips. Using the information on public debt issue and maturity of the debt, I construct the amount of public debt outstanding for each firm in a given year. I measure this variable as *Public*/*Assets*, where *Public* is the amount of public debt of the firm.

The third proxy measures access to the public market. The expectation is that access may be established in anticipation of innovative activity and future rounds of financing. First, I construct a dummy variable called $Public^s$, which 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. I also follow Faulkender and Petersen (2006) 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, I code the firm as having access to public debt financing. Therefore, I create an indicator variable called $Public^c$, which takes the 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 the sample, $Public^c$ and $Public^s$ observations overlap to the extent of 90.9%.

3.3. Other Financial Variables

The data on sales (*Sales*), industry SIC, R&D expenditures (*RD*), debt (*Debt*), net property plant and equipment (*PPE*), cash (*Cash*), operating profits (*EBIDTA*), market-to-book earnings (*Q*), and retained earnings (*RetEarn*) come from Compustat.

The data used to construct the market and firm stock returns come from the Center for Research in Security Prices (CRSP). I construct this measure based on the years from a firm's IPO as reported in CRSP. All the variables in the analysis are winsorized at the 1st and 99th percentiles to protect the results from the influence of extreme outliers.

3.4. Empirical Specification

I estimate the following equation in most of the empirical analysis:

$$Innovation_{it} = \exp\{\alpha Financing_{it} + \delta Z_{it} + \mu_i \text{ or } \{\mu_j + \mu_s\} + \mu_t\}, \qquad (1)$$

where *Financing* are the arm's length financing variables and Z are firm characteristics that affect a firm's R&D output. Following the literature (e.g., Aghion et al. 2005), the matrix of control variables Z includes industry concentration measured by the sales Herfindahl index (*HI*) and the squared term of the Herfindahl index to capture a possible nonlinear relationship between competition and innovation. The industry sales Herfindahl index is constructed at the four-digit SIC level and, for robustness, at the Fama and French (1997) 48 industry level. The matrix Z also includes firm age (*Age*), where the age is measured by years because the IPO to control for life-cycle effects. In the estimation, I follow Hall and Ziedonis (2001) and also control for size, measured by sales (Log(*Sales*)) and investments in innovative projects measured by R&D expenditures (Log(*RD*)).[9] Finally, I also include as control variables market-to-book ratio of the firm (*Q*) to capture the investment opportunities faced by the firm and controls for financial constraints faced by the firm (profitability of the firm (*EBIDTA*/*Assets*), operating cash (*Cash*/*Assets*), retained earnings (*RetEarn*/*Assets*), and asset tangibility (*Tangible*)). Finally, μ_i, μ_j, μ_s, and μ_t capture firm, industry, state, and time fixed effects, respectively.

4. Empirical Results

4.1. Descriptive Statistics: Distribution of Patents and Citations per Patent

Panel A in Table 1 reports the distribution of patent grants from 1974 to 2000. As the table shows, the distribution of patent grants is very left skewed, with the 75th percentile of the distribution at zero. To gain more insight, in panel B of Table 1, I divide the sample into patent classes and report the

[9] Note that the use of Log(*Sales*) and Log(*RD*) as explanatory variables, together with a Poisson specification, is equivalent to scaling the dependent variable by RD^{δ_1} or by $Sales^{\delta_2}$, and this allows us to control for nonlinear differences in size.

Table 1 Patent and Citations per Patents Counts

Panel A: Aggregate distribution of patent counts

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

Panel B: Yearly distribution of patent counts

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

Panel C: Distribution of patent counts by industry

	Number of patents					
Industry name	0	1–2	3–10	11–100	>100	Firm-years
Agriculture	358	4	0	0	0	362
Aircraft	286	86	164	144	54	734
Apparel	1,852	137	47	6	0	2,042
Automobiles and trucks	1,209	189	234	271	103	2,006
Beer and liquor	418	26	18	7	0	469
Business and office supplies	973	171	201	158	2	1,505
Candy and soda	284	36	32	38	0	390
Chemicals	2,390	221	239	428	108	3,386
Communication	2,612	21	10	10	24	2,677
Computers	2,727	295	248	276	94	3,640
Construction and related materials	3,922	538	459	298	24	5,241
Consumer goods	2,924	319	284	304	135	3,966
Defense	126	29	24	15	10	204
Electrical equipment	2,886	206	208	131	24	3,455
Electronic equipment	3,368	639	515	368	92	4,982
Entertainment	1,198	22	8	3	0	1,231
Fabricated products	399	96	43	19	0	557
Food products	1,705	187	190	112	0	2,194
Healthcare	1,498	19	7	0	0	1,524
Machinery	2,293	551	687	473	62	4,066

Table 1 (Continued)

Panel C: Distribution of patent counts by industry

Industry name	Number of patents: 0	1–2	3–10	11–100	> 100	Firm-years
Measurement equipment	2,974	276	239	132	11	3,632
Medical equipment	2,911	237	272	135	36	3,591
Miscellaneous	3,689	279	153	58	3	4,182
Nonmetallic and industrial mining	760	28	57	39	0	884
Personal and business services	7,644	156	139	52	4	7,995
Petroleum and natural gas	8,514	138	99	146	65	8,962
Pharmaceutical products	2,690	158	144	308	103	3,403
Precious metals	834	6	2	0	0	842
Printing and publishing	1,416	52	23	0	0	1,491
Recreation	1,125	158	73	71	24	1,451
Restaurants, hotels, and motels	3,304	31	3	0	0	3,338
Retail	6,643	37	23	0	0	6,703
Rubber and plastics	1,035	143	99	27	0	1,304
Shipbuilding and railroad equipment	139	14	24	39	0	216
Shipping containers	489	135	184	71	10	889
Steel	2,433	209	215	131	6	2,994
Textiles	1,152	138	133	17	0	1,440
Tobacco products	580	18	15	0	0	613
Transportation	4,468	11	2	0	0	4,481
Wholesale	6,292	92	43	29	2	6,458
Total	92,520	6,108	5,560	4,316	996	109,500

Panel D: Distribution of citations per patent (whole sample)

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

Panel E: Distribution of citations per patent (patenting firms)

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

Notes. This table reports the summary statistics of the distribution of number of patents granted in the sample. Patent information comes from the NBER patent data set provided by Hall et al. (2001). This information includes the number of patents by each firm and the number of citations received by each patent. I select all public firms from the NBER patent file, which have financial data available in the S&P's Compustat database. I include all the firms in Compustat that operate in the same industries as the firms in the patent database, but do not have patents. Panel A gives information on the distribution of number of patents granted in the sample between 1974 and 2000. Panel B reports the number of firms by number of patents granted for each year during the sample period. Panel C reports the number of patenting firm-years by industry and number of patents granted during the sample period. Panel D gives information on the distribution of citations per patent for each patent granted during the sample period corrected for time truncation. Panel E gives information on the distribution of citations per patent only among patenting firms during the sample period.

number of firms for each patent class each year. Firm-years with zero patents represent roughly 84% of the sample, firm-years with 1 or 2 patents and 3–10 patents about 6% and 5%, respectively, and firm-years with 11–100 patents about 4%. The remaining 1% of the sample comprises firm-years with more than 100 patent applications. These trends are consistent with those reported in Hall et al. (2001).

Panel C of Table 1 shows the distribution of patenting firm-years by industry, excluding financials and utilities. There is a large variation across industries, and a large variation within industries, in that even in the most innovative industries (e.g., chemicals) up to 70% of the firm-years are without patents.

Panels D and E of Table 1 report the distribution of citations per patent in the sample ($CitedPatent^{Time}$). As is indicated, the distribution is left skewed with only about 20% patents reporting more than one cite. This suggests that most of the citations in the sample are received by a relatively small number of highly cited patents. As I will show, these are the more valuable patents.

4.2. Descriptive Statistics: Patents, Citations per Patent, and Firm Characteristics

Table 2 provides preliminary evidence that firms with more arm's length financing tend to be more innovative. In panel A, I present descriptive statistics for firms with one or more patent grants over the sample period compared with firms that did not receive any patents (the median number of patents per firm in the sample is 0). As indicated by the

Table 2 Summary Statistics

Panel A: Firm characteristics and patents

	Patent ≤ Median (= 0)			*Patent* > Median(= 0)			All firms
	Mean (1)	Max (2)	Min (3)	Mean (4)	Max (5)	Min (6)	Mean (7)
Sales ($million)	931	15,610	0.11	2,799	40,993	4.03	1,118
RD ($million)	38	820	0.01	111	1,998	0.12	53
Tangible	0.32	0.92	0.01	0.33	0.87	0.04	0.32
Equity/Assets	0.49	0.88	0.05	0.54	0.91	0.05	0.50
Public/Assets	0.02	0.43	0.00	0.05	0.47	0.00	0.03
$Public^s$	0.12	1	0	0.35	1	0	0.13
HI	0.43	0.94	0.13	0.49	0.95	0.22	0.44
Q	1.60	10.1	0.43	1.86	8.82	0.56	1.80
Observations		92,520			16,980		109,500

Panel B: Firm characteristics and citations per patent for patenting firms

	$CitedPatent^{Time}$ ≤ Median (= 6.6)			$CitedPatent^{Time}$ > Median (= 6.6)			All firms
	Mean (1)	Max (2)	Min (3)	Mean (4)	Max (5)	Min (6)	Mean (7)
Sales ($million)	2,594	38,236	4.03	2,994	40,993	2.53	2,799
RD ($million)	107	2,018	0.12	121	2,098	0.62	111
Tangible	0.32	0.78	0.04	0.33	0.87	0.05	0.32
Equity/Assets	0.51	0.89	0.05	0.58	0.93	0.06	0.54
Public/Assets	0.05	0.42	0.00	0.07	0.47	0.00	0.05
$Public^s$	0.33	1	0	0.37	1	0	0.35
HI	0.49	0.94	0.22	0.50	0.94	0.22	0.49
Q	1.49	6.6	0.56	1.95	10.1	0.59	1.86
Observations		7,524			9,456		16,980

Panel C: Correlation matrix of main explanatory variables

	Log(*Sales*) (1)	Log(*RD*) (2)	*Tangible* (3)	*Equity/Assets* (4)	*Public/Assets* (5)	*HI* (6)	*Q* (7)	*EBIDTA/Assets* (8)
Log(*Sales*)	1.00							
Log(*RD*)	0.29	1.00						
Tangible	0.13	0.03	1.00					
Equity/Assets	−0.01	−0.04	−0.07	1.00				
Public/Assets	0.06	0.05	0.05	−0.04	1.00			
HI	−0.05	−0.03	0.02	−0.03	0.02	1.00		
Q	−0.03	−0.001	−0.10	−0.05	−0.03	−0.06	1.00	
EBIDTA/Assets	0.03	0.02	0.05	0.32	0.02	0.03	−0.20	1.00

Notes. This table reports the summary statistics of the key variables used in the analysis. Patent information comes from the NBER patent data set provided by Hall et al. (2001). This information includes the number of patents by each firm and the number of citations received by each patent. I select all public firms from the NBER patent file, which have financial data available in the S&P's Compustat database. I include all the firms in Compustat which operate in the same industries as the firms in the patent database, but do not have patents. Data on sales, R&D expenditures, the Herfindahl index, leverage, and net property plant and equipment come from Compustat. I exclude firms in financial sector and utilities. I collect data on public debt issues from SDC Platinum. Panel A corresponds to firm-years for firms with above and below median *Patent* in the sample. Among the firms that patent, panel B corresponds to firm-years for firms with above and below median citations per patent corrected for time truncation ($CitedPatent^{Time}$) in the sample period. All differences between column (1) and column (4) in panels A and B are statistically significant at the 1% level. Panel C presents the correlation between the key variables used in the analysis. Data are for the period from 1974 to 2000.

mean values reported in the table, firms with patents are larger (sales of $2.7 billion vs. $0.9 billion per year), have higher R&D expenditure ($111 million vs. $38 million per year), have a higher market-to-book ratio (1.86 vs. 1.60), and belong to more concentrated industries (Herfindahl index of 0.49 vs. 0.43) than firms without patents. Firms with patents over the sample period have a higher mean public debt to asset ratio (0.05 vs. 0.02 per year) and have a higher mean equity to asset ratio (0.54 vs. 0.49 per year) than firms without patents. Moreover, a larger proportion of firms with patents access the public debt market than firms without patents (0.35 vs. 0.12 per year). The differences in various statistics between the two groups of firms are significant at the 1% level. These univariate comparisons are in line with the hypothesis that firms with patents should have a higher equity to assets ratio and a higher public debt to assets ratio. Interestingly, the differences in the two samples are not on account of differences in R&D intensity (*RD/Sales*), which is approximately the same in both samples.

In panel B of Table 2, I compare, among the firms that have patents in a given year, the characteristics of firms with above and below median number of citations per patent (median is 6.6). Firms with above median citations per patent are, on average, larger, have higher R&D expenditures, have more tangible assets, have a higher market-to-book ratio, have a higher public debt to assets and equity to assets ratio, and have a larger proportion of firms accessing the public debt market. The differences in capital structure are again in line with my expectations.

Finally, in panel C of Table 2, I present the pairwise correlations between the key explanatory variables. As is indicated in the table, there is little evidence of collinearity among the variables. Since these are only summary statistics, for more meaningful comparisons, I next turn to multivariate analysis.

4.3. The Number of Patents and Arm's Length Debt and Equity

In Table 3, I report the first set of regression results. I 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, I estimate the following model using the truncation bias adjusted patent count $Patent^c$ as a dependent variable:

$$\begin{aligned} Patent^c_{it} &= \lambda_{it} \\ &= \exp\{\alpha Financing_{it} + \delta_1 \mathrm{Log}(RD)_{it} \\ &\qquad + \delta_2 \mathrm{Log}(Sales)_{it} + \delta \mathbf{Z}_{it} \\ &\qquad + \mu_i \text{ or } \{\mu_j + \mu_s\} + \mu_t\}. \end{aligned} \tag{2}$$

The explanatory variables I am most interested in are different proxies for arm's length financing and are captured in *Financing*. In columns (1) and (2), I use only *Equity/Assets* to proxy for arm's length financing. In columns (3) and (4), I also include the public debt dummy ($Public^c$ and $Public^s$, respectively), whereas in columns (5)–(8), I use the proportion of public debt (*Public/Assets*) in addition to the public debt dummy ($Public^s$). In all regressions, I ensure that the inferences are not affected by the noninteger values by rounding each nonzero observation to its nearest integer. All regressions in this table are estimated with time, state, and industry fixed effects and the reported standard errors are heteroskedastic consistent to control for overdispersion.

The results demonstrate that arm's length financing is positively associated with innovation. Specifically, I find that the estimated coefficient on *Equity/Assets* is positive and significant at the 1% level in columns (1)–(8). Similarly, the estimated coefficients on the public debt dummy ($Public^c$ or $Public^s$) in columns (3) and (4) and on the proportion of public debt (*Public/Assets*) in columns (5)–(8) are positive and significant at the 1% level. These findings are different from the studies that find a positive association between equity and R&D expenditure (e.g., Titman and Wessels 1988, Hall 1990) because I find a positive relationship between innovative *output* of the firm and *all* the arm's length financing variables (*Equity/Assets*, *Public/Assets* and *Public*), while controlling for its investments in R&D.

Note that in column (6) of Table 3, I conduct the estimation with firm fixed effects and find qualitatively similar results. Using firm fixed effects alleviates concerns that unobservable firm specific differences might be affecting the estimates. This indicates that the effect of arm's length financing on innovation is evident in a time-series form as well. Intuitively, on average an increase in the equity or public debt in a firm's capital structure is associated with the firm creating more innovations. The results are robust to an alternative model specification (negative binomial) that accounts for the possible overdispersion of the count dependent variable (column (7)). Finally, in column (8), I restrict attention only to innovative industries and find qualitatively similar though stronger results (e.g., coefficient estimate on *Equity/Assets* in column (5) with entire sample is 0.398 vs. 0.593 in column (8)).[10] This suggests that the relationship might be more important for industries where patenting is more important. I return to this issue in §6.3.

The results in Table 3 are economically significant. Specifically, in column (5) of Table 3, controlling for other factors at their mean levels, a one-standard-deviation increase in *Equity/Assets* ($= 0.2$) is associated with an 8.4% increase ($\exp\{0.398 * 0.20\} - 1$) in the number of patents produced by the firm as compared to the mean patenting firm in its industry (mean number of patent counts in the whole sample is 4.65). Similarly, a one-standard-deviation increase in *Public/Assets* ($= 0.10$) is associated with a 4.4% increase ($\exp\{0.425 * 0.10\} - 1$) in patents produced by the firm as compared to the mean patenting firm in its industry. Moreover, access to public debt markets is associated with 6% more patents as compared to firms that do not have access to the public debt market. Although the change in the absolute number of patents may seem small, in §7 I will show that even small changes in the number of patents

[10] I define an industry as being innovative if more than 20% of the firms are granted a patent in a given year. I take all the industries in Table 1, panel C and apply this criteria. I also try alternative cutoffs of 15%–40% and the results are unaffected.

Table 3 Patents and Financing Arrangements

	Model specification							
	Poisson (1)	Poisson (2)	Poisson (3)	Poisson (4)	Poisson (5)	Poisson (6)	NegBin (7)	Poisson (8)
Log(*Sales*)	0.597 (0.002)***	0.561 (0.003)***	0.540 (0.003)***	0.418 (0.003)***	0.563 (0.003)***	0.770 (0.006)***	0.277 (0.009)***	0.562 (0.003)***
Log(*RD*)	0.394 (0.002)***	0.407 (0.002)***	0.406 (0.002)***	0.408 (0.002)***	0.409 (0.002)***	0.140 (0.004)***	0.061 (0.006)***	0.410 (0.002)***
HI	2.197 (0.093)***	3.024 (0.093)***	2.912 (0.093)***	1.634 (0.094)***	2.867 (0.093)***	0.766 (0.100)***	0.766 (0.310)**	2.862 (0.093)***
HI^2	−2.553 (0.072)***	−3.406 (0.072)***	−3.331 (0.072)***	−2.410 (0.073)***	−3.254 (0.072)***	−1.881 (0.078)***	−0.859 (0.264)***	−3.250 (0.072)***
Equity/Assets	0.184 (0.014)***	0.227 (0.014)***	0.211 (0.014)***	0.243 (0.015)***	0.398 (0.014)***	0.305 (0.019)***	0.292 (0.023)***	0.593 (0.013)***
$Public^c$			0.062 (0.005)***					
$Public^s$				0.066 (0.004)***	0.058 (0.009)***	0.057 (0.021)***	0.053 (0.018)***	0.048 (0.008)***
Public/Assets					0.425 (0.022)***	0.733 (0.033)***	0.344 (0.040)***	0.640 (0.033)***
Q		0.067 (0.002)***	0.063 (0.002)***	0.051 (0.002)***	0.070 (0.002)***	0.044 (0.002)***	0.034 (0.008)***	0.053 (0.021)***
Tangible		1.060 (0.017)***	0.994 (0.017)***	0.990 (0.017)***	1.071 (0.017)***	0.374 (0.024)***	0.253 (0.073)***	1.082 (0.016)***
EBIDTA/Assets		0.823 (0.026)***	0.786 (0.026)***	0.768 (0.026)***	0.754 (0.026)***	1.291 (0.033)***	0.848 (0.080)***	0.712 (0.026)***
Age		0.049 (0.002)***	0.051 (0.002)***	0.050 (0.003)***	0.045 (0.002)***	0.047 (0.002)***	0.044 (0.003)***	0.048 (0.002)***
Cash/Assets		−0.21 (0.26)	−0.20 (0.29)	−0.19 (0.31)	−0.29 (0.36)	−0.30 (0.33)	−0.28 (0.80)	−0.21 (0.29)
RetEarn/Assets		−0.03 (0.01)*	−0.02 (0.03)	−0.03 (0.03)	−0.03 (0.02)	−0.03 (0.03)	−0.02 (0.02)	−0.05 (0.04)
Observations	109,300	109,300	109,300	109,300	109,300	57,000	57,000	13,020
Log-likelihood	−33,644.7	−33,841.0	−33,843.4	−33,851.6	−33,855.1	−19,840.3	−19,680.8	−17,780.1
p-value, χ^2 test	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes			Yes
State fixed effects	Yes	Yes	Yes	Yes	Yes			Yes
Firm fixed effects						Yes	Yes	

Notes. This table reports the results relating patents produced in a firm to the type of its financing. Specifically, I estimate Poisson models in all the columns but one (column (7)), where a negative binomial model is employed. All variable definitions are provided in the appendix. The dependent variable is $Patent^c$ with each nonzero observation rounded to its nearest integer. In column (8), I only restrict attention to innovative industries where I take all the industries where more than 20% of the firms are granted a patent in a given year to be innovative. All regressions are estimated with time, state, and industry fixed effects, and the standard errors reported in the parentheses are heteroskedastic consistent to account for overdispersion in Poisson models and are adjusted for clustering at the industry (columns (1)–(5) and (8)) or the firm (columns (6) and (7)) level. Data are for the period from 1974 to 2000.

***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

(above industry means) can have significant value implications for a firm.

In all the regression models, the coefficients on *HI* are positive and the coefficients on HI^2 are negative. This finding has been interpreted as evidence that, although some monopoly power encourages innovation, too much does not (Aghion et al. 2005). Consistent with the findings in the literature (e.g., Griliches 1990), the estimates indicate that firms with more R&D expenditures create more patents. The elasticity of innovations to R&D expenditure is 0.40 in column (5), which is similar to previous findings (e.g., Hall and Ziedonis 2001, Lerner 2006). This coefficient implies that a doubling of R&D expenditures is associated with a 40% increase in the number of patents created by the firm. The coefficient on Log(*Sales*) is positive, indicating that larger firms develop more innovations in the sample. More mature firms (*Age*) have more patents, though the economic significance of the estimate is small. The results also indicate that firms with higher market to book, more tangible assets, and higher profitability create more innovations.

I now turn to testing the hypothesis using citations per patent to proxy for the quality of research output of the firm. As mentioned earlier, because a lot of patents are incremental in nature, accounting for the citations a patent receives makes citations per patent a better proxy of the novelty of innovations than the simple count of patents. Consequently, I expect the

Table 4 Citations per Patent and Financing Arrangements

	Model specification						
	$CitedPatent^{Time}$						$CitedPatent^{Time-Tech}$
	Poisson (1)	Poisson (2)	Poisson (3)	Poisson (4)	Poisson (5)	Poisson (6)	Poisson (7)
Log(*Sales*)	0.208	0.203	0.199	0.192	0.190	0.179	0.167
	(0.008)***	(0.008)***	(0.008)***	(0.008)***	(0.008)***	(0.007)***	(0.005)***
Log(*RD*)	0.267	0.267	0.253	0.266	0.262	0.260	0.161
	(0.009)***	(0.009)***	(0.009)***	(0.009)***	(0.008)***	(0.008)***	(.003)***
HI	2.381	2.371	2.369	2.366	2.365	2.011	0.460
	(0.662)***	(0.663)***	(0.661)***	(0.661)***	(0.660)***	(0.617)***	(0.201)**
HI^2	−1.549	−1.546	−1.510	−1.546	−1.542	−1.501	−0.121
	(0.562)***	(0.564)***	(0.562)***	(0.562)***	(0.556)***	(0.315)***	(0.070)*
Equity/Assets	0.801	0.805	0.804	0.801	0.809	0.952	0.748
	(0.043)***	(0.041)***	(0.045)***	(0.044)***	(0.044)***	(0.071)***	(0.022)***
$Public^c$		0.081					
		(0.022)***					
$Public^s$			0.079	0.068	0.069	0.066	0.063
			(0.020)***	(0.020)***	(0.019)***	(0.014)***	(0.024)***
Public/Assets				0.537	0.662	0.881	0.590
				(0.008)***	(0.007)***	(0.022)***	(0.010)***
Q	0.015	0.017	0.016	0.015	0.012	0.011	0.027
	(0.002)***	(0.003)***	(0.003)***	(0.002)***	(0.004)***	(0.003)***	(0.001)***
Tangible	0.740	0.713	0.714	0.747	0.685	0.688	0.384
	(0.085)***	(0.026)***	(0.026)***	(0.025)***	(0.029)***	(0.024)***	(.027)***
EBIDTA/Assets	0.054	0.054	0.053	0.053	0.050	0.051	0.044
	(0.023)**	(0.025)**	(0.024)**	(0.024)**	(0.025)**	(0.022)***	(0.014)***
Age	0.041	0.043	0.049	0.043	0.049	0.041	0.036
	(0.003)***	(0.002)***	(0.002)***	(0.003)***	(0.004)***	(0.003)***	(0.005)***
Cash/Assets	−0.14	−0.13	−0.13	−0.15	−0.16	−0.12	−0.16
	(0.11)	(0.12)	(0.11)	(0.10)	(0.15)	(0.07)*	(0.08)**
RetEarn/Assets	−0.07	−0.08	−0.07	−0.07	−0.09	−0.08	−0.06
	(0.06)	(0.07)	(0.09)	(0.07)	(0.08)	(0.05)*	(0.06)
Observations	109,300	109,300	109,300	109,300	109,300	13,020	109,300
Log-likelihood	−20,330.31	−20,342.68	−20,359.38	−20,363.30	−20,390.81	−14,789.38	−16,585.8
p-value, χ^2 test	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes		Yes
State fixed effects	Yes	Yes	Yes	Yes	Yes		Yes
Firm fixed effects						Yes	

Note. This table reports the results relating cited patents produced in a firm to the type of its financing. Specifically, I estimate Poisson model in all the columns with the dependent variable as $CitedPatent^{Time}$ in columns (1)–(6) and $CitedPatent^{Time-Tech}$ in column (7). I round each nonzero observation to its nearest integer for the dependent variables that I employ. In column (6), I only restrict attention to innovative industries where I take all the industries where more than 20% of the firms are granted a patent in a given year to be innovative (a list of industries is provided in panel C of Table 1). All variable definitions are provided in the appendix. All regressions are estimated with time, state, and industry fixed effects, and the standard errors reported in the parentheses are heteroskedastic consistent to account for overdispersion in Poisson models and are adjusted for clustering at the industry (columns (1)–(5) and (7)) or the firm (column (6)) level. Data are for the period from 1974 to 2000.

***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

relationship between citations per patent and arm's length financing to be stronger than the relationship between arm's length financing and the simple patent count.

4.4. Citations per Patent and Arm's Length Debt and Equity

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

I start the analysis with Table 4, where I use a fixed-effects panel regression to study the relationship between $CitedPatent^{\mathrm{Time}}$ and financing arrangements. Specifically, I estimate,

$$
\begin{aligned}
&CitedPatent_{it}^{\mathrm{Time}}\\
&\quad = \lambda_{it} = \exp\{\alpha_0 + \alpha Financing_{it} + \delta_1 \mathrm{Log}(RD)_{it}\\
&\qquad + \delta_2 \mathrm{Log}(Sales)_{it} + \delta \mathbf{Z}_{it}\\
&\qquad + \mu_i \text{ or } \{\mu_j + \mu_s\} + \mu_t\}. \qquad (3)
\end{aligned}
$$

The control variables (Z) are the same as the ones used in Table 3. I find that the *Financing* variables are statistically significant and positively associated with more novel innovations in columns (1)–(5). In column (6) of the table, to examine whether the main results are stronger for industries where patenting might be considered more important, I estimate the regression only for innovative industries. I also include firm fixed effects in this specification. I find qualitatively similar but stronger results (e.g., coefficient estimate on *Equity*/*Assets* in column (4) with the entire sample is 0.801 vs. 0.952 in column (6)). I discuss this issue further when I conduct a more detailed industry by industry analysis in the subsequent subsection. For robustness, I use $CitedPatent^{\mathrm{Time-Tech}}$ as a dependent variable instead of $CitedPatent^{\mathrm{Time}}$ in column (7) to control for any cohort effects within a technology class. The results from this model are statistically and economically significant and similar to the findings from the other models in Table 4. I also employ $CitedPatents^{\mathrm{Quasi}}$ as an alternative measure of the quality of innovations and other specifications that address the concern that the sample has many firms with zero citations per patent (e.g., zero-inflated Poisson specification) and find similar results (unreported). For brevity, most of the remaining results in the paper are presented using citations per patent to measure the novelty of innovations.

Consistent with my expectations, the relationship between citations per patent and arm's length financing is found to be stronger than the relationship between arm's length financing and a simple patent count. This can be best seen if one notes that estimated coefficients of the variables that proxy for arm's length financing are larger in model (5) of Table 4 than in model (5) of Table 3. Specifically, controlling for other factors at their mean levels, a one-standard-deviation increase in *Equity*/*Assets* is associated with 19.5% more ($\exp\{0.809 * 0.2\} - 1$) citations per patent by the firm as compared to the mean patenting firm in its industry (mean citations per patent in the whole sample is 0.7). Similarly, a one-standard-deviation increase in *Public*/*Assets* is accompanied by 6.8% more ($\exp\{0.66 * 0.10\} - 1$) citations per patent by the firm as compared to the mean patenting firm in its industry. I also find that access to public debt markets is associated with 7% more citations per patent. As mentioned earlier, I will show in §7 that small changes in citations per patent (above industry means) can have significant value implications for the firm.

5. Arm's Length Financing, Tolerance to Experimentation, and Innovation

This section investigates the hypothesis that arm's length financing is associated with greater flexibility and tolerance to experimentation. According to Manso (2011), greater tolerance to experimentation and failure is key to innovation. I conduct several tests that are grouped in two subsections. In the first subsection, I hypothesize that, if arm's length financing exhibits greater tolerance to experimentation, I would expect that it is positively related to innovative volatility. I would also expect that firms with arm's length financing will be more likely to create innovations in new technology areas. In the second subsection, I focus only on banking relationships and test the hypothesis that firms with banking relationships that are more arm's length, and that allow greater flexibility, will have a greater number of high-quality innovations, measured by citations per patent.

5.1. Arm's Length Financing, Innovation Volatility, and Patent Originality and Generality

I explore three measures that allow us to assess if arm's length financing provides firms with more flexibility to experiment with new technologies. First, I test whether arm's length financing is positively associated with more volatile innovative output. The idea is that more volatile output would be an indication of greater experimentation with new technologies. To measure the volatility of innovative output, I calculate the standard deviation of patent count over the subsequent five years. Specifically, patent volatility equals

$$PatentVolatility = \sqrt{\frac{\sum_{i=1}^{5}(P_{t+i} - \bar{P})^2}{4}}, \qquad (4)$$

where P_{t+i} is the number of patents applied for in year $t+i$ and $\bar{P}$ is the average number of patents over the same five-year period from $t+1$ to $t+5$. Alternatively, I measure the volatility of citations per patent. I calculate the standard deviation of citations per patent, which equals

$$CitedPatentVolatility = \sqrt{\frac{\sum_{i=1}^{5}(CP_{t+i} - \overline{CP})^2}{4}}, \qquad (5)$$

where CP_{t+i} is the number of citations per patent for patents applied in year $t+i$ and $\overline{CP}$ is the average number of citations per patent over the same five-year period from $t+1$ to $t+5$.

Table 5 Arm's Length Financing, Patent and Citation Volatility, Originality, and Generality

	PatentVolatility	*CitedPatentVolatility*	*Originality*	*Generality*
	(1)	(2)	(3)	(4)
Public[c]	2.187***	0.063***	0.020***	0.027***
	(0.415)	(0.013)	(0.005)	(0.005)
Public/Assets	−0.007	0.0003	0.0002	0.0001
	(0.020)	(0.0007)	(0.0002)	(0.0002)
Equity/Assets	0.594***	0.080***	0.036***	0.039***
	(0.201)	(0.006)	(0.002)	(0.002)
Log(*Sales*)	1.482***	0.027***	0.025***	0.027***
	(0.023)	(0.0007)	(0.0003)	(0.0003)
EBIDTA/Assets	0.165	0.004	−0.0006	−0.0008
	(0.053)***	(0.002)***	(0.0003)*	(0.0003)**
Tangible	1.154***	−0.015	0.010***	0.010***
	(0.297)	(0.010)	(0.003)	(0.003)
Age	−2.13e−08	−2.26e−10	−3.19e−10	−4.11e−10
	(3.42e−08)	(1.10e−09)	(4.15e−10)	(4.31e−10)
Cash/Assets	3.158***	0.185***	0.067***	0.057***
	(0.400)	(0.013)	(0.004)	(0.004)
Q	0.002*	0.00004	0.00003*	0.00004***
	(0.001)	(0.00004)	(1.00e−05)	(1.00e−05)
Observations	108,939	108,939	109,158	109,158
R^2	0.092	0.127	0.236	0.252
Time fixed effects	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes
State fixed effects	Yes	Yes	Yes	Yes

Notes. This table reports the results relating the type of financing to the volatility of innovative output, and to patent originality and generality. Specifically, I estimate OLS in columns (1)–(4), where the dependent variable is *PatentVolatility* in column (1), *CitedPatentVolatility* in column (2), *Originality* in column (3), and *Generality* in column (4). Controls include Log(*Sales*), *RD/Assets* (unreported), *Cash/Assets*, *Age*, *EBIDTA/Assets*, *Tangible*, *HI* (unreported), and HI^2 (unreported). All variable definitions are provided in the appendix. All regressions are estimated with time, state, and industry fixed effects, and the standard errors reported in the parentheses are clustered at the industry level. Data are for the period from 1976 to 2000.

***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

The results are presented in Table 5, columns (1) and (2). They largely support my hypothesis. More specifically, the *Public* debt indicator variable and the proportion of equity to assets are positively related to the volatility of both patents and citations per patent. The proportion of public debt to assets has no significant relation to innovation volatility.

Second, I also show that arm's length financing is positively associated with measures of originality and generality of patents. The goal here is to assess if arm's length financing is associated with greater flexibility and tolerance to experimentation. If this is the case, I would expect firms to produce patents that are in new areas of research and also influence new areas of research. The originality measure, suggested by Hall et al. (2001) will be high if a patent cites previous patents that belong to a wide range of technological fields, whereas if a patent cites other patents that are mostly concentrated in a few technological fields, it will be low (close to zero). More specifically, originality is equal to

$$Originality = 1 - \sum_{i=1}^{n_i} s_{ij}^2, \tag{6}$$

where s_{ij} denotes the percentage of citations made by patent i that belong to patent class j, out of n_i patent classes (note that the sum is the Herfindahl concentration index).

Generality is defined the same way, except that r refers to the number of citations received:

$$Generality = 1 - \sum_{i=1}^{n_i} r_{ij}^2. \tag{7}$$

Thus, if a patent is cited by subsequent patents that belong to a narrow set of technologies, the generality score will be low, whereas a patent that is cited by subsequent patents in a wide range of fields would render a high score. Therefore, a high generality score suggests that the patent presumably had a widespread impact.

The results presented in columns (3) and (4) of Table 5 largely support my prediction. More specifically, the public debt dummy and the proportion of equity to total assets are positively and significantly related to both *Originality* and *Generality*, whereas the proportion of public debt to assets has no significant relation to these measures.

5.2. Banking Relationships, Flexibility, and Innovation

In this subsection, I examine whether, among firms with no public debt access in my sample, the types of lending relationships that are more arm's length, or that provide more flexibility and tolerance to experimentation are positively related to innovation. First, I investigate whether firms with multiple banks innovate more than those with a single-bank relationship. Having multiple banks resembles arm's length financing more than borrowing from a single bank, because for a given size of the initial investment, the exposure of each bank is small. As a result, if one bank decides not to finance a novel project that it does not understand, because of the diversity of opinion, other banks may step in and provide financing. Moreover, it might be more difficult for multiple banks to act in a coordinated manner when they need to terminate the project that has already been financed. This hypothesis also finds support in the previous theoretical and empirical literature (e.g., Rajan 1992, Houston and James 1996). Therefore, empirically, I expect a positive association between borrowing from multiple banks and the number of citation weighted patents.

To test this prediction, I start with firms that *do not* have public debt. For these firms, I create a variable called *Multiple*, which takes the value of 1 if the firm borrows from multiple banks in a given year and 0 otherwise. To construct this variable, I 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 (see Dahiya et al. 2003 and Chava and Roberts 2008 for more detailed discussions on the DealScan database). I match the data from DealScan to financial data from Compustat using the link file provided by Chava and Roberts (2008). In terms of sample size, there are two possible caveats. First, because the coverage of firms in DealScan is relatively limited, the number of observations used in the tests that involve the variables related to *Multiple* is much smaller than in other tests. Second, the detailed coverage of loan types, loan purpose, and covenants in DealScan begins from 1996, and therefore the tests are run only for the 1996–2006 period. There are 8,475 firms and 29,920 firm-years. I find that, compared with firms that borrow from a single bank, firms that borrow from multiple banks are, on average, larger in terms of sales ($4,867 million vs. $2,453 million), more profitable in terms of *EBIDTA/Assets* (0.12 vs. 0.06) and have lower cash to assets ratio (0.06 vs. 0.10).

I use a fixed-effects 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 column (1) of Table 6, I estimate Equation (3) with *Financing* proxied by *Multiple*. I control for the size of investments for innovative projects by including *R&D/Assets*. I also control for the size of the loans a firm obtains by including the total dollar amount of all loans for each firm in each year.

As is reported in the table, *Multiple* is statistically significant and positively associated with more novel innovations. Despite the smaller sample size as compared to other tests, these results are robust to using different specifications (negative binomial and Poisson with firm fixed effects), and alternative dependent variable definitions. Note that I already control for firm size through sales, cash, R&D, and total loan amount, and therefore this variable captures something more than the lack of resources to finance innovation.

Second, I investigate whether the primary purpose of the loan could be related to innovation. The expectation is that loans that are given for corporate purpose or specific projects might be more conducive to innovation than loans given for debt repayment, leverage buyouts, management buyouts, or commercial paper backup. The results in column (2) of Table 6 do not support this expectation. The coefficient on the indicator variable *CorpPurpose* is insignificant. One possible explanation of that result is that corporate purpose is too general and might include very innovative and less innovative projects. The result suggests that the primary purpose of the loan is not related to innovation.

Third, I examine whether the loan type is related to innovation. If a given type loan provides more flexibility, then I expect that firms that predominantly use such loans, will have greater opportunity to experiment with novel technologies and as a result innovate more (Manso 2011, Azoulay et al. 2011). I hypothesize that lines of credit provide more flexibility, whereas term loans are usually fixed and inflexible. According to Sufi (2009), bank lines of credit are a flexible source of debt financing and lines of credit debt are adjusted upward and downward more often and in larger magnitude than any other debt instruments. The empirical findings from columns (3) and (4) of Table 6 provide support for this hypothesis. Firms that have credit lines innovate more than firms that have other types of loans, whereas firms that have term loans innovate less.

Fourth, I investigate whether the strength of covenants is related to innovation. Similar to loan

Table 6 Innovation and Banking Relationships

	(1)	(2)	(3)	(4)	(5)	(6)
Multiple	0.015***					
	(0.006)					
CorpPurpose		0.005				
		(0.004)				
CreditLine			0.018***			
			(0.006)			
TermLoan				−0.021***		
				(0.006)		
CovenantIntensity					−0.003**	
					(0.001)	
CovenantViolation						−0.006*
						(0.004)
Log(*Sales*)	0.037***	0.040***	0.039***	0.039***	0.039***	0.038***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
RD/Assets	0.434***	0.444***	0.445***	0.445***	0.445***	0.421***
	(0.031)	(0.031)	(0.031)	(0.031)	(0.031)	(0.036)
Leverage	−0.052***	−0.052***	−0.047***	−0.048***	−0.050***	−0.043***
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.012)
EBIDTA/Assets	0.040***	0.039***	0.039***	0.039***	0.040***	0.037***
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.010)
Tangible	0.002	0.001	0.002	0.002	0.003	0.022
	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.019)
Age	0.001***	0.001***	0.001***	0.001***	0.001***	0.0009***
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
HI	0.296***	0.278***	0.277***	0.277***	0.266***	0.349***
	(0.061)	(0.060)	(0.060)	(0.060)	(0.060)	(0.102)
HI^2	−0.319***	−0.299***	−0.296***	−0.297***	−0.288***	−0.433***
	(0.066)	(0.065)	(0.065)	(0.065)	(0.065)	(0.106)
Cash/Assets	0.112***	0.104***	0.105***	0.104***	0.105***	0.112***
	(0.022)	(0.022)	(0.022)	(0.022)	(0.022)	(0.029)
Q	0.007***	0.006***	0.006***	0.006***	0.006***	0.007***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
LoanAmount	6.25e−12***	6.04e−12***	6.12e−12***	5.99e−12***	5.84e−12***	1.34e−11***
	(1.46e−12)	(1.46e−12)	(1.46e−12)	(1.46e−12)	(1.46e−12)	(2.55e−12)
Observations	24,822	25,940	25,940	25,940	25,719	14,098
R^2	0.303	0.305	0.305	0.305	0.306	0.299
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

Notes. 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 the sample. Specifically, I estimate OLS in columns (1)–(6), where the dependent variable is Log(1 + $CitedPatent^{Time}$). The main explanatory variables are *Multiple* in column (1) (equal to 1 if the firm has multiple lenders and 0 otherwise), *CorpPurpose* in column (2) (equal to 1 if the primary purpose of the loan is "corporate purpose'' and 0 otherwise), *CreditLine* in column (3) (equal to 1 if the loan type is credit line and 0 otherwise), *TermLoan* in column (4) (equal to 1 if the loan type is a term loan and 0 otherwise), *CovenantIntensity* in column (5), and *CovenantViolation* in column (6). Other controls include Log(*Sales*), *RD/Assets*, *Cash/Assets*, *Age*, *EBIDTA/Assets*, *Tangible*, *Leverage* (*Total Debt/Assets*), *HI*, HI^2, and *LoanAmount*. All variable definitions are provided in the appendix. All regressions are estimated with time, state, and industry fixed effects, and the standard errors reported in the parentheses are clustered at the industry level. Data are for the period from 1996 to 2006.

***, **, and * denote significance at 1%, 5%, and 10% levels, respectively.

types, loans that are more covenant-light, will provide more flexibility than loans that have more stringent covenants. To test this hypothesis, I use two measures: covenant intensity and covenant violations. To define the restrictiveness of debt covenants, I follow Bradley and Roberts (2004) to construct a covenant intensity index, which equals the sum of six covenant indicators representing the existence of a secured covenant, a dividend restriction, more than two financial covenants, an equity issuance sweep, a debt issuance sweep, and an asset sales sweep. The index ranges from zero to six, where higher index values indicate more restrictive loan contracts. These covenants either limit borrower actions or provide lenders with rights triggered by adverse events. The sweeps are known as prepayment covenants that require the borrower to prepay a portion of the loan conditional on an event. For instance, an asset sale sweep indicates the percentage amount of net proceeds a company receives from an asset sale that must be used to pay down any outstanding loan balance. Financial covenants require the borrower to maintain certain financial ratios at a prespecified level throughout the duration of the loan. Dividend covenants place restrictions on the borrowers ability to distribute cash to stockholders. Secured covenant refers to the existence of assets pledged as collateral for the loan.

Covenant information comes from the Loan Pricing Corporations DealScan database. The sample includes all DealScan loans to U.S. public corporations from the 1996–2006 period for which financial and patent information is available. Column (5) of Table 6 provides the results. I find that firms that have loans with more intense covenants innovate less.

As another check for the role of covenants in innovation, I use the instances of covenant violations. Roberts and Sufi (2009) and Nini and Smith (2012) collect information on financial covenant violations from 10-Q or 10-K filings for all nonfinancial firms in Compustat from 1996 to 2008. In column (6) of Table 6, *CovenantViolation* is a dummy that equals 1 if the company has violated a financial covenant at any time during the fiscal year and 0 otherwise. I find that firms that have covenant violations innovate less. This finding again provides support for the hypothesis that strong covenants reduce firm flexibility and their ability to experiment with novel projects, and as a result, innovation declines. This result is similar to Gu et al. (2014).

Overall, the evidence indicates that firms that have more arm's-length-type bank borrowing and firms with more flexible loan types and less stringent covenants create more novel innovations.

6. Controlling for Endogeneity

6.1. An Instrumental Variable Approach

I mitigate endogeneity concerns by first predicting the source of financing with instruments (first stage), and then using the predicted values in Equation (3) (second stage). The second stage specification is similar to Equation (3) with citations per patent as the dependent variable. The instruments should explain the source of financing that firms use and should be unrelated to innovative activity except through the source of financing. I construct two such variables based on Faulkender and Petersen (2006).

The first instrument for the source of financing is based on how known or visible the firm is. The notion is that financiers are more likely to provide capital (through equity (SEO) or public debt) to firms that are better known. As a measure of whether the firm is more visible, I construct a dummy variable called *S&P* 500, which takes the value of 1 if the firm is in the S&P 500 index in a given year and 0 otherwise. I argue that such an inclusion automatically makes the company more visible than an otherwise similar company that is not included. I also do not have any theoretical argument or empirical evidence that the mere inclusion in the index will make the company more innovative, except through the increased proportion of arm's length financing in its capital structure.

The second instrument, the percentage of firms in the industry of a given firm in a year (without including this firm) that have public debt ($\text{Log}(1+\%\mathit{Public})$), proxies for familiarity. The notion here is that the public markets are likely to provide funds to firms that are well known. For instance, a new firm which manufactures automobiles may be able to issue stocks or bonds more easily, because the market already knows the industry and the competitors, as most auto manufacturers have outstanding shares and public debt. Again, there is no reason for us to believe that this variable affects innovative activity directly. Both of these variables are discussed in detail in Faulkender and Petersen (2006).

For the first stage, I estimate three regression equations with three financing variables—*Equity/Assets*, *Public/Assets*, and Public^s—as dependent variables. For *Equity/Assets* and *Public/Assets*, I employ an OLS specification, whereas for Public^s, I use a logit specification. As explanatory variables, I include the two instruments: *S&P* 500 and $\text{Log}(1+\%\mathit{Public})$. I also control for size, tangible assets, age, operating performance, growth opportunities, and financial constraints.

In Table 7(A), I find that both instruments are significant predictors of whether or not a firm obtains capital from arm's length financiers. In particular, the amount of equity and public debt financing is positively related to whether or not the firm is included in the S&P 500 index, and to the proportion of firms in its industry that have public debt. The instruments are also positively related to the probability of a firm having issued public debt. The point estimates on the instruments are economically significant—for instance, a firm in the S&P 500 index has, on average, about 16% more equity and 13% more public debt in its capital structure as compared to a firm that is not in the S&P 500 index. Importantly, the *F*-test rejects the null that the coefficients on both instruments are jointly zero. Moreover, the test of overidentifying restrictions fails to reject the joint null hypothesis that the instruments are uncorrelated with the error term and are correctly excluded from the second-stage regression.

Table 7(A) Instrumental Variable Analysis: First Stage

	Equity/Assets	*Public/Assets*	*Public^s*
	OLS (1)	OLS (2)	Logit (3)
S&P 500	0.017	0.024	0.996
	(0.004)***	(0.001)***	(0.052)***
Log(1+%*Public*)	0.026	0.039	1.155
	(0.006)***	(0.0004)***	(0.162)***
Log(*Sales*)	−0.026	0.005	0.689
	(0.001)***	(0.001)***	(0.013)***
Tangible	−0.059	0.031	1.035
	(0.004)***	(0.005)***	(0.074)***
Q	0.011	−0.002	−0.084
	(0.005)**	(0.001)***	(0.014)***
EBIDTA/Assets	0.013	−0.019	−0.683
	(0.003)***	(0.006)***	(0.113)***
Observations	109,300	109,300	109,300
Other controls	Yes	Yes	Yes
Adjusted R^2	0.19	0.28	
Log-likelihood			−36,599.9
p-value, χ^2 test			0.00
Time fixed effects	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes
State fixed effects	Yes	Yes	Yes

Notes. This table reports the results of the first stage of the instrumental variable analysis. The specification in this table uses the *Financing* variables as the dependent variables and the instruments *S&P* 500 and Log(1+%*Public*) as the main explanatory variables. Specifically, I estimate the OLS models with *Equity/Assets* and *Public/Assets* as financing variables in columns (1) and (2), respectively. In column (3), I employ a logit model with *Public^s* as the dependent variable. Controls include Log(*Sales*), *Tangible*, *Q*, and *EBIDTA/Assets*. Other controls (not reported) include *Cash/Assets*, *RetEarn/Assets*, *Age*, and $\sigma_{\text{firm}, it}$. All variable definitions are provided in the appendix. All regressions are estimated with time, state, and industry fixed effects, and clustered standard errors by industry are reported in the parentheses. Data are for the period from 1974 to 2000.

*** and ** denote significance at the 1% and 5% levels, respectively.

In the second stage, I employ Equation (3) and use the arm's length financing variables that I instrumented in the first stage. I use the generalized methods of moments (GMM) to model Equation (3) since this equation employs a nonlinear specification (Poisson) with instrumented financing variables (e.g., see Mullahy 1996). More specifically, in Table 7(B), I estimate the GMM using the specification discussed above. I use *CitedPatent*$^{\text{Time}}$ as the dependent variable in column (1), *CitedPatent*$^{\text{Time}-\text{Tech}}$ in column (2), and *CitedPatents*$^{\text{Quasi}}$ in column (3).

Comparing results between Tables 4 and 7(B), I observe that the estimates of arm's length financing variables are statistically significant though slightly smaller in magnitudes when the financing variables are instrumented. The point estimates in column (2) suggest that a one-standard-deviation increase in *Equity/Assets* is associated with 14.2% more ($\exp\{0.67 * 0.2\} - 1$) citations per patent by the firm as compared to the mean patenting firm in its industry. Similarly, a one-standard-deviation increase in *Public/Assets* is accompanied by 6.0% more ($\exp\{0.58 * 0.10\} - 1$) citations per patent by the firm as compared to the mean patenting firm in its industry. I also find that access to public debt markets is associated with 6.3% more citations per patent. I find similar results in columns (2) and (3). These results

Table 7(B) Instrumental Variable Analysis: Second Stage

	CitedPatent$^{\text{Time}}$	*CitedPatent*$^{\text{Time}-\text{Tech}}$	*CitedPatent*$^{\text{Quasi}}$
	Poisson (1)	Poisson (2)	Poisson (3)
Equity/Assets$^{\text{Instrumented}}$	0.670	0.659	0.623
	(0.154)***	(0.139)***	(0.194)***
Public/Assets$^{\text{Instrumented}}$	0.583	0.580	0.570
	(0.140)***	(0.132)***	(0.137)***
Public$^{s\,\text{Instrumented}}$	0.059	0.056	0.057
	(0.024)***	(0.023)***	(0.023)***
Log(*Sales*)	0.163	0.152	0.140
	(0.008)***	(0.006)***	(0.004)***
Log(*RD*)	0.230	0.147	0.132
	(0.009)***	(0.003)***	(0.004)***
HI	2.365	0.440	0.370
	(0.690)***	(0.213)***	(0.180)**
HI^2	−1.542	−0.117	−0.091
	(0.514)***	(0.090)*	(0.060)*
Q	0.011	0.025	0.029
	(0.004)***	(0.001)***	(0.002)***
Tangible	0.671	0.360	0.298
	(0.031)***	(0.029)***	(0.032)***
EBIDTA/Assets	0.050	0.041	0.033
	(0.025)**	(0.020)***	(0.012)***
Age	0.040	0.034	0.030
	(0.005)***	(0.004)***	(0.004)***
Cash/Assets	−0.14	−0.15	−0.17
	(0.14)	(0.07)**	(0.08)**
RetEarn/Assets	−0.09	−0.09	−0.05
	(0.08)	(0.06)*	(0.07)
PastCumReturns	−0.02	−0.02	−0.01
	(0.009)***	(0.009)***	(0.004)***
Observations	109,300	109,300	109,300
Other controls	Yes	Yes	Yes
Log-likelihood	−20,300.2	−16,661.7	−18,240.1
p-value, χ^2 test	0.00	0.00	0.00
Time fixed effects	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes
State fixed effects	Yes	Yes	Yes

Notes. This table reports the second stage of the instrumental variable analysis. The second stage uses the generalized methods of moments to model the innovation production function with the instrumented values of the financing variables. The details on the technique is outlined in (Mullahy 1996). Controls include Log(*Sales*), Log(*RD*), *HI*, *HI*^{2}, *Q*, *Tangible*, *EBIDTA/Assets*, *Age*, *Cash/Assets*, *RetEarn/Assets*, and *PastCumReturns*. All variable definitions are provided in the appendix. All regressions are estimated with time, state, and industry fixed effects, and clustered standard errors by industry are reported in the parentheses. Data are for the period from 1974 to 2000.

***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

suggest a causal relationship from arm's length to the creation of novel innovations.

There is a potential concern that, although the S&P 500 variable might be orthogonal to future innovation, it is not random. As Aghion et al. (2013) discuss, the companies that are included in the S&P 500 usually exhibit significant cumulative stock returns in the years before the inclusion in the index. Therefore, to alleviate this concern, I control for the cumulative stock returns over the three years before the inclusion. The coefficients on the main explanatory variables that measure the source of financing are unaffected.

6.2. Innovation Subsequent to Substantial Capital Infusions

In this subsection, I continue to investigate whether there is a causal relation from the source of financing to innovation. Specifically, if there is such a relation, I expect that an infusion of arm's length financing in the form of public debt or seasoned equity will be followed by a significant increase in innovative activity, whereas little or no such increase will be observed after an infusion of bank financing.

I examine the change in the innovative activity of firms subsequent to the increase of arm's length or bank capital by constructing the indicator variables $Post^D_{0-1}$ ($Post^E_{0-1}$; $Post^B_{0-1}$), which takes the value of 1 if it is the first year since the firm issued public debt for the first time (issued equity through an SEO; took new bank loan) over the sample period and 0 otherwise, and the variables $Post^D_{1-2}$ ($Post^E_{1-2}$; $Post^B_{1-2}$), which takes the value of 1 if it is the second year since the firm issued public debt for the first time (issued equity through an SEO; took new bank loan) over the sample period and 0 otherwise.

To measure whether the innovative activity is affected over longer time periods, I also construct the dummy variables $Post^D_{2-3}$ ($Post^E_{2-3}$; $Post^B_{2-3}$) if it is the third year since the firm issued public debt for the first time (issued equity through an SEO; took a new bank loan), and the variables $Post^D_{3-4}$ ($Post^E_{3-4}$; $Post^B_{3-4}$) if it is the fourth year since the firm issued public debt for the first time (issued equity through an SEO; took a new bank loan). For the construction of these variables, I collect data on *all* public debt issues and SEOs available in the SDC database. After matching the firms with the patent and financial data, I find that I have 1,239 firms that issued public debt for the first time and 2,845 firms (4,166 issues) that had an SEO during the sample period. Information on bank loans comes from the Loan Pricing Corporation's DealScan database. The coverage of firms in DealScan is relatively limited; the number of observations used in the tests is smaller than in other tests. Moreover, the coverage of DealScan begins from 1985, and therefore the tests are run only for the 1985–2000 period. There are 2,896 firms and 10,540 firm-years with 645 firms taking new bank loans over this period.

I estimate the following model with various explanatory variables:

$$\begin{aligned} CitedPatent^{\text{Time}}_{it} &= \exp\{\alpha_0 + \alpha Financing_{it} + \beta Post^k_{jit} \\ &\quad + \delta_1 \text{Log}(RD)_{it} + \delta_2 \text{Log}(Sales)_{it} \\ &\quad + \delta \mathbf{Z}_{it} + \mu_t + \mu_j + \mu_s\}, \end{aligned} \tag{8}$$

where $k \in \{D, E, B\}$ corresponds to the first time public debt issue, SEO, and a new bank loan, respectively; and j is equal to 0–1, 1–2, 2–3, or 3–4. More precisely, in columns (1) and (2) of Table 8, I analyze the change in innovation following the initial offering of public debt. A similar analysis is conducted for the periods following seasoned equity offerings (columns (3) and (4)) and new bank loans (columns (5) and (6)). Based on the main hypothesis, I expect the coefficient estimate on $Post^k_{jit}(\beta)$ to be positive and significant for the arm's length financing variables. Controls in each case include all the variables used in the model in Table 4. I also estimate these regressions with time, state and industry fixed effects.

As is evident from the table, the results are consistent with the main hypothesis: firms that issue public debt for the first time (through an SEO) have more significant innovations as measured by citations per patent in the years 2, 3, and 4, but not in year 1, subsequent to the first-time issue of public debt (SEO). The coefficient estimates on $Post^D_{jit}$($Post^E_{jit}$) are positive and significant for j equal to 1–2, 2–3, and 3–4. Moreover, the coefficients which measure innovations subsequent to a bank loan ($Post^B_{jit}$) are insignificant.

Note that the estimate on $Post^k_{jit}$ for j equal to 2–3 and 3–4 three and four years after the initial issue of public debt (after an SEO) in column (2) (column (4)) are smaller in magnitude than the estimate for the second year after the public debt issue (after the SEO). There are at least two possible reasons for this difference. First, firms may be adjusting their innovative behavior in anticipation of future increase in arm's length financing. That is, the causality may still go from arm's length financing to innovation, but innovative output may respond quicker because firms may increase their experimentation with novel technologies in anticipation of receiving arm's length financing, well before the actual financing is obtained. Second, the standard errors of the coefficient estimates may increase because there may be more noise as I move the dependent variables too far into the future.

To alleviate concerns that the results on bank loans are weak because they are estimated on a smaller sample, for robustness, I conduct the tests with public debt issue and SEO offerings after restricting the sample to firms in the DealScan database. The results

Table 8 Citations per Patent Subsequent to First-Time Public Debt Issue, a Seasoned Equity Offering and a Bank Loan

	First-time public debt issue		Seasoned equity offering		Bank loan	
	Poisson					
	(1)	(2)	(3)	(4)	(5)	(6)
$Post^{D}_{0-1}$	0.083 (0.097)	0.079 (0.094)				
$Post^{D}_{1-2}$	0.249 (0.051)***	0.260 (0.061)***				
$Post^{D}_{2-3}$		0.042 (0.021)**				
$Post^{D}_{3-4}$		0.050 (0.024)**				
$Post^{E}_{0-1}$			0.105 (0.101)	0.109 (0.117)		
$Post^{E}_{1-2}$			0.315 (0.103)***	0.263 (0.127)**		
$Post^{E}_{2-3}$				0.031 (0.016)**		
$Post^{E}_{3-4}$				0.025 (0.014)*		
$Post^{B}_{0-1}$					−.043 (0.048)	−.047 (0.051)
$Post^{B}_{1-2}$					−.059 (0.061)	−.063 (0.065)
$Post^{B}_{2-3}$						0.004 (0.065)
$Post^{B}_{3-4}$						0.005 (0.068)
Equity/Assets	0.774 (0.057)***	0.781 (0.060)***	0.773 (0.057)***	0.765 (0.056)***	0.695 (0.217)***	0.694 (0.221)***
Public/Assets	0.421 (0.064)***	0.498 (0.063)***	0.721 (0.075)***	0.787 (0.063)***	0.503 (0.049)***	0.565 (0.049)***
$Public^{s}$	0.062 (0.023)***	0.065 (0.021)***	0.070 (0.030)**	0.069 (0.031)**	0.030 (0.015)*	0.028 (0.014)*
Observations	109,300	109,300	109,300	109,300	10,540	10,540
p-value, χ^2 test	0.00	0.00	0.00	0.00	0.00	0.00
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
State fixed effects	Yes	Yes	Yes	Yes	Yes	Yes

Notes. This table reports the results relating novel patents produced in a firm to the type of its financing subsequent to a public debt offering, a seasoned equity offering, and a bank loan. I estimate a Poisson model in all the columns with the dependent variable $CitedPatent^{Time}$. I round each nonzero observation to its nearest integer for the dependent variable that I employ. Other controls (not reported in the table) include Log(*Sales*), Log(*RD*), *Q*, *Tangible*, *Age*, *Cash/Assets*, *RetEarn/Assets*, *EBIDTA/Assets*, *HI*, and HI^2. All variable definitions are provided in the appendix. All regressions are estimated with time, state, and industry fixed effects. The standard errors reported in the parentheses are heteroskedastic consistent to account for overdispersion in Poisson models and are adjusted for clustering at the industry level. Data are for the period from 1974 to 2000.

***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

are qualitatively similar. The results are also robust to alternative dependent variable definitions and model specifications.[11]

[11] In particular, I also conducted the estimation using $CitedPatent^{Time}$ and a Tobit random effects regression. Using Tobit alleviates concerns that the results in this section are partly driven by a significant number of firms with zero patents, because there may be an upward bias on the coefficient estimate on $Post^{k}_{jit}$.

6.3. Variation in the Relationship Between Arm's Length Financing and Innovation: Evidence from Innovative Firms and Industries

According to the main hypothesis, the relationship between type of financing and innovation should be stronger for firms for which innovative activity is important. In this subsection, I test this prediction by confining ourselves to subsamples where innovation might ex ante be considered more important.

I start by conducting tests only on innovating firms. Specifically, in columns (1) and (2) of panel A of Table 9, I restrict the sample to include only firms that have at least one patent during a given year ($Patent_t > 0$). Because 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, I re-estimate Equation (3) on this sample. In column (3), I employ firm fixed effects as well. The coefficients on *Equity/Assets*, $Public^s$, and *Public/Assets* are positive and significant at the 1% level. The coefficients on the financing variables in these equations have a larger economic impact than those when the full sample of firms was used (Table 4). For instance, estimates in column (3) of Table 9 suggest that, *among patenting firms*, a one-standard-deviation increase in *Equity/Assets* is associated with 28.4% more ($\exp\{0.962 * 0.26\} - 1$) citations per patent and a one-standard-deviation increase in *Public/Assets* is associated with 12.4% more ($\exp\{0.785*0.15\}-1$) citations per patent (mean citations per patent is 7.31 among patenting firms). Similarly, *among the firms that innovate*, access to public debt markets is associated with 11.1% more citations per patent. This is consistent with the notion that the form of financing has a significantly greater influence on novel innovations among patenting firms. For robustness, in column (4), I conduct the analysis restricting the sample to firms with at least one patent in that year or any year before it and find similar results.

In columns (5) and (6) of panel A in Table 9, I construct an alternative variable to confirm that *among patenting firms* those with arm's length financing are more likely to be drastic innovators than incremental innovators. I 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. I estimate the following panel fixed-effects logit regression:

$$\begin{aligned} DrasticIncrem_{it} = \Phi\{&\alpha_0 + \alpha Financing_{it} + \delta_1 \mathrm{Log}(RD)_{it} \\ &+ \delta_2 \mathrm{Log}(Sales)_{it} + \delta \mathbf{Z}_{it} + \mu_t + \mu_j + \mu_s\}. \quad (9) \end{aligned}$$

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

Finally, because there is a significant variation in the distribution of patents both *across* and *within* various industries (panel C of Table 2), I examine whether the results are stronger in industries with more patenting activity. The estimates of Equation (3) for each of these industry sectors are reported in panel B of Table 9. As can be observed, the estimates are statistically significant and larger in industries where patenting might be considered to be important. The results also suggest that even for industries where patenting is not considered to be important, there may still be a connection between R&D output and arm's length financing.

6.4. Omitted Variables and Robustness Tests

6.4.1. Impact of Financial Constraints. Although the sample of publicly traded U.S. firms are less likely to be financially constrained, I examine in greater detail the possibility that financial constraints may impact the results. To measure the extent to which a firm is financially constrained, I follow Lamont et al. (2001) and Baker et al. (2003) and construct the five-variable Kaplan and Zingales (1997) index (KZ index) for each firm-year. For each year, I rank firms into quintiles according to their KZ index, and estimate Equation (3) in each KZ quintile using the dependent variable $CitedPatent^{\mathrm{Time}}$.

The results reported in panel A of Table 10 demonstrate a positive and significant association between arm's length financing variables (*Equity/Assets* and *Public/Assets*) and citations per patent for each of the KZ quintiles. For conciseness, I do not report the coefficients of the other control variables (including $Public^s$) in the table. The estimates of these control variables are similar in sign and magnitude to those reported in the main regressions. Notably, the results are economically significant and the effects are similar to those reported earlier. The fact that I 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. The finding of a negative association between *Cash/Assets* and innovation in less constrained quintiles is somewhat surprising and suggests that the presence of excess internal cash (relative to the industry mean because the estimation is with industry effects) is potentially associated with greater agency problems (e.g., Harford 1999) that may, in turn, hinder innovation.

For robustness, in panels B and C of Table 10, I conduct the analysis using operating cash (*Cash/Assets*)

Table 9 Subsample Analysis: Patenting Firms and Innovative Industries

Panel A: Subsample of patenting firms

	CitedPatent^{Time}				*DrasticIncrem* = 1	
	Patent in year $t > 0$			Patent in year t or any year before > 0	Patent in year $t > 0$	
	Poisson				Logit	
	(1)	(2)	(3)	(4)	(5)	(6)
Equity/Assets	0.987	0.981	0.962	1.17	0.363	0.395
	(.021)***	(0.023)***	(0.022)***	(0.041)***	(0.169)**	(0.148)**
Public/Assets		0.791	0.785	0.796		0.772
		(0.372)***	(0.358)**	(0.368)**		(0.240)***
Public^s		0.119	0.105	0.113		0.305
		(0.039)***	(0.040)***	(0.051)**		(0.141)***
Observations	15,300	15,300	12,040	22,700	10,200	10,200
Log-likelihood	−16,342.2	−16,666.4	−13,387.3	−18,666.4	−4,529.4	−4,547.3
p-value, χ^2 test	0.00	0.00	0.00	0.00	0.00	0.00
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes		Yes	Yes	Yes
State fixed effects	Yes	Yes		Yes	Yes	Yes
Firm fixed effects			Yes			

Panel B: Subsample of innovative industries

	CitedPatent^{Time}					
	Poisson					
	Drugs (1)	Chemicals (2)	Computers (3)	Electrical (4)	Metals (5)	Low-tech (6)
Equity/Assets	1.32	1.88	1.92	0.84	0.38	0.52
	(0.020)***	(0.022)***	(0.026)***	(0.024)***	(0.180)**	(0.271)**
Public/Assets	1.90	1.69	1.51	0.99	0.45	0.20
	(0.421)***	(0.410)***	(0.553)***	(0.383)***	(0.249)*	(0.109)**
Public^s	0.109	0.101	0.102	0.079	0.039	0.019
	(0.030)***	(0.031)***	(0.027)***	(0.029)***	(0.019)**	(0.010)*
Observations	12,312	10,477	26,548	23,876	10,051	26,036
Log-likelihood	−16,342.2	−16,666.4	−13,387.3	−18,666.4	−4,529.4	−4,547.3
p-value, χ^2 test	0.00	0.00	0.00	0.00	0.00	0.00
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
State fixed effects	Yes	Yes	Yes	Yes	Yes	Yes

Notes. This table reports the results of regressions relating innovations to the type of financing for a subsample of firms as defined below. In columns (1)–(4) of panel A, I estimate the Poisson panel regression of *CitedPatent*^{Time} on various explanatory variables for firms which have at least one patent in a given year during the sample. I round each nonzero observation to its nearest integer for the dependent variable that I employ. Columns (1)–(3) include all the firms that patent in a given year, whereas in column (4) the sample includes firms that have at least one patent in a given year or any year before it. In columns (5) and (6) of panel A, I estimate the panel logit regression of the modified innovation variable (*DrasticIncrem*) on various explanatory variables. *DrasticIncrem* is a dummy variable that equals 1 if a firm is in the top 1% in terms of the citations received for a given year in a given industry, and 0 if the citations received for a given year in a given industry are in the bottom 30%. In panel B, I estimate Equation (3) for each of the six industry sectors classified based on Hall et al. (2005): drugs, chemicals, computers, electrical, metals, and low-tech. Other controls (not reported in the table) include *Q*, *Tangible*, *Age*, *Cash/Assets*, *RetEarn/Assets*, *EBIDTA/Assets*, *HI*, and HI^2. All variable definitions are provided in the appendix. All regressions are estimated with time, state, and industry fixed effects. The standard errors reported in the parentheses are heteroskedastic consistent to account for overdispersion in Poisson models and are adjusted for clustering at the industry level. Data are for the period from 1974 to 2000.

***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

and operating income (*EBIDTA/Assets*) as the sorting variables instead of *KZ* and find qualitatively similar results. In addition, I also use the methodology of Korajczyk and Levy (2003) and Whited and Wu (2006) for classifying firms as constrained. I again find support for my predictions in both the constrained and unconstrained set of firms classified based on these two measures.

Overall, the evidence in this section suggests that financial constraints and internal financing do play an

Table 10 Innovation, Financing Arrangements, and Financial Constraints: Quintile Analysis

	Q1	Q2	Q3	Q4	Q5
			Model: Poisson		
	Low				High
			Panel A: *KZ* quintiles		
Equity/Assets	0.540	0.770	0.901	0.873	0.940
	(0.120)***	(0.194)***	(0.123)***	(0.155)***	(0.040)***
Public/Assets	0.651	0.650	1.340	0.541	0.627
	(0.319)***	(0.180)***	(0.283)***	(0.142)***	(0.116)***
Cash/Assets	−1.109	−0.251	−0.219	−0.210	0.133
	(0.190)***	(0.249)	(0.295)	(0.279)	(0.040)***
EBIDTA/Assets	0.080	0.172	0.070	0.201	0.026
	(0.13)	(0.20)	(0.38)	(0.26)	(0.040)
Mean quintile value	−0.73	0.45	1.00	1.64	3.08
Observations	22,716	21,112	21,125	21,130	23,076
			Panel B: *Cash/Assets* quintiles		
Equity/Assets	0.860	0.731	0.902	0.911	0.760
	(0.040)***	(0.070)***	(0.053)***	(0.039)***	(0.057)***
Public/Assets	0.688	0.404	0.727	0.720	0.590
	(0.183)***	(0.133)***	(0.156)***	(0.121)***	(0.142)***
Mean quintile value	0.005	0.02	0.05	0.12	0.37
Observations	23,530	21,860	21,509	20,657	21,738
			Panel C: *EBIDTA/Assets* quintiles		
Equity/Assets	0.601	0.770	0.922	0.691	0.904
	(0.028)***	(0.053)***	(0.102)***	(0.097)***	(0.061)***
Public/Assets	0.391	0.684	0.748	0.514	0.881
	(0.038)***	(0.221)***	(0.144)***	(0.192)***	(0.280)***
Mean quintile value	0.001	0.05	0.10	0.15	0.26
Observations	21,930	22,105	21,507	21,909	21,803
Time fixed effects	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes
State fixed effects	Yes	Yes	Yes	Yes	Yes

Notes. 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, I sort all the firms year-wise into quintiles according to a firm characteristic. In the second stage, for each characteristic quintile, I estimate a Poisson panel regression of $CitedPatent^{Time}$ on various explanatory variables. I round each nonzero observation to its nearest integer for the dependent variable that I employ. Panels A, B, and C present coefficient estimates with firms sorted into quintiles based on *KZ*, *Cash/Assets*, and *EBIDTA/Assets*, respectively. Other controls (not reported in the table) include $Public^s$, Log(*Sales*), Log(*RD*), *Q*, *Tangible*, *Age*, *Cash/Assets*, *RetEarn/Assets*, *EBIDTA/Assets*, *HI*, and HI^2. All variable definitions are provided in the appendix. All regressions are estimated with time, state, and industry fixed effects. The standard errors reported in the parentheses are heteroskedastic consistent to account for overdispersion in Poisson models and are adjusted for clustering at the industry level. Data are for the period from 1974 to 2000.

***Denotes significance at the 1% level.

important role in explaining the innovative activity of a firm. However, financial constraints and internal financing cannot explain away the relationship I find between arm's length financing and innovation.

6.4.2. Impact of Other Firm Characteristics. In this subsection, I conduct further tests to examine whether nonlinear differences in size, investment opportunities, and maturity of firms could be influencing both the type of financing they choose and the innovations they produce. I follow the empirical strategy of the last subsection and conduct the analysis in each of the quintiles formed on the basis of sales (to control for size), market-to-book ratio (to control for investment opportunities), and age (to control for maturity of the firm).

The analysis follows §6.4.1 and estimates Equation (3) in each quintile that is formed after sorting firms based on a firm characteristic. Specifically, in Table 11, I sort firms into quintiles based on *Sales* in panel A, market-to-book ratio (*Q*) in panel B, and *Age* in panel C. In each case, I estimate regressions with time, state, and industry fixed effects. The results indicate that even after grouping firms by their firm characteristics, for every quintile, firms with more equity and more public debt tend to innovate more. In particular, the results hold for a range of sales quintiles (means \$4 million to \$1,848 million), market-to-book

Table 11 Innovation, Financing Arrangements, and Firm Characteristics: Quintile Analysis

	Q1	Q2	Q3	Q4	Q5
	Model: Poisson				
	Low				High
			Panel A: *Sales* quintiles		
Equity/Assets	0.530	0.667	0.631	0.950	1.017
	(0.018)***	(0.077)***	(0.065)***	(0.150)***	(0.200)***
Public/Assets	0.630	0.410	0.580	0.655	0.470
	(0.014)***	(0.017)***	(0.015)***	(0.204)***	(0.221)***
Mean quintile value ($million)	4.2	25.11	87.95	336.45	1,848.87
Observations	22,606	21,796	21,165	21,222	22,305
			Panel B: *Q* quintiles		
Equity/Assets	0.594	0.900	0.987	0.992	0.991
	(0.230)**	(0.132)***	(0.130)***	(0.110)***	(0.069)***
Public/Assets	0.510	0.878	0.519	0.497	0.510
	(0.123)***	(0.160)***	(0.020)***	(0.118)***	(0.184)***
Mean quintile value	0.72	0.96	1.19	1.63	4.67
Observations	21,144	21,188	22,170	22,188	22,179
			Panel C: *Age* quintiles		
Equity/Assets	0.604	0.930	0.921	0.860	0.759
	(0.052)***	(0.059)***	(0.079)***	(0.080)***	(0.070)***
Public/Assets	0.710	0.579	0.681	0.517	0.554
	(0.116)***	(0.180)***	(0.173)***	(0.188)***	(0.251)**
Mean quintile value (years from IPO)	1.99	5.50	10.93	14.72	31.94
Observations	21,598	23,414	21,321	20,797	21,964
Time fixed effects	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes
State fixed effects	Yes	Yes	Yes	Yes	Yes

Notes. 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, I sort all the firms year-wise into quintiles according to a firm characteristic. In the second stage, for each characteristic quintile, I estimate a Poisson panel regression of $CitedPatent^{Time}$ on various explanatory variables. I round each nonzero observation to its nearest integer for the dependent variable that I employ. Panels A, B and, C present coefficient estimates with firms sorted into quintiles based on *Sales*, *Q*, and *Age*, respectively. Other controls (not reported in the table) include $Public^s$, Log(*Sales*), Log(*RD*), *Q*, *Tangible*, *Age*, *Cash/Assets*, *RetEarn/Assets*, *EBIDTA/Assets*, *HI*, and HI^2. All variable definitions are provided in the appendix. All regressions are estimated with time, state, and industry fixed effects. The standard errors reported in the parentheses are heteroskedastic consistent to account for overdispersion in Poisson models and are adjusted for clustering at the industry level. Data are for the period from 1974 to 2000.

*** and ** denote significance at the 1% and 5% levels, respectively.

quintiles (means 0.7 to 4.6) and age quintiles (means 1.99 years to 31.9 years).

For robustness, I also sort on firm specific characteristics that measure a firm's asymmetric information (analyst forecast dispersion and firm specific stock variance) and agency problem within the firm (Gompers, Ishi Metrick governance index. and outside block holdings) because they could affect both the type of financing and innovation. I find that the main results are similar in each of the quintiles formed based on these characteristics. Note that because of limited data, these tests are conducted on a smaller sample (1990–2000).

6.4.3. Other Robustness Tests. I end this section by conducting several additional tests to verify the robustness of the main regression results. For brevity, the results are not reported, but are available upon request. First, I follow Schoar (2002) and conduct the analysis in two subperiods (1974–1987 and 1988–2000) to allay concerns that having more mature firms in later years may introduce a survivorship bias. The results show that a similar positive relation between innovation and arm's length financing exists in both sample periods. Second, I check the robustness of the results by employing additional measures of the significance of a firm's innovative activity using ranking procedures such as the ratio of all the forward to backward citations for the firm's patents in a year (Hall et al. 2001).[12]

I find that the regression results are essentially unchanged. I also construct all the measures after excluding self-citations (a firm citing its own patents

[12] I use two alternative ranking procedures to measure the overall significance of a firm's patents: (1) I rank firms by the total number of citations received by the firm for all its patents in a given year and by the ratio of forward to backward citations for a firm for all its patents in a year (Hall et al. 2001) and (2) I construct a variable for each firm in a year as the sum of all patents whose citations are two standard deviations above the mean citations of all the patents in a technology class in a year.

in subsequent patents that it obtains) and find that it has little effect on the results.

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

7. Innovation and Firm Value

The main hypothesis implicitly assumes that producing novel innovations has value implications that are large enough for the firms to take into account when making capital structure decisions. In this section I examine whether producing novel innovations has an economically meaningful impact on firm value.

In Table 12, I examine the impact of significant patents on the firm's subsequent stock market valuation by investigating the relationship between future market-to-book value (Q) of firms sorted into quintiles based on the quality of their innovations. I do the analysis in quintiles because, as noted earlier, the distribution of citations is very skewed and thus the effect of citations on firm value may not be fully revealed by estimating value regressions with citations per patent as an explanatory variable. To conduct the analysis, I first sort all the firms that have at least one patent during the sample period each year into quintiles based on $\mathit{CitedPatent}^{\mathrm{Time}}$. I continue to conduct the analysis relative to the application year of patents because the work surveyed in Griliches (1990) finds that patent counts by application date are closer to the actual innovation and are more tightly linked to market value than counts by granting date. In the second step, for each of the quintiles, I estimate the following model for firms in each quintile for each year:

$$y_{it+k} = \{\gamma_t + \delta \mathbf{X}_{it} + \mu_j + \mu_s\}. \qquad (10)$$

The dependent variable y is equal to the future market-to-book ratio: one year forward in the future in column (1), two years in the future in column (2), and three years in column (3). I use the value of the dependent variable up to three years after the patent has been granted because it may be difficult for financial intermediaries and other market participants to evaluate the value of patents immediately. It may, therefore, take time for information about the value of the innovation to get incorporated into the firm's market value.

Other explanatory variables (X) used are size (*Size*), maturity of the firm (*Age*), cash (*Cash/Assets*), and firm profitability (*EBIDTA/Assets*). Morck and Yang (2001) show that inclusion in the S&P 500 index has a positive impact on Q. Thus, as a control, I use a dummy variable equal to 1 if a firm is in the S&P 500. I include state dummies in the regression to account for differences in Q values for Delaware and non-Delaware firms (Daines 2001). Industry fixed effects are also included to control for cross-industry differences in value. Finally, I use an estimation technique that is a variant of the methods of Fama and MacBeth (1973). In particular, I estimate annual cross-sectional regressions of Equation (10) with statistical significance assessed within each year (by cross-sectional standard errors) and across all years (with the time-series standard error of the mean coefficient). Table 12 summarizes the results for each quintile. Each row gives the Fama–MacBeth coefficient estimates of γ and standard errors averaged across years of the sample. The difference in average coefficient estimates γ between various quintiles can be interpreted as the difference in value between firms in the innovative quintiles after controlling for other factors that explain future Q.

Table 12 Citations per Patent and Future Firm Value

Future value and cited patents	Q_{t+1} (1)	Q_{t+2} (2)	Q_{t+3} (3)
Firms with no patents (Cites per patent: 0)	1.25 (0.047)***	1.20 (0.068)***	1.17 (0.053)***
Quintile$_1$: Q_1 (Cites per patent: 0.69)	1.31 (0.145)***	1.24 (0.063)***	1.22 (0.19)***
Quintile$_2$: Q_2 (Cites per patent: 1.97)	1.65 (0.092)***	1.61 (0.067)***	1.36 (0.071)***
Quintile$_3$: Q_3 (Cites per patent: 7.31)	1.73 (0.073)***	1.68 (0.088)***	1.53 (0.087)***
Quintile$_4$: Q_4 (Cites per patent: 10.33)	1.93 (0.253)***	1.91 (0.263)***	1.58 (0.215)***
Quintile$_5$: Q_5 (Cites per patent: 16.85)	2.01 (0.142)***	1.97 (0.112)***	1.61 (0.123)***
Difference: $Q_5 - Q_3$	0.27 (0.04)***	0.29 (0.14)**	0.07 (0.05)
Difference: $Q_5 - Q_1$	0.70 (0.08)***	0.73 (0.36)**	0.39 (0.23)

Notes. This table reports the results relating cited patents produced in a firm to its subsequent market-to-book value. The coefficient estimate reported in the table is obtained using a two-stage procedure. In the first stage, I sort all the firms who have at least one patent over the sample period year-wise into quintiles according to their $\mathit{CitedPatent}^{\mathrm{Time}}$. Mean citations per patent for each of the quintiles is reported in the table. In the second stage, for each quintile, I estimate a Fama and MacBeth (1973) regression of future market to book on various explanatory variables. Control variables include *Size*, *Age*, *S&P* 500, *Cash/Assets*, *EBIDTA/Assets*, and state and industry dummies. I also report the results for all the firms who do not have any patents in the first row. All variable definitions are provided in the appendix. Data are for the period from 1974 to 2000.

*** and ** denote significance at the 1% and 5% levels, respectively.

The difference in the estimates of γ (26 in each quintile) between the third (Q_3: mean citation per patent of 7.3) and the last quintile (Q_5: mean citation per patent of 16.8) in column (2) suggests that firms in the highest citations per patent quintile have a 17% higher ($\{Q_5 - Q_3\}/Q_3 = 0.29/1.68$) market-to-book value two years after the innovation than firms in the median citations per patent quintile. These results suggest that novel innovations have a significant impact on firm value even after controlling for other factors that might explain differences in value. The results (about 1.8% for an increase of one citation per patent for highly cited firms) are broadly in line with the "patent market premium" reported in Hall et al. (2005).

Clearly, this is a very large impact, but then one has to keep in mind that getting an additional citation per patent above industry average is very hard, considering that the distribution of citations is extremely skewed (Table 1), with about one-quarter of patents receiving no citations. Similar effects are also prevalent for firms who produce below average citations per patent. The findings in the table also show that the value differences persist for up to two years subsequent to the sorting year, suggesting the time period over which the value of the innovation is incorporated in the stock price. The results are consistent with Kogan et al. (2012).

For robustness, I estimate a panel regression with time fixed effects that is similar to Equation (10) on all the patenting firms after including measures that capture the novelty of innovation. To account for skewness in citations per patent, I break the citations per patent variable into five groups and include dummy variables for each group. The groups are 0–0.69, 0.70–1.97, 1.98–7.30, 7.31–10.33, and >10.33. The results on value implications for the five groups are qualitatively similar to those reported in the paper. Finally, in unreported tests, I also find that firms in the highest citations per patent quintile have about 31.5% higher operating performance (*ROA*) two years after the innovation than firms in the median citations per patent quintile.

Overall, the analysis in this section in conjunction with that in §4 (relationship between citations per patent and financing) suggests that the source of external financing can have significant impact on firm value by affecting the quantity and quality of innovative output.

8. Conclusion

Using a large panel of U.S. companies from 1974 to 2000, I find that firms that rely more on arm's length financing have a larger number of patents and these patents are more significant in terms of influencing subsequent patents. I hypothesize that one possible reason for this finding is the increased flexibility and tolerance to experimentation associated with arm's length financing. I find support for this hypothesis—firms with arm's length financing have more volatile innovative output and they innovate in more diverse technological fields. Firm's that have multiple banking relationships, that have a higher proportion of credit lines, and less intense covenants also innovate more. I mitigate potential endogeneity concerns by using instrumental variable analysis, and by showing a significant increase in innovative activity following a large infusion of arm's length financing in the form of equity and public debt, and no such increase after an infusion of bank financing. I also find that highly cited patents are positively and significantly related to future firm value. I believe that the results of the paper may have broader implications. The results suggest, for instance, that innovative firms may benefit from internal policies that give greater tolerance to experimentation and early failure to their managers. Hence, innovative firms might be expected to rely more heavily on incentive based compensation—rather than monitoring—to maximize firm value. Interestingly, some evidence in this direction has been provided in a recent study by Lerner and Wulf (2007) and Ederer and Manso (2013). At a macrolevel, the findings suggest that financial development or, at least, the establishment of arm's length financing institutions, may affect the innovation process and economic growth.

Acknowledgments

The author thanks Gustavo Manso (the department editor), the two anonymous referees, Andres Almazan, Philippe Aghion, Gautam Ahuja, George Baker, Sugato Bhatacharyya, Larry Dann, Diane Del Guercio, John DiNardo, Amy Dittmar, Robert Dittmar, Mara Faccio, Michael Faulkender, Radhakrishnan Gopalan, Charles Hadlock, Thomas Hellmann, Alexander Koch, Francine Lafontaine, Xiaoding Liu, Stephen McKeon, Tobias Moskowitz, Kevin Murphy, Vikram Nanda, Amiyatosh Purnanandam, Uday Rajan, Amit Seru, Merih Sevilir, Ravi Singh, P.K. Toh, Rosemary Ziedonis, and Luigi Zingales, as well as the seminar participants at the Ross School of Business at the University of Michigan, the University of Oregon, European Finance Association 2006, Pacific Northwest Finance Conference 2006, and the American Finance Association 2007 conference for suggestions and helpful comments. The author thanks the National Bureau of Economic Research for making their patent data available for public use.

J. Atanassov's current affiliation is College of Business Administration, University of Nebraska–Lincoln, Lincoln, Nebraska 68588.

Appendix. Key Variable Definitions and Data Sources

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

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

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

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

$CitedPatent_{it}^{\text{Time}}$: Measures the number of citations per patent applied for in year t by firm i corrected for time truncation. 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.)

$CitedPatent_{it}^{\text{Time-Tech}}$: Measures the number of citations per patent applied for in year t by firm i corrected for time truncation and for technology class. 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.)

$CitedPatent_{it}^{\text{Quasi}}$: 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. The weighting index is computed from the econometrically estimated distribution of the citation lag. (Source: NBER patent data.)

CitedPatentVolatility is defined as

$$CitedPatentVolatility = \sqrt{\frac{\sum_{i=1}^{5}\left(CP_{t+i} - \overline{CP}\right)^2}{4}}, \qquad (11)$$

where CP_{t+i} is the number of citations per patent for patents applied in year $t+i$ and $\overline{CP}$ is the average number of citations per patent over the same five-year period from $t+1$ to $t+5$. (Source: NBER patent data.)

$CorpPurpose_{it}$: The percentage of firm loans that have "corporate purpose." (Source: DealScan.)

$CovenantIntensity_{it}$: Equals the sum of six covenant indicators representing the existence of a secured covenant, a dividend restriction, more than two financial covenants, an equity issuance sweep, a debt issuance sweep, and an asset sales sweep. The index ranges from zero to six, where higher index values indicate more restrictive loan contracts. (Source: DealScan and Bradley and Roberts 2004.)

$CovenantViolation_{it}$: Equals 1 if the company has violated a financial covenant at any time during the fiscal year and 0 otherwise. (Source: Nini and Smith 2012.)

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

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

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

$(Equity/Assets)_{it}$: 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.

Generality is defined as

$$Generality = 1 - \sum_{i=1}^{n_i} r_{ij}^2, \qquad (12)$$

where r_{ij} denotes the percentage of citations received by patent i that belong to patent class j, out of n_i patent classes (note that the sum is the Herfindahl concentration index). (Source: NBER patent data.)

HI_{it}: Herfindahl index of firm i in year t constructed based on sales at both a four-digit SIC and for robustness for the Fama and French (1997) 48 industries. (Source: Compustat; Kenneth French's website (http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html#Research).)

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

$CreditLine_{it}$: The percentage of firm loans that are lines of credit (Source: DealScan.)

$\text{Log}(1 + \%Public)_{it}$: 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.)

$Multiple_{it}$: A dummy variable that takes the value of 1 if firm i borrows from multiple banks and 0 otherwise. (Source: DealScan.)

Originality is defined as

$$Originality = 1 - \sum_{i=1}^{n_i} s_{ij}^2, \qquad (13)$$

where s_{ij} denotes the percentage of citations made by patent i that belong to patent class j, out of n_i patent classes (note that the sum is the Herfindahl concentration index). (Source: NBER patent data.)

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

$Patent_{it}^{c}$: Number of patents in application year t by firm i corrected for the truncation bias in patents granted toward the end of the sample using the "weight factors" provided by Hall et al. (2001, 2005). The weight factors are computed from an application-grant empirical distribution. (Source: NBER patent data.)

PatentVolatility is defined as

$$PatentVolatility = \sqrt{\frac{\sum_{i=1}^{5}\left(P_{t+i} - \bar{P}\right)^2}{4}}, \qquad (14)$$

where P_{t+i} is the number of patents applied for in year $t+i$ and $\bar{P}$ is the average number of patents over the same five-year period from $t+1$ to $t+5$ (Source: NBER patent data.)

$Public_{it}$: 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.)

$Public^s_{it}$: A dummy variable that takes the 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.)

$Public^c_{it}$: A dummy variable that takes the 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.)

Q_{it}: Market-to-book ratio of firm i in year t. (Source: Compustat (Assets + Data 199 $*$ Data 25 − book equity) assets, where Data 199 is the year end closing price and Data 25 is year-end outstanding shares.)

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

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

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

$S\&P\ 500_{it}$: A dummy variable that takes a value of 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.)

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

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

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

$TermLoan_{it}$: The percentage of firm loans that are term loans. (Source: DealScan.)

References

Acharya V, Subramanian K (2009) Bankruptcy codes and innovation. *Rev. Financial Stud.* 22:4949–4988.

Aghion P, Van Reenen J, Zingales L (2013) Innovation and institutional ownership. *Amer. Econom. Rev.* 103:277–304.

Aghion P, Bloom N, Blundell R, Griffith R, Howitt P (2005) Competition and innovation: An inverted-U relationship. *Quart. J. Econom.* 120:701–28.

Allen F, Gale D (1999) Diversity of opinion and financing of new technologies. *J. Financial Intermediation* 8:68–89.

Atanassov J (2013) Do hostile takeovers stifle innovation? Evidence from antitakeover legislation and corporate patenting. *J. Finance* 68:1097–1131.

Azoulay P, Zivin JG, Manso G (2011) Incentives and creativity: Evidence from the academic life sciences. *RAND J. Econom.* 42: 527–554.

Baker M, Stein J, Wurgler J (2003) When does the market matter? Stock prices and the investment of equity-dependent firms. *Quart. J. Econom.* 118:969–1005.

Baumol W (1965) *The Stock Market and Economic Efficiency* (Fordham University Press, New York).

Bekaert G, Harvey C, Lundblad C (2005) Does financial liberalization spur growth. *J. Financial Econom.* 77:3–56.

Bond P, Alex E, Itay G (2012) The real effects of financial markets. *Annual Rev. Financial Econom.* 4:339–360.

Bradley M, Roberts MR (2004) The structure and pricing of corporate debt covenants. Presented at the 6th Annual Texas Finance Festival. http://dx.doi.org/10.2139/ssrn.466240.

Brown JR, Martinsson G, Petersen BC (2012) Do financing constraints matter for R&D? *Eur. Econom. Rev.* 56:1512–1529.

Brown JR, Martinsson G, Petersen BC (2013) Law, stock markets, and innovation. *J. Finance* 68:1517–1549.

Cameron AC, Trivedi PK (1998) *Regression Analysis of Count Data* (Cambridge University Press, New York).

Campbell J, Lettau M, Malkiel B, Xu Y (2001) Have individual stocks become more volatile? An empirical exploration of idiosyncratic risk. *J. Finance* 1:1–43.

Chava S, Roberts M (2008) How does financing impact investment? The role of debt covenants. *J. Finance* 63:2085–2121.

Cockburn I, Henderson R (1998) Absorptive capacity, coauthoring behavior, and the organization of research in drug discovery. *J. Indust. Econom.* 46:157–182.

Cornaggia J, Mao Y, Tian X, Wolfe B (2015) Does banking competition affect innovation? *J. Financial Econom.* 115:189–209.

Dahiya S, Saunders A, Srinivasan A (2003) Financial distress and bank lending relationships. *J. Finance* 58:375–399.

Daines R (2001) Does Delaware law improve firm value? *J. Financial Econom.* 62:525–558.

Diamond D (1984) Financial intermediation and delegated monitoring. *Rev. Econom. Stud.* 51:393–414.

Ederer F, Manso G (2013) Is pay for performance detrimental to innovation? *Management Sci.* 59:1496–1513.

Fama E, French K (1997) Industry costs of equity. *J. Financial Econom.* 43:153–193.

Fama E, MacBeth J (1973) Risk, return, and equilibrium: Empirical tests. *J. Political Econom.* 81:607–636.

Faulkender M, Petersen M (2006) Does the source of capital affect capital structure? *Rev. Financial Stud.* 19:45–79.

Griliches Z (1990) Patent statistics as economic indicators: A survey. *J. Econom. Literature* 28:1661–1707.

Griliches Z, Pakes A, Hall B (1987) The value of patents as indicators of inventive activity. Dasgupta P, Stoneman P, eds. *Economic Policy and Technological Performance* (Cambridge University Press, Cambridge, UK), 97–124.

Gu Y, Mao CX, Tian X (2014) Creditor interventions and firm innovation: Evidence from debt covenant violations. Working paper, Indiana University, Bloomington.

Hadlock C, James C (2002) Do banks provide financial slack? *J. Finance* 57:1383–1419.

Hall B (1990) The impact of corporate restructuring on industrial research and development. *Brookings Papers Econom. Activity* 1990:85–136.

Hall B, Jaffe A, Trajtenberg M (2001) The NBER patent citations data file: Lessons, insights and methodological tools. NBER Working Paper 8498, National Bureau of Economic Research, Cambridge, MA.

Hall B, Ziedonis R (2001) The determinants of patenting in the U.S. semiconductor industry, 1980–1994. *RAND J. Econom.* 32: 101–128.

Hall B, Jaffe A, Trajtenberg M (2005) Market value and patent citations. *RAND J. Econom.* 36:16–38.

Harford J (1999) Corporate cash reserves and acquisitions. *J. Finance* 54:1969–1997.

Holmstrom B (1989) Agency costs and innovation. *J. Econom. Behav. Organ.* 12:305–327.

Holmstrom B, Tirole J (1993) Market liquidity and performance monitoring. *J. Political Econom.* 101:678–709.

Houston J, James C (1996) Bank information monopolies and the mix of private and public debt claims. *J. Finance* 5:1863–1889.

Hsu P-H, Tian X, Xu Y (2014) Financial development and innovation: Cross-country evidence. *J. Financial Econom.* 112:116–135.

Kaplan S, Zingales L (1997) Do investment-cash flow sensitivities provide useful measures of financing constraints? *Quart. J. Econom.* 112:169–215.

Kogan L, Papanikolaou D, Seru A, Stoffman N (2012) Technological innovation, resource allocation and growth. Working paper, Massachusetts Institute of Technology, Cambridge.

Korajczyk R, Levy A (2003) Capital structure choice: Macroeconomic conditions and financial constraints. *J. Financial Econom.* 68:75–109.

Lamont O, Polk C, Saa-Requejo J (2001) Financial constraints and stock returns. *Rev. Financial Stud.* 14:529–554.

Lerner J (2006) The new new financial thing: The origins of financial innovations. *J. Financial Econom.* 79:223–255.

Lerner J, Wulf J (2007) Innovation and incentives: Evidence from corporate R&D. *Rev. Econom. Statist.* 89:634–644.

Levine R, Zervos S (1998) Stock markets, banks, and economic growth. *Amer. Econom. Rev.* 88:537–558.

Manso G (2011) Motivating innovation. *J. Finance* 66:1823–1869.

Morck R, Yang F (2001) The mysterious growing value of the S&P 500 membership. Working paper, University of Alberta, Edmonton, Alberta, Canada.

Mullahy J (1996) Instrumental-variable estimation of count data models: Applications to models of cigarette smoking behavior. *Rev. Econom. Statist.* 79:586–593.

Nini G, Smith D (2012) Creditor control rights, corporate governance, and firm value. *Rev. Financial Stud.* 25:1713–1761.

Pakes A, Schankerman M (1984) The rate of obsolescence of patents, research gestation lags, and the private rate of return to research resources. Zvi G, ed. *R&D, Patents, and Productivity* (University of Chicago Press, Chicago), 98–112.

Rajan R (1992) Insiders and outsiders: The choice between informed and arm's-length debt. *J. Finance* 47:1367–1400.

Rajan R, Zingales L (2003) Banks and markets: The changing character of European finance. *Second ECB Central Banking Conf., Frankfurt am Main, Germany*.

Roberts M, Sufi A (2009) Control rights and capital structure: An empirical investigation. *J. Finance* 64:1657–1695.

Scherer FM (1984) *New Perspectives on Economic Growth and Technological Innovation* (Brookings Institution Press, Washington, DC).

Schoar A (2002) The effect of diversification on firm productivity. *J. Finance* 62:2379–2403.

Seru A (2014) Firm boundaries matter: Evidence from conglomerates and R&D activity. *J. Financial Econom.* 111:381–405.

Solow R (1957) Technical change and the aggregate production function *Rev. Econom. Statist.* 39:312–320.

Stulz R (2004) Does financial structure matter for economic growth? A corporate finance perspective. Demirgüç-Kunt A, Levine R, eds. *Financial Structure and Economic Growth: A Cross-Country Comparison of Banks, Markets, and Development* (MIT Press, Cambridge, MA), 143–188.

Sufi A (2009) Bank lines of credit in corporate finance: An empirical analysis. *Rev. Financial Stud.* 22:1057–1088.

Tian X, Wang TY (2014) Tolerance for failure and corporate innovation. *Rev. Financial Stud.* 27:211–255.

Titman S, Wessels R (1988) The determinants of capital structure choice. *J. Finance* 43:1–19.

Trajtenberg M (1990) A penny for your quotes: Patent citations and the value of information. *RAND J. Econom.* 21:325–342.

Whited TM, Wu G (2006) Financial constraints risk. *Rev. Financial Stud.* 19:531–559.