Less is More: Financial Constraints and Innovative Efficiency

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Abstract

Unlike conventional wisdom, financial constraints may improve the efficiency of innovative activities. We measure firm-level innovative efficiency by patents (or patent citations) scaled by R&D (research and development) investment or the number of employees, and find that financial constraints are positively associated with future innovative efficiency. Tests using the 1989 junk bond crisis and mandatory pension contributions as exogenous shocks to financial constraints suggest a causal interpretation for the link. Consistent with agency problems, the positive effect of financial constraints on innovative efficiency is stronger among firms with high excess cash holdings and low investment opportunities, and among firms in less competitive industries. Financial constraints appear to be mitigating free cash flow problems that induce firms to make unproductive R&D investments in fields out of their direct expertise. Our findings point to a bright side of the role of financial constraints in corporate investment, especially in intangible assets.

JEL Classification: G32, G34, O32

Keywords: Financial constraints, innovation, patents, R&D, free cash flow, agency problems, investment.

1. Introduction

Innovation is the driving force for business success and a key source of competitive advantages in today's economy. Conventional wisdom suggests that financial constraints hurt innovations by reducing firms' R&D spending in innovative projects and thus lowering the probability of winning patent races in the long term. However, anecdotal evidence suggests that more financial resources do not necessarily lead to more and better innovation.

For example, some question whether U.S. firms' R&D investments generated commensurate inventions (*Economist* 1990; Jensen 1993; Jaffe 2000; Lanjouw and Schankerman 2004; Skinner 2008).[1] Furthermore, a recent report shows that small biotechnology companies spend on aggregate around $28 billion annually on R&D, which is much lower than the $50 billion R&D spending for large pharmaceutical companies.[2] However, the dominance of large pharmaceutical companies in R&D spending did not make them the winner in discovering new drugs. Munos (2009) shows that the share of approved new drugs from large pharmaceutical companies has gradually declined from roughly 75% since the early 1980s to nearly 35% in 2008. At the same time, the share attributable to small biotechnology and pharmaceutical companies has jumped from 23% to nearly 70% during the same period. In other words, small firms collectively produce more for less.[3] These findings suggest that when it comes to innovative *efficiency* in converting innovative input into valuable output, less can be more.

[1] Jensen (1993) shows that U.S. real R&D expenditures grow at an average annual rate of 5.8% from 1975 to 1990 without generating appropriate economic and financial gains. Skinner (2008) reports that, over the period from 1980 to 2005, U.S. public firms' R&D expenditures increase by about 250%, while their capital expenditures increase by less than 50%. The *Economist* (1990) notes that "American industry went on an R&D spending spree, with few big successes to show for it." Jaffe (2000) and Lanjouw and Schankerman (2004) also observe that the escalating R&D investment does not generate commensurate patents since the 1980s.
[2] Life sciences: a 20/20 vision to 2020. http://www.burrillandco.com/content/BT08_execSum.pdf
[3] See also Kortum and Lerner (1998).

Existing studies mainly focus on the link between financial constraints and innovative input or output, and leave the effect of financial constraints on innovative *efficiency* unexplained.[4] Thus, the link between financing constraints and firms' innovative efficiency is an important issue that calls for investigation.

This paper shows that tighter financial constraints improve firms' innovative efficiency. Firms that are more likely to be constrained generate more patents and citations per unit of R&D investment and per employee. This relation between financial constraints (FC) and innovative efficiency (IE) has a causal interpretation, and is stronger among firms with excess cash holdings and low investment opportunities, and among firms in less competitive industries. We also find evidence that suggests that the marginal value of R&D investment is negative for financially unconstrained firms with large cash holdings, while always positive for financially constrained firms. Furthermore, the FC-IE relation appears to be due to the fact that firms with large free cash flow make less productive R&D investments that are out of their areas of expertise and thus less valuable to shareholders. Tighter constraints (*less* slack) thus lead to *more* productive and value-enhancing innovation.

The "less is more" effect can be a consequence of Jensen's (1986) free cash flow argument. Firms with large free cash flow are more likely to invest in unproductive projects due to agency problems. Financial constraints can force firms to make optimal investment decisions. This disciplinary benefit of financial constraints can be particularly important for innovative investments which are more subject to agency problems due to their unique

[4] Schumpeter (1942) suggests that firms with financial slack and stable internally generated funds can secure risky R&D projects and generate more technological inventions (see also Cohen, Levin, and Mowery 1987). Henderson and Cockburn (1996) find that research programs located within larger firms are more productive due to within-firm spillovers. Aghion, Angeletos, Banerjee, and Manova (2010) argue that constrained firms are less likely to engage in long-term innovative investments because they are subject to long-run macroeconomic shocks. Brown, Martinsson, and Petersen (2010) find that financing constraints effectively limit R&D activities. Ciftci and Cready (2011) find that larger firms' R&D investments are associated with substantially higher future profitability. Li (2011) show that financial constraints increase the risk of R&D-intensive firms.

features such as high uncertainty, long horizon to resolve the uncertainty, intangibility, and severe information asymmetry (e.g., Kumar and Langberg 2009; Hall and Lerner 2010). These features may make it easier for managers to seek private benefits and disguise their suboptimal investment decisions when investing in innovation.[5]

Alternatively, a simple neoclassical model with decreasing returns to R&D investment may also predict higher innovative efficiency for more constrained firms. Financial constraints raise the firm's cost of capital and lower its resources available for innovative investments. As a result, the firm only invests in its most promising projects achieving higher *average* innovative efficiency.[6]

To empirically test whether financial constraints (FC) lead to higher IE and whether such a relation can be attributed to free cash flow problems or decreasing returns to scale, we measure FC by the SA index (Hadlock and Pierce, 2010), the WW index (Whited and Wu, 2006), or size (market capitalization), and IE by patents (or citations) scaled by R&D investment or the number of employees.[7] Firms with higher SA index, higher WW index, or smaller size are more financially constrained.

We first examine the hypothesis that financial constraints increase innovative efficiency by regressing IE measures on lagged FC measures along with relevant control variables. We

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[5] Private benefits from wasteful R&D investment come in many ways. For example, managers may gain insider profits from their R&D investment. Aboody and Lev (2000) find that R&D investment is positively associated with information asymmetry and leads to significant insider gains. Moreover, having a large R&D budget represents power, which can help enhance managers' self-esteem. Conducting topical, high-profile R&D projects (e.g., developing drugs targeting currently untreatable diseases such as cancer, AIDS, Alzheimer) enhances CEOs' ego or social image.

[6] Cohen and Klepper (1996) find that the number of patents per dollar of R&D declines with firm size in the 1970s and argue that the positive in-house R&D externalities encourage larger firms to undertake more marginal R&D projects and result in a negative relation between firm size and R&D productivity.

[7] Patents are materialized innovations of business value and liquidity (e.g., Griliches 1990; Lev 2001). To measure the input-output relation in innovative activities, Lanjouw and Schankerman (2004) and Hirshleifer, Hsu, and Li (2012) scale patents by R&D expenses, while Acharya, Baghai, and Subramanian (2012a and 2012b) scale patents by employees.

find that more constrained firms generate significantly more patents and citations per unit of R&D investment and per employee. This relation is economically significant, and is robust to controlling for variables that have been used to explain innovation in prior studies.[8] For example, a one standard deviation increase in the SA index enhances IE measures by 23.1% to 42.8% from sample averages.

Although size is often used as a proxy of financial constraints in the literature, it may reflect other dimensions in addition to financial constraints such as firms' life cycle or organizational structure (Seru 2010). To ensure our results are not driven *only* by size, we also conduct similar tests using the residual financial constraints indices measured by the residuals from Fama-MacBeth regressions of the SA or WW index on size as additional proxies of constraints. The results show that the FC-IE effect is robust to controlling for size. Furthermore, we find the FC-IE effect is also robust to excluding conglomerates from the sample.

To address potential endogeneity issues, we consider two identification strategies by using the junk bond crisis and mandatory pension contributions as exogenous shocks to financial constraints. We first conduct difference-in-differences tests using the collapse of the junk bond market in 1989 as an exogenous shock to financial constraints (e.g., Lemmon and Roberts 2010; Almeida, Campello, and Hackbarth 2011). This event is unexpected by junk-bond issuing firms and significantly tightens up those firms' financial constraints. It is also unlikely to directly affect innovation activities through channels other than financial constraints. We find that the increase in IE following the shock for junk bond issuers (treatment group) is significantly higher than that for unrated firms (control group). Compared

[8] See Bhagat and Welch (1995); Lev and Sougiannis (1996); Aghion, Bond, Klemm, and Marinescu (2004); Atanassov, Nanda, and Seru (2007); Aghion, Van Reenen, and Zingales (2009); Hirshleifer, Hsu, and Li (2012); and Cohen, Diether, and Malloy (2012).

to the control group, the treatment group's IE measures increase by 11.7% to 27.0% from sample averages after the shock.

We then use the non-zero mandatory contributions to defined benefit (DB) pension plans as exogenous shocks to firms' financial constraints.[9] Rauh (2006) shows that mandatory contributions serve as useful instruments in identifying the response of corporate investment activities to changes in internal financial resources, since they affect financial constraints and can be separated from variation in firms' investment opportunities. Our findings suggest that, when a firm experiences an increase of one standard deviation in exogenous mandatory contributions, its average IE measures increase by 11.6% to 33.7%. Our two identification tests point to a causal interpretation for the link between FC and IE.

To examine whether the positive FC-IE relation is due to agency problems and/or a neoclassical argument of decreasing returns to scale, we conduct further tests. First, we examine how the effect of FC on IE varies with firms' *excess* cash holdings and investment opportunities measured by the market-to-book asset ratio (MTB). We find that the FC-IE relation is substantially stronger among firms that are more prone to agency problems (i.e., firms with excess cash holdings above the 70th percentile and MTB below the 30th percentile). This evidence supports the agency explanation.

Second, we investigate how the marginal value of R&D investment to shareholders varies with cash holdings across financial constraints subsamples using the methodology of Faulkender and Wang (2006). We find that the marginal value of R&D is always above one for constrained firms, but below one for cash-rich unconstrained firms. This evidence suggests that marginal R&D dollar is spent on positive NPV projects for constrained firms,

[9] We define that firm i makes exogenous pension contributions in year t when firm i reports non-zero mandatory pension contributions in year t and zero mandatory pension contributions in year $t-1$.

but on negative NPV projects for cash-rich unconstrained firms. These findings further illustrate the disciplinary benefit of financial constraints and suggest that FC increase IE by reducing investments in negative NPV projects as predicted by the free cash flow argument.

Third, we examine the interaction of product market competition with the FC-IE relation. Competition can be a proxy of external governance and substitute for financial constraints in alleviating agency problems. Thus, a stronger FC-IE relation in less competitive industries is consistent with the free cash flow explanation. In contrast, the neoclassical argument does not have a clear prediction for competition. Consistent with the free cash flow explanation, we find that the FC-IE link is significantly stronger in less competitive industries (i.e., lower external governance).

Fourth, we examine how financial constraints affect a firm's innovative strategies that serve as a channel through which financial constraints influence innovative efficiency. We classify firms' innovative strategies into "exploratory" and "exploitative" using patent data. Firms focusing on their existing expertise fields and current competitive advantages are expected to produce more exploitative patents, while firms exploring new areas and reaching out for new competitive advantages are expected to produce more exploratory patents (e.g., Sorensen and Stuart 2000, Benner and Tushman 2002, Katila and Ahuja 2002, and Phelps 2010). Our analysis shows that exogenous shocks to financial constraints are associated with a lower percentage of exploratory patents (both absolute and relative to exploitative patents) one-year ahead. We also report that a lower percentage of exploratory patents is positively associated with higher innovative efficiency. These results suggest that free cash flow problems induce firms to make unproductive R&D investments in fields out of their direct expertise and result in lower efficiency.

This paper contributes to the literature in several ways. First, it challenges conventional wisdom that suggests that financial constraints hurt innovation performance by reducing firms' R&D spending and the probability of winning patent races. Second, it shows that free cash flow problems may adversely affect the productivity of firms' innovative investments, which are more susceptible to agency problems due to high uncertainty, intangibility, and severe information asymmetry. Third, based on the detailed information contained in patent data, we are able to propose and empirically test a new and explicit channel (i.e., exploratory or exploitative innovative strategies) that connects firms' financial status to managers' investment behaviors.

A related study by Seru (2010) shows that conglomerates conduct less-novel R&D and that conglomerates with more novel R&D tend to operate with decentralized R&D budgets. Since financial constraints are negatively correlated with firm size, these results are related to ours in that they imply that innovation is better conducted outside the boundaries of large firms. Nevertheless, we show that the FC-IE relation is robust to controlling for size and excluding conglomerates from the sample. Thus, our results are unlikely to be driven by the same mechanism that explains the results in Seru (2010).[10]

This paper continues as follows. Section 2 discusses the data and the construction of the IE and FC measures. Section 3 examines the relation between financial constraints and innovative efficiency. Section 4 studies whether agency problems or decreasing returns to

[10] Previous studies have also shown that firm-level innovation performance is related to shareholder composition and risk preferences (Aghion, Van Reenen, and Zingales 2009; Ederer and Manso 2010; Tian and Wang 2011), private ownership (Lerner, Sorensen, and Stromberg 2011; Ferreira, Manso, and Silva 2012; Bernstein 2012), law environments (Acharya and Subramanian 2009; Acharya, Baghai, and Subramanian 2012a, 2012b; Atanassov 2012), conglomerate form (Seru 2010), CEO overconfidence and characteristics (Hirshleifer, Low, and Teoh 2012), CEO contract and compensation (Manso 2011; Lerner and Wulf 2007; Francis, Hasan, and Sharma 2009; Baranchuk, Kieschnick, and Moussawi 2011; Bereskin and Hsu 2012), corporate governance and anti-takeover provision (Sapra, Subramanian, and Subramanian 2011; Chemmanur and Tian 2012), investment cycles in financial markets (Nanda and Rhodes-Kropf 2011, 2012), and product market competition (Aghion, Bloom, Blundell, Griffith, and Howitt 2005).

scale explain the FC-IE relation. Section 5 examines how exogenous shocks to financial constraints affect firms' innovative strategies and how these strategies are related to innovative efficiency. Section 6 concludes.

2. The data and the measures of innovative efficiency and financial constraints

Our sample consists of firms in the intersection of three databases: the NBER patent database for public firms' patenting records, the CRSP (Center for Research in Security Prices) database for stock price and return data, and the Compustat database for accounting data. All domestic common shares trading on NYSE, AMEX, and NASDAQ with accounting and price data and patent data available are included except financial and utilities firms (with standard industrial classification (SIC) codes between 6000 and 6999 or equal to 4900). Following Fama and French (1993), we also exclude closed-end funds, trusts, American Depository Receipts, Real Estate Investment Trusts, units of beneficial interest, and firms with negative book value of equity. In addition, we require firms to be listed on Compustat for two years before including them in the sample to mitigate backfilling bias. Institutional ownership data are from the Thomson Reuters Institutional (13f) Holdings dataset.

We use the 2006 edition of the NBER patent database (Hall, Jaffe, and Trajtenberg 2001) that contains detailed information on all U.S. patents granted by the U.S. Patent and Trademark Office (USPTO) between January 1976 and December 2006: patent assignee names and Compustat-matched identifiers (if available), the number of citations received by each patent, technological class, application years, and other details.[11] Patents are included in this database only if they are eventually granted.

[11] The NBER patent database is available at https://sites.google.com/site/patentdataproject/Home/downloads.

Using the patent data, we construct four IE measures for each firm in each year: Patents/R&D, Patents/Employees, Citations/R&D, and Citations/Employees.[12] Specifically, Patents/R&D (Patents/Employees) is the total number of *adjusted* patents applied in year *t* scaled by *adjusted* R&D expense (number of employees) in year *t*.[13] The unit of R&D expenses (employees) is millions (thousands). Citations/R&D (Citations/Employees) is the total number of *adjusted* citations received by a firm's patents applied in year *t* from the grant year till 2006 scaled by *adjusted* R&D expense (number of employees) in year *t*.

The method of adjusting patents and citations follows the literature (e.g., Seru 2010; Bena and Garlappi 2011) and helps control for the patenting and citing propensities associated with application year and technological class. Specifically, to compute the adjusted patents, we scale the number of patents in each technological class by the cross-sectional average number of patents applied in the same year and assigned to the same technological class by the USPTO. To compute the adjusted citations, we scale the number of citations received by each patent by the average number of citations received by patents applied in the same year and assigned to the same technological class.[14] Similarly, we also adjust innovative input (the denominator of the IE measures) by scaling R&D (Employees) by the corresponding industry

[12] Patent citations are usually regarded as a better proxy for innovation output than patent counts because they may better reflect the economic and technical impact of firms' inventions (e.g., Trajtenberg 1990; Aghion, Van Reenen, and Zingales 2009; Lerner, Sorensen, and Stromberg 2011; Bernstein 2012). The employee-based IE measures reflect a firm's innovative efficiency from the perspective of human capital (e.g., Acharya, Baghai, and Subramanian 2012a, 2012b).

[13] We use the application year as the effective year for patents following the corporate finance literature on innovation. In addition, patents applied in earlier years are likely to receive more citations since it takes time for a patent to be cited. Thus, we adjust citations using the weighting factor developed by Hall, Jaffe, and Trajtenberg (2001) to control for this truncation bias. Following Lanjouw and Schankerman (2004), we scale a firm's patents and citations by contemporaneous R&D because previous studies show that R&D has a strong effect on contemporaneous patent applications and a weak effect on subsequent patent applications (Hausman, Hall, and Griliches 1984; Hall, Griliches, and Hausman 1986). Nevertheless, we construct alternative measures of IE using R&D capital (i.e., accumulated R&D expenditures over the most recent five years with a depreciation rate of 20%) as the denominator that deliver similar test results.

[14] Alternatively, we adjust the total number of patents (citations) for each firm-year observation by its corresponding industry average patents (citations) in the same application year based on the Fama-French (1997) 48 industry classifications. The results are similar (unreported).

average R&D expenses (number of employees) in the same year based on Fama-French (1997) 48 industry classifications to remove the industrial component in R&D expenditures and employees.

We construct these IE measures for each firm from 1980 to 2004. Our sample begins in 1980 because U.S. firms started to actively patent their inventions since the early 1980s (Hall and Ziedonis 2001; Hall 2005). Our sample ends in 2004 because patent counts toward the end of the NBER patent database are subject to truncation bias as it takes on average two years for a patent application to be processed (Hall, Jaffe, and Trajtenberg 2001).

We use three primary measures of financial constraints (FC): the SA index (Hadlock and Pierce 2010), the WW index (Whited and Wu 2006), and firm size (market capitalization).[15] Financially more constrained firms have higher SA index, higher WW index, or smaller size.

The SA index is a combination of asset size and firm age and is calculated as ($-0.737*Assets + 0.043*Assets^2 - 0.040*Age$), where *Assets* is the natural log of inflation-adjusted book assets and is capped at (the natural log of) $4.5 billion, and *Age* is the number of years a firm is listed with a non-missing stock price on Compustat and is capped at 37 years. The WW index is a linear combination of the following variables with signs in parentheses: cash flow to total assets (−), sales growth (−), long-term debt to total assets (+), log of total assets (−), dividend policy indicator (−), and the firm's three-digit SIC industry sales growth (+).[16]

[15] In addition, we use payout ratio, asset size, and sales as alternative measures of financial constraints. The results (unreported) are qualitatively similar. We also experiment with the Kaplan and Zingales (1997) index, but the index is weakly correlated with the other measures of financial constraints as shown in other literature(e.g., Almeida, Campello, and Weisbach 2004; Whited and Wu 2006; Hennessy and Whited 2007; and Hadlock and Pierce 2010).

[16] Following Whited and Wu (2006), we compute the WW index using Compustat quarterly data according to the following formula: $WW = -0.091*CF - 0.062*DIVPOS + 0.021*TLTD - 0.044*LNTA + 0.102*ISG - 0.035*SG$, where *CF* is the ratio of cash flow to total assets; *DIVPOS* is an indicator that takes the value of one if the firm pays cash dividends; *TLTD* is the ratio of the long-term debt to total assets; *LNTA* is the natural log of total assets; *ISG* is the firm's three-digit SIC industry sales growth; and *SG* is the firm's sales growth. All variables are deflated by the replacement cost of total assets as the sum of the replacement value of the capital

By construction, both indexes are higher for firms that are financially more constrained. Market capitalization (size) is a popular measure of financial constraints (e.g., Livdan, Sapriza, and Zhang 2009) and is yearend market capitalization. Since our IE measures span from 1980 to 2004, we construct each firm's FC measures from 1979 to 2003.

In examining the effect of FC on future IE, we control different sets of variables including market-to-book asset ratio (MTB), leverage (DE), the natural logarithm of the assets-to-employees ratio (ln(K/L)), R&D-to-sales ratio (RDS), and institutional ownership (IO). MTB is defined as the market value of assets divided by book value of assets, where market value of assets is measured by total assets minus book equity plus market value of equity. MTB reflects growth opportunities perceived by the stock market. DE is the ratio of long-term debt to market value of equity. A firm's capital structure can potentially affect a firm's R&D and patenting activities (e.g., Bhagat and Welch 1995; Aghion, Bond, Klemm, and Marinescu 2004; Atanassov, Nanda, and Seru 2007). RDS is R&D expenses divided by sales, which reflects the R&D input and investment intensity and is positively associated with future operating performance (Lev and Sougiannis 1996). ln(K/L) is the natural log of the ratio of total assets to the number of employees, and IO is institutional ownership defined as the percentage of shares outstanding owned by institutional investors.[17] Both variables are related to innovation output as suggested in Aghion, Van Reenen, and Zingales (2009).

Panel A of Table 1 reports summary statistics of the IE and FC measures and these control variables. All variables and measures are winsorized at the 5% and 95% levels to mitigate the influence of outliers. The averages (standard deviations) of Patents/R&D,

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stock plus the rest of the total assets. Whited (1992) details the computation of the replacement value of the capital stock.

[17] It is worth noting that the IO data used in this paper contain 157,865 firm-year observations with non-missing IO, while the data of Aghion, Van Reenen, and Zingales (2009) only cover 6,208 observations with non-missing IO. This reflects the difference in the IO databases used.

Citations/R&D, Patents/Employees, and Citations/Employees are 16.5, 58.4, 12.2, and 53.5, respectively (44.0, 168.0, 26.1, and 139.9, respectively). In addition, the IE measures are highly skewed. For example, the average Patents/R&D is 16.5, whereas the median and maximum Patents/R&D are 3.1 and 324.5, respectively. The statistics for the other variables are largely consistent with those reported in prior studies.

Panel B of Table 1 reports the Pearson and Spearman rank correlations and associated *p*-values among these variables. The IE measures are one year ahead of all the other variables. The four IE measures are highly correlated with correlations ranging from 0.27 to 0.82 and significant at the 1% level. The three FC measures are also highly correlated with statistical significance. For example, the Pearson correlation between log of size and the SA (WW) index is –0.70 (–0.83). In addition, the univariate correlations between the FC measures and the one-year ahead IE measures largely suggest that more constrained firms tend to be more efficient in innovation.

3. The effect of financial constraints on innovative efficiency

In this section, we employ regression analyses to examine the effect of financial constraints on innovative efficiency and provide empirical evidence that more constrained firms generate more patents and citations per dollar of R&D expenses and per employee. We also conduct further analyses using the collapse of the junk bond market in the late 1980s and unexpected mandatory pension contributions as exogenous shocks to financial constraints. All results point to a positive causal effect of financial constraints on innovative efficiency.

3.1. Financial constraints and innovative efficiency

We first conduct the following annual Fama-MacBeth (1973) cross-sectional regressions following the set-up of Aghion, Van Reenen, and Zingales (2009):

$$IE_{i,t} = \alpha_0 + \alpha_1 FC_{i,t-1} + \alpha_2 MTB_{i,t-1} + \alpha_3 DE_{i,t-1} + \alpha_4 \ln(K/L)_{i,t-1} + \alpha_5\, RDS_{i,t-1} + \alpha_6\, IO_{i,t-1} + \sum_{j=1}^{48} \gamma_j Industry_j, \qquad (1)$$

where $IE_{i,t}$ is one of the four innovative efficiency measures for firm *i* in year *t*, $FC_{i,t-1}$ is one of the three financial constraints measures for firm *i* in year *t* – 1, and $Industry_j$ is a dummy variable that equals 1 for the industry that firm *i* belongs to and 0 otherwise based on the Fama and French (1997) 48 industry classifications. The detailed definitions of all the other variables are provided in Section 2. To reduce the influence of outliers, we winsorize all independent variables (except dummy variables) at the top and bottom 5% levels.

MTB is included to control for differences in investment opportunities. We also control for leverage because the use of debt affects a firm's R&D and patenting activities (see Bhagat and Welch 1995; Aghion, Bond, Klemm, and Marinescu 2004; Atanassov, Nanda, and Seru 2007). Including ln(K/L) in the regression helps control for a potential link between capital-intensity and firms' innovation performance (Aghion, Van Reenen, and Zingales 2009). The inclusion of RDS helps control for R&D intensity. In unreported tables, we find that excluding R&D intensity generates very similar results. We also control for institutional ownership as Aghion, Van Reenen, and Zingales (2009) show that institutional ownership is associated with more innovation *output* measured by patent citations. Lastly, we control for industry fixed effects because previous studies report heterogeneous patenting intensity across industries (e.g., Hirshleifer, Hsu, and Li 2012). However, in unreported results, we find that regressions without controlling for industry effects generate very similar results.

We propose that financially constrained firms (i.e., firms with higher SA index, higher WW index, or smaller market capitalization) are more efficient in innovation due to the disciplinary benefit of constraints. Therefore, if our hypothesis is supported, the slopes on the SA index and the WW index should be significantly positive, and the slopes on ln(Size) should be significantly negative. We use the natural log of size (ln(Size)) since size is highly skewed.

Table 2A reports the time series average slopes and their *t*-statistics. The results show that more constrained firms have significantly higher IE and that the relation is robust to alternative FC and IE measures. Specifically, the slopes on the SA index are 7.94 (t = 5.69), 18.82 (t = 4.99), 7.26 (t = 23.87), and 22.78 (t = 18.53) for Patents/R&D, Citations/R&D, Patents/Employees, and Citations/Employees, respectively. Furthermore, the effect of the SA index on IE is also *economically* significant. Based on the standard deviation of the SA index and the mean of IE measures reported in Table 1, these slopes imply that a one standard deviation increase in the SA index enhances average IE by 34.7%, 23.1%, 42.8%, and 30.6% for Patents/R&D, Citations/R&D, Patents/Employees, and Citations/Employees, respectively.

Similar results are found for the WW index and size. A one standard deviation increase in the WW index enhances average IE by 5.0% to 18.8%, and a one standard deviation decrease in ln(Size) increases average IE by 2.9% to 15.1%.

In unreported tables, we re-estimate Equation (1) augmented with year fixed effects using pooled regressions with standard errors clustered by firm and year, and obtain similar results. We also estimate Equation (1) using IE measures based on industry-adjusted (instead of technology class adjusted) patents and citations and obtain similar results. These additional results suggest that the positive effect of financial constraints on subsequent innovative efficiency is robust to estimation methods, year fixed effects, and methods of adjusting patents and citations.

Since the SA and WW indices are highly correlated with size, which could capture dimensions other than financial constraints (such as life cycle of a firm), we use the residual SA and WW indices, measured by the residuals from Fama-MacBeth regressions of the SA and WW indices on size, as additional proxies of financial constraints. In addition, we augment Equation (1) by controlling for ln(Size). The results in Table 2B show that the positive FC-IE effect is robust to controlling for size and remains economically and statistically significant. Thus, the findings reported in Table 2A cannot be simply attributed to life cycles or size-specific effects. In untabulated results, we conduct the same tests in the sample that excludes conglomerates and find very similar results.

3.2. Exploring shocks to financial constraints

We recognize that the empirical results reported in Tables 2A and 2B could be subject to various endogeneity issues such as an omitted variable problem. There may exist aggregate, industry, and firm-level omitted variables that influence *both* financial constraints and subsequent IE, leading to a seemingly significant FC-IE relation. Economy cycles, industry-specific business cycles, and innovation waves are all potential aggregate- and industry-level factors that could affect the availability of extra financing and innovation opportunities. Our empirical design addresses this problem by controlling for industry and year fixed effects. We also remove any time-varying industry component from the IE measures by adjusting patents, citations, R&D, and employees by their industrial/technological class averages. Therefore, our findings are less likely subject to economy/industry effects.

Firm-level omitted variables, on the other hand, could be more challenging. Although we have considered several control variables at the firm level in the regressions, we cannot fully rule out the possibility that there is an omitted firm-level variable influencing the results. To further address this issue and improve the identification of the FC-IE relation, we conduct the following tests using the junk bond market crisis and mandatory pension contributions as exogenous shocks to financial constraints.

3.2.1. The collapse of junk bond market and innovative efficiency

Lemmon and Roberts (2010) report that a series of bond market developments in 1989 effectively made junk-bond issuing firms lose access to liquidity provided by the corporate bond market.[18] The tightening in financial constraints affects most firms that rely on junk bonds for their financing prior to the crisis. If there is a causal link between financial constraints and innovative efficiency, we would expect IE to increase more following the collapse for junk bond-reliant firms (treatment group) relative to firms that do not rely on bond markets for financing (control group).

The key identification assumption behind this difference-in-differences (Dif-in-Dif) test is that the junk bond collapse does not affect the innovative efficiency of junk bond issuing firms (relative to the control group) for reasons other than financing constraints. We believe this assumption is likely satisfied. In addition, there are no notable contemporary shocks in

[18] In 1989, financial institutions such as savings and loans are precluded to acquire junk bonds due to the introduction of new regulatory standards. Later in that same year, a major operator in the junk bond market, Drexel-Burnham-Lambert (DBL), collapsed due to the investigation from Securities and Exchange Commission and eventually filed for bankruptcy in February 1990. Almeida, Campello, and Hackbarth (2011) also use this event as a proxy of exogenous shock to financial constraints.

the late 1980s (such as major technological breakthroughs) that may generate similar implications to the junk bond market collapse.

Following Lemmon and Roberts (2010), we focus on an event window that spans from 1986 to 1993 and assign the 1986-1989 and 1990-1993 periods as the pre- and post-event periods, respectively. Similarly, we use S&P's long-term domestic issuer credit rating to classify firms. According to S&P, firms rated BBB– or higher are investment-grade; firms rated BB+ or lower are junk bond issuers; and firms without an S&P rating are unrated. The sample for the Dif-in-Dif test only includes junk bond issuers and unrated firms during the period 1986-1993 and satisfying three additional criteria: first, unrated firms are always unrated throughout the entire 1986-1993 period; second, junk bond issuers retain their status and do not change to or from investment grade during the period; and third, each firm needs to have at least one observation in both pre- and post-event periods.

We use pooled regressions to estimate the following model for the Dif-in-Dif test:

$$\begin{aligned} IE_{i,t} = \alpha_0 &+ \alpha_1 Dummy(Post)_t * Dummy(Junk)_i + \alpha_2 Dummy(Post)_t \\ &+ \alpha_3 Dummy(Junk)_i + \alpha_4 MTB_{i,t-1} + \alpha_5 DE_{i,t-1} + \alpha_6 \ln\left(\frac{K}{L}\right)_{i,t-1} \\ &+ \alpha_7\, RDS_{i,t-1} + \alpha_8\, IO_{i,t-1} + \alpha_9\, SP500_i + \alpha_{10}\, NYSE_i + \alpha_{11}\, Age_{i,t-1} \\ &+ \alpha_{12}\, CF_{i,t-1} + \alpha_{13}\, IEgrowth_{i,t-1} + \sum_{j=1}^{48} \gamma_j Industry_j + \sum_{t=1}^{8} \rho_t Year_t, \quad (2) \end{aligned}$$

where $Dummy(Post)_t$ is one for observations occurring in 1990-1993 and zero otherwise, and $Dummy(Junk)_i$ is one if firm *i* is below investment grade and zero otherwise.

Following Lemmon and Roberts (2010), we control for variables that explain firms' financing choices and whether they issue junk bonds. Specifically, $SP500_i$ is a dummy variable that equals one if firm *i* is included in the S&P 500 index during 1986–1993 and zero otherwise, and $NYSE_i$ is a dummy variable that equals one if a firm is listed in New York Stock Exchange and zero otherwise. $Age_{i,t-1}$ is the natural log of one plus the number of years firm *i* exists in Compustat with nonmissing pricing data in year *t* – 1. $CF_{i,t-1}$ is defined as firm *i*'s income before extraordinary items scaled by lagged total assets in year *t* – 1.

Moreover, we control for $IEgrowth_{i,t-1}$, the annual growth rate in IE from year *t* – 2 to year *t* – 1, to help ensure that the parallel trend assumption (i.e., sample firms are expected to have the same growth trend in IE before the event) is satisfied. Since $IEgrowth_{i,t-1}$ also captures growth in IE post the event, we estimate Equation (2) with and without this variable. $Year_t$ is the year dummy, and all the other variables are defined in Section 3.1. To reduce the impact of outliers, all variables except the dummy variables are winsorized at the 5% and 95% levels. In addition, we cluster the standard errors at the firm level.

The focus is the coefficient on the interaction term, $Dummy(Post)_t * Dummy(Junk)_i$, which captures the average change in IE from pre-1989 to post-1989 for the junk bond issuers minus the change in IE from pre-1989 to post-1989 for the unrated firms. A significantly positive coefficient on the interaction term would support our hypothesis that financial constraints increase innovative efficiency.

Table 3A reports the results from estimating Equation (2) without and with growth in IE in Models 1 and 2, respectively. Both models support our hypothesis. For example, for Model 1, the coefficients of $Dummy(Post)_t * Dummy(Junk)_i$ are 3.04 (*t* = 1.74), 15.75 and (*t* = 2.35), 1.43 (*t* = 1.86), and 7.36 (*t* = 2.05) in Panels A, B, C, and D for Patents/R&D, Citations/R&D, Patents/Employees, and Citations/Employees, respectively. These slopes imply that the effect of tightening financial constraints due to the collapse of the junk bond market on IE is significantly higher for junk bond issuers than for unrated firms. In terms of economic significance, compared to unrated firms, a junk bond issuing firm's IE increases by at least 18.5%, 27.0%, 11.7%, and 13.7% for Patents/R&D, Citations/R&D, Patents/Employees, and Citations/Employees, respectively, from their averages. Consistent with our expectation, the coefficients on $Dummy(Post)_t$ are insignificant, suggesting that the junk bond market collapse do not affect unrated firms' IE significantly.

Our difference-in-differences analysis suggests that junk bond issuing firms, whose financing should be adversely affected by the junk bond collapse, significantly improve their innovative efficiency after the collapse. This evidence addresses the concern that our results are driven by firm-level omitted variables and suggests a causal interpretation of the FC-IE link.

3.2.2. Mandatory pension contributions and innovative efficiency

We develop proxies based on mandatory contributions to defined benefit (DB) pension plans to measure exogenous shocks to firms' financial constraints that help us identify the impact of financial constraints on innovative efficiency. Mandatory contributions to underfunded DB pension plans have adverse effects on firms' internal financial resources and significantly affect their investment decisions. Rauh (2006) uses the non-linear funding rules for DB pension plans to show that mandatory contributions serve as useful instruments in identifying the response of corporate investment activities to changes in internal financial resources, since they are related to financing constraints and can be separated from variation in firms' investment opportunities.[19]

[19] Moreover, since plan investment in the sponsoring firm's securities is limited to a maximum of 10% under Section 407(a)(2) of the Employee Retirement Income Security Act (ERISA), it is generally not the case that a mandatory pension contribution is driven by a price decline of the sponsoring firm's securities.

We use the annual mandatory pension contributions and projected pension obligation of 1,927 public firms over the period 1997-2008 estimated by Bereskin (2010) that are based on Rauh's (2006) methodology and Compustat pension data. We define that firm i makes exogenous pension contributions in year t when firm i reports non-zero mandatory pension contributions in year t and zero mandatory pension contributions in year $t-1$ during the period 1997–2004. Mandatory pension contributions, projected pension obligation, and cash flow are in logarithm. We treat these contributions as exogenous shocks to sample firms' financial constraints for two reasons. First, first mandatory contributions are commonly triggered by unexpected market downturns, and usually result in unanticipated managerial and financing costs for firms. Second, subsequent mandatory contributions are at least partly expected, amortized mandatory contributions to underfunded pension plans and are thus less exogenous to investment decisions.

The effect of exogenous pension contributions on firms' innovative efficiency is examined using the following pooled regressions:

$$\begin{aligned} IE_{i,t} = {} & \alpha_0 + \alpha_1 Mandatory_{i,t-1} + \alpha_2 MTB_{i,t-1} + \alpha_3 DE_{i,t-1} + \alpha_4 \ln(K/L)_{i,t-1} \\ & + \alpha_5\, RDS_{i,t-1} + \alpha_6\, IO_{i,t-1} + \alpha_7\, Obligation_{i,t-1} + \alpha_8\, CF_{i,t-1} \\ & + \sum_{j=1}^{48} \gamma_j Industry_j + \sum_{t=1}^{T} \rho_t Year_t \end{aligned} \tag{3}$$

where $Mandatory_{i,t\text{-}1}$ is firm i's exogenous pension contributions, $Obligation_{i,t\text{-}1}$ is firm i's projected pension obligation (Obligation), and $CF_{i,t\text{-}1}$ is in year $t-1$. Following Rauh (2006), we include projected pension obligation and cash flow in our regression, and scale $Mandatory_{i,t\text{-}1}$, $Obligation_{i,t\text{-}1}$, and $CF_{i,t\text{-}1}$ by lagged total assets. We then use the logarithmic values of these three scaled variables in regressions. All other variables have been defined in

Section 3.1. Our sample includes only firm-year observations in which sample firms experience exogenous pension contributions. We adopt a pooled regression set-up because we do not have enough firms per year with non-missing IE and exogenous pension contributions to form a cross-section. Year dummies are thus included in our regression. Our statistical inferences are based on standard errors clustered by industry.

Table 3B reports the test results for Equation (3) and provides strong evidence for the positive relation between exogenous shortfalls in internal financial resources and innovative efficiency. The coefficient associated with *Mandatory* are 2.30 (t = 1.96), 10.41 (t = 2.02), 0.75 (t = 1.76), and 4.03 (t = 2.47) for Patents/R&D, Citations/R&D, Patents/Employees, and Citations/Employees, respectively. Given that the standard deviation of *Mandatory* is 1.89, when a firm experiences an increase of one standard deviation in sudden mandatory pension contributions, its Patents/R&D, Citations/R&D, Patents/Employees, and Citations/Employees increases by 26.4%, 33.7%, 11.6%, and 14.2%, respectively. Our findings thus provide support to the positive effect of exogenous financial constraints on innovative efficiency, and confirms a causal interpretation of the FC-IE relation.

4. Why do financial constraints increase innovative efficiency?

The evidence above shows that financial constraints increase innovative efficiency. What is the driving force for this relation? One possible explanation has to do with decreasing returns to scale in innovation. A firm with many R&D investment opportunities should select projects following a pecking order, from the one with the highest value to the one with the lowest value. When this firm is under stricter financial constraints, its cost of capital increases and resources available for R&D investment drop. As a result, it only invests in more efficient innovation projects, resulting in higher IE on average. On the other hand, the positive FC-IE relation can also be a manifestation of free cash flow problems. Specifically, a firm with financial slack may overinvest in innovation, especially in the fields that are beyond its expertise, and thereby destroy shareholder value. An increase in financial constraints forces the firm to cut down on wasteful innovation activities.

To understand to what extent the abovementioned stories explain our findings, we further implement three sets of empirical tests. First, we examine whether the effect of financial constraints on innovative efficiency depends on firms' excess cash holdings and investment opportunities (proxied by MTB). The free cash flow story would suggest that the FC-IE link should be stronger among firms with high excess cash and low investment opportunities because FC refrain these firms from wasteful innovative investments. In contrast, the decreasing returns to scale hypothesis would suggest that the FC-IE link should be mitigated for firms with high excess cash, as these firms can use cash to avoid losing profitable innovation opportunities. Second, we investigate how the marginal value of R&D investment to shareholders varies with financial constraints and cash holdings. The free cash flow story predicts that the marginal value of R&D dollar for unconstrained firms with high cash holdings could be less than one dollar. In other words, the marginal R&D is spent on negative NPV projects for these firms. Third, we argue that, if free cash flow problems exist, the effect of financial constraints on innovative efficiency should be stronger in uncompetitive industries because product market competition can also restrain managers from potential wasteful investments.

We find evidence that is consistent with the free cash flow story. The positive effect of financial constraints on innovative efficiency is more pronounced in firms with high excess cash holdings and low MTB. We also find that the marginal value of R&D to shareholders is lower than one dollar for unconstrained firms with high cash holdings. In contrast, the marginal value of R&D is always greater than one dollar for financially constrained firms. Moreover, we observe a stronger FC-IE relation in uncompetitive industries that are of lower external governance. These findings support the argument that financial constraints mitigate agency problems associated with intangible investments.

4.1. Interaction of the FC-IE relation with excess cash holdings and investment opportunities

If the relation between financial constraints and innovative efficiency is driven by agency problems, we would expect it to be stronger among firms with high excess cash holdings and low MTB. These firms both have financial slack, and lack growth opportunities according to the market's view. Specifically, we conduct the following annual Fama-MacBeth cross-sectional regressions that augment Equation (1) with a dummy as follows:

$$\begin{aligned} IE_{i,t} = {} & \alpha_0 + \alpha_1 FC_{i,t-1} * Dummy(Agency)_{i,t-1} + \alpha_2 FC_{i,t-1} + \alpha_3 Dummy(Agency)_{i,t-1} \\ & + \alpha_4 MTB_{i,t-1} + \alpha_5 DE_{i,t-1} + \alpha_6 \ln(K/L)_{i,t-1} \\ & + \alpha_7\, RDS_{i,t-1} + \alpha_8\, IO_{i,t-1} + \sum_{j=1}^{48} \gamma_j Industry_j, \end{aligned} \tag{4}$$

where $Dummy(Agency)_{i,t-1}$ is one for firms with excess cash holdings above the 70th percentile and the market-to-book assets (MTB) below the 30th percentile of all sample firms in year $t-1$. We define excess cash holdings as the cash-to-assets ratio minus estimated normal cash-to-assets ratio following DeAngelo, DeAngelo, and Stulz (2010).[20] All the other variables are defined in Section 3.1.

If financial constraints improve innovative efficiency by mitigating free cash flow problems, we would expect the slope on the interaction term, $FC * Dummy(Agency)$, to be significantly positive for the WW and SA indices and significantly negative for ln(Size).

Table 4A shows that the slopes on the interaction term, $SA * Dummy(Agency)$, are 2.40 (t = 2.57), 7.99 (t = 3.16), 1.75 (t = 3.62), and 5.36 (t = 2.54) for Patents/R&D, Citations/R&D, Patents/Employees, and Citations/Employees, respectively. In terms of economic significance, these slopes imply that a one standard deviation increase in the SA index enhances IE of a potentially wasteful firm by 10.5%, 9.8%, 10.3%, and 7.2% for Patents/R&D, Citations/R&D, Patents/Employees, and Citations/Employees, respectively, in comparison with the average.

We find similar results using the WW index and ln(Size) as financial constraints measures. A one standard deviation increase in the WW index enhances a potentially wasteful firm's IE from 8.5% to 11.9% in comparison with an average firm. A one standard deviation decrease in ln(Size) increases a potentially wasteful firm's IE from 7.6% to 15.6% in comparison with an average firm.

Similarly, we re-estimate Equation (4) by using the *residual* SA and WW indices as defined in Section 3.1 and controlling for ln(Size). The results in Table 4B show the same pattern. Overall, our results are consistent with a free cash flow explanation for the FC-IE link.

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[20] Normal cash-to-assets ratio is calculated by sorting all sample firms in a given year into three equal size groups based on total book assets and three equal size groups based on the market-to-book assets. Each firm is then allocated to one of the nine groups based on its total book assets and market-to-book assets. Within each of the nine groups, a normal cash-to-assets ratio is calculated for each two-digit SIC industry as the median ratio among all firms in that industry for that year.

4.2. Financial constraints, cash holdings, and the marginal value of R&D

If financial slack causes firms to overinvest in innovation, we should observe a low, and possibly even negative marginal value of R&D for firms with high financial slack. More specifically, if unconstrained firms with high cash holdings invest in negative NPV projects due to agency problems, their marginal value of R&D should be less than one. To examine this hypothesis, we use the methodology of Faulkender and Wang (2006) to estimate the value that the stock market places on an extra dollar of R&D investment made by firms with different levels of financial constraints and cash holdings. We first form constrained and unconstrained subsamples based on the 30th and 70th percentiles of the FC measures in year t – 1.[21] We then run the following pooled regression within each subsample:

$$\begin{aligned} ExcessReturn_{i,t} = {} & \alpha_0 + \alpha_1 \Delta RD_{i,t} + \alpha_2 \Delta RD_{i,t} * C_{i,t-1} + \alpha_3 C_{i,t-1} + \alpha_4 \Delta C_{i,t} + \alpha_5 \Delta D_{i,t} \\ & + \alpha_6 \Delta E_{i,t} + \alpha_7 \Delta I_{i,t} + \alpha_8 \Delta NA_{i,t} + \alpha_9 \Delta C_{i,t} * C_{i,t-1} + \alpha_{10} L_{i,t} + \alpha_{11} \Delta C_{i,t} \\ & * L_{i,t} + \alpha_{12} NF_{i,t} + \sum_{j=1}^{48} \gamma_j Industry_j + \sum_{t=1}^{T} \rho_t Year_t, \qquad (5) \end{aligned}$$

where i indexes firm and t indexes year. $ExcessReturn_{i,t}$ is a proxy for shareholders' value, defined as the annualized difference between firm i's monthly stock return and the value-weighted monthly return of one of the Fama and French 25 (5 by 5) size and book-to-market (BTM) portfolios to which the stock belongs.[22] $RD_{i,t}$ is R&D expense. $C_{i,t}$ is cash plus

[21] For the SA and WW indices, the constrained (unconstrained) subsample includes firms in the top (bottom) 30% in year t – 1. For Size, the constrained (unconstrained) subsample includes firms in the bottom (top) 30% in year t – 1.

[22] We form the size and book-to-market portfolios at the end of June of year t based on size at the end of June of year t and BTM in fiscal year ending in calendar year t – 1. The breakpoints for size and BTM are based on NYSE firms. For each firm, we compute the monthly excess return first and then compute the cumulative excess returns over the 12 months prior to its fiscal year end.

marketable securities, $E_{i,t}$ is earnings before extraordinary items plus interest, deferred tax credits, and investment tax credits. $NA_{i,t}$ is total assets minus cash holdings. $I_{i,t}$ is interest expense. $D_{i,t}$ is total dividends measured as common dividends paid. $L_{i,t}$ is market leverage, and $NF_{i,t}$ is total equity issuance minus repurchases plus debt issuance minus debt redemption. All independent variables except $L_{i,t}$ are deflated by the market value of equity in year t – 1. $\Delta X_{i,t}$ is compact notation for the 1-year change, $X_{i,t}-X_{i,t-1}$. All variables are defined following Faulkender and Wang (2006). $Year_t$ is the year dummy for year t and $Industry_j$ is the industry dummy for industry j.

Table 5A shows that the marginal value of R&D decreases with the level of cash holdings for both constrained and unconstrained firms, but at a much faster speed for unconstrained firms. Specifically, the coefficients on $\Delta RD_{i,t} * C_{i,t-1}$ are –2.52 (t = –2.03) and –1.15 (t = –1.65) for the low and high SA index groups, respectively. The coefficients on $\Delta RD_{i,t} * C_{i,t-1}$ are –4.12 (t = –2.70) and –1.73 (t = –2.19) for the low and high WW index groups, respectively. In addition, the coefficients on $\Delta RD_{i,t} * C_{i,t-1}$ are –3.90 (t = –2.26) and –1.40 (t = –2.16) for the small and big groups, respectively.

To better illustrate these results, we plot the marginal value of R&D at different levels of cash holdings for the constrained and unconstrained groups in Figure 1. The coefficients on $\Delta RD_{i,t}$ reported in Table 5A reflect the marginal value of R&D when cash holdings are zero. We can also calculate the marginal value of R&D for different levels of cash holdings, by adding the coefficients on $\Delta RD_{i,t}$ to the coefficients on the interaction term $\Delta RD_{i,t} * C_{i,t-1}$ over the relevant range of cash holdings (0.00 to 0.64 for both subsamples). We find that the marginal value of R&D for constrained firms always exceeds 1, suggesting that marginal R&D of these firms is spent on positive NPV R&D projects. However, the marginal value of R&D for unconstrained firms based on the SA index, the WW index, and Size falls below one dollar when their cash holdings exceeds 0.17, 0.10, and 0.16, respectively.[23] This finding suggests that unconstrained firms' marginal R&D investment is value-destroying when their cash holdings are high, consistent with the free cash flow argument.

To check whether the marginal value of R&D for constrained firms is significantly higher than that for unconstrained firms, we run regressions similar to Equation (5) in the combined sample of constrained and unconstrained firms with $\Delta RD_{i,t}$ and the other control variables interacting with a dummy, $UC_{i,t}$, that equals one for unconstrained firms and zero for constrained firms.[24] Table 5B shows that the coefficients on the interaction term, $UC_{i,t} * \Delta RD_{i,t}$, are significantly negative, indicating that the marginal value of R&D dollar is significantly lower for unconstrained firms. Specifically, the coefficients on $UC_{i,t} * \Delta RD_{i,t}$ are –0.90 (t = –3.19), –1.37 (t = –4.25), and –0.74 (t = –2.42) for the dummy defined on the SA index, the WW index, and Size, respectively. Table 5B also confirms that the marginal value of R&D for constrained firms defined on the SA index, the WW index, and Size is always above 1 since the coefficients on $\Delta RD_{i,t}$ are 1.78 (t = 10.66), 1.79 (t = 10.15), and 1.57 (t = 10.07), respectively. Furthermore, the sum of these two sets of coefficients, which reflects the marginal value of R&D for unconstrained firms, is below 1 for all the three constraints measures.

[23] As a benchmark, the average cash holdings (and corresponding marginal values of R&D dollar) in the unconstrained groups based on the SA index, the WW index, and Size are 0.14, 0.12, and 0.11 (1.06, 0.89, and 1.16), respectively.

[24] We interact the other control variables with the dummy variable to allow the slopes on these control variables to vary across the constraints groups.

Overall, these findings suggest that the marginal R&D dollar of constrained (unconstrained) firms is spent on positive (negative) NPV R&D projects, consistent with the free cash flow argument.

4.3. Interaction of product market competition with the financial constraints effect

Product market competition can serve as external governance and a substitute of financial constrains in restraining managers from inefficient investments because stronger competition lowers future cash flows and puts managers in contests. Firms in uncompetitive industries should be subject to free cash flow problems to a greater extent because they do not have much outside competition and shareholders have difficulty in assessing managers' capabilities. We thus hypothesize a stronger effect of financial constraints on innovative efficiency in uncompetitive industries than that in competitive industries. On the other hand, the decreasing returns to scale explanation does not necessarily predict a stronger FC-IE link in uncompetitive industries.

To test our proposition, we first calculate a competition index for each of Fama-French 48 industries every year, defined as one minus the Herfindahl index based on annual sales of all firms in the same industry. In year t, we then assign firms into the competitive and uncompetitive groups based on the 30th and 70th percentiles of the competition index of their industries in year $t - 1$: the bottom 30% forms the uncompetitive group, and the top 30% forms the competitive group. Within each group for the period 1980-2004, we conduct the same Fama-MacBeth cross-sectional regression as specified in Equation (1).

Consistent with our hypothesis, Table 6 shows a stronger positive effect of financial constraints on innovative efficiency in the uncompetitive group with higher (lower) time-series mean slopes of the SA and WW indices (ln(Size)). In the first column for the uncompetitive group, we find statistically significant slopes on FC in most cases. In contrast, the FC slopes and associated *t*-statistics in the competitive group (second column) are in general less significant and lower in magnitude than their counterparts in the uncompetitive group. These results support the proposition that financial constraints improve firms' innovative efficiency to a greater extent in a less competitive environment.

To gauge the statistical significance of the cross-subsample difference in the FC effect, we pooled the uncompetitive and competitive groups together and augment Equation (1) with an interaction term, *Dummy(Uncompetitive)*FC*, in which *Dummy(Uncompetitive)* equals one if the sample firm belongs to the uncompetitive group and zero otherwise. As shown in the third column of Table 6, the slopes on *Dummy(Uncompetitive)*FC* are always positive (negative) for the SA and WW indices (ln(Size)), consistent with the argument of a stronger FC-IE relation in an uncompetitive environment. Moreover, these slopes are generally statistically significant in most cases except when we measure IE by Patents/R&D in Panel A.

Overall, Table 6 supports our proposition that product market competition substitutes financial constraints in restraining managers from wasteful innovative investments and further confirms that financial constraints help firms innovate more efficiently by mitigating free cash flow problems.

5. Financial constraints shocks, innovative strategies, and innovative efficiency

If financial constraints improve innovative efficiency by lowering agency costs, they are expected to affect firms' project choices and innovative strategies. We hypothesize that financial constraints force managers to stay away from overly risky, exploratory projects and focus on better established, safer projects that can be implemented more easily. To test such a channel, we first examine whether exogenous shocks to financial constraints affect firms' choices of innovative activities, and then test whether these choices explain firms' innovative efficiency.

We classify firms' innovative strategies into "exploratory" and "exploitative" using patent data. Following the management literature, we define patents built on a firm's existing knowledge and aimed to deepen the firm's expertise in current territories as "exploitative patents", and patents tangential or even irrelevant to the firm's existing knowledge and serving as pilot trials into new fields as "exploratory patents" (e.g., Sorensen and Stuart, 2000; Benner and Tushman, 2002; Katila and Ahuja, 2002; Phelps, 2010).

We classify a firm's innovative strategy based on the percentage of exploratory or exploitative patents relative to the total number of newly granted patents. Firms focusing on their existing expertise fields and concentrating on current competitive advantages are expected to produce higher percentage of exploitative patents, while firms exploring new areas and reaching out for new competitive advantages are expected to produce higher percentage of exploratory patents.

We propose that tightened financial constraints motivate firm managers to adopt more exploitative innovative strategies, which can contribute to higher IE. On the other hand, exploratory strategies involve distant search of new knowledge and shifting technological trajectory, and are usually more costly and associated with higher uncertainty. Tightened financial constraints can force managers to stay focused and continue investing in fields in which they have the greatest competitive advantages. When firms are doing what they are already good at, they perform more efficiently in general. Therefore, tightened financial constraints could lead to higher innovative efficiency by encouraging firms to stay focused in innovative activities and to curtail ambitious yet potentially inefficient divergence.

To test this hypothesis, we first determine if a firm's newly granted patents are exploratory or exploitative based on the extent to which a patent is built on new knowledge or the firm's existing knowledge. A patent is categorized as "exploratory" if at least 60%) of the patents it cites are from the firm's "new knowledge" (i.e., patents not in the firm's existing knowledge). On the other hand, a patent is categorized as "exploitative" if at least 60% of the patents it cites are from the firm's "existing knowledge".[25]

We then construct two proxies of a firm's innovative strategies. The first is the percentage of exploratory patents, defined as the number of exploratory patents filed by firm i in year t divided by the number of all patents filed by the firm in the same year. A lower percentage of exploratory patents suggests a more focused innovative strategy. The second is the difference between the percentage of exploratory patents and the percentage of exploitative patents, when the latter is defined as the number of exploitative patents filed by firm i in year t divided by the number of all patents filed by the firm in the same year. A lower difference also suggests a more focused innovative strategy.

[25] As defined in Benner and Tushman (2002), a firm's "existing knowledge" consists of two sources: its own previously filed patents over the past five years, and other companies' patents cited by the firm's patents filed over the past five years. A patent can be neither exploratory nor exploitative. For example, if 50% of the patents cited by a patent are from a firm's "existing knowledge", it is neither exploitative nor exploratory under the 60% threshold. Therefore, the sum of the percentage of exploratory patents and exploitative patents is not necessarily equal to 1. Moreover, we also use the 80% threshold in tests and obtain qualitative empirical results.

We first empirically examine the relation between the junk bond crisis, as a shock to exogenous financial constraints, and innovative strategies. We conduct Dif-in-Dif test similar to Equation (2) using the proposed proxies for innovative strategies as the dependent variables. The results reported in Table 7A show that junk bond issuers become significantly more focused in innovation than unrated firms after the junk bond market collapse, as the coefficients associated with $Dummy(Post) * Dummy(Junk)$ are significantly negative, suggesting that junk bond issuers curtail their exploratory innovations more than other firms after 1989. This effect is robust to different proxies of innovative strategies and different sets of control variables.

We then examine the relation between exogenous pension contributions, as another shock to financial constraints, and innovative strategies. We conduct tests using Equation (3) with the proxies of innovative strategies as the dependent variables. The results reported in Table 7B show that the coefficient associated with *Mandatory* range are –0.04 and –0.07 (both statistically significant at the 5% level) for two measures of firms' exploratory innovation activities, suggesting that firms under the pressure of exogenous pension contributions tend to quit exploring different technology areas. Tables 7A and 7B collectively support a significant relation between financial constraints and innovative strategies.

Lastly, to establish the channel based on innovative strategies, we examine the relation between innovative strategies and innovative efficiency by estimating the following model using the annual Fama-MacBeth regressions:[26]

[26] In unreported tables, we re-estimate Equation (6) augmented with year fixed effects using pooled regressions with standard errors clustered by firm and year, and obtain qualitatively consistent results.

$$IE_{i,t} = \alpha_0 + \alpha_1 Strategy_{i,t} + \alpha_2 MTB_{i,t-1} + \alpha_3 DE_{i,t-1} + \alpha_4 \ln(K/L)_{i,t-1}$$

$$+ \alpha_5 \, RDS_{i,t-1} \;\; + \alpha_6 \, IO_{i,t-1} + \sum_{j=1}^{48} \gamma_j Industry_j, \qquad (6)$$

where $Strategy_{i,t}$ is the percentage of exploratory patents or the difference between the percentage of exploratory patents and the percentage of exploitative patents for firm i in year t. A significantly positive coefficient of $Strategy_{i,t}$ would support our proposition that exploratory innovations lead to inefficiency.

Table 8 reports our estimation of Equation (6) and provides strong evidence for the impact of innovative strategies on innovative efficiency. Firms adopt more exploratory strategies tend to generate fewer patents per R&D dollar or employee. Panel A shows significantly negative slopes on the percentage of exploratory patents. In terms of economic significance, when a firm decreases its exploratory innovations by 10%, its Patents/R&D, Citations/R&D, Patents/Employees, and Citations/Employees increases by 41.2%, 204.1%, 44.3%, and 227.8%, respectively. Similar results are reported in Panel B, when we use the difference between the percentage of exploratory patents and the percentage of exploitative patents as another proxy.

Overall, Tables 7A and 7B suggest that financial constraints lead to more concentrated innovative activities, and Table 8 suggests that more concentrated innovative activities improve firms' efficiency in innovations. We interpret these results as confirming our proposition that managers may spend free cash in exploratory innovation that they know little about, while focusing on areas of expertise as financial constraints tighten.

6. Conclusion

This paper challenges conventional wisdom that suggests that financial constraints hurt innovation performance. We find that financial constraints actually increase innovative efficiency by generating more patents or citations per dollar of R&D expenses or per employee. Tests using the 1989 junk bond crisis and mandatory pension contributions as exogenous shocks to financial constraints suggest a causal interpretation for our findings.

Further analyses suggest that such a relation may be largely attributed to agency problems. We find that the positive effect of financial constraints on IE is stronger among firms with high excess cash holdings and low investment opportunities, and among firms in less competitive industries. Moreover, the marginal R&D dollar of unconstrained firms with high cash holdings is likely spent on negative NPV projects, while the marginal R&D dollar of constrained firms is always spent on positive NPV projects. Finally, the effect seems to mitigate free cash flow problems that induce firms to make unproductive R&D investments in fields out of their direct expertise.

Overall, this paper contributes to the literature that studies the drivers of corporate innovation. In particular, we show that agency problems may adversely affect the productivity of firms' innovative investments due to their unique features such as high uncertainty, severe information asymmetry, and intangibility. Our empirical evidence suggests the possibility of using financial constraints as a tool to improve efficiency of firms' innovation activities. While financial constraints have important exogenous determinants that are difficult to change (such as transaction costs and asset type), they can also be shaped by policy variables such as cash, payout and debt maturity. In addition, firms can also reap the benefit of constraints by outsourcing R&D to and/or collaborating with leaner and more efficient firms.

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Table 1. Summary statistics and correlations

Panel A reports summary statistics of measures of innovative efficiency (IE) from 1980 to 2004, measures of financial constraints, and other characteristics from 1979 to 2003. The IE measures are: Patents/R&D, Citations/R&D, Patents/Employees, and Citations/Employees. Patents/R&D (Patents/Employees) is the number of adjusted patents applied in year *t* scaled by adjusted R&D expense (number of employees) in year *t*. Citations/R&D (Citations/Employees) is the number of adjusted citations received by a firm's patents applied in year *t* from the year granted till 2006 scaled by adjusted R&D expense (number of employees) in year *t*. We scale Patents (Citations) by the average patents (citations) in the same application year and the same technological class assigned by the USPTO. We scale R&D (Employees) by the average R&D expense (number of employees) in the same year and same industry based on Fama-French (1997) 48 industry classifications. The SA index and the WW index are financial constraints indices as in Hadlock and Pierce (2010) and Whited and Wu (2006), respectively. ln(Size) is the natural log of a firm's market capitalization at year end. Market-to-book assets (MTB) is market value of assets divided by book value of assets, where market value of assets is measured by total assets minus book equity plus market value of equity. DE is the ratio of long-term debt to market value of equity. ln(K/L) is the natural log of the ratio of total assets to the number of employees. RDS is R&D expense divided by sales. IO is institutional ownership defined as the percentage of shares outstanding owned by institutional investors. We winsorize all variables at the 5% and 95% levels. Panel B reports the Pearson (Spearman rank) correlations and associated *p*-values in parentheses between the IE measures and these characteristics below (above) the diagonal.

Panel A. Summary statistics

	Mean	StdDev	Min	25%	Median	75%	Max
Patents/R&D	16.45	44.00	0.02	0.84	3.14	11.35	324.48
Citations/R&D	58.43	167.96	0.00	1.88	9.72	37.95	1261.24
Patents/Employees	12.18	26.11	0.06	1.27	3.72	10.70	185.45
Citations/Employees	53.52	139.87	0.00	2.04	9.70	36.91	984.13
SA index	-3.24	0.72	-4.60	-3.76	-3.27	-2.78	-1.26
WW index	-0.27	0.11	-0.53	-0.36	-0.27	-0.19	-0.03
ln(Size)	5.62	2.07	1.34	4.11	5.47	7.01	10.91
MTB	2.04	1.74	0.61	1.05	1.45	2.27	11.17
DE	0.28	0.50	0.00	0.01	0.10	0.33	3.11
ln(K/L)	4.74	1.15	2.45	3.89	4.70	5.56	7.53
RDS	0.31	1.37	0.00	0.00	0.03	0.10	11.48
IO	0.41	0.25	0.00	0.19	0.40	0.60	0.96

Panel B. Correlations

	Patents /R&D	Citations /R&D	Patents /Employees	Citations /Employees	SA index	WW index	ln(Size)	MTB	DE	ln(K/L)	RDS	IO
Patents/R&D	1.00	0.82	0.55	0.38	0.01	-0.07	-0.09	-0.10	0.10	-0.45	-0.27	-0.04
		(0.00)	(0.00)	(0.00)	(0.09)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Citations/R&D	0.79	1.00	0.49	0.71	0.00	-0.06	-0.02	-0.03	0.03	-0.31	-0.12	-0.01
	(0.00)		(0.00)	(0.00)	(0.85)	(0.00)	(0.04)	(0.00)	(0.00)	(0.00)	(0.00)	(0.15)
Patents/Employees	0.44	0.43	1.00	0.77	0.36	0.25	-0.19	0.18	-0.23	0.13	0.29	-0.16
	(0.00)	(0.00)		(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Citations/Employees	0.27	0.48	0.74	1.00	0.24	0.17	-0.07	0.19	-0.22	0.12	0.31	-0.08
	(0.00)	(0.00)	(0.00)		(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
SA index	0.06	0.06	0.36	0.32	1.00	0.84	-0.70	0.24	-0.37	0.28	0.40	-0.51
	(0.00)	(0.00)	(0.00)	(0.00)		(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
WW index	-0.03	-0.03	0.23	0.21	0.84	1.00	-0.82	0.18	-0.32	0.27	0.41	-0.57
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)		(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
ln(Size)	-0.07	-0.01	-0.16	-0.09	-0.70	-0.83	1.00	0.08	0.08	0.00	-0.09	0.67
	(0.00)	(0.35)	(0.00)	(0.00)	(0.00)	(0.00)		(0.00)	(0.00)	(0.83)	(0.00)	(0.00)
MTB	-0.04	0.03	0.22	0.25	0.30	0.22	0.03	1.00	-0.58	0.31	0.40	0.01
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)		(0.00)	(0.00)	(0.00)	(0.03)
DE	0.06	0.01	-0.15	-0.18	-0.23	-0.18	-0.02	-0.43	1.00	-0.29	-0.43	0.07
	(0.00)	(0.31)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)		(0.00)	(0.00)	(0.00)
ln(K/L)	-0.35	-0.25	0.14	0.21	0.26	0.26	0.00	0.27	-0.19	1.00	0.48	-0.05
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.97)	(0.00)	(0.00)		(0.00)	(0.00)
RDS	-0.16	-0.08	0.28	0.33	0.40	0.35	-0.12	0.41	-0.24	0.44	1.00	-0.08
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)		(0.00)
IO	-0.02	0.01	-0.15	-0.10	-0.51	-0.56	0.65	-0.04	0.00	-0.05	-0.13	1.00
	(0.02)	(0.16)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.76)	(0.00)	(0.00)	

Table 2A. Financial constraints and innovative efficiency

This table reports the time-series mean slopes and their corresponding *t*-statistics from the Fama-MacBeth (1973) cross-sectional regressions of firms' innovative efficiency (IE) in year *t* from 1980-2004 on their financial constraints (FC), market-to-book assets (MTB), debt-to-equity ratio (DE), log of capital-to-labor ratio (ln(K/L)), R&D-to-sales ratio (RDS), and institutional ownership (IO) in year $t-1$. We use four IE measures: Patents/R&D, Citations/R&D, Patents/Employees, and Citations/Employees. We measure FC by the SA index (Hadlock and Pierce 2010), the WW index (Whited and Wu 2006), and ln(Size). All variables are defined in Table 1. All regressions control for industry effects based on the Fama-French (1997) 48 industry classifications. All variables are winsorized at the 5% and 95% levels except the industry dummy variables. The R-square and # Obs are time-series average of cross-sectional R-square and number of observations, respectively.

Panel A. IE = Patents/R&D										
FC proxy	FC	MTB	DE	ln(K/L)	RDS	IO	Intercept	Industry	R^2	# Obs
SA index	7.94	1.11	1.64	-6.47	-50.89	3.72	58.63	Yes	0.31	667
	(5.69)	(4.58)	(3.05)	(-22.62)	(-3.72)	(4.50)	(11.00)			
WW index	22.37	1.13	0.82	-7.03	-48.44	-1.28	42.95	Yes	0.29	622
	(3.51)	(5.30)	(1.52)	(-15.86)	(-3.51)	(-1.92)	(12.19)			
ln(Size)	-1.19	1.56	0.60	-6.89	-39.43	-1.63	41.95	Yes	0.29	667
	(-4.22)	(4.66)	(1.18)	(-18.01)	(-3.69)	(-1.57)	(14.72)			
Panel B. IE = Citations/R&D										
FC proxy	FC	MTB	DE	ln(K/L)	RDS	IO	Intercept	Industry	R^2	# Obs
SA index	18.82	5.01	2.79	-19.51	-113.41	13.93	156.41	Yes	0.27	667
	(4.99)	(7.09)	(1.27)	(-19.11)	(-3.53)	(4.42)	(11.80)			
WW index	25.74	5.04	-0.27	-20.38	-100.29	-1.63	110.97	Yes	0.26	622
	(1.38)	(7.34)	(-0.13)	(-20.11)	(-3.43)	(-0.65)	(13.81)			
ln(Size)	-0.82	5.79	0.21	-20.57	-81.31	-8.05	107.89	Yes	0.25	667
	(-0.87)	(6.33)	(0.10)	(-20.15)	(-3.46)	(-2.84)	(13.45)			
Panel C. IE = Patents/Employees										
FC proxy	FC	MTB	DE	ln(K/L)	RDS	IO	Intercept	Industry	R^2	# Obs
SA index	7.26	1.31	-1.81	0.31	12.73	1.15	28.03	Yes	0.32	818
	(23.87)	(9.95)	(-4.41)	(2.41)	(7.20)	(2.21)	(14.51)			
WW index	20.24	1.43	-2.18	0.20	15.99	-3.02	11.07	Yes	0.27	765
	(12.61)	(10.85)	(-5.50)	(1.25)	(7.51)	(-6.66)	(6.59)			
ln(Size)	-0.89	1.68	-2.68	0.43	20.16	-4.09	9.50	Yes	0.26	818
	(-7.72)	(11.61)	(-6.45)	(2.69)	(7.27)	(-7.83)	(5.81)			
Panel D. IE = Citations/Employees										
FC proxy	FC	MTB	DE	ln(K/L)	RDS	IO	Intercept	Industry	R^2	# Obs
SA index	22.78	5.67	-9.71	3.42	86.09	7.14	75.88	Yes	0.28	818
	(18.53)	(8.19)	(-3.52)	(4.16)	(7.19)	(2.56)	(8.75)			
WW index	55.58	6.17	-11.01	3.15	100.09	-7.68	22.98	Yes	0.26	765
	(9.52)	(8.08)	(-3.90)	(3.12)	(8.06)	(-2.40)	(2.96)			
ln(Size)	-1.13	6.64	-12.44	-16.85	108.22	-16.85	10.53	Yes	0.25	818
	(-2.30)	(8.76)	(-4.35)	(-4.42)	(7.42)	(-4.42)	(1.56)			

Table 2B. Residual financial constraints indices and innovative efficiency

This table reports the time-series mean slopes and their corresponding *t*-statistics from the Fama-MacBeth (1973) cross-sectional regressions of firms' innovative efficiency (IE) in year *t* from 1980-2004 on their financial constraints (FC), ln(Size), market-to-book assets (MTB), debt-to-equity ratio (DE), log of capital-to-labor ratio (ln(K/L)), R&D-to-sales ratio (RDS), and institutional ownership (IO) in year $t-1$. We use four IE measures: Patents/R&D, Citations/R&D, Patents/Employees, and Citations/Employees. We measure FC by the residual SA index or the residual WW index from Fama-MacBeth cross-sectional regressions of the SA index (Hadlock and Pierce 2010) or the WW index (Whited and Wu 2006) on size. All variables are defined in Table 1. All regressions control for industry effects based on the Fama-French (1997) 48 industry classifications. All variables are winsorized at the 5% and 95% levels except the industry dummy variables. The R-square and # Obs are time-series average of cross-sectional R-square and number of observations, respectively.

FC proxy	FC	ln(Size)	MTB	DE	ln(K/L)	RDS	IO	Intercept	Industry	R^2	# Obs
Panel A. IE = Patents/R&D											
Residual SA index	8.18	-0.12	1.05	2.14	-6.88	-50.92	3.42	37.53	Yes	0.32	665
	(7.02)	(-0.65)	(3.86)	(3.22)	(-24.85)	(-3.72)	(3.71)	(14.42)			
Residual WW index	14.71	-0.69	1.14	1.12	-7.26	-50.02	0.22	43.87	Yes	0.30	621
	(3.27)	(-2.97)	(3.86)	(1.71)	(-20.56)	(-3.55)	(0.30)	(14.51)			
Panel B. IE = Citations/R&D											
FC proxy	FC	ln(Size)	MTB	DE	ln(K/L)	RDS	IO	Intercept	Industry	R^2	# Obs
Residual SA index	25.30	2.49	3.63	3.87	-20.50	-112.27	9.48	91.46	Yes	0.27	665
	(7.86)	(3.34)	(4.56)	(1.55)	(-20.56)	(-3.30)	(3.18)	(11.10)			
Residual WW index	63.85	1.32	3.97	0.91	-21.70	-112.89	1.46	108.16	Yes	0.26	621
	(5.13)	(1.51)	(4.15)	(0.38)	(-23.02)	(-3.01)	(0.56)	(10.98)			
Panel C. IE = Patents/Employees											
FC proxy	FC	ln(Size)	MTB	DE	ln(K/L)	RDS	IO	Intercept	Industry	R^2	# Obs
Residual SA index	7.43	0.26	1.09	-1.51	0.33	13.90	-0.36	3.36	Yes	0.32	818
	(34.59)	(2.69)	(7.50)	(-3.94)	(3.28)	(7.09)	(-0.60)	(2.61)			
Residual WW index	19.87	-0.19	1.28	-2.08	0.24	15.77	-2.31	6.17	Yes	0.28	766
	(11.48)	(-1.60)	(8.03)	(-5.39)	(1.99)	(6.92)	(-4.13)	(4.21)			
Panel D. IE = Citations/Employees											
FC proxy	FC	ln(Size)	MTB	DE	ln(K/L)	RDS	IO	Intercept	Industry	R^2	# Obs
Residual SA index	27.13	2.95	4.57	-7.85	3.33	88.03	-3.33	-9.01	Yes	0.29	818
	(12.89)	(4.47)	(6.50)	(-2.75)	(4.45)	(7.83)	(-1.06)	(-1.44)			
Residual WW index	94.39	1.89	5.30	-9.80	2.90	94.35	-8.96	-0.09	Yes	0.26	766
	(8.49)	(2.68)	(6.82)	(-3.56)	(3.40)	(8.44)	(-2.73)	(-0.01)			

Table 3A. Effect of the junk bond market collapse on innovative efficiency — difference-in-differences tests

This table reports the results from the difference-in-differences tests for the effect of the junk bond market collapse on firms' innovative efficiency (IE). The sample only includes below-investment-grade (BB+ or lower) and unrated firms in the annual Compustat database (excluding financial firms) during the period 1986-1993 and satisfying three additional criteria: i) unrated firms are always unrated throughout the entire 1986–1993 period, ii) below-investment-grade firms do not change status to or from investment grade during the period, and iii) each firm contains at least one observation both before and after 1989. We regress firms' IE in year *t* on a junk bond issuer dummy (Junk) that equals one if a firm is a junk bond issuer and zero otherwise, a post-collapse dummy (Post) that equals one if year *t* is in period 1990-1993, an interaction term, Junk*Post, and other control variables in year $t-1$. SP500 is a dummy variable that equals one if a firm is included in the S&P 500 index during 1986–1993 and zero otherwise. NYSE is a dummy variable that equals one if a firm is listed in NYSE and zero otherwise. Age is the natural log of one plus the number of years a firm is in Compustat with nonmissing pricing data. Cash flow (CF) is defined as income before extraordinary items scaled by lagged total assets. IE growth is the annual growth rate in IE. All models control for industry and year fixed effects, where industry is based on the Fama-French 48 industry classifications. The other variables are defined in Table 1. All variables except the dummy variables are winsorized at the 5% and 95% levels. The *t*-statistics in parentheses are based on standard errors clustered at the firm level.

Panel A. IE = Patents/R&D

Model	Post*Junk	Post	Junk	MTB	DE	ln(K/L)	RDS	IO	SP500	NYSE	Age	CF	IE growth	Intercept	R^2	# Obs
1	3.04	0.27	-4.11	0.53	1.33	-3.28	-15.42	-7.83	-2.08	-4.23	1.23	1.98		15.31	0.22	2088
	(1.74)	(0.24)	(-2.22)	(1.53)	(0.83)	(-6.19)	(-3.93)	(-3.93)	(-0.84)	(-2.58)	(0.91)	(3.28)		(3.81)		
2	2.58	-0.16	-3.97	0.62	2.29	-3.23	-18.09	-8.39	-4.39	1.19	2.22	-2.47	0.09	16.45	0.22	1878
	(1.39)	(-0.14)	(-2.01)	(1.57)	(1.22)	(-5.43)	(-3.73)	(-3.86)	(-2.56)	(0.79)	(2.99)	(-0.88)	(0.82)	(3.69)		

Panel B. IE = Citations/R&D

Model	Post*Junk	Post	Junk	MTB	DE	ln(K/L)	RDS	IO	SP500	NYSE	Age	CF	IE growth	Intercept	R^2	# Obs
1	15.75	-1.52	-12.97	3.82	2.71	-9.54	-46.51	-22.65	-14.31	-11.63	4.15	6.01		42.78	0.19	2088
	(2.35)	(-0.40)	(-2.35)	(3.16)	(0.53)	(-5.20)	(-3.21)	(-3.37)	(-1.53)	(-2.09)	(0.98)	(2.91)		(3.12)		
2	15.98	-3.67	-13.64	3.78	5.42	-9.50	-50.13	-24.28	-11.64	3.34	6.57	-13.06	0.17	48.01	0.19	1865
	(2.22)	(-0.97)	(-2.33)	(2.80)	(0.92)	(-4.70)	(-2.85)	(-3.39)	(-2.00)	(0.71)	(2.64)	(-1.23)	(0.82)	(3.21)		

Panel C. IE = Patents/Employees

Model	Post*Junk	Post	Junk	MTB	DE	ln(K/L)	RDS	IO	SP500	NYSE	Age	CF	IE growth	Intercept	R^2	# Obs
1	1.43	-0.14	-1.01	0.62	-1.11	-0.17	8.28	-3.32	-3.79	-0.43	-0.71	0.26		9.47	0.23	2421
	(1.86)	(-0.35)	(-1.85)	(4.11)	(-2.60)	(-0.80)	(3.80)	(-4.05)	(-2.75)	(-0.86)	(-2.02)	(1.08)		(2.50)		
2	1.47	-0.08	-1.03	0.64	-1.03	-0.17	8.17	-3.20	-0.64	-0.72	0.25	-4.17	0.07	11.76	0.23	2210
	(1.83)	(-0.18)	(-1.72)	(4.03)	(-2.20)	(-0.78)	(3.29)	(-3.81)	(-1.30)	(-1.97)	(0.92)	(-2.74)	(1.11)	(4.08)		

Panel D. IE = Citations/Employees

Model	Post*Junk	Post	Junk	MTB	DE	ln(K/L)	RDS	IO	SP500	NYSE	Age	CF	IE growth	Intercept	R^2	# Obs
1	7.36	-2.50	-5.02	3.59	-2.62	-0.19	46.18	-8.25	-20.88	-1.09	-2.40	0.85		16.20	0.30	2421
	(2.05)	(-1.43)	(-1.90)	(5.21)	(-1.70)	(-0.22)	(4.89)	(-2.43)	(-3.46)	(-0.55)	(-1.86)	(0.85)		(1.98)		
2	7.81	-2.23	-5.71	3.58	-2.17	-0.06	48.65	-8.44	-1.45	-2.24	0.80	-21.72	-0.01	19.76	0.29	2193
	(2.07)	(-1.15)	(-1.93)	(4.78)	(-1.25)	(-0.06)	(4.38)	(-2.34)	(-0.72)	(-1.64)	(0.71)	(-3.10)	(-0.05)	(2.62)		

Table 3B. Effect of exogenous pension contributions on innovative efficiency

This table reports the results from testing the effect of exogenous mandatory pension contributions on firms' innovative efficiency (IE). We regress firms' IE in year t on exogenous mandatory pension contributions (Mandatory), market-to-book assets (MTB), debt-to-equity ratio (DE), log of capital-to-labor ratio (ln(K/L)), R&D-to-sales ratio (RDS), institutional ownership (IO), projected pension obligation (Obligation), and cash flow (CF) in year $t-1$, and industry and year fixed effects, where industry is based on the Fama-French 48 industry classifications. Mandatory pension contributions and projected pension obligation follow Bereskin (2010) and cash flow is defined as income before extraordinary items scaled by lagged total assets. We define a firm-year event as exogenous pension contributions when firm i reports non-zero mandatory pension contributions in year t after reporting zero mandatory pension contributions in year $t-1$ during the period 1997–2004. Mandatory pension contributions, projected pension obligation, and cash flow are in logarithm. The sample only includes the firm-year observations when the sample firm reports exogenous pension contributions. The other variables are defined in Table 1. All variables except the dummy variables are winsorized at the 5% and 95% levels. The t-statistics in parentheses are based on standard errors clustered by industry.

Panel A. IE = Patents/R&D												
Mandatory	MTB	DE	ln(K/L)	RDS	IO	Obligation	CF	Intercept	Year	Industry	R^2	# Obs
2.30	-0.59	-4.70	-4.32	-43.89	-6.25	-1.64	0.83	44.38	Yes	Yes	0.38	208
(1.96)	(-0.58)	(-0.80)	(-2.10)	(-1.27)	(-0.86)	(-1.41)	(0.59)	(4.03)				
Panel B. IE = Citations/R&D												
Mandatory	MTB	DE	ln(K/L)	RDS	IO	Obligation	CF	Intercept	Year	Industry	R^2	# Obs
10.41	3.03	-2.79	-22.14	-88.27	-45.41	-5.23	-5.09	118.35	Yes	Yes	0.33	208
(2.02)	(0.53)	(-0.11)	(-3.67)	(-0.75)	(-1.21)	(-0.97)	(-0.63)	(2.40)				
Panel C. IE = Patents/Employees												
Mandatory	MTB	DE	ln(K/L)	RDS	IO	Obligation	CF	Intercept	Year	Industry	R^2	# Obs
0.75	0.50	-6.30	3.05	31.72	-2.08	0.47	1.70	9.45	Yes	Yes	0.31	283
(1.76)	(0.48)	(-2.07)	(1.97)	(1.44)	(-0.67)	(0.53)	(3.24)	(1.78)				
Panel D. IE = Citations/Employees												
Mandatory	MTB	DE	ln(K/L)	RDS	IO	Obligation	CF	Intercept	Year	Industry	R^2	# Obs
4.03	5.34	-23.13	11.52	200.81	-28.58	2.07	6.32	22.99	Yes	Yes	0.25	283
(2.47)	(0.70)	(-1.59)	(1.49)	(1.75)	(-1.20)	(0.46)	(2.04)	(0.68)				

Table 4A. Interaction of the relation between financial constraints and innovative efficiency with excess cash holdings and investment opportunities

This table reports time-series mean slopes and their corresponding *t*-statistics (in parentheses) from the Fama-MacBeth (1973) cross-sectional regression of firms' innovative efficiency (IE) in year *t* from 1980-2004 on their financial constraints proxy (FC), a dummy variable for agency problems (defined later), an interaction term (FC*dummy), market-to-book assets (MTB), debt-to-equity ratio (DE), log of capital-to-labor ratio (ln(K/L)), R&D-to-sales ratio (RDS), and institutional ownership (IO) in year $t - 1$. We use four IE measures: Citations/R&D, Patents/R&D, Citations/Employee, and Patents/Employee. We use three FC proxies: the SA index (Hadlock and Pierce 2010), the WW index (Whited and Wu 2006), and ln(Size). The dummy variable is equal to one for firms with abnormal cash holdings above the 70th percentile and MTB below the 30th percentile of all sample firms in year $t - 1$. Abnormal cash holdings is defined as the cash-to-assets ratio minus estimated normal cash-to-assets ratio following DeAngelo, DeAngelo, and Stulz (2010). Normal cash-to-assets ratio is calculated by sorting all sample firms in a given year into three equal size groups based on total book assets and three equal size groups based on the market-to-book assets. Each firm is then allocated to one of the nine groups based on its total book assets and market-to-book assets. Within each of the nine groups, a normal cash-to-assets ratio is calculated for each two-digit SIC industry as the median ratio among all firms in that industry for that year. All the other variables are defined in Table 1. All models control for industry effects based on the Fama-French 48 industries. All variables are winsorized at the 5% and 95% levels except the industry dummy variables. The R-square and # Obs are time-series average of cross-sectional R-square and the number of observations, respectively.

Panel A. IE = Patents/R&D												
FC proxy	FC*Dummy	FC	Dummy	MTB	DE	ln(K/L)	RDS	IO	Intercept	Industry	R^2	# Obs
SA index	2.40	7.69	7.86	1.23	1.68	-6.48	-50.97	3.57	57.68	Yes	0.32	667
	(2.57)	(5.77)	(2.48)	(4.21)	(2.96)	(-22.74)	(-3.69)	(4.46)	(11.46)			
WW index	17.31	20.80	5.09	1.26	0.87	-7.06	-48.43	-1.45	42.49	Yes	0.30	622
	(1.95)	(3.55)	(2.01)	(4.89)	(1.59)	(-15.64)	(-3.51)	(-2.03)	(12.54)			
ln(Size)	-1.24	-1.08	6.94	1.71	0.66	-1.88	-39.69	-1.88	41.13	Yes	0.29	667
	(-3.42)	(-4.22)	(3.40)	(4.41)	(1.26)	(-1.71)	(-3.66)	(-1.71)	(15.38)			
Panel B. IE = Citations/R&D												
FC proxy	FC*Dummy	FC	Dummy	MTB	DE	ln(K/L)	RDS	IO	Intercept	Industry	R^2	# Obs
SA index	7.99	18.31	22.79	5.10	2.66	-19.46	-113.17	13.77	154.28	Yes	0.27	667
	(3.16)	(4.95)	(2.97)	(6.63)	(1.18)	(-19.20)	(-3.49)	(4.35)	(11.78)			
WW index	56.33	22.08	13.53	5.21	-0.34	-20.39	-99.09	-1.97	109.74	Yes	0.26	622
	(2.73)	(1.20)	(2.36)	(6.70)	(-0.16)	(-20.17)	(-3.43)	(-0.75)	(13.45)			
ln(Size)	-3.43	-0.57	18.34	6.00	0.22	-20.51	-81.43	-8.48	105.83	Yes	0.25	667
	(-3.72)	(-0.63)	(3.39)	(5.95)	(0.10)	(-20.07)	(-3.43)	(-2.82)	(13.17)			
Panel C. IE = Patents/Employees												
FC proxy	FC*Dummy	FC	Dummy	MTB	DE	ln(K/L)	RDS	IO	Intercept	Industry	R^2	# Obs
SA index	1.75	7.13	4.95	1.31	-1.84	0.31	12.82	1.12	27.59	Yes	0.32	818
	(3.62)	(23.63)	(3.03)	(9.04)	(-4.27)	(2.42)	(7.31)	(2.18)	(14.17)			
WW index	9.48	19.58	2.14	1.44	-2.18	0.19	16.13	-3.02	10.87	Yes	0.27	765
	(3.05)	(12.17)	(2.24)	(9.78)	(-5.23)	(1.20)	(7.61)	(-6.65)	(6.48)			
ln(Size)	-0.45	-0.87	1.89	1.68	-2.69	0.43	20.20	-4.10	9.36	Yes	0.26	818
	(-2.43)	(-7.71)	(1.79)	(10.76)	(-6.17)	(2.66)	(7.33)	(-7.82)	(5.85)			
Panel D. IE = Citations/Employees												
FC proxy	FC*Dummy	FC	Dummy	MTB	DE	ln(K/L)	RDS	IO	Intercept	Industry	R^2	# Obs
SA index	5.36	22.43	15.40	5.66	-9.79	3.42	86.45	7.21	74.63	Yes	0.29	818
	(2.54)	(17.80)	(2.20)	(8.12)	(-3.59)	(4.17)	(7.22)	(2.55)	(8.49)			
WW index	40.22	53.15	10.32	6.26	-10.89	3.11	100.62	-7.53	22.13	Yes	0.26	765
	(3.45)	(8.86)	(2.99)	(8.07)	(-3.90)	(3.10)	(8.11)	(-2.32)	(2.83)			
ln(Size)	-2.10	-1.02	11.31	6.71	-12.34	4.11	108.44	-16.73	9.70	Yes	0.25	818
	(-2.69)	(-2.08)	(2.57)	(8.75)	(-4.37)	(3.87)	(7.43)	(-4.36)	(1.44)			

Table 4B. Interaction of the relation between residual financial constraints indices and innovative efficiency with excess cash holdings and investment opportunities

This table reports time-series mean slopes and their corresponding *t*-statistics (in parentheses) from the Fama-MacBeth (1973) cross-sectional regression of firms' innovative efficiency (IE) in year *t* from 1980-2004 on their financial constraints proxy (FC), a dummy variable for agency problems (defined later), an interaction term (FC*dummy), ln(Size), market-to-book assets (MTB), debt-to-equity ratio (DE), log of capital-to-labor ratio (ln(K/L)), R&D-to-sales ratio (RDS), and institutional ownership (IO) in year $t - 1$. We use four IE measures: Citations/R&D, Patents/R&D, Citations/Employee, and Patents/Employee. We measure FC by the residual SA index or the residual WW index from Fama-MacBeth cross-sectional regressions of the SA index (Hadlock and Pierce 2010) or the WW index (Whited and Wu 2006) on size. The dummy variable is equal to one for firms with abnormal cash holdings above the 70th percentile and MTB below the 30th percentile of all sample firms in year $t - 1$. Abnormal cash holdings is defined as the cash-to-assets ratio minus estimated normal cash-to-assets ratio following DeAngelo, DeAngelo, and Stulz (2010). Normal cash-to-assets ratio is calculated by sorting all sample firms in a given year into three equal size groups based on total book assets and three equal size groups based on the market-to-book assets. Each firm is then allocated to one of the nine groups based on its total book assets and market-to-book assets. Within each of the nine groups, a normal cash-to-assets ratio is calculated for each two-digit SIC industry as the median ratio among all firms in that industry for that year. All the other variables are defined in Table 1. All models control for industry effects based on the Fama-French 48 industries. All variables are winsorized at the 5% and 95% levels except the industry dummy variables. The R-square and # Obs are time-series average of cross-sectional R-square and the number of observations, respectively.

FC proxy	FC*Dummy	FC	Dummy	ln(Size)	MTB	DE	ln(K/L)	RDS	IO	Intercept	R^2	# Obs
Panel A. IE = Patents/R&D												
Residual SA index	2.41	7.93	0.64	-0.11	1.24	2.28	-6.89	-51.37	3.33	37.28	0.32	665
	(2.73)	(7.05)	(0.84)	(-0.59)	(3.91)	(3.22)	(-25.13)	(-3.70)	(3.77)	(14.57)		
Residual WW index	27.56	13.05	-0.02	-0.68	1.27	1.32	-7.29	-49.72	0.23	43.66	0.31	621
	(2.79)	(3.05)	(-0.03)	(-2.95)	(3.91)	(1.91)	(-20.42)	(-3.53)	(0.31)	(14.43)		
Panel B. IE = Citations/R&D												
Residual SA index	3.79	24.96	-0.73	2.52	3.84	3.89	-20.44	-112.91	9.10	90.91	0.27	665
	(1.41)	(8.01)	(-0.34)	(3.41)	(4.44)	(1.50)	(-20.55)	(-3.30)	(3.19)	(11.17)		
Residual WW index	56.35	60.06	-1.82	1.32	4.06	1.10	-21.68	-111.59	1.20	108.04	0.27	621
	(1.82)	(4.86)	(-0.87)	(1.51)	(3.88)	(0.43)	(-22.65)	(-2.98)	(0.47)	(11.06)		
Panel C. IE = Patents/Employees												
Residual SA index	1.81	7.29	-0.46	0.25	1.12	-1.50	0.33	13.89	-0.37	3.36	0.32	818
	(4.62)	(36.18)	(-1.84)	(2.61)	(7.22)	(-3.76)	(3.18)	(7.21)	(-0.61)	(2.59)		
Residual WW index	9.53	19.24	-0.35	-0.19	1.29	-2.06	0.24	16.03	-2.33	6.16	0.28	766
	(2.75)	(11.03)	(-1.56)	(-1.61)	(7.86)	(-5.25)	(1.92)	(6.97)	(-4.22)	(4.20)		
Panel D. IE = Citations/Employees												
Residual SA index	5.99	26.71	-1.51	2.93	4.63	-7.81	3.32	88.28	-3.25	-9.07	0.29	818
	(2.58)	(12.53)	(-1.22)	(4.46)	(6.63)	(-2.68)	(4.40)	(7.84)	(-1.03)	(-1.45)		
Residual WW index	37.40	91.56	-0.65	1.87	5.39	-9.64	2.85	95.20	-8.94	-0.03	0.27	766
	(2.88)	(8.35)	(-0.58)	(2.67)	(6.84)	(-3.46)	(3.33)	(8.44)	(-2.72)	(-0.00)		

Table 5A. Financial constraints and the marginal value of R&D investment — subsample regressions

This table reports results from regressing firms' excess stock return in fiscal year t on changes in firm characteristics over the fiscal year within the constrained and unconstrained subsamples, following Faulkender and Wang (2006). A stock's excess return in fiscal year t is computed based on the difference between the stock's monthly return and the value-weighted monthly return of one of the 25 (5 by 5) size and book-to-market portfolios to which the stock belongs at the end of June of year t – 1. All variables except L_t and excess stock return are deflated by the lagged market value of equity. R&D (RD_t) is R&D expense. C_t is cash plus marketable securities, E_t is earnings before extraordinary items plus interest, deferred tax credits, and investment tax credits, and NA_t is total assets minus cash holdings. I_t is interest expense, total dividends (D_t) are measured as common dividends paid, L_t is market leverage, and NF_t is the total equity issuance minus repurchases plus debt issuance minus debt redemption. ΔX_t is compact notation for the 1-year change, $X_t - X_{t-1}$. The subscript t – 1 means the value of the variable is at the end of fiscal year t – 1. We use the SA index (Hadlock and Pierce 2010), the WW index (Whited and Wu 2006), and Size (market capitalization) in year t – 1 to form the constrained and unconstrained subsamples. For the SA and WW indices, the constrained (unconstrained) subsample includes firms in the top (bottom) 30% in year t – 1. For Size, the constrained (unconstrained) subsample includes firms in the bottom (top) 30% in year t – 1. The t-statistics in parentheses are computed based on standard errors clustered at the firm level. The sample is from 1980-2008 for the SA index and Size, but from 1980 to 2006 for the WW index. All regressions control for year effect and industry effect based on Fama and French 48 industry classifications. All independent variables are winsorized at the 5% and 95% levels. All variables are converted to real values in 2008 dollars using the consumer price index (CPI).

	FC proxy											
	SA index				WW index				ln(Size)			
	Constrained		Unconstrained		Constrained		Unconstrained		Constrained		Unconstrained	
	Slope	*t*-stat	Slope	*t*-stat	Slope	*t*-stat	Slope	*t*-stat	Slope	*t*-stat	Slope	*t*-stat
ΔRD_t	2.03	(8.35)	1.41	(4.29)	2.15	(8.28)	1.38	(3.51)	1.94	(8.40)	1.59	(4.00)
$\Delta RD_t * C_{t-1}$	-1.15	(-1.65)	-2.52	(-2.03)	-1.73	(-2.19)	-4.12	(-2.70)	-1.40	(-2.16)	-3.90	(-2.26)
C_{t-1}	0.46	(20.42)	0.28	(12.70)	0.42	(16.83)	0.28	(10.24)	0.31	(15.52)	0.34	(12.24)
ΔC_t	1.77	(26.57)	1.31	(16.88)	1.82	(25.73)	1.50	(17.21)	1.66	(25.80)	2.12	(23.84)
ΔD_t	17.98	(6.83)	6.70	(6.42)	13.54	(4.77)	6.92	(6.14)	18.32	(8.70)	5.01	(4.50)
ΔE_t	0.76	(25.41)	0.74	(23.97)	0.77	(25.82)	0.75	(21.34)	0.70	(29.52)	0.82	(21.41)
ΔI_t	0.26	(6.45)	0.11	(3.59)	0.13	(3.31)	0.12	(3.50)	0.10	(3.52)	0.13	(3.20)
ΔNA_t	0.28	(12.86)	0.15	(7.99)	0.31	(14.15)	0.19	(8.84)	0.26	(16.20)	0.23	(9.34)
$\Delta C_t * C_{t-1}$	-1.25	(-7.98)	-0.53	(-2.85)	-1.27	(-7.63)	-0.47	(-1.97)	-1.18	(-8.46)	-1.16	(-4.72)
L_t	-0.60	(-31.16)	-0.41	(-25.12)	-0.49	(-23.69)	-0.39	(-21.98)	-0.45	(-27.09)	-0.42	(-21.98)
$\Delta C_t * L_t$	-1.26	(-8.32)	-1.30	(-8.16)	-1.34	(-8.52)	-1.75	(-9.12)	-1.09	(-9.70)	-2.81	(-14.40)
NF_t	0.19	(6.08)	-0.09	(-3.07)	0.13	(3.93)	-0.15	(-4.56)	0.03	(0.97)	-0.18	(-4.77)
Intercept	-0.15	(-5.58)	0.08	(4.13)	-0.86	(-23.38)	-0.16	(-1.28)	-0.10	(-4.10)	0.08	(4.22)
Industry	Yes		Yes		Yes		Yes		Yes		Yes	
Year	Yes		Yes		Yes		Yes		Yes		Yes	
R^2	0.25		0.20		0.25		0.20		0.24		0.19	
# Obs	19570		20577		16804		17354		19580		20589	

Table 5B. Financial constraints and the marginal value of R&D investment

This table reports results from regressing firms' excess stock return in fiscal year *t* on changes in firm characteristics over the fiscal year, following Faulkender and Wang (2006). A stock's excess return in fiscal year *t* is computed based on the difference between the stock's monthly return and the value-weighted monthly return of one of the 25 (5 by 5) size and book-to-market portfolios to which the stock belongs at the end of June of year $t - 1$. We use the SA index (Hadlock and Pierce 2010), the WW index (Whited and Wu 2006), and Size (market capitalization) in year $t - 1$ to define the dummy (UC_t) that equals 1 for unconstrained firms, and 0 for constrained firms. For the SA and WW indices, constrained (unconstrained) firms are in the top (bottom) 30% in year $t - 1$. Firms in the middle group are excluded from the regressions. For Size, constrained (unconstrained) firms are in the bottom (top) 30% in year $t - 1$. L_t, RD_t, C_t, E_t, NA_t, I_t, and D_t have been defined in Table 5A. ΔX_t is compact notation for the 1-year change, $X_t - X_{t-1}$. The subscript $t - 1$ means the value of the variable is at the end of fiscal year $t - 1$. The *t*-statistics in parentheses are computed based on standard errors clustered at the firm level. The sample is from 1980-2008 for the SA index and Size, but from 1980 to 2006 for the WW index. All regressions control for year effect and industry effect based on Fama and French 48 industry classifications. All independent variables are winsorized at the 5% and 95% levels. All variables are converted to real values in 2008 dollars using the consumer price index (CPI).

	FC proxy					
	SA index		WW index		ln(Size)	
	Slope	*t*-stat	Slope	*t*-stat	Slope	*t*-stat
$UC_t * \Delta RD_t$	-0.90	(-3.19)	-1.37	(-4.25)	-0.74	(-2.42)
UC_t	0.13	(17.37)	0.11	(13.02)	0.00	(-0.20)
ΔRD_t	1.78	(10.66)	1.79	(10.15)	1.57	(10.07)
C_{t-1}	0.49	(22.87)	0.46	(19.44)	0.34	(17.87)
ΔC_t	1.25	(32.00)	1.24	(29.78)	1.04	(30.14)
ΔD_t	20.51	(7.91)	15.69	(5.54)	19.20	(8.98)
ΔE_t	0.77	(25.68)	0.78	(26.12)	0.72	(30.23)
ΔI_t	0.24	(5.96)	0.11	(2.75)	0.09	(3.12)
ΔNA_t	0.29	(13.31)	0.32	(14.41)	0.26	(16.01)
L_t	-0.55	(-29.97)	-0.44	(-23.38)	-0.43	(-27.73)
NF_t	0.22	(7.10)	0.16	(5.00)	0.05	(1.77)
$UC_t * C_{t-1}$	-0.21	(-6.99)	-0.18	(-4.96)	-0.03	(-0.90)
$UC_t * \Delta C_t$	-0.53	(-9.44)	-0.41	(-6.32)	0.11	(1.75)
$UC_t * \Delta D_t$	-14.75	(-5.30)	-9.16	(-3.02)	-15.15	(-6.30)
$UC_t * \Delta E_t$	-0.02	(-0.46)	-0.02	(-0.49)	0.08	(1.86)
$UC_t * \Delta I_t$	-0.12	(-2.37)	0.03	(0.61)	0.02	(0.39)
$UC_t * \Delta NA_t$	-0.15	(-5.38)	-0.14	(-4.48)	-0.02	(-0.81)
$UC_t * L_t$	0.11	(4.66)	0.02	(0.84)	0.00	(-0.06)
$UC_t * NF_t$	-0.30	(-6.94)	-0.28	(-6.08)	-0.19	(-4.22)
Intercept	-0.10	(-5.54)	-0.48	(-2.40)	-0.02	(-1.33)
Industry	Yes		Yes		Yes	
Year	Yes		Yes		Yes	
R^2	0.22		0.22		0.21	
# Obs	40147		34158		40169	

Table 6. Effect of financial constraints on innovative efficiency conditional on product market competition

This table reports time-series mean slopes and their corresponding *t*-statistics (in parentheses) of financial constraints (FC) proxy from the Fama-MacBeth (1973) cross-sectional subsample regression of firms' innovative efficiency (IE) in year t from 1980-2004 on their FC, market-to-book assets (MTB), debt-to-equity ratio (DE), log of capital-to-labor ratio (ln(K/L)), R&D-to-sales ratio (RDS), and institutional ownership (IO) in year $t-1$. We use four IE measures: Citations/R&D, Patents/R&D, Citations/Employee, and Patents/Employee. We use three FC proxies: the SA index (Hadlock and Pierce 2010), the WW index (Whited and Wu 2006), and ln(Size). The uncompetitive (competitive) subsample includes all firm-years that are in industries of bottom (top) 30% of one minus Herfindahl index of sales in year $t-1$. The pooled sample includes both uncompetitive and competitive subsamples. In pooled sample regression, the main explanatory variable is Dummy(Uncompetitive)*FC, in which Dummy(Uncompetitive) equals one if the sample firm belongs to uncompetitive subsample and zero otherwise. All the other variables are defined in Table 1. All models control for industry effects based on the Fama-French 48 industries. All variables are winsorized at the 5% and 95% levels except the industry dummy variables.

Panel A. IE = Patents/R&D			
	Uncompetitive subsample	Competitive subsample	Pooled sample
FC proxy	FC	FC	Dummy(Uncompetitive)*FC
SA index	7.44	6.57	0.73
	(5.41)	(5.75)	(0.69)
WW index	30.35	18.73	5.28
	(4.16)	(2.41)	(0.97)
ln(Size)	-1.38	-0.63	-0.35
	(-4.02)	(-1.26)	(-1.11)
Panel B. IE = Citations/R&D			
	Uncompetitive subsample	Competitive subsample	Pooled sample
FC proxy	FC	FC	Dummy(Uncompetitive)*FC
SA index	18.59	11.19	6.86
	(3.78)	(2.50)	(1.55)
WW index	51.82	-19.54	56.53
	(1.71)	(-0.54)	(2.21)
ln(Size)	-1.66	2.75	-2.87
	(-1.30)	(1.16)	(-2.41)
Panel C. IE = Patents/Employees			
	Uncompetitive subsample	Competitive subsample	Pooled sample
FC proxy	FC	FC	Dummy(Uncompetitive)*FC
SA index	7.11	6.39	1.14
	(11.45)	(11.03)	(1.86)
WW index	26.25	17.56	9.36
	(9.43)	(4.71)	(2.46)
ln(Size)	-1.26	-0.47	-0.74
	(-7.40)	(-2.00)	(-3.85)
Panel D. IE = Citations/Employees			
	Uncompetitive subsample	Competitive subsample	Pooled sample
FC proxy	FC	FC	Dummy(Uncompetitive)*FC
SA index	17.95	17.68	4.79
	(8.96)	(6.48)	(2.22)
WW index	63.05	10.80	61.44
	(6.66)	(0.57)	(3.40)
ln(Size)	-2.14	1.65	-3.99
	(-3.13)	(1.54)	(-4.05)

Table 7A. Effect of the junk bond market collapse on innovative strategies — difference-in-differences tests

This table reports the results from the difference-in-differences tests for the effect of the junk bond market collapse on firms' innovative strategies. We use two proxies of innovative strategies: the percentage of exploratory patents and the difference between the percentage of exploratory patents and the percentage of exploitative patents defined in Section 5. The sample only includes below-investment-grade (BB+ or lower) and unrated firms in the annual Compustat database (excluding financial firms) during the period 1986-1993 and satisfying three additional criteria: i) unrated firms are always unrated throughout the entire 1986–1993 period, ii) below-investment-grade firms do not change status to or from investment grade during the period, and iii) each firm contains at least one observation both before and after 1989. We regress firms' innovative strategies proxies in year *t* on a junk bond issuer dummy (Junk) that equals one if a firm is a junk bond issuer and zero otherwise, a post-collapse dummy (Post) that equals one if year *t* is in period 1990-1993, an interaction term, Junk*Post, and other control variables in year $t-1$. SP500 is a dummy variable that equals one if a firm is included in the S&P 500 index during 1986–1993 and zero otherwise. NYSE is a dummy variable that equals one if a firm is listed in NYSE and zero otherwise. Age is the natural log of one plus the number of years a firm is in Compustat with nonmissing pricing data. Cash flow (CF) is defined as income before extraordinary items scaled by lagged total assets. All models control for industry and year fixed effects, where industry is based on the Fama-French 48 industry classifications. The other variables are defined in Table 1. All variables except the dummy variables are winsorized at the 5% and 95% levels. The *t*-statistics in parentheses are based on standard errors clustered at the firm level.

Panel A. Dependent variable = Percentage of exploratory patents

Model	Post*Junk	Post	Junk	MTB	DE	ln(K/L)	RDS	IO	SP500	NYSE	Age	CF	Intercept	R^2	# Obs
1	-0.10	0.12	0.10	-0.03	0.01	0.01	-0.20	0.00	0.03	0.01			0.75	0.07	2551
	(-2.47)	(3.80)	(3.57)	(-2.96)	(0.33)	(1.17)	(-1.78)	(0.02)	(0.90)	(0.69)			(5.25)		
2	-0.10	0.12	0.12	-0.03	0.01	0.01	-0.12	-0.01	0.03	0.01	0.00	0.13	0.71	0.07	2349
	(-2.38)	(3.68)	(3.53)	(-3.38)	(0.33)	(0.98)	(-0.78)	(-0.22)	(0.77)	(0.55)	(0.14)	(1.44)	(4.21)		

Panel B. Dependent variable = Percentage of exploratory patents - Percentage of exploitative patents

Model	Post*Junk	Post	Junk	MTB	DE	ln(K/L)	RDS	IO	SP500	NYSE	Age	CF	Intercept	R^2	# Obs
1	-0.17	0.21	0.17	-0.04	0.04	0.02	-0.34	-0.02	0.07	0.04			0.55	0.07	2551
	(-2.15)	(3.89)	(3.16)	(-2.43)	(0.79)	(1.24)	(-1.68)	(-0.29)	(1.08)	(0.91)			(2.05)		
2	-0.18	0.21	0.19	-0.05	0.04	0.03	-0.21	-0.05	0.06	0.03	0.02	0.23	0.44	0.07	2349
	(-2.15)	(3.78)	(3.18)	(-2.96)	(0.71)	(1.27)	(-0.76)	(-0.52)	(0.89)	(0.65)	(0.51)	(1.43)	(1.32)		

Table 7B. Effect of exogenous pension contributions on innovative strategies

This table reports the results from testing the effect of exogenous pension contributions on firms' innovative strategies: the percentage of exploratory patents and the difference between the percentage of exploratory patents and the percentage of exploitative patents defined in Section 5. We regress firms' innovative strategies in year t on exogenous pension contributions (Mandatory), market-to-book assets (MTB), debt-to-equity ratio (DE), log of capital-to-labor ratio (ln(K/L)), R&D-to-sales ratio (RDS), institutional ownership (IO), projected pension obligation (Obligation), and cash flow (CF) in year $t-1$, and industry and year fixed effects, where industry is based on the Fama-French 48 industry classifications. Mandatory pension contributions and projected pension obligation follow Bereskin (2010) and cash flow is defined as income before extraordinary items scaled by lagged total assets. We define a firm-year event as exogenous pension contributions when firm i reports non-zero mandatory pension contributions in year t after reporting zero mandatory pension contributions in year $t-1$ during the period 1997–2004. Mandatory pension contributions, projected pension obligation, and cash flow are in logarithm. The sample only includes the firm-year observations when the sample firm reports exogenous mandatory pension contributions. The other variables are defined in Table 1. All variables except the dummy variables are winsorized at the 5% and 95% levels. The t-statistics in parentheses are based on standard errors clustered by industry.

Panel A. Dependent variable = Percentage of exploratory patents

Mandatory	MTB	DE	ln(K/L)	RDS	IO	Obligation	CF	Intercept	R^2	# Obs
-0.04	-0.00	0.12	0.03	-0.45	-0.12	0.02	0.03	0.97***	0.24	274
(-2.01)	(-0.16)	(2.04)	(0.95)	(-0.50)	(-0.91)	(0.84)	(1.94)	(7.03)		

Panel B. Dependent variable = Percentage of exploratory patents - Percentage of exploitative patents

Mandatory	MTB	DE	ln(K/L)	RDS	IO	Obligation	CF	Intercept	R^2	# Obs
-0.07	-0.01	0.20	0.03	-0.57	-0.22	0.04	0.04	1.00	0.24	274
(-2.02)	(-0.33)	(1.67)	(0.58)	(-0.38)	(-0.93)	(0.82)	(1.51)	(4.08)		

Table 8. Innovative strategies and innovative efficiency

This table reports the results from testing the effect of firms' innovative strategies on their innovative efficiency. We conduct annual Fama-MacBeth regressions by regressing firms' innovative efficiency (IE) in year *t* from 1980-2004 on innovative strategies (Explore) in year *t*, market-to-book assets (MTB), debt-to-equity ratio (DE), log of capital-to-labor ratio (ln(K/L)), R&D-to-sales ratio (RDS), and institutional ownership (IO) in year *t*, and industry fixed effect, where industry is based on the Fama-French 48 industry classifications. We use four IE measures: Patents/R&D, Citations/R&D, Patents/Employees, and Citations/Employees, defined in Table 1. Innovative strategies are measured with the percentage of exploratory patents and the difference between the percentage of exploratory patents and the percentage of exploitative patents defined in Section 5. The other variables are defined in Table 1. All variables except the dummy variables are winsorized at the 5% and 95% levels.

Panel A. Explore = Percentage of exploratory patents										
Dependent	Explore	MTB	DE	ln(K/L)	RDS	IO	Intercept	Industry	R^2	# Obs
Patents/R&D	-4.12	1.45	0.03	-6.99	-48.46	-9.42	36.11	Yes	0.30	611
	(-7.12)	(5.11)	(0.04)	(-17.93)	(-4.19)	(-4.25)	(11.87)			
Citations/R&D	-20.41	5.88	-1.18	-21.68	-114.00	-19.20	111.78	Yes	0.27	611
	(-14.71)	(6.57)	(-0.51)	(-23.37)	(-4.01)	(-3.26)	(12.73)			
Patents/Employees	-4.43	1.50	-2.64	0.33	23.91	-9.68	8.47	Yes	0.26	745
	(-13.03)	(10.47)	(-5.89)	(2.21)	(6.83)	(-14.93)	(4.19)			
Citations/Employees	-22.78	5.83	-12.22	3.61	113.43	-26.49	19.54	Yes	0.26	745
	(-8.64)	(8.22)	(-4.19)	(3.77)	(7.59)	(-7.60)	(2.47)			
Panel B. Explore = Percentage of exploratory patents - Percentage of exploitative patents										
Dependent	Explore	MTB	DE	ln(K/L)	RDS	IO	Intercept	Industry	R^2	# Obs
Patents/R&D	-2.44	1.44	-0.01	-7.00	-48.58	-9.49	32.99	Yes	0.31	611
	(-6.73)	(5.04)	(-0.01)	(-17.97)	(-4.16)	(-4.25)	(11.04)			
Citations/R&D	-11.47	5.86	-1.29	-21.71	-113.95	-19.32	97.64	Yes	0.27	611
	(-16.31)	(6.49)	(-0.56)	(-23.42)	(-3.98)	(-3.26)	(12.19)			
Patents/Employees	-2.51	1.49	-2.67	0.33	23.90	-9.71	6.73	Yes	0.27	745
	(-13.82)	(10.43)	(-5.94)	(2.20)	(6.88)	(-14.76)	(3.31)			
Citations/Employees	-12.37	5.83	-12.38	3.57	113.48	-26.51	11.69	Yes	0.26	745
	(-9.34)	(8.19)	(-4.23)	(3.76)	(7.59)	(-7.61)	(1.42)			

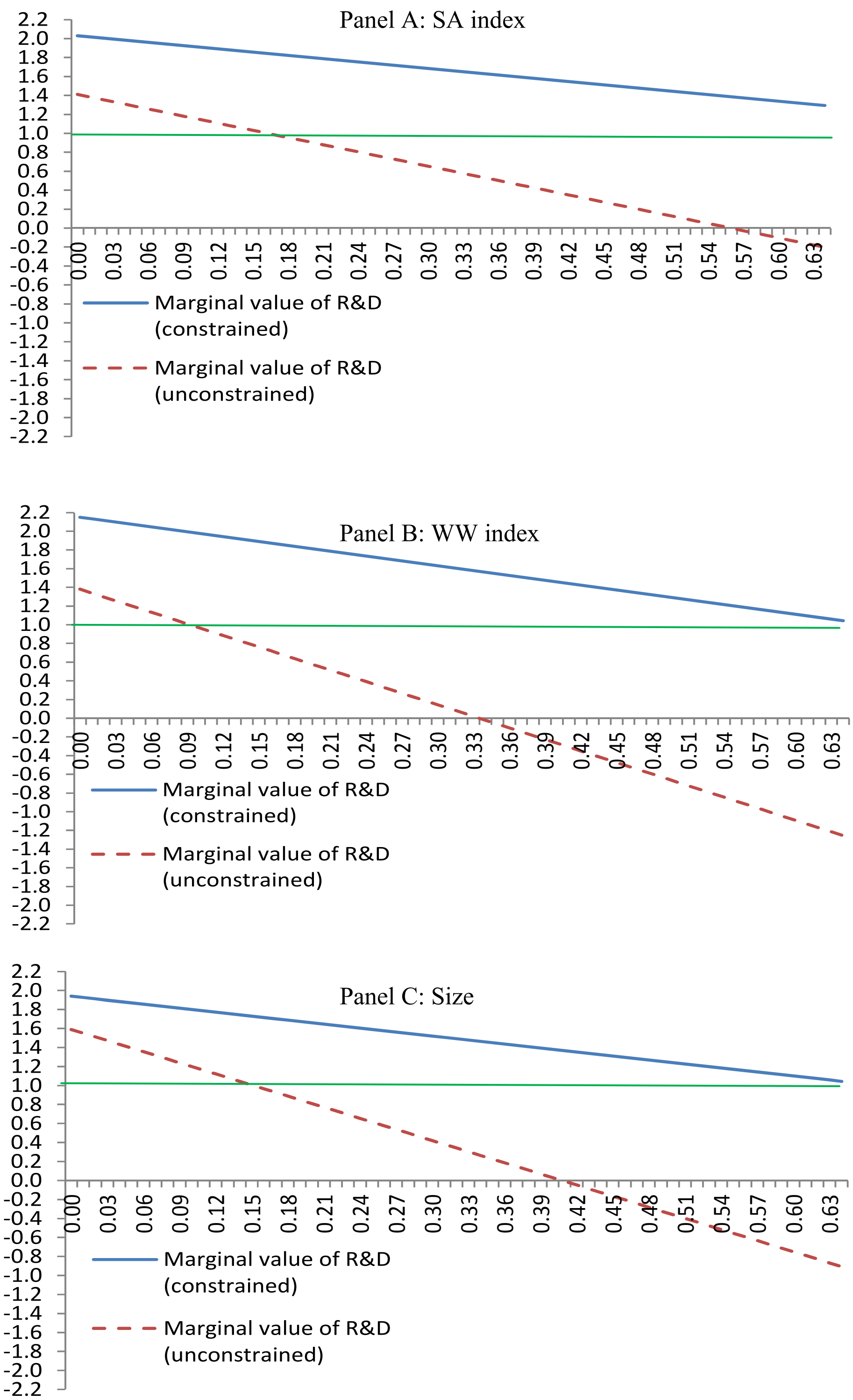

Figure 1. Variation of marginal value of R&D with cash holdings

The vertical axis denotes the marginal value of an R&D dollar, defined as the coefficient ΔRD_t plus the coefficient of $\Delta RD_t * C_{t\text{-}1}$ times the value of $C_{t\text{-}1}$., while the horizontal axis denotes the cash holdings scaled by market value, ranging from 0.00 (minimum) to 0.64 (maximum). Panels A, B, and C are based on the SA index, the WW index, and Size, respectively.