Golden Handcuffs and Corporate Innovation:

Evidence from Defined Benefit Pension Plans

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ABSTRACT

In this study, I exploit a natural experiment of defined benefit (DB) plans to identify the effects of deferred compensation on corporate innovation. Using DB pension and patenting data, I find that from 1990 to 2007, firms with higher DB plan value secured more patents and patent citations. An instrumental variable approach and a treatment effects model both support the causal effect of DB plans on corporate innovation. Further analysis reveals that DB plans foster innovation through longer tenures, greater productivity, and more risk-taking on the part of employees. Consistent with bonding theory, my findings suggest the bright side of DB plans despite recent pension freezes.

Keywords: Corporate innovation, defined benefit pension plan, deferred compensation, inventor

JEL classification: G31; G32; O31; O32

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I. Introduction

As far as the objective of the firm is concerned, there is a long-standing debate between proponents of the stakeholder society and advocates for the maximization of shareholder value (Tirole (2006), p. 15). Researchers have paid significant attention to executives' incentives and investors' returns. However, other "stakeholders" (e.g., employees) have yet to receive the attention they deserve, despite a vested interest in firm operations and the capacity to affect the outcomes of corporate financial decisions. For example, Chang et al. (2015) show a positive effect of rank-and-file employee stock options on corporate innovation, a core competency of a firm. In this paper, I examine the impact of another incentive scheme on corporate innovation by exploiting its sharply nonlinear funding rules. This scheme, called a pension plan, typically covers all employees, both executive and non-executive employees alike. It can be used as a form of deferred compensation to address the agency problem. It also embodies a broad managerial mission to provide steady income to post-retirement employees.

Employer pension programs are typically classified into two broad types: defined contribution (DC) and defined benefit (DB). A DC plan has a defined amount of employer and/or employee contributions (typically specified as a percentage of the employee's salary) set aside each year. The employee's total retirement benefit is determined by the accumulation of these contributions at the time of retirement. In contrast, a DB plan is one in which the retirement benefit (rather than the employer's contribution) is defined. For DB plans, the retirement benefit is generally expressed in terms of the employee's salary and length of service (Winklevoss (1993)). Tax considerations have driven the popularity of both DB and DC plans, as company contributions are tax deductible and employee taxes are deferred. At retirement, employee income tax rates are typically lower than during their employment years because employees usually earn less income at the time of retirement. DB plans provide an additional tax benefit when plan assets are invested in bonds since the full pretax return on plan assets is delivered to the corporation after payment of corporate taxes and then is distributed to corporate shareholders; interest income from bonds held by the plan is taxed at a lower individual equity income rate (Shivdasani and Stefanescu (2010)).

Because with DC plans, there is no obligation beyond the initial contribution (and hence, no long-term horizon and diversification concerns affect innovation), I mainly focus on DB plans in this paper[2]. Corporate DB pension liabilities are sizable firm obligations. In the 1990s, approximately one-quarter of listed firms—accounting for more than half of Compustat firms' book value—had DB pension plans (Rauh (2006)). In 2013, publicly traded pension sponsors had DB liabilities of almost $5 trillion, compared to general financial liabilities of $18 trillion (Dimitrova (2014))[3]. A DB scheme is a form of deferred compensation, the value of which is linked to the economic success of the company. Workers maintain high levels of effort over the long run, and do not gain from quitting or collective shirking (Blake (2006)). DB plans create incentives for workers to remain with the firm, since pension benefits are based on years of service and final wage (Ippolito (1985)). For this reason, DB plans are colloquially characterized as "golden handcuffs." Ghilarducci (2006) provides an excellent summary of DB advantages.

[2] In Section VIII, I add DC firms to my sample and find qualitatively similar results.
[3] According to the Department of Labor, in 2013, there were 15,749,000 active participants in DB plans, compared to 5,414,000 active participants in DC plans.

To illustrate the computation of benefits in a DB plan, consider a plan in which the employee receives 1% of average salary (during the last five years of service) multiplied by the number of years of service. The normal retirement age is 65 and there are no options for early retirement, therefore, a DB plan is a deferred annuity (Bodie et al. (1988)). Within certain limits, DB plan benefits are protected by federal insurance through the Pension Benefit Guaranty Corporation (PBGC). Appendix A offers a more detailed example to assist the reader in understanding the incentives associated with DB plans.

In recent years, however, the advantages have eroded, and many companies have frozen or terminated their DB pension plans in favor of DC plans. This historic shift is widely believed to be a major reason for the the growing deficit in retirement savings, which the Employee Benefits Research Institute estimates is currently greater than $4 trillion. An increase in costs is the most often cited reason for the change (see Shivdasani and Stefanescu (2010), for example)[4]. Despite the popularity of this assertion, costs alone may not be sufficient explanation for the shift in plan preference. If the benefits of DB plans still outweigh their costs, they should not have been frozen or terminated. As such, the movement toward DC plans warrants investigation into the benefits of DB plans. To this end, I examine one of the potential benefits associated with DB plans—their capacity for promoting technological innovation, a crucial competitive advantage for firms.

[4] In fact, in a recent cost analysis to achieve a target retirement benefit under both a DB and DC structure, the National Institute on Retirement Security (NIRS) found that the DB plan cost nearly half as much as the DC plan. That is, the cost of delivering the same retirement income to a group of employees is 46% lower in the DB plan than in the DC plan. Source: http://www.pentegra.com/announcements/IssueBrief-_who_killed_the_private_sector_db_plans.pdf, accessed on October 30, 2015.

Using a large panel of U.S. firms jointly covered by Standard & Poor's Compustat Pension database and the Boston College's 5500-CRR data, I find that DB pension plans foster corporate innovation[5]. My main results are that the total DB pension contributions scaled by the book value of total assets is positively associated with the quantity and quality of innovation output, as respectively measured by the number of patents and the number of patent citations[6]. The association is both economically and statistically significant. To ensure the robustness of these results, I perform a number of analyses using alternative model specifications and variable definitions. Furthermore, I employ the instrumental variable approach to address the possibility of reverse causality and the problem of omitted variables, which could drive both innovation and DB pension contributions. Specifically, I use as an instrument mandatory pension contributions, which are determined by the sharp nonlinearities of pension funding legal requirements. That is, pension contributions are only mandatory for underfunded plans (i.e., overfunded pension plans are not required to make contributions). Additionally, mandatory contributions for firms with underfunded plans dramatically increase as the firm's pension plan funding deteriorates. I include the firm's funding status (i.e., the fair value of designated pension plan assets less the discounted value of projected pension liabilities) as a control variable. Mandatory contributions are a kinked and discontinuous function of funding status. Corporate innovation should not be associated with mandatory pension contributions when the funding status itself is controlled for, except when mandatory

[5] The full name of the 5500-CRR database is: Center for Retirement Research at Boston College. 5500-CRR data: Panel of Current and Usable Form 5500 Data. Chestnut Hill, MA.

[6] I also use the number of citations per patent to measure innovation quality in my empirical analysis and find similar results.

pension contributions capture a direct response of innovation to total pension contributions. In other words, funding status adequately controls for capital investment in innovation. My instrument variable is thus exogenous to corporate innovation and a firm's overall operating environment with appropriate controls (Rauh (2006), Campbell et al., (2012)). The unique setting of DB plans helps mitigate the endogeneity problem of innovation determinants that plagues many related studies. Rauh (2006) first uses mandatory pension contributions as a natural experiment in which they are exogenous to investment opportunities. Franzoni (2009), Campbell et al. (2010), and Campbell et al. (2012) follow this identification strategy as well.

This paper contributes to the extant literature on multiple fronts. First and foremost, my findings identify another determinant of corporate innovation. In the current knowledge economy, decision-makers are keenly interested in knowing what factors drive innovation. I show that contributing to DB pension plans represent one of these factors. This paper also alleviates concerns that DB plan contributions siphon off R&D funds, thereby stifling innovation. This misconception is likely one of the triggers of the widespread switch from DB to DC plans. As illustrated below, pension contributions do not necessarily reduce R&D expenditures. Second, I add to the literature on stakeholder society by showing that an employee-friendly pension scheme can be compatible with firm value creation via innovation. By taking on the challenges of managing pension plan assets and by promising employees a fixed amount of benefits after retirement, DB plans provide an enormous incentive to recipients to ensure their firms' economic success in the long run. Given that it aligns the financial interests of firms and their insiders, this innovation-friendly horizon on the part of employees is pursued by many policies and is tremendously beneficial to stockholders. To illustrate, Bae et al. (2011) find that firms that treat their employees fairly maintain low debt ratios. Related to this, I demonstrate that DB pension plans can be another lever to leverage for innovative firms. Third, I highlight the importance of human capital for investing in intangible assets, which has practical implications for financial managers. Firms undertake two major types of capital investments: capital expenditures (tangible assets) and R&D (intangible assets). Prior literature documents a significant and negative relationship between capital expenditures and mandatory pension contributions, erring on the side of caution with DB plans (Rauh (2006), Franzoni (2009), Campbell et al. (2010), Campbell et al. (2012)). Unlike capital expenditures, however, corporate investments in R&D and innovation face exacerbated opportunistic behaviors, adverse selection, and moral hazard (Hall et al. (2015)). Therefore, it is crucial to extend employees' horizon and align their interests with those of shareholders. In doing so, it becomes possible to shore up innovation by introducing a proper incentive scheme without necessarily increasing R&D expenditures, as shown in this paper. Almeida et al. (2013) similarly find that by mitigating free cash flow problems, financial constraints are positively associated with innovation efficiency. Furthermore, firms tend to smooth R&D expenditures to avoid laying off knowledge workers. Because MCs are treated as an exogenous shock to internally generated cash flows, it is important to distinguish the two types of investments when evaluating cash flow-investment sensitivity and investment efficiency. Fourth, I address the open question as to whether deferred compensation enhances productivity. This question is difficult to answer due to difficulties measuring productivity (Prendergast (1999)). Patent counts and citations jointly provide a relatively reliable measure of productivity. Firms incentivize workers through current compensation and deferred compensation. Ouimet and Simintzi (2016) find that wages (above market-clearing rates) as a type of current compensation positively affect firm performance, while I show that deferred compensation in the form of DB pension makes workers more productive. Fifth, there is a burgeoning line of research that examines the impact of the switch from DB to DC plans. Rauh et al. (2013) demonstrate that switching from a DB to a DC plan can save a sponsor between 2.7 and 3.6% on payroll annually. Using a sample of firms that have declared a hard freeze on their DB plans, Choy et al. (2014) observe greater risk-taking on the part of sponsors following the freeze. Phan and Hegde (2013) show that although investors welcome DB pension freezes with positive post-announcement abnormal stock returns, the freezes seem to be irrelevant with firm investment efficiency and long-term stock performance. Because the decision to freeze is likely endogenous, my use of DB mandatory contributions as exogenous shocks mitigates the issue of endogeneity and provides more nuanced information for decision-makers while imposing DB plan freezes.

In particular, this paper is closely related to recent studies that have examined the role employees play in the process of innovation. Chen et al. (2016), Mayer et al. (2015), and Mao and Weathers (2015) find that employee treatment positively affects corporate innovation. Chang et al. (2015) demonstrate that non-executive stock options spur firm innovation. In evaluating the causal effect of unionization on corporate innovation, Bradley et al. (2015) illustrated that patent quantity and quality decrease after a firm passes a union election. Acharya et al. (2014) detect a positive association between employee job protection and innovative output. I add to this literature by focusing on a particular (different) incentive scheme—DB plans—with a unique setting that can be utilized to address endogeneity.

The remainder of the paper proceeds as follows. Section 2 describes the regulations of pension plans. Section 3 provides additional discussions of literature and the hypotheses. Section 4 describes the data and presents summary statistics. Section 5 details the methodology used and discusses the results. Section 6 conducts robustness checks. Section 7 examines the impact of pension freezes on corporate innovation. Section 8 addresses sample selection and self-selection biases. Section 9 explores possible underlying mechanisms. Finally, Section 10 concludes the paper.

II. Institutional background of pension plans

A. Funding requirements for pension plans

In the United States, firms can choose between a DC plan and a DB plan to offer its employees. In a DC plan, once the firm makes a contribution, it has no more obligations regarding any deficit between funds available in the employee's account and the employee's expectations. In a DB plan, the firm promises to pay a fixed amount of benefits, and therefore assumes all the investment risk and longevity risk. Under the 1974 Employment Retirement Income Security Act (ERISA), employers with DB plans are legally bound to fund the plans with assets to sufficiently meet their pension obligations. Firms are required to make a minimum pension contribution each year, but have the discretion to make additional tax-deductible contributions up to a certain level mandated by law. The minimum funding contribution (MFC) depends on the funding ratio of the plan and equals the normal cost of the plan plus amortization of underfunded liability over 5–30 years. The unfunded liability in the context of ERISA is the part of the projected benefit liability that is neither funded by plan assets nor scheduled to be funded by future normal cost contributions.

The Pension Protection Act (PPA) of 1987 changed the laws to improve DB plan funding. This act introduced the concept of deficit reduction contribution (DRC), which required between 13.75% and 30% of any funding gap to be contributed to the plan as a deficit reduction or "catch-up" contribution. The fraction of the funding gap required to be deposited was min{0.30, [0.30-0.25×(Plan Assets/Plan Liabilities-0.35)]}, and the required contribution was the larger of the MFC and the DRC.

The Retirement Protection Act (RPA) of 1994 exempted plans that are less than 10% underfunded from DRCs. It also exempted certain plans that are between 80% and 90% funded. For 1995 and later, the DRC was changed to be equal to min{0.30, [0.30-0.40×(Plan Assets/Plan Liabilities -0.6)]}. The calculation of the required contribution during the sample period for this study is discussed in detail in Section 3.3.

In 2006, Congress enacted the PPA of 2006, which was deemed the most comprehensive pension reform since the ERISA. The PPA of 2006 required firms to fully fund their pension plans within seven years. This requirement, which took effect in 2008, could cause near-term pension contributions to increase sharply for all sponsors. I take this into consideration where necessary.

B. Pension accounting

The Financial Accounting Standards Board (FASB) issued a series of rules (sometimes called Statement of Financial Accounting Standards, or SFAS) regarding DB plans. SFAS 35, effective from 1980, established standards of financial accounting and reporting for the annual financial statements of a DB plan. Additionally, it left firms with leeway regarding the presentation of benefit information and changes. SFAS 87, issued in 1985, mandated that both the fair value of plan assets and projected value of plan liabilities should be in the footnotes of annual financial statements. Issued in the same year, SFAS 88 established standards for employers to account for the settlement of DB pension obligations, curtail DB pension plans, and terminate benefits. SFAS 132, issued in 1998, revised employers' requirements for disclosures about pension and other post-retirement benefit plans. It required accumulated plan liabilities to be disclosed only for severely underfunded plans. SFAS 158, adopted in 2006, required an employer to recognize the overfunded or underfunded status of a DB plan as an asset or liability in its statement of financial position. In addition, SFAS 158 also mandated that with limited exceptions, employers must measure the funding status of a plan as of the date of its year-end statement of financial position. Based on these accounting rules, I discuss the computation of the DB plan assets and liabilities in Section 3.3 as well.

C. Pension funding reporting

Since this paper examines the incentives provided by a firm's investments in DB pensions for its employees, one important question to ask is whether employees are aware of how well-funded the DB plan is. The answer is a firm yes. Title I and Title IV of the ERISA of 1974 and the Internal Revenue Code (IRC) require all private retirement plan sponsors to provide an overview of the plan's financial status to employees. This overview is known as the Summary Annual Report (SAR). The SAR must be provided within nine months from the close of the plan year (no later than September 30 for calendar year plans); plus a two month extension if an extension was filed. The SAR should be distributed to all participants of the plan during the year for which the plan information is being reported. Distribution can be paper or electronic, but must meet the DOL distribution requirements. The DOL requires that notices be provided in a manner reasonably calculated to ensure actual receipt of the material by the participant. These methods include:

- Hand-delivered to employees at their worksite (merely posting material is not acceptable).
- U.S. mail via first, second or third class only if return and forwarding postage is guaranteed and address correction is requested.
- Electronic media (in accordance with electronic distribution guidelines).

The PPA of 2006 eliminates the SAR but requires both single and multiemployer defined benefit pension plans to provide annual plan funding notices[7]. These funding notices inform pension plan participants about the financial status of their pension plans. Specifically, the PPA requires all defined benefit pension plans, funded and underfunded, single and multiemployer plans to distribute annual plan funding notices to all plan participants and beneficiaries, labor organizations representing participants,

[7] For the original legal text, please refer to Section 501 of the Pension Protection Act of 2006 Public Law 109-280.

employers having an obligation to contribute under the plan, and the PBGC. The notices must contain whether the plan is 100 percent funded and, if not, the actual funded percentage, the total assets and liabilities of the plan for the current year and the two preceding years, as well as a description of the benefits insured by the PBGC and any limitations on benefits that apply.

III. Literature and hypotheses

The corporate finance literature has identified a myriad of factors that are correlated to corporate innovation. These factors can be summarized (though by no means in an exhaustive or mutually exclusive manner) into three categories in light of the mechanisms through which they affect innovative success.

The first mechanism affects employees' attitudes toward high risks inherent in innovation. The factors mainly relying on this mechanism include CEO overconfidence (Galasso and Simcoe (2011), Hirshleifer et al. (2012)), CEO connection (Faleye et al. (2014)), wrongful discharge laws (Acharya et al. (2014)), and local gambling preferences (Chen et al. (2014), Adhikari and Agrawal (2016)).

The second mechanism alleviates the high agency and contracting costs associated with innovation. Factors related to this mechanism include institutional ownership (Aghion et al. (2013)), organizational design (Seru (2014)), corporate governance (Sapra et al. (2014)), and board friendliness (Kang et al. (2014)). On the other hand, this mechanism can exacerbate agency problems or managerial myopia. Examples of factors that are closely related to this flip side of the mechanism are analyst coverage (He and

Tian (2013)), hostile takeover (Atanassov (2013)), accounting conservatism (Chang et al. (2013)), stock liquidity (Fang et al. (2014)), and initial public offerings (Bernstein (2015)).

Finally, dependence on external financing appears to be another underlying mechanism through which innovation is affected. Factors that fall into this category are banking competition (Cornaggia et al. (2015)), financial development (Hsu et al. (2014)), and global diversification (Gao and Chou (2015)).

In line with the first and second mechanisms, I posit that compensation systems can influence firm innovation. Specifically, I predict that DB plans affect corporate innovative activities. On one hand, DB plans differ from other forms of employee compensation because they create an ongoing liability for the firm. In this regard, DB plan obligations are fundamentally different from DC plan obligations and employee salaries because DB plans do not come off the books if an employee leaves the firm. Sundaram and Yermack (2007) argue that DB pension plans are an important form of "inside debt." Specifically, they report that more than half of the CEOs of S&P500 firms have service-based DB pensions, and that those pensions are a substantial fraction of their overall incentive compensation. They argue that these typically unsecured, debt-like claims on the firm alter managerial incentives by aligning the interests of managers more closely with those of outside debt holders (i.e., bondholders). This "debt bias" arises because managers generally bear the same default risk faced by the firm's other unsecured (outside) creditors. Therefore, Sundaram and Yermack (2007) conclude that as the firm's managers have more debt-like (pensions) versus equity-like (stock options) incentive compensation, the firm is likely to take on less risk.

Dimitrova (2014) further argues that DB claimants are less diversified than traditional debtors because their pension wealth is invested entirely in the firm. She also provides evidence to suggest that firms are less likely to file for bankruptcy when DB liabilities comprise a greater share of their overall liabilities. This suggests that both firm contributions and plan value are inversely related to pensioner willingness to risk losing their earned contributions. In addition, Choy et al. (2014) examine the impact of a DB pension plan freeze on the sponsoring firm's risk and risk-taking activities. Using a sample of firms that declared a hard freeze on their DB plans between 2002 and 2007, they observe an increase in total risk (as measured by the standard deviation of EBITDA and asset beta), equity risk (standard deviation of returns), and credit risk following a DB-plan freeze. They also find a shift in investment from capital expenditures before the freeze to more-risky R&D projects after the freeze, and an increase in leverage. In the same vein, I conjecture that employees with DB plans would be reluctant to take the high risks inherent in innovation. Rauh (2006) shows that if a firm is financially constrained, DB contribution requirements may affect its ability to invest in projects[8]. Therefore, DB plan contributions may be associated with the reduced likelihood of innovative success. This assumption serves as the basis for the first hypothesis, which I call the *debt bias hypothesis*.

Debt Bias Hypothesis: *By discouraging employees from taking risks, the defined benefit pension plan negatively affects the output and quality of a firm's innovation.*

On the other hand, because I focus on DB plans for rank-and-file employees (i.e., the so-called "(tax) qualified plans"), Sundaram and Yermack (2007)'s findings may not be

[8] However, Rauh (2006) did not find evidence that pension contributions cause R&D expenditures to decrease.

salient to my analyses. Qualified plans differ from most executive DB plans (typically in the form of a Supplemental Executive Retirement Plan, or SERP), the so-called "non-qualified" plans, in two relevant aspects: First, qualified plans with over 100 employees must file IRS 5500 forms. Non-qualified plans do not[9]. Because my data are from the IRS Form 5500, SERPs are excluded from my analyses. Second, unlike non-qualified plans, qualified plans are sufficiently guaranteed by the PBGC. As a result, the default risk borne by their participants is substantially lower than that faced by unsecured (outside) creditors. With this downside protection via put options (Bodie (1990)), rank-and-file employees may actually be willing to take on greater risk. Moreover, Ippolito (1985) show that DB plans increase productivity by backloading firms' compensation packages and implicitly promising to pay workers' marginal product of labor (MPL) in their later years of employment. Therefore, even if pension contributions reduce R&D expenditures, the strong incentives provided by DB plans can still possibly offset this adverse impact on innovation output. Furthermore, Phan and Hegde (2013) find little evidence that freezing DB pension plans and replacing them with DC plans increases investment efficiency and firm value.

In a related study, Quinn and Rivoli (1991) propose a theoretical framework suggesting that a compensation system based on lifetime employment and profit-sharing (i.e., "the Japanese system") may spur innovation, while systems based on employment-at-will and fixed wages (i.e., "the American system") may stifle innovation.

[9] DB plans for top executives typically consist of two parts: regular qualified plans that can only cover annual benefits up to a limit imposed by the IRS and SERPs that cover the remaining pension benefits. For top executives of large U.S. companies, pension benefits under SERPs are typically multiples of those under the regular qualified plans (Stefanescu et al. (2014)).

The authors argue that employees in the Japanese system have the same payoff profile as buyers of call options. They further argue that employees in the American system have the same payoff profile as sellers of call options. Buyers of call options prefer underlying assets to be risky, but sellers have the opposite preference. Therefore, we may deduce that employees under the Japanese-style system will be pro-innovation and produce more or higher-quality innovative outputs, and that employees under the American-style system behave just conversely. Job assurance with a fixed base wage and profit sharing provides employees with the security and incentive to innovate. In contrast, when the fire-at-will doctrine is paired with straight wages, neither job security nor the incentive necessary for innovation is present. In this sense, DB plans are very similar to the Japanese system with respect to economic incentives.

Moreover, classical labor economics theory (e.g., Borjas (2013)) dictates that by delaying compensation into the future, firms elicit greater effort and productivity from workers. They know that their activities are likely monitored, and that they could be caught and fired if they shirk their duties. When a firm utilizes delayed-compensation, an employee's shirking of activities carries the risk of substantial loss in income. This theory (sometimes called the "bonding theory") has two implications for corporate innovation[10]. First, delayed-compensation contracts—like DB plans—are typically offered by firms where the chances of bankruptcy are remote. As a result, delayed-compensation contracts tend to be offered in large, established firms. Therefore, concerns related to "less-diversification" are largely invalid in these cases. Second, delayed compensation is

[10] For details about the "bonding theory," see Fundamentals of Private Pensions，McGill et al. (2010, p. 150), Oxford University Press.

particularly relevant for encouraging innovation. This compensation scheme is irrelevant for workers who are employed in jobs where it is easy to monitor output. Workers employed in easy-to-monitor jobs find it difficult to shirk, and firms do not have to tilt age-earnings profiles to induce them to behave properly. Indeed, the key reason for offering delayed compensation is that some activities, like innovation, are by nature difficult to monitor—output is not seen in a short time, and failed endeavors are indistinguishable from shirking (Gross (2016)). Therefore, in the case of innovation, tolerance of early failure is even crucial for success (Manso (2011)). Taken together, I predict that DB plans should be associated with a higher likelihood of innovative success. This rationale leads to the second hypothesis, which I call the *deferred compensation hypothesis*.

Deferred Compensation Hypothesis: *By eliciting greater effort and higher productivity from workers, defined benefit pension plans positively affect the output and quality of a firm's innovation.*

I find overall support for the deferred compensation hypothesis by showing that the value of DB plans enhances innovation. Using DB plan and patenting data, I observe that firms with a higher DB plan value obtain more patents and patent citations during the period 1990–2007, even when controlling for the relationship between the pension funding status and the firm's innovation output.

IV. Data, variables, and summary statistics

A. Data and sample

I obtained data on DB plan assets and liabilities from the Compustat Pension Annual Database, which covers all listed firms' DB pensions from the year 1987 onward. Prior to 1987, reporting of DB plan obligations was not required, and therefore not standard. Compustat pension data from SEC filings are pre-aggregated to the firm level. Pension liabilities in the SEC filings are calculated according to the projected benefit obligation method, in which prospective salary increases are accounted for. I collect data on total pension contributions and mandatory pension contributions from the Boston College 5500-CRR data—the Panel of Current and Usable Form 5500 Data. The 5500-CRR data are available from 1990 to 2007. They start from 1990 because IRS 5500 forms are first available in a standardized format from the Department of Labor (DOL) in this year. They end in 2007 possibly to avoid data inconsistency due to the changes in reporting requirements[11]. The IRS 5500 filings contain plan-level information necessary to calculate total contributions and required contributions at the firm level. Accounting data are retrieved from the Compustat Fundamentals database. Finally, I obtain data on stock prices and returns from the Center for Research in Security Prices (CRSP) files.

For the purposes of this study, I focus on the subsample of Compustat firms that file an IRS 5500 form with the DOL, have SEC filings, and sponsor DB pension plans. I match plans to firms primarily by employer identification numbers (EINs). For those firms that cannot be matched with the Compustat data based on EINs, I use a fuzzy text matching algorithm to match by firm name and reported state (which presumably houses the firms' headquarters). I then manually check and delete mismatches. As acknowledged by Phan

[11] Beginning with the 2008 Form 5500, actuarial information is filed on the Schedule SB for single-employer plans and the MB for multiemployer plans.

and Hegde (2013), this matching process is imperfect and results in a smaller sample than expected. This is likely due to the fact that Compustat does not report EINs for many firms and matching by firm name only partially remedies this shortcoming[12]. I do not match by CUSIPs because in 1998, reporting requirements no longer forced pension plans to list the CUSIP pertaining to the plan. The majority of observations in the IRS 5500 belonging to private firms cannot be matched to those in Compustat.

To measure the quantity and quality of innovation output, I use data constructed by Kogan et al. (2015), which provides detailed information on all U.S. patents granted by the U.S. Patent and Trademark Office (USPTO) between 1926 and 2010[13]. Following Hirshleifer et al. (2012), I exclude firms in any four-digit Standard Industrial Classification (SIC) industries that have no patents, as well as firms in the financial and utility industries (SIC codes: 6000–6999 and 4900–4999, respectively). Also excluded are firms with missing values for DB plan variables and control variables employed in the regressions. Consistent with Seru (2014), I augment the USPTO patent sample with all the firms in Compustat that operate in the same four-digit SIC industries as the firms in the patent database but who do not have patents. I set the patent count to zero for these firms. These criteria result in a final sample of 627 firms (4,217 firm-years) from 1990 to 2007. Following Chang et al. (2015), I use a one-year lag of the DB plan value when predicting innovation output.

B. Measuring innovation output

[12] In Section 6, I conduct a robustness check that does not require merging by EINs and find consistent results.

[13] The data set is available at https://iu.app.box.com/patents. Last accessed on July 3, 2015. For details of construction of the data, see Kogan et al. (2013).

My first measure of innovation output is the number of patents for which a firm applied (and were eventually granted) in a given year (Patents). On average, the granting of patents lagged patent application by two years. My sample period ends three years prior to the last year for which patent information is available. Therefore, I expect little truncation bias in the sample. However, patent counts imperfectly capture innovation success because patents vary in their technological and economic significance (Hirshleifer et al. (2012)). I therefore follow Hall et al. (2001, 2005) and use a patent's forward citations to measure its quality or importance. Citation measures are subject to truncation bias toward the end of the sample period, as patents in this period will have relatively less time to accumulate citations. I correct for these truncation errors by adjusting fixed effects in a manner consistent with Hall et al. (2001) and Seru (2014). Specifically, I divide the number of citations for each firm in a given year by the mean number of citations in that year and within the same patent technology class as defined by USPTO (Citations)[14]. In later analyses, I also use citations per patent as the dependent variable for regression analysis.

I include self-citations since Hall et al. (2005) find that self-citations have higher value than external citations. They argue that self-citations, which come from subsequent patents, reflect strong competitive advantages, a reduced need to acquire other technology, and a lower risk of rapid entry. Firms may rely on secrecy or other means to protect its innovation, so patent count and citations are imperfect measures of innovation.

[14] Technology classes are available for download at http://www.google.com/googlebooks/uspto-patents-class.html. I thank Noah Stoffman for providing the link. Last accessed on May 2, 2016.

Nevertheless, there is no other widely accepted method for quantifying corporate technological inventions (Griliches (1990)).

C. Measuring defined benefit pension plan value

Employees not only consider their expectations regarding retirement benefits, but also how well the plans are funded. To capture these concerns, I include firm-level funding status and pension contributions as explanatory variables in the model. Moreover, I use an alternative measure of DB plan value on a projected basis for the regressions in Appendix C. Using data from Compustat, I calculate funding status as pension assets minus pension liabilities divided by the book value of total assets. Figure 1 shows the distribution of the beginning-of-year pension funding status for Compustat firms from 1990 to 2007. This figure illustrates the variation in the distribution of pension funding status across time. This variation reflects the relative changes in pension assets and liabilities.

There are two measures of pension liabilities: accumulated benefit obligation (ABO) and projected benefit obligation (PBO). ABO reflects the present value of pension benefits based on current employee salaries and indicates what a plan sponsor is legally liable for in the event of plan termination. PBO is calculated as the actuarial present value of the promised benefits for financial accounting purposes, taking into account projected increases in salary between now and retirement. This measure of pension liability treats the company as a going concern and is calculated according to current service and future expected salaries. Starting in 1987, the FASB required firms to report their PBO

(SFAS87). As required by SFAS132, firms were also required to disclose their ABO until 1998. Hence, to ensure a longer sampling period, I use PBO as the main measure of DB plan liabilities and as an alternative measure of DB plan value[15]. Prior to 1998, firms reported a liability (an asset) if the pension expense exceeded (was lower than) cash contributions to the plan. These items were reported separately as overfunded and underfunded plans. Therefore, I aggregate these liabilities for over- and underfunded plans (Compustat items: pbpro+pbpru). Between 1998 and 2007, firms reported the same variables on balance sheets, but consolidated them across plans regardless of their funding status. For these fiscal years, I use pbpro as PBO. I follow the same practice when calculating pension plan assets. See Appendix B for variable definitions.

[Insert Figure 1 here]

Firms' total contributions (TCs) to DB pension plans are reported on IRS 5500 forms. For the sake of comparison, Figure 2 combines two distribution graphs of mean TCs during the sample period. The top graph covers only firms in the final sample. The bottom graph covers all publicly traded DB sponsors. The similarity of the two graphs indicates that my final sample is representative of the Compustat Pension universe. TCs increased sharply starting in 2001, possibly triggered by the deterioration in plan funding (see Figure 1) due to the burst of the dot com bubble.

[Insert Figure 2 here]

[15] I obtain qualitatively similar results by using the ABO in a robustness check (see Section 5).

Mandatory contributions (MCs) are a constructed estimate of the firm's required contributions. MCs are zero for firms without any underfunded pension plan. Firms with underfunded plan(s) must contribute the greater of the MFC and the DRC. As in Munnell and Soto (2004) and Rauh (2006), I calculate MFC as the present value of pension benefits accrued during the year (called the "normal cost") plus 10% of the ERISA unfunded liabilities. The MFC can be offset by accumulated funding credits, which can be estimated from the IRS 5500 filings. The DRC as a fraction of the funding gap is min{0.30, [0.30-0.25*(Plan Assets/Plan Liabilities -0.35)]} until 1994 (inclusive) and min{0.30, [0.30-0.40*(Plan Assets/Plan Liabilities -0.6)]} from 1995 (inclusive) forward. The change to the DRC in 1995 exempted plans that are more than 90% funded from DRCs. It also exempted plans that were at least 80% funded and that had a recent history of being overfunded. The minimum and maximum in the above definitions create sharp nonlinearities in MCs, which are thus a kinked and discontinuous function of the funding status. Figure 3 depicts these requirements, showing mandatory contributions in dollar terms for a firm with sample mean characteristics (liabilities of $10.02 million and "normal cost" of $2.08 million). As indicated above, companies must contribute the larger of the MFC or DRC for a given funding status. Discontinuity will occur at the point of full funding, where MCs fall to zero. Within the underfunded section, the mandatory contribution function is characterized by further sharp nonlinearities. There is no reason that MCs will directly affect innovation when funding status is controlled for. Thus, I argue that MCs are exogenous to a firm's innovation. To mitigate heteroskedasticity, I scale the TCs (MCs) using the book value of total assets. One of the resulting measures, the total contribution ratio (TcAt), is the key variable of my interest in the regression analyses in this study.

[Insert Figure 3 here]

D. Control variables

To isolate the effect of DB plans on innovation output, I control for a vector of firm characteristics that previous researchers have documented as important determinants of innovation. The first of these control variables is R&D intensity (R&D/Assets), which serves as a critical input to innovation (Atanassov (2013)). Hall and Ziedonis (2001) argue that large firms and capital-intensive firms generate more patents and citations. Given this, I use the natural logarithm of total assets (Ln(Assets)) in my analyses to control for firm size. My results are robust to the use of net sales or the number of employees as proxies for firm size. I employ the logarithm of the net Property, Plant, and Equipment (PPE) scaled by the number of employees (Ln(PPE/#employees)) to account for capital intensity. Moreover, I include the logarithm of the net sales scaled by the number of employees (Ln(Sales/#employees)) to proxy for labor productivity and quality since higher labor productivity may lead to more innovation. Return on assets (ROA) is included to capture operating profitability, and the buy-and-hold stock return computed over the fiscal year (Stock return) is included to control for stock performance. Also included are sales growth and the market-to-book ratio (M/B) as proxies for growth opportunities. The cash-to-assets ratio (Cash/Assets) and the leverage ratio (Leverage) are added to account for the respective effects of cash holdings and capital structure on innovation. To capture the effect of a firm's life cycle on its innovation ability, I use the natural logarithm of firm age, Ln(Firm age), which is estimated as the number of years elapsed since a firm entered the CRSP database.

Stock volatility (standard deviation of daily stock returns over the fiscal year) is included as an additional control since Chan et al. (2001) find that stock volatility positively affects R&D investments. Additionally, Aghion et al. (2005) discover an inverted U-shaped relationship between product market competition and innovation. Accordingly, similar to Atanassov (2013) and Chemmanur and Tian (2011), I include as control variables the three-digit SIC Herfindahl index (HHI) and its squared term (HHI^2).

All control variables are winsorized at 1% and 99% to remove the effect of outliers that could bias my analyses. With the exception of Stock return and Stock volatility, which are measured between year t - 1 and t, all control variables are measured at t - 1 in the regressions.

E. Descriptive statistics

Columns 1–3 of Table 1 report the means, medians, and standard deviations of the variables used for the whole sample. With respect to the innovation measures, an average firm in my sample applies for 55 patents that were eventually granted, and receives roughly 59 fixed-effects-adjusted citations for its patents every year. On average, each firm spends 0.55% of its total assets on pension contributions every year, while the median firm has roughly 0.17% of its total assets on DB plan contributions every year. Per employee value of DB plans (measured by projected pension liabilities divided by number of employees) is $56,000 (mean) or $32,000 (median). The relative lowness of these figures can be explained by the fact that DB plans only cover a portion of the workforce at those firms. The statistics of the control variables suggest that an average firm in the sample is relatively large in size, both in terms of assets and employees.

I divide firms into two subsamples according to the median value of TcAt (total pension contributions scaled by the book value of total assets) each year and report mean values of the variables in columns 4 and 5 for high- and low-TcAt firms separately. I test the distribution differences (hence mean differences) of variables between the two subsamples and report the level of significance in column 5. Similar inferences are drawn using the Wilcoxon-Mann-Whitney median tests (untabulated) on the differences in median values between the two subsamples[16]. Results show that, compared to low-TcAt firms, high-TcAt firms produce more and higher-quality patents. The difference in patents (citations) between high- and low-TcAt firms is 3 (4), which is statistically significant at 1%. Most control variables exhibit a significant difference between high-TcAt firms and their counterparts. For example, relative to low-TcAt firms, high-TcAt firms tend to have lower funding status, lower leverage, and lower stock volatility but higher stock returns, higher ROA, higher R&D intensity, and higher cash-to-asset ratios. Interestingly enough, an average low-TcAt firm is actually larger in in terms of assets and workforce, and older in age. This indicates that compared to smaller, newer firms, the larger and older firms lag behind in making contributions (especially voluntary contributions) to meet their pension obligations. Not surprisingly, an average high-TcAt firm has higher per-employee value

[16] I also conduct two sample t tests and find no significant differences across any of the patenting measures.

for its DB plans than an average low-TcAt firm. Whereas TcAt is measured on a historical basis, per-employee DB value is measured on a projected basis. Later, I will use both measures in my regressions to check the robustness of my results.

[Insert Table 1 here]

V. Main results

A. The baseline model

I examine the effect of DB plans on a firm's innovation output using the following baseline model:

$$Ln(1+Innovation_{i,t}) = \alpha + \beta TcAt_{i,t-1} + \gamma X_{i,t-1} + \delta Industry_{i,t} + \theta Year_t + \varepsilon_{i,t} \qquad (1)$$

where Innovation refers to my innovation measures (Patents and Citations). The key explanatory variable is the total contribution ratio (TcAt), defined as total pension contributions divided by total assets of the firm, as measured at the end of one year lagged. To (a) reduce skewness in the distribution of my innovation measures and (b) include zero values of innovation, I use the logarithm of one plus the dependent variables in the regression analyses. X represents the set of control variables, including funding status, defined in Section 3.4. I also include two-digit SIC industry and year fixed effects in the model.

Columns 1 and 5 in Table 2 report the results of my baseline regressions in Equation (1). Results show that TcAt is positively and significantly associated with both measures of innovation, Ln(1+Patents) and Ln(1+Citations), with respective t-statistics of 3.41 and 3.42. Economically, for an average firm with the mean number of Patents (55) and Citations (59), a one-standard-deviation increase in the TcAt will boost the patent count by approximately 7 to 62, and will also boost the Citations by approximately 8 to 67[17]. To put these effects in perspective, the effects of a 0.1% increase in the total contribution ratio on patent counts and patent citations are approximately 1.1 times the effects of the same percentage increase in R&D intensity, as indicated by the estimates on TcAt and those on R&D intensity. The coefficients of funding status are significant at the 5% level, confirming my previous argument that employees consider how well plans are funded. The coefficients of other control variables are generally consistent with prior literature. For example, I find that firms with higher R&D intensity are associated with higher innovation productivity. Larger and older firms have more patents and citations. Firms with lower leverage, lower sales growth, higher ROA, or higher stock volatility have more innovation output.

Since the distributions of TcAt and patents/citations are highly skewed to the right, which may still cause estimation bias even after winsorization and taking the natural logarithm, I use a quantile regression specification to alleviate concerns related to outlier effects. Specifically, I estimate the coefficients at three quantiles: the 25th, 50th, and 75th quantiles, by including the list of explanatory variables in Equation (1) for each of these quantiles. For comparison purposes, I also report the conditional quantile estimates in Table 2 (Columns 2–4 and 6–8). Consistent with the OLS regressions, all coefficients of the key independent variable of interest (TcAt) are statistically significant at the 1% level.

[17] The two results are calculated as (1+55)* [exp(0.0091*13.166)-1]=7.13 and (1+59)*[exp(0.0091*13.337)-1]=7.74, respectively.

In most of the quantile regressions, innovation is a concave function of the Herfindahl index, a measure of product market competition, consistent with the literature.

[Insert Table 2 here]

I also perform an additional test to ensure that my main results are robust to an alternative measure of the DB plan value—the ratio of the projected benefit obligation to the number of employees (PBO/#employees). These results are qualitatively similar to those presented above (see Appendix C). In separate analyses, I also scale the total contributions and the ABO by the firm's number of employees, and run all OLS regressions without industry and year fixed effects. The unreported results offer similar inferences.

B. Industry Innovativeness

I expect the effect of DB plan value on innovative outcomes to be greater in industries in which innovation is more important and better fostered. I therefore split the sample to separately test the effect of DB plan value on more versus less innovative industries. In addition to providing an examination of whether industry matters, a test that shows differential impacts on (non)innovative industries is a powerful way to strengthen my evidence that DB plans have an effect on innovation. To conserve space, I report only the coefficients and t-statistics associated with the DB plan value measures, while all the control variables are included.

Following Adhikari and Agrawal (2016), I define an industry as innovative if the average fixed-effects-adjusted citation count per patent for the industry during the year is greater than the median fixed-effects-adjusted citation count per patent across all industries, classified at the four-digit SIC level. Table 3 shows that among innovative industries, the regression of Ln(1+Patents) (Ln(1+Citations)) obtains a coefficient of 14.420 (15.618) on the DB plan value (TcAt), which is statistically significant at the 1% (1%) level. In the sample of non-innovative industries, the DB plan value (TcAt) obtains a much smaller coefficient of 10.137 (8.837), which is significant at the 10% (10%) level. A similar pattern emerges if I alternatively use the ratio of the PBO to the number of employees as the DB plan value. These results suggest, upholding my hypothesis, that the DB plan value has a greater effect on a firm's innovation output in innovative industries.

[Insert Table 3 here]

C. Endogeneity issues

Although my results show a strongly positive association between DB pension and innovation output, the results are potentially subject to two types of endogeneity. The first type is the omitted variable bias. While I have controlled for a standard set of variables that have been shown by previous studies to affect innovation, the observed relationship may be spurious if my model omits any variables that affect both corporate innovation and pension contributions. Corporate governance represents one such variable.

However, adding the G-Index (Gompers et al. (2003)) as a control variable keeps the TcAt estimate positive and statistically significant at the 1% level: Unreported t-statistics in the two baseline regressions are 3.85 and 3.81, respectively. The second issue related to endogeneity concerns reverse causality. It is possible that innovation induces contributions to DB pension plans rather than the other way around. In other words, innovative firms may be more profitable and thus have more cash to make pension contributions. In both cases, the coefficient estimates from the OLS regressions are biased and inconsistent.

To address these endogeneity issues, I employ the instrumental variable (IV) approach, which allows unobserved heterogeneity to change over time and is therefore more powerful than most other identification strategies. Specifically, I use an IV that is correlated with total contributions made to DB pension plans but is unrelated to innovation output. The instrument is the mandatory contribution ratio (McAt), defined as mandatory contributions (MCs) divided by the book value of the firm's total assets. MCs are plausibly exogenous because the distance from the funding threshold is largely determined by stock market values, which the firm cannot manipulate. From the definition, it is easy to know that MCs are part of and thus correlated with TCs. Therefore, my instrument satisfies the relevance criterion. One may assume MCs to impede innovation by drawing down internal financial resources that could otherwise be invested in R&D. However, Rauh (2006) finds that MCs do not affect R&D expenditures, possibly because their adjustment involves high fixed costs. This empirical finding is also confirmed by the data in my sample. I run OLS regressions of R&D Intensity on McAt and other non-pension control variables, both contemporaneously and with one-year lag.

Unreported results of these analyses show statistically insignificant estimates on McAt (t-statistic = 1.29 and 0.98, respectively) in both model specifications. Tobit regressions yield similar references (t = 1.64 and 1.37, respectively)[18]. These results suggest that MCs do not directly affect innovation by siphoning off funds for R&D. Thus, my instrument is likely to meet the exclusion restriction condition as well[19]. Taken together, these results suggest that McAt affects a firm's innovation outcomes only through the incentives provided by plan funding (i.e., total pension contributions), rather than through other channels (e.g., R&D expenditures).

I report results obtained using this IV approach in the framework of a two-stage least squares (2SLS) regression in Table 4. The first-stage regression is presented in Column 1. McAt is significantly and positively related to TcAt (t-statistic = 26.77). The instrument also passes the relevance test as the value of the F-statistic from the joint test of excluded instruments is 33, which is significant at the 1% level.

Columns 2 and 3 show the second stage of the 2SLS regressions for each of the two dependent variables. Similar to the OLS regressions, I find that the total DB pension plan contributions significantly and positively predict patent counts (t = 2.99) and number of adjusted citations (t = 2.82). I also conduct a Wu-Hausman test to assess the endogeneity of TcAt; the untabulated result indicates that TcAt is indeed endogenous at the 1% significance level. This justifies my use of the IV method. The dependent

[18] I use Tobit regressions since R&D expenditures are censored from below at zero.

[19] The insignificant relationship between DB contributions and R&D further indicates that firms with high DB contributions do not spend more on R&D, suggesting that the greater innovation output attributed to DB plans comes from enhanced innovative efficiency. This is supported by the larger coefficients of TcAt (13.448 and 13.617, respectively) if R&D intensity is omitted from the two baseline models. See Section 7 for another test of this hypothesis at the inventor level.

variables for the above baseline and IV analyses are patent counts and citations. Results of a similar analysis of citations per patent (CPP), Ln(1+CPP) are presented in Appendix D.

[Insert Table 4 here]

VI. Robustness tests based on alternative estimation of MCs

In addition to Rauh's (2006) measure, Campbell et al. (2012) employ an alternative method developed by Moody's (2006) to estimate MCs. In this section, I use Moody's measure to rerun the OLS and IV analyses. This alternative method has at least two benefits. First, it does not rely on Form 5500 data that are only available with a significant time lag. Instead, it uses more timely data from 10-K filings. This is useful in the sense that debt and equity holders may wish to know the impact of DB plans as early as possible. Second, Moody's method may increase the sample size, as merging by EINs can be circumvented. In spite of these benefits, this method also has some drawbacks. For example, the sharp nonlinearities of MCs nearly disappear due to the simplification of the calculation. For this reason, I turn back to Rauh's measure in the next section and on.

According to Moody's (2006) and consistent with Rauh (2006), MC reflects the fact that firms with overfunded pension plans are not required to contribute to their pension plans. Specifically, MC equals the total of (a) the portion of pension expense earned by employees during the current period (i.e., service cost) and (b) the amortization of any funding shortfall, which is (Accumulated Benefit Obligation – Fair Value of Pension Plan Assets)/30. As a construct validity check, I compare the descriptive statistics of Moody's and Rauh's measures. The mean (0.003), median (0.001), and standard deviation (0.004) of Moody's measure are similar in magnitude to those of Rauh's measure (0.003, 0.001, and 0.005, respectively; untabulated). Because the Compustat Pension database does not report total pension contributions before 2000, I use the alternative measure, PBO (specifically, the natural logarithm of one plus per-employee PBO), to gauge the DB plan value[20]. The final sample consists of 1,192 unique firms (7,529 firm-years). As expected, this sample is much larger than the sample for Rauh's measure. I then conduct OLS and IV analyses by using patent counts and citations as dependent variables; the results of these analyses are summarized in Table 5. Consistent with the findings based on Rauh's measure, DB plan value positively and significantly affects sponsoring firms' innovation output (significant at 5% or better).

[Insert Table 5 here]

VII. Impact of pension freezes on corporate innovation

If DB plans are pro-innovation, then pension freezes should have a negative effect on patent success. To test this hypothesis, I collect DB pension freeze data from Form 5500 for the years 2002 to 2007. My sample period starts from 2002 because although 2001 is the first year firms were required to report DB pension freeze on Form 5500, no firms did

[20] I also use accumulated benefit obligations (ABO) as an alternative to PBO and find qualitatively unchanged results, as is the case if I extend the sample period to 2010, the final year for which patent data are available.

so in that year. I search Form 5500 for firms that imposed a hard freeze on their DB plans during the sample period. Only firms with a hard freeze of their pension plan are included in my freeze sample. All other firms that file Form 5500 are considered as non-freeze sample observations. After ensuring that the freezing firms have data for the variables to be used for regressions later, I am left with 175 firms that instituted a hard freeze on their DB pension plans during my sample period. If a firm has instituted multiple plan freezes, then the year when the first freeze took place is used as the event year.

While the main objective of this section is to examine the change in firms' innovation output after DB-plan freezes, the decision to freeze a DB plan is endogenous. The freezing decision can be triggered by macroeconomic changes, new regulations, changes in the firm's operations, and the funding status of pension plans. These same factors can also lead to changes in firm innovation. Therefore, I follow the Heckman (1976) two-stage estimation procedure to adjust for this selection bias. In the first stage, I analyze the determinants of a firm's decision to freeze its DB plan using the model proposed by Choy et al. (2014). Specifically, I include the change in the dividend payout, leverage, and investment policies in the period prior to the pension freeze decision in the model to examine the lead-lag relationship between the change in innovation and the pension freeze decision:

$$\begin{aligned} Freeze &= \alpha + \beta_1 Underfund + \beta 2 Funding\% + \beta 3 Firm\ Size + \beta 4 Plan\ Size \\ &+ \beta 5 Operating\ Cash\ Flow + \beta 6 Loss + \beta 7 \Delta Sales\% + \beta 8 \Delta Dividend + \beta 9 \Delta Leverage \\ &+ \beta 10 \Delta R\&D + \beta 11 \Delta Capex + \beta 12 Union\ Plan + \varepsilon \end{aligned} \tag{2}$$

Freeze is an indicator variable equal to one in any year in which the firm's DB plans are frozen, and zero otherwise. Underfund is an indicator variable equal to one if the fair value of the plan assets is less than the projected benefit obligation and zero otherwise.

Funding% is the percentage the pension plan is funded and is computed as the pension plan assets divided by the projected benefit obligation. Firm Size is the natural logarithm of total assets. Plan Size is the projected benefit obligation divided by total assets. Operating Cash Flow is cash flow from operations scaled by total assets. Loss is an indicator variable equal to one if the firm reported a loss in the prior year, and zero otherwise. ΔSales% is the percentage change in sales. ΔDividend is the change in dividend payout in the prior year. ΔLeverage is the change in debt to asset ratio in the prior year. ΔR&D is the change in research and development expense (R&D) to asset ratio in the prior year. ΔCapex is the change in capital expenditure to asset ratio in the prior year. Union Plan is an indicator variable equal to one if the firm's DB plans are subject to a collective-bargaining agreement, and zero otherwise. I also include year and industry fixed effects to control for the effect of changes in macroeconomic or industry conditions on pension freeze decisions. I use this regression as the first stage to compute the inverse Mills ratio. These ratios are then included in the second-stage regression analyses of change in corporate innovation to control for the endogeneity of the DB-plan freeze decision. Specifically, I regress innovation on the inverse Mills ratio and the set of control variable included in Equation (1). I am essentially conducting a difference-in-differences estimation with multiple events because the pension freeze was instituted in multiple years by multiple groups of firms. The treatment group is my freeze sample, while the control group is the non-freeze DB firms. Following Bertrand and Mullainathan (2003) and Choy et al. (2014), I estimate the following model:

$$\mathrm{Ln}(1 + Innovation_{i,t}) = \alpha + \beta \mathrm{P}ost\ Freeze + \gamma Inverse\ Mills\ Ratio + X_{i,t-1} + \varepsilon_{i,t} \tag{3}$$

The results are presented in Table 6. The standard errors in the regressions are robust to heteroscedasticity and serial correlation, and are clustered at the firm level. All regressions also contain year- and industry- fixed effects to control for the impact of business cycles, macroeconomic conditions, and changes in legislation and industry conditions.

Column 1 presents the results when corporate innovation is measured by patent counts. Columns 2-3 present the results when patent citations and citations per patent are used to measure innovation quality. Post-freeze has negative coefficients in all columns, and the coefficients are significantly different from zero at the 1% level. Hence, I conclude that there is a significant decrease in corporate innovation after DB-plan freezes, consistent with my previous hypothesis discussed at the beginning of this section.

This conclusion seems to contradict with Choy et al. (2014), who find that management deliberately increases risk-taking after DB-plan freezes by shifting from less risky capital expenditure investments to more risky R&D projects. One possible explanation for reconciling the contradiction is that R&D investment is only part of the inputs of innovation. Another more crucial input is human capital. As Ouimet and Zarutskie (2014) argue, labor and human capital play increasingly important roles in production, especially in the R&D-intensive industries. Chang et al. (2015) point out that skills and efforts of employees are fundamental inputs to the innovation process. Therefore, if a firm increases R&D expenditures but at the same time takes away an important incentive scheme, corporate innovation will still suffer and experience decline. This observation once again emphasizes the importance of distinguishing capital expenditures and R&D investments discussed in the introduction, and the importance of striking a delicate balance between financial capital and human capital in the innovation process.

[Insert Table 6 here]

VIII. Adding DC firms to the sample

To address sample selection bias, I now expand my sample to the whole Compustat universe to include DC firms. Since firms could simultaneously offer both DB and DC plans to different groups of its employees, to avoid double counting, I here refer to DC firms strictly as those with DC plans only and without any DB plan[21]. I do so by adding the Compustat firms not matched to my DB sample above. I then set all the DB-related variables to be zeros for DC firms and run the above OLS and IV regressions. Results are reported in Table 7.

Column 1-2 present the OLS regression. TcAt has positive coefficients in both columns, and the coefficients are significantly different from zero at the 1% level. Columns 3 presents the first-stage regression result of the 2SLS method. The coefficient of McAt is positive (t=23.61). F statistic is 31, suggesting that McAt is not a weak instrument for TcAt. Endogeneity test indicates TcAt is indeed endogenous in corporate innovation. Columns 4-5 report the second-stage regression results when corporate innovation is measured by patent counts and citations, respectively. TcAt has positive coefficients in both columns, and the coefficients are significantly different from zero at the 1% level. If I use citations per patent as dependent variable, untabulated results (to

[21] Accordingly, DB firms refer to firms that offer DB plans only (if any) and firms that offer both DB and DC plans.

save space) show that the coefficient of TcAt in OLS regression is 4.764 (t=6.67) and in the second stage of 2SLS regression is 7.703 (t=2.80). Therefore, I conclude that after including DC firms, there is still a causal effect running from DB pension contributions to corporate innovation.

[Insert Table 7 here]

As a robustness check, I use a treatment effects model to address the endogeneity of DB contributions because firms can self-select into DB plans. In this case, the observed relation between DB plans and firm innovation may be subject to alternative interpretations. For instance, firms with lower costs of capital may see more innovation and are willing to sponsor DB plans. Also, more innovative firms may be able to generate more cash that enables the firm to sponsor DB plans.

I use treatment effects models to address such self-selection and reverse causality concerns. The treatment indicator is a dummy that equals one for firms that have DB plans. Following Shivdasani and Stefanescu (2010), I estimate a pension choice model. Variables that determine the probability of offering DB plans include median employee tenure (Tenure) for firms in the same two-digit SIC industry, ROA, ROA volatility (ROA Vol), percentage of unionized workers in an industry (Unionization), firm assets, market-to-book, and collateral (net PP&E scaled by book assets). Column 1 of Table 8 reports the estimates from the pension choice model. Consistent with the literature, firms are more likely to sponsor DB plans when they are large in size and in more unionized industries. High earnings volatility, high tangible assets, low MB ratio, and lower profitability are also positively associated with the incidence of DB plans. Industries requiring firm-specific human capital investment in employees (longer tenures) are more likely to offer DB plans.

The treatment effect regressions are estimated, using Heckman's (1979) two-step procedure. To meet the exclusion restrictions that are necessary for identification in Heckman's model, I include two variables in the probit model that I do not include in the second-stage regression, namely, median employee tenure and the degree of unionization of the industry. Data on both variables are retrieved from the U.S. Bureau of Labor Statistics website. I use median tenure as an instrument because employee turnover in an industry should be determined by industry characteristics, rather than individual firms' pension decisions. To add another layer of identification, I include the degree of unionization of the industry, measured as percent of employed workers who are union members. Bradley et al. (2015) argue that firms passing a union election experience decline in patent quantity (quality). In my sample, however, I find no correlation between industry-level unionization and corporate innovation. This result is similar to that of Shivdasani and Stefanescu (2010), who find industry-level unionization to be uncorrelated with another firm-level variable, financial leverage. Columns 2–4 in Table 8 show results from the estimation of the treatment effect models: Column 2 reports the coefficients of the patent counts regression; Column 3 reports the estimates of patent citations model; and Column 4 reports the coefficients of the citations per patent regression. The coefficients of TcAt in the three models are 12.922 (t=3.89), 11.584 (t=3.33), and 2.497 (t=2.90), respectively. The results indicate that DB plans promote corporate innovation.

[Insert Table 8 here]

IX. Underlying mechanisms

I find strong evidence corroborating the deferred compensation hypothesis. In this section, I explore possible underlying mechanisms by focusing on the inventors of the patents, following Bradley et al. (2015). The instrumental variable approach introduced in Section 5.3 is then used to examine inventor-level activity. Retaining highly educated scientists and engineers as potential inventors could be an underlying mechanism. For innovation, a significant portion of investment is dedicated to human capital. This investment can be lost when employees leave the firm. Thus, firms tend to smooth R&D expenditures over time to avoid laying off knowledge workers (Hall and Lerner (2010)). By the same token, DB plans can contribute to innovation by increasing inventor tenures (or reducing inventor departures). Section 6.1 examines this mechanism. Accordingly, I find that inventors at high-TcAt firms stay with their firms longer than their counterparts at low-TcAt firms do.

Because the value of DB plans is linked to a firm's long-term success, knowledge workers' incentives to shirk may decrease. Another factor related to this mechanism is the degree to which inventors are willing to engage in risk-taking. Inventors can choose between exploratory and exploitative innovation strategies (as described by Manso (2011)). An exploratory strategy is riskier because it requires inventors to pursue innovation projects with which they are less familiar or are more likely to fail. Higher pension contributions provide a certain guarantee to the realization of inventors' pension benefits and thus may encourage more risk-taking. To test this possibility, I investigate individual inventors' different levels of productivity and risk-taking in the high- and low-TcAt firms in Section 6.2. I find evidence that the total contribution ratio is positively related to productivity and risk-taking on the part of individual inventors.

A. Inventor tenure

In this subsection, I examine whether inventors in high-TcAt firms stay with their employers longer than those in low-TcAt firms during the sample period. To the extent that innovative employees have better job prospects and are highly sought after in the labor market, more deferred compensation (and therefore, greater opportunity cost associated with leaving the firm) may induce inventors to stay with their firms for a longer period of time. This may contribute to greater innovation output in DB firms.

To test this possibility, I collect data from the Harvard Business School (HBS) patent and inventor database[22]. The HBS patent and inventor database contains information on inventors (i.e., individuals credited with producing the patent) and assignees (the entities that possess the patents). It thus provides a unique identifier for each inventor so that I can track employer changes of individual inventors. I define "inventor tenure" as the number of year(s) between the first year an inventor produces at least one patent at a firm and the last year the same inventor produces another patent at the same firm in the sample period. This definition is meant to capture the number of productive years (which is of more interest to the firm), but not necessarily actual years, that an inventor stays at a particular firm. A two-sample t-test shows that this number is statistically significantly

[22] This database is available for download from https://dataverse.harvard.edu/dataverse/patent. Last accessed on July 2, 2015.

higher for the high-TcAt firms than for the low-TcAt firms. Panel A of Table 9 reports the results. During 1990–2007, inventors at high-TcAt firms stayed for 4.54 years on average at the same firm, 6% longer than the average tenure of those at low-TcAt firms. The difference is statistically significant at the 1% level.

[Insert Table 9 here]

To formally assess this mechanism, I follow Chen et al. (2016) and measure average tenure as the average number of inventor tenures for each firm. I then run a pure cross-sectional regression, in which the dependent variable is the natural logarithm of the average tenure of inventors with a firm (one data point per firm) and the independent variables are the firm-level averages of the full set of control variables. For example, the total contribution ratio variable is the average TcAt across time for each firm. This process retains only those firms that have non-missing values for every year over the 1990–2007 period. I include industry fixed effects in my regression. Results are reported in Table 10. Column 1 shows that the 2SLS estimate on TcAt is positive and statistically significant at the 5% level. The result, consistent with my conjecture, suggests that a higher total contribution ratio leads to longer tenure of inventors[23].

B. Inventor productivity and risk-taking

[23] Inventors at high-TcAt firms have a probability of 4.0% to leave, which is lower than the 4.9% for those at low-TcAt firms (untabulated). I also test whether higher TcAt reduces inventor departures, as measured by the ratio of leavers to all inventors at a firm. Unreported 2SLS analysis in which I control only for funding status, generates a significant estimate on TcAt (t =-1.84), suggesting an inverse relationship between DB contributions and inventor departures.

The other possible mechanism leading to higher innovation is an increase in inventor productivity and risk-taking because of aligned interests among inventors and firms (Blake (2006)). I test this possibility by investigating the differences in innovation productivity and risk-taking among individual inventors that respectively belong to high-TcAt and low-TcAt firms. Exploratory innovation should exhibit higher variance in the quality of patents that inventors obtain than exploitative innovation. As such, I introduce a new measure, Citation Variance, as a proxy for inventor risk-taking. For each subsample, I compute the number of patents, citation counts, citations-per-patent ratios, and citation variance for each inventor between 1990 and 2007. To calculate citation variance, I retain only inventors (for each year) who have filed at least two patents that were eventually granted. This condition results in a sample with a mean of 3.34 citations, a variance of 2.49, a minimum of 2 and a maximum of 58 patents per inventor (untabulated). Unlike in the firm-level analysis, I do not add one to the actual values when taking the natural logarithm because all observations are positive. I then conduct t-tests to test for mean differences. Panel B of Table 9 indicates that inventors at high-TcAt firms are indeed more productive than their peers at low-TcAt firms, as measured by patent count, patent citation, and the citations-per-patent ratio (all significant at the 1% level). Inventors at high-TcAt firms also take more risks than their counterparts at low-TcAT firms, as measured by citation variance (significant at the 10% level). Specifically, mean patent count per inventor for the high-TcAt and low-TcAt firms is 1.87 versus 1.82, mean citations is 25.40 versus 23.70, mean citations per patent is 12.54 versus 11.67, and mean citation variance is 0.950 versus 0.847.

To more rigorously test whether DB pension contributions encourage inventor productivity and risk-taking, I separately regress the three innovation measures described above on TcAt and other control variables in Equation (1), using the 2SLS specification. The results of this analysis are also reported in Table 10. Surprisingly, Column 2 shows an insignificant correlation between inventors' patent counts and the total contribution ratios of their employers. However, Columns 3 and 4 illustrate a positive correlation between citation counts (citations per patent) attributed to individual inventors and the total contribution ratios of their firms; the t-statistic is 1.90 (2.15). This finding lends credence to my prediction that DB pension contributions make inventors more productive. Column 5 provides evidence that higher DB pension contributions are correlated with higher citation variance (t = 1.95), suggesting greater risk-taking on the part of inventors.

[Insert Table 10 here]

VIII. Summary and conclusion

Innovation gives corporations enormous competitive advantages and has become an important topic of research for corporate finance economists. Therefore, there has been a burgeoning literature on what determines innovation output. Innovation occurs where financial capital meets intellectual capital. Despite abundant literature on various factors that facilitate or impede innovation, few studies have examined the role of employees and employees' incentive schemes in the innovation process, particularly in the very-long term. Prior studies of DB plans have focused primarily on their direct effects on sponsoring firms; researchers have rarely examined how DB plans affect employees. My paper fills this gap and enriches the stakeholder society theory of corporate finance.

The nonlinear funding rules of DB pension plans provide a unique opportunity to exploit the effect of pension funding on corporate innovation. Using a large sample of firms covered by the USPTO, 5500-CRR, Compustat Fundamentals, and Compustat Pension databases from 1990 to 2007 (and after controlling for R&D intensity), I find a positive effect of DB pensions on innovation output, as measured by patent counts and citations. These results are robust across a variety of tests that use different model specifications and variable definitions. They also stand up to endogeneity issues.

One practical implication of my findings is that firms that rely on innovation to compete, but have frozen or terminated their DB pension plans, may need to adjust their strategic approach to remain competitive. From a marginal effect perspective, investing in DB plans may be a stronger driver of innovation than R&D investment. In addition, policymakers must redraft regulations to encourage DB plan adoption and retention, or at least to enable leveraging the positive elements of DB plans. Recently issued stringent regulations, such as the PPA of 2006, and higher PBGC insurance premiums – set to rise from $57 per covered worker in 2015 to $78 in 2019 – could motivate even more firms to freeze or close out their DB plans that pay retirees a guaranteed monthly check for life.

REFERENCES

Acharya, V. V.; R. P. Baghai; and K. V. Subramanian. "Wrongful Discharge Laws and Innovation." *Review of Financial Studies,* 27 (2014), 301–346.

Adhikari, B. K., and A. Agrawal. "Religion, Gambling Attitudes and Corporate Innovation." *Journal of Corporate Finance*, 37 (2016), 229–248.

Aghion, P.; N. Bloom; R. Blundell; R. Griffith; and P. Howitt. "Competition and Innovation: An Inverted-U Relationship." *Quarterly Journal of Economics*, 120 (2005), 701–728.

Aghion, P.; J. V. Reenen; and L. Zingales. "Innovation and Institutional Ownership." *American Economic Review*, 103 (2013), 277–307.

Almeida, H.; P. H. Hsu; and D. Li. "Less is More: Financial Constraints and Innovative Efficiency." Working Paper, (2013).

Atanassov, J. "Do Hostile Takeovers Stifle Innovation? Evidence from Antitakeover Legislation and Corporate Patenting." *The Journal of Finance,* 68 (2013), 1097–1131.

Bae, K. H.; J. K. Kang; and J. Wang. "Employee Treatment and Firm Leverage: A Test of the Stakeholder Theory of Capital Structure." *Journal of Financial Economics,* 100 (2011), 130–153.

Bernstein, S. "Does Going Public Affect Innovation?" *The Journal of Finance,* 70 (2015), 1365–1403.

Blake, D. *Pension Finance.* Hoboken, NJ: John Wiley & Sons (2006).

Bodie, Z.; A. Marcus; and R. Merton. "Defined Benefit versus Defined Contribution Pension Plans: What Are the Real Trade-offs?" In *Pensions in the U.S. Economy,* Z.

Bodie; J. B. Shoven; and D. A. Wise, eds. Chicago, IL: University of Chicago Press (1988).

Bodie, Z. “The ABO, the PBO and Pension Investment Policy.” *Financial Analyst Journal,* 46 (1990), 27–34.

Borjas, G. J. *Labor Economics*. 6th Ed. New York, NY: McGraw-Hill Education (2013).

Bradley, D.; I. Kim; and X. Tian. “Do Unions Affect Innovation?” *Management Science,* forthcoming.

Campbell, J.; D. Dhaliwal; and W. Schwartz Jr. "Equity Valuation Effects of the Pension Protection Act of 2006.” *Contemporary Accounting Research,* 27 (2010), 469–536.

Campbell, J.; D. Dhaliwal; and W. Schwartz Jr. “Financing Constraints and the Cost of Capital: Evidence from the Funding of Corporate Pension Plans.” *Review of Financial Studies,* 25 (2012), 868–912.

Chan, L. K. C.; J. Lakonishok; and T. Sougiannis. “The Stock Market Valuation of Research and Development Expenditures.” *Journal of Finance,* 56 (2001), 2431–2456.

Chang, X.; G. Hilary; J. K. Kang; and W. Zhang. “Does Accounting Conservatism Impede Corporate Innovation?” Working Paper, (2013).

Chang, X.; K. Fu; A. Low; and W. Zhang. “Non-executive Employee Stock Options and Corporate Innovation.” *Journal of Financial Economics,* 115 (2015), 168–188.

Chemmanur, T. J., and T. Xuan. “Do Anti-takeover Provisions Spur Corporate Innovation?” Unpublished Working Paper, Boston College and Indiana University, (2011).

Chen, C.; Y. Chen; P. H. Hsu; and E. J. Podolski. "Be Nice to Your Innovators: Employee Treatment and Corporate Innovation Performance." *Journal of Corporate Finance,* 39 (2016), 78–98.

Chen, Y.; E. J. Podolski; S. G. Rhee; and M. Veeraraghavan. "Local Gambling Preferences and Corporate Innovative Success," *Journal of Financial and Quantitative Analysis,* 49 (2014), 77–106.

Choy, H.; J. Lin; and M. S. Officer. "Does Freezing a Defined Benefit Pension Plan Affect Firm Risk?" *Journal of Accounting and Economics,* 57 (2014), 1–21.

Cornaggia, J.; Y. Mao; X. Tian; and B. Wolfe. "Does Banking Competition Affect Innovation?" *Journal of Financial Economics,* 1 (2015), 189–209.

Dimitrova, M. "Corporate Defined Benefit Pension Plans and Chapter 11 Bankruptcy." Job Market Paper.

Faleye, O.; T. Kovacs; and A. Venkateswaran. "Do Better-Connected CEOs Innovate More?" *Journal of Financial and Quantitative Analysis,* 49 (2014), 1201–1225.

Fang, V.; X. Tian; and S. Tice. "Does Stock Liquidity Enhance or Impede Firm Innovation?" *Journal of Finance*, 5 (2014), 2085–2125.

Franzoni, F. "Underinvestment vs. Overinvestment: Evidence from Price Reactions to Pension Contributions." *Journal of Financial Economics,* 92 (2009), 491–518.

Galasso, A., and T. S. Simcoe. "CEO Overconfidence and Innovation." *Management Science,* 57 (2011), 1469–1484.

Gao, W., and J. Chou. "Innovation Efficiency, Global Diversification, and Firm Value." *Journal of Corporate Finance*, 30 (2015), 278–298.

Ghilarducci, T. “Future Retirement Income Security Needs Defined Benefit Pensions.” Notre Dame Working Paper, (2006).

Gompers, P.; J. Ishii; and A. “Metrick. Corporate Governance and Equity Prices.” *Quarterly Journal of Economics*, 118 (2003), 107–155.

Griliches, Z. “Patent Statistics as Economic Indicators: A Survey.” *Journal of Economic Literature,* 28 (1990), 1661–1707.

Gross, D. P. “Creativity under Fire: The Effects of Competition on Creative Production.” Working Paper, Harvard Business School (2016).

Hall, B. H.; A. B. Jaffe; and M. Trajtenberg. “The NBER Patent Citation Data File: Lessons, Insights and Methodological Tools.” Working Paper No. 8498, National Bureau of Economic Research (2001).

Hall, B. H.; A. B. Jaffe; and M. Trajtenberg “Market Value and Patent Citations.” *RAND Journal of Economics,* 36 (2005), 16–38.

Hall, B. H., and J. Lerner. “Financing R&D and innovation.” In *Handbook of the Economics of Innovation,* B. H. Hall and N. Rosenberg (eds.), Amsterdam: Elsevier (2010), 609–639.

Hall B. H.; P. M. P. Castello; S. Montresor; and A. Vezzani. “Financing Constraints, R&D Investments and Innovative Performances: New Empirical Evidence at the Firm Level for Europe.” Working Paper, 2015.

Hall, B. H., and R. H. Ziedonis. “The Patent Paradox Revisited: An Empirical Study of Patenting in the U.S. Semiconductor Industry, 1979–1995.” *RAND Journal of Economics,* 32 (2001), 101–128.

He, J., and X. Tian. “The Dark Side of Analyst Coverage: The Case of Innovation.” *Journal of Financial Economics,* 109 (2013), 856–878.

Hirshleifer, D.; A. Low; and S. H. Teoh. “Are Overconfident CEOs Better Innovators?” *The Journal of Finance,* 67 (2012), 1457–1498.

Hsu, P. H.; X. Tian; and Y. Xu. “Financial development and innovation: Cross-country Evidence.” *Journal of Financial Economics,* 112 (2014),116–135.

Ippolito, R. “The Economic Function of Underfunded Pension Plans.” *The Journal of Law & Economics,* 28 (1985), 611–651.

Kang, J. K.; W. L. Liu; A. Low; and L. Zhang. "Friendly Boards and Innovation.” Working Paper, (2014).

Kogan, L.; D. Papanikolaou; A. Seru; and N. Stoffman. “Technological Innovation, Resource Allocation and Growth.” Working Paper, (2015).

Manso, G. “Motivating Innovation.” The Journal of Finance, 66 (2011), 1823–1860.

Mao, C. X., and J. Weathers. “Employee Treatment and Firm Innovation.” Working Paper, (2015).

Mayer, R. C.; R. S. Warr; and J. Zhao. “Does Employee Treatment and Workforce Diversity Impact Corporate Innovative Efficiency?” Working Paper, (2015).

Moody’s Investors Service. “Pension Reform Will Increase Funding Requirements for Underfunded U.S. Pension Plans.” New York: Moody’s Investor Service, Inc (August 2006).

Munnell, A. H., and M. Soto. "The Outlook for Pension Contributions and Profits in the U.S.” *Journal of Pension Economics and Finance*, 3 (2004), 77–97.

Ouimet, P. and E. Simintzi. “Wages and Firm Performance: Evidence from the 2008 Financial Crisis.” Working Paper, (2016).

Ouimet, P. and R. Zarutskie. “Who Works for Startups? The Relation between Firm Age, Employee Age, and Growth.” Journal of Financial Economics, 112 (2014), 386–407.

Phan, H., and S. Hegde. “Pension Contributions and Firm Performance: Evidence from Frozen Defined Benefit Plans.” *Financial Management,* 42 (2013), 373–411.

Prendergast, C. “The Provisions of Incentives in Firms.” *Journal of Economic Literature,* 37 (1999), 7–63.

Quinn, D., and P. Rivoli. “The Effects of American-and Japanese-Style Employment and Compensation Practices on Innovation.” *Organization Science,* 2 (1991), 323–341.

Rauh, J. “Investment and Financing Constraints: Evidence from the Funding of Corporate Pension Plans.” *The Journal of Finance,* 61 (2006), 33–71.

Rauh, J.; I. Stefanescu; and S. P. Zeldes. “Cost Shifting and the Freezing of Corporate Pension Plans.” Working Paper, 2013.

Sapra, H.; A. Subramanian; and K. Subramanian. “Corporate Governance and Innovation: Theory and Evidence.” *Journal of Financial and Quantitative Analysis*, 49 (2014), 957–1003.

Seru, A. “Firm Boundaries Matter: Evidence from Conglomerates and R&D Activity.” *Journal of Financial Economics*, 111 (2014), 381–405.

Shivdasani, A., and I. Stefanescu. “How Do Pensions Affect Corporate Capital Structure Decisions?” *The Review of Financial Studies,* 23 (2010), 1287–1323.

Sundaram, R., and D. Yermack. “Pay Me Later: Inside Debt and Its Role in Managerial Compensation.” *The Journal of Finance,* 62 (2007), 1551–1588

Tirole, J. *The Theory of Corporate Finance*. Princeton, NJ: Princeton University Press (2006).

Winklevoss, H. E. *Pension Mathematics with Numerical Illustration*, 2nd Ed, Philadelphia, PA: University of Pennsylvania Press (1993).

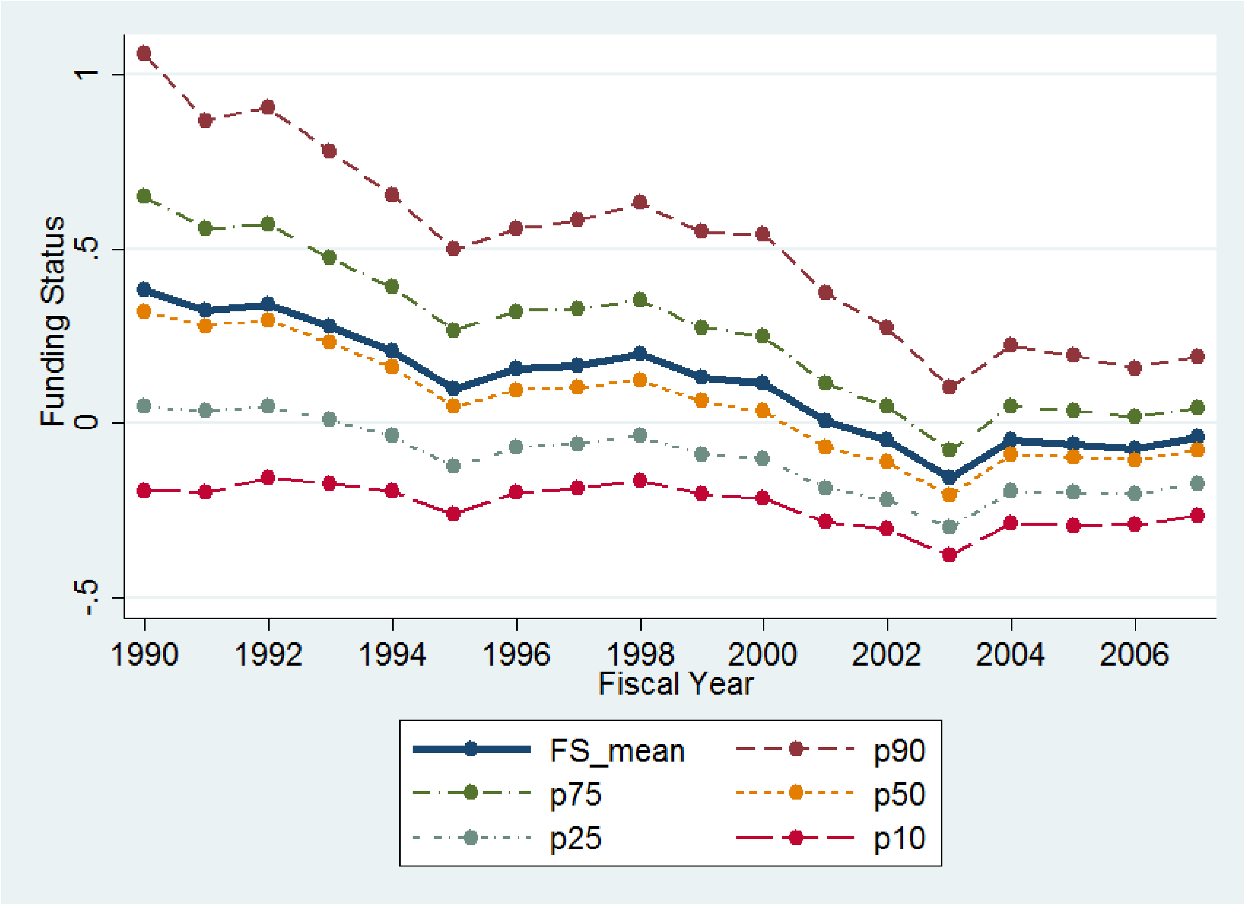

Figure 1. Distribution of beginning-of-year funding status (FS). This figure depicts the distribution of firm-level pension funding status of Compustat firms at the start of fiscal years from 1990 to 2007. Funding status is defined as pension assets minus pension liabilities divided by firm assets. Data are retrieved from the annual filings of firms in the Compustat databases, with pension liabilities on a projected benefit obligation (PBO) basis.

Figure 2. Distributions of mean total contributions in dollar terms. The top graph depicts firms in my final sample, jointly covered by the 5500-CRR, Compustat, and UTPSO patent databases. The bottom graph depicts a larger sample of firms jointly covered by the 5500-CRR and Compustat databases from 1990 to 2007, regardless of whether they have secured patents. Data are from IRS 5500 filings.

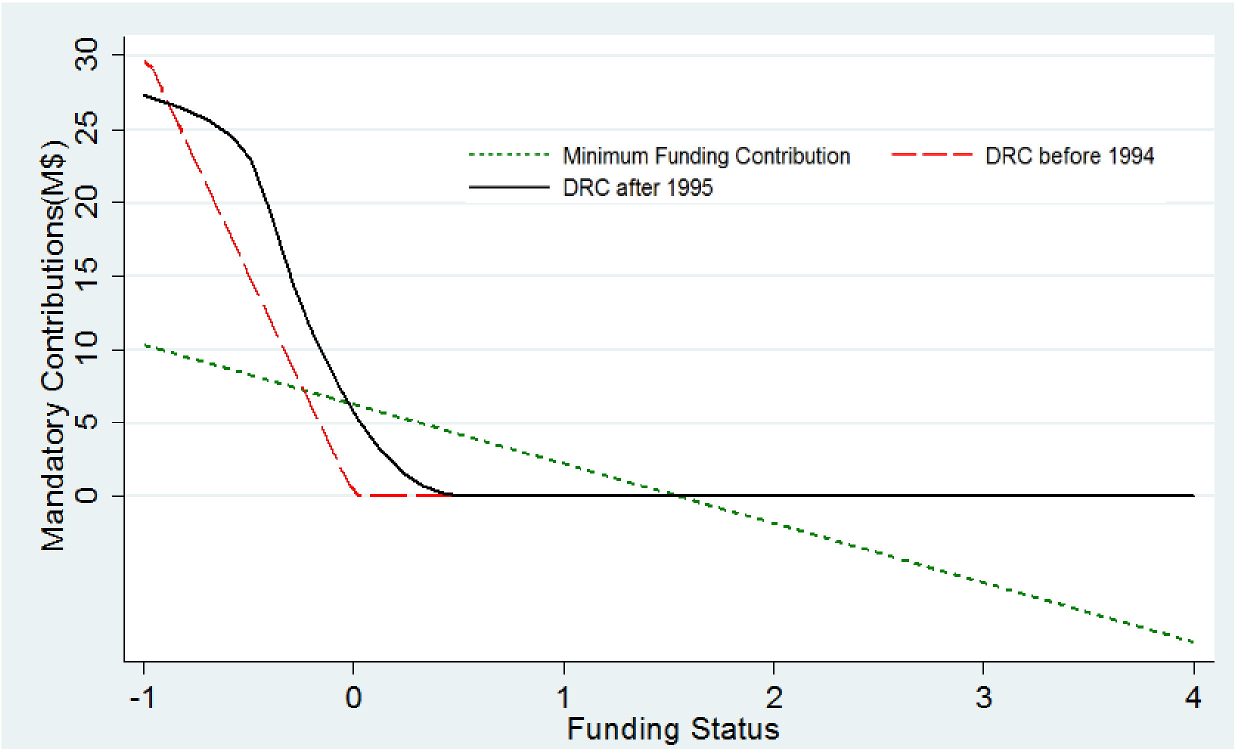

Figure 3. Mandatory pension contributions. A firm's mandatory contribution is the maximum of two elements: the minimum funding contribution (MFC) and the deficit reduction contribution (DRC). The graph shows mandatory contributions in dollar terms for a firm with characteristics equivalent to the sample means (liabilities of $10.02m and "normal cost" of $2.08m). The MFC is equal to the "normal cost" plus 10% of the ERISA unfunded liabilities. The DRC as a fraction of the funding gap is min{0.30, [0.30-0.25*(Plan Assets/Plan Liabilities -0.35)]} until 1994 (inclusive), and min{0.30, [0.30-0.40*(Plan Assets/Plan Liabilities -0.6)]} from 1995 (inclusive) forward.

Table 1

Summary statistics.

The sample consists of 4,217 firm-years jointly covered in the Compustat Fundamentals, Compustat Pension, and UTPSO Patent and Citation databases as well as Boston College 5500-CRR data from 1990 to 2007. TcAt is total pension contributions scaled by firm total assets. Funding Status (FS) is the difference between total pension assets and total pension liabilities (measured by projected pension obligations or PBO), scaled by Assets. Assets is book value of total assets. Patents is the number of patents applied for (and eventually granted) during the year. Citations is citation count in a given year divided by the mean number of citations in that year and within the same patent technology class as defined by USPTO. PPE/#employees is net Property, Plant, and Equipment (PPE) scaled by the number of employees. Sales/#employees is net sales scaled by the number of employees. ROA is Earnings Before Interest, Taxes, and Depreciation and Amortization (EBITDA) over Assets. Sales growth is change in net sales scaled by lagged net sales. Market-to-book ratio (M/B) is (Assets+Market value of equity-Book value of equity)/Assets. Cash/Assets is cash-to-assets ratio. Leverage is (Short-term debt+Long-term debt)/Assets. Firm age is the number of years elapsed since a firm entered the CRSP database. R&D intensity is R&D expenses scaled by the book value of total assets. Stock return is buy-and-hold stock returns computed over the fiscal year. Stock volatility is the standard deviation of daily stock returns over the fiscal year. The Herfindahl index is based on the three-digit SIC codes. Variable definitions are provided in Appendix B. All variables are winsorized at the 1% level at both tails of the distribution. Wilcoxon rank-sum tests are conducted to test for differences in distributions/mean values between the high and low TcAt subsamples. The symbols ***, **, and * indicate that subsample means are significantly different from each other at the 1%, 5%, and 10% levels, respectively.

	Whole Sample N=4,217			High TcAt N=2,108	Low TcAt N=2,109
	Mean (1)	Median (2)	Standard Deviation (3)	Mean (4)	Mean （5）
Number of patents(raw)	55.0	3.0	227.0	57	54***
Citations(fixed-effects adjusted)	58.8	2.5	233.4	61	57***
TcAt (total pension contributions/total assets)	0.0055	0.0017	0.0091	0.0110	0.0005***
Funding status (FS)	-0.0165	-0.0125	0.0575	-0.0310	-0.0022***
Per-employee PBO in $ 1,000 (PBO/#employees)	56	32	110	57	54***
Assets in $ millions	7,376	1,205	33,955	5,219	9,524***
Number of employees (in 1,000)	21.7	6.4	44.6	19.7	23.8***
R&D intensity (R&D expenditures/assets)	0.029	0.019	0.035	0.031	0.028**
Firm age	32	29	22	30	32***
PPE/#employees(in $1,000)	78	42	13	74	81
Sales/#employees(in $1,000)	255	192	277	247	264
ROA	0.140	0.139	0.078	0.143	0.138**
M/B	1.735	1.477	0.919	1.76	1.71
Sales growth	0.070	0.062	0.176	0.070	0.069
Leverage	0.25	0.23	0.16	0.24	0.25*
Cash/Assets	0.062	0.039	0.068	0.063	0.061**
Stock volatility	0.0253	0.0221	0.0141	0.0257	0.0249**
Stock return	0.17	0.11	0.48	0.18	0.16***
Herfindahl index	0.41	0.35	0.24	0.411	0.403

Table 2

Effects of DB plan contributions on innovation output.

The sample consists of 4,217 firm-years jointly covered in the Compustat Fundamentals, Compustat Pension, and UTPSO Patent and Citation databases as well as Boston College 5500-CRR data from 1990 to 2007. TcAt is total pension contributions scaled by book value of total assets of the firm. Funding status (FS) is the difference between total pension assets and total pension liabilities (PBO), scaled by Assets. Assets is book value of total assets. Patents is the number of patents applied for (and eventually granted) during the year. Citations is the number of citations in a given year divided by the mean number of citations in that year and within the same patent technology class as defined by USPTO. PPE/#employees is net Property, Plant, and Equipment (PPE) scaled by the number of employees. Sales/#employees is net sales scaled by the number of employees. ROA is Earnings Before Interest, Taxes, and Depreciation and Amortization (EBITDA) over Assets. Sales growth is change in net sales scaled by lagged net sales. Market-to-book ratio (M/B) is (Assets+Market value of equity-Book value of equity)/Assets. Cash/Assets is cash-to-assets ratio. Leverage is (Short-term debt+Long-term debt)/Assets. Firm age is the number of years elapsed since a firm entered the CRSP database. RDIntensity is R&D expenses scaled by book value of total assets. Stock return is buy-and-hold stock returns computed over the fiscal year. Stock volatility is standard deviation of daily stock returns over the fiscal year. The Herfindahl index is based on the three-digit SIC codes. Constant terms are included but not reported here. The t-statistics in parentheses are calculated from standard errors clustered at the firm level. For quantile regressions, standard errors are bootstrapped with 100 repetitions. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	Ln(1+Patents)				Ln(1+Citations)			
	OLS	25^{th} Quan	50^{th} Quan	75^{th} Quan	OLS	25^{th} Quan	50^{th} Quan	75^{th} Quan
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
TcAt	13.169^{***}	12.010^{***}	14.081^{***}	12.231^{***}	13.337^{***}	13.995^{***}	13.788^{***}	10.412^{***}
	(3.41)	(3.16)	(4.42)	(4.40)	(3.42)	(3.51)	(4.59)	(3.62)
Funding status	1.529^{**}	0.928	1.553^{***}	1.004^{**}	1.438^{**}	0.624	1.222^{**}	1.010^{*}
	(2.30)	(1.20)	(3.17)	(2.00)	(2.14)	(0.90)	(2.32)	(1.94)
R&D intensity	11.912^{***}	10.934^{***}	12.779^{***}	11.741^{***}	11.941^{***}	10.210^{***}	12.490^{***}	12.073^{***}
	(8.48)	(9.82)	(14.32)	(13.07)	(8.11)	(7.71)	(12.68)	(12.65)
Ln(Assets)	0.735^{***}	0.613^{***}	0.753^{***}	0.780^{***}	0.745^{**}	0.587^{***}	0.773^{***}	0.801^{***}
	(21.59)	(20.28)	(33.49)	(47.71)	(20.93)	(14.96)	(41.06)	(35.98)
Ln(Firm Age)	0.147^{***}	0.168^{***}	0.134^{***}	0.093^{***}	0.146^{**}	0.166^{***}	0.127^{***}	0.118^{***}
	(3.13)	(4.21)	(3.74)	(3.35)	(3.06)	(4.91)	(3.58)	(4.29)
Ln(PPE/#employees)	0.025	-0.019	0.087^{**}	0.125^{**}	0.012	-0.027	0.059	0.155^{***}
	(0.30)	(-0.36)	(2.01)	(2.32)	(0.14)	(-0.57)	(1.17)	(3.30)
Ln(Sales/#employees)	-0.154	-0.094	-0.221^{***}	-0.209^{**}	-0.211	-0.096	-0.187^{**}	-0.245^{***}
	(-1.29)	(-1.18)	(-2.85)	(-2.51)	(-1.58)	(-1.21)	(-2.41)	(-3.23)
Sales growth	-0.397^{***}	-0.317	-0.372^{***}	-0.305^{**}	-0.342^{**}	-0.274	-0.437^{***}	-0.245
	(-3.17)	(-1.64)	(-2.80)	(-2.03)	(-2.59)	(-0.57)	(-2.91)	(-1.46)
ROA	1.481^{***}	1.191^{*}	1.490^{***}	2.011***	1.517^{**}	1.550^{***}	1.489^{***}	2.159^{***}
	(2.58)	(1.83)	(3.42)	(4.98)	(2.55)	(2.46)	(3.22)	(5.28)
M/B	-0.013	0.037	-0.003	-0.016	-0.002	0.013	0.010	-0.019
	(-0.26)	(0.64)	(-0.11)	(-0.50)	(-0.03)	(0.25)	(0.28)	(-0.50)
Leverage	-0.558^{**}	-0.563^{***}	-0.528^{***}	-0.560^{***}	-0.628^{**}	-0.729^{***}	-0.626^{***}	-0.537^{***}
	(-2.17)	(-2.92)	(-2.81)	(-3.31)	(-2.41)	(-3.46)	(-3.12)	(-2.92)
Cash/Assets	-0.152	0.301^{*}	-0.111	-0.219	-0.169	0.328	0.053	-0.229
	(-0.29)	(0.70)	(-0.29)	(-0.60)	(-0.31)	(0.73)	(0.10)	(-0.57)
Stock return	0.007	0.008	0.031	0.039	0.032	0.098	0.012	0.016
	(0.16)	(0.14)	(0.55)	(0.85)	(0.74)	(1.54)	(0.18)	(0.29)
Stock volatility	6.570^{**}	2.514	6.306^{***}	4.895^{***}	6.705^{**}	4.498^{*}	5.773^{**}	6.447^{***}
	(2.35)	(0.88)	(2.89)	(2.61)	(2.27)	(1.74)	(2.49)	(2.98)
Herfindahl	0.546	-0.914^{**}	0.892^{**}	1.390^{***}	0.565	-0.747	0.605	1.912^{***}
	(0.77)	(-1.97)	(1.98)	(3.31)	(0.76)	(-1.33)	(1.32)	(4.72)
Herfindahl^2	-0.276	1.105^{***}	0.543	-1.136^{***}	-0.274	0.970^{**}	-0.227^{***}	-1.558^{***}
	(-0.44)	(2.71)	(-1.35)	(-2.98)	(-0.41)	(2.02)	(-0.55)	(-4.16)
Industry and year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N/(Pseudo) R-squared	4,217/0.64	4, 217/0.20	4,217/0.43	4,217/0.51	4, 217/0.62	4,217/0.16	4, 217/0.42	4, 217/0.49

Table 3

Effect of industry innovativeness.

The table presents the results from regressions of patent count and patent citations on total contribution ratio (TcAt), where firms are classified according to whether they belong to an innovative industry, with industry and year fixed effects controlled for. An innovative industry is one where the average fixed-effects-adjusted citation count per patent for the industry is greater than the median fixed-effects-adjusted citation count per patent across all industries. Only the coefficients and t-statistics associated with the DB value variables are reported. Each cell in the table is from one regression of the dependent variable on either DB value (TcAt) or DB value (Ln(PBO/#employees)), control variables, and year and industry fixed effects, based on the two-digit SIC codes. Variable definitions are provided in Appendix B. The t-statistics in parentheses are calculated from standard errors clustered at the firm level. The symbols ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	No. of Observations		Ln(1+Patents)		Ln(1+Citations)	
	Innovative Industries	Non-innovative industries	Innovative Industries	Non-innovative industries	Innovative Industries	Non-innovative industries
DB value (TcAt)	2,593	1,624	14.420*** (3.62)	10.137* (1.83)	15.618*** (3.70)	8.837* (1.84)
DB value (Ln(PBO/#employees))	2,501	1,655	0.234*** (3.33)	0.196*** (2.68)	0.212** (2.93)	0.179** (2.46)

Table 4

Instrumental variable approach.

The sample consists of 4,217 firm-years jointly covered in the Compustat Fundamentals, Compustat Pension, and UTPSO Patent and Citation databases as well as Boston College 5500-CRR data from 1990 to 2007. TcAt is total pension contributions scaled by book value of total assets of the firm. McAt is mandatory contributions scaled by book value of total assets of the firm. Variable definitions are provided in Appendix B. Column 1 reports the estimates of the first-stage regression and Columns 2–4 report the estimates of the second-stage regressions using the 2SLS model. The t-statistics in parentheses are calculated from standard errors clustered at the firm level. The symbols ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	1st Stage	2nd Stage	
	TcAt (1)	Ln(1+Patents) (2)	Ln(1+Citations) (3)
TcAt	N/A	28.650*** (2.99)	27.259*** (2.82)
McAt	0.598*** (26.77)	N/A	N/A
Funding status	-0.043*** (-18.06)	2.502*** (2.81)	2.313** (2.56)
R&D intensity	-0.001 (-0.27)	11.883*** (8.52)	11.915*** (8.14)
Ln(Assets)	-0.0003*** (-3.55)	0.745*** (21.70)	0.754*** (20.99)
Ln(Firm Age)	0.0002 (1.41)	0.141*** (3.01)	0.141*** (2.95)
Ln(PPE/#employees)	0.0004* (1.87)	0.021 (0.25)	0.003 (0.03)
Ln(Sales/#employees)	0.0004 (1.27)	-0.160*** (-1.36)	-0.183 (-1.45)
Sales growth	-0.003*** (-4.07)	-0.340*** (-2.69)	-0.291** (-2.18)
ROA	0.007*** (3.18)	1.420** (2.52)	1.462*** (2.51)
M/B	0.0003* (1.71)	-0.021 (-0.43)	-0.009 (-0.18)
Leverage	-0.003*** (-3.54)	-0.526** (-2.03)	-0.599** (-2.29)
Cash/Assets	0.004** (1.96)	-0.240 (-0.46)	-0.248 (-0.47)
Stock return	-0.0005* (-1.80)	0.017 (0.41)	0.041 (0.95)
Stock volatility	-0.004 (-0.35)	6.337** (2.28)	6.495** (2.22)
Herfindahl	0.002 (0.83)	0.536 (0.76)	0.556 (0.75)
Herfindahl^2	-0.001 (-0.57)	-0.286 (-0.46)	-0.283 (-0.43)
Industry and year fixed effects	Yes	Yes	Yes
N/Adj. R-squared	4,217/0.35	4,217/0.64	4,217/0.62

Table 5

OLS and IV analyses based on per-employee-PBO DB plan value and Moody's measure of MCs.
The sample consists of observations jointly covered in the Compustat Fundamentals, Compustat Pension, and UTPSO Patent and Citation databases from 1990 to 2007. PBO/#employees is the ratio of projected benefit obligations (PBO) to the number of employees. McAt is mandatory contributions scaled by book value of total assets of the firm. Mandatory contributions are calculated according to Moody's (2006) and equal service cost plus (Accumulated Benefit Obligation [ABO] – Fair Value of Pension Plan Assets [FVPA] / 30) if PBO > FVPA; and zero otherwise. Control variables are the same as those in Table 2. Column 3 reports the estimates of the first-stage regression and Columns 4–5 report the estimates of the second-stage regressions using the 2SLS model. Variable definitions are provided in Appendix B. The t-statistics in parentheses are calculated from the standard errors clustered at the firm level. The symbols ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	OLS		IV		
			1st Stage	2nd Stage	
	Ln(1+Patents) (1)	Ln(1+Citations) (2)	Ln(1+PBO/#employees) (3)	Ln(1+Patents) (4)	Ln(1+Citations) (5)
Ln(1+PBO/#employees)	0.095*** (2.85)	0.076** (2.19)	N/A	0.161*** (4.26)	0.147*** (3.73)
McAt	N/A	N/A	153.155*** (37.56)	N/A	N/A
Funding status	0.614 (0.94)	0.581 (0.88)	6.316*** (18.71)	1.038*** (2.77)	0.768** (1.97)
R&D intensity	7.153*** (7.98)	7.095*** (7.52)	-1.314 (-0.28)	7.410*** (15.66)	7.539*** (15.31)
Ln(Assets)	0.665*** (24.43)	0.664*** (23.66)	0.168*** (20.12)	0.634*** (46.36)	0.639*** (44.87)
Ln(Firm Age)	0.212*** (5.28)	0.226*** (5.53)	0.140*** (10.15)	0.218*** (10.44)	0.230*** (10.59)
Ln(PPE/#employees)	0.020 (0.32)	0.012 (0.18)	0.153* (7.31)	0.018 (0.60)	0.007 (0.22)
Ln(Sales/#employees)	-0.131* (-1.69)	-0.138* (-1.71)	0.445*** (15.27)	-0.167*** (-3.82)	-0.181*** (-3.97)
Sales growth	-0.181** (-2.27)	-0.145* (-1.74)	-0.568*** (-9.54)	-0.126 (-1.41)	-0.064 (-0.69)
ROA	0.557* (1.68)	0.451 (1.34)	-0.412*** (-2.74)	0.671*** (3.16)	0.557** (2.52)
M/B	0.084** (2.58)	0.106*** (3.13)	-0.042*** (-2.87)	0.079*** (3.77)	0.099*** (4.55)
Leverage	-0.766*** (-3.81)	-0.788*** (-3.86)	0.306*** (3.78)	-0.756*** (-6.60)	-0.765*** (-6.42)
Cash/Assets	0.569 (1.58)	0.464 (1.26)	-0.270 (-1.62)	0.396* (1.67)	0.372 (1.51)
Stock return	0.002 (0.08)	0.027 (0.92)	-0.001 (-0.04)	0.013 (0.37)	0.040 (1.07)
Stock volatility	9.316*** (5.02)	9.338*** (4.78)	-5.082*** (-5.28)	10.696** (7.73)	11.114*** (7.71)
Herfindahl	0.670 (1.16)	0.713 (1.18)	1.439*** (6.79)	0.498* (1.61)	0.431 (1.34)
Herfindahl^2	-0.245 (-0.48)	-0.276 (-0.52)	-1.349*** (-6.79)	-0.198 (-0.68)	-0.112 (-0.37)
Industry and year fixed effects	Yes	Yes	Yes	Yes	Yes
N/Adj. R-squared	7,529/0.60	7,529/0.57	5,435/0.65	5,435/0.60	5,435/0.58

Table 6
Impact of pension freezes on corporate innovation.
This table presents results of regressions explaining changes in corporate innovation following DB pension plan freezes. The sample consists of freeze and non-freeze firms jointly covered in the Compustat Fundamentals, Compustat Pension, Form 5500, and UTPSO Patent and Citation databases from 2002 to 2007. Post-freeze is an indicator variable that equals one if the observation is from a quarter after the firm freezes its DB plan, and zero otherwise. Inverse Mills ratio is computed using the first-stage regression reported, and used to account for the endogeneity of the pension freeze decision. Underfund is an indicator variable equal to one if the fair value of the plan assets is less than the projected benefit obligation and zero otherwise. Variable definitions are provided in Appendix B. The symbols ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	Ln(1+Patents) (1)	Ln(1+Citations) (2)	Ln(1+CPP) (3)
Post freeze	-0.513*** (-3.16)	-0.519*** (-3.10)	-0.076** (-2.06)
Inverse Mills ratio	0.667*** (3.94)	0.651*** (3.72)	0.138*** (3.80)
McAt	11.009*** (2.79)	11.291*** (2.84)	0.745 (0.87)
Funding status	2.194*** (3.27)	2.189*** (3.24)	0.276* (1.77)
R&D intensity	11.492*** (7.13)	11.505*** (6.93)	1.310*** (4.21)
Ln(Assets)	0.781*** (18.43)	0.789*** (18.10)	0.093*** (11.06)
Ln(Firm Age)	0.121** (2.47)	0.120** (2.40)	0.005 (0.45)
Ln(PPE/#employees)	0.072 (0.86)	0.059 (0.67)	-0.009 (-0.41)
Ln(Sales/#employees)	-0.525*** (-4.21)	-0.557*** (-4.18)	-0.081*** (-2.76)
Sales growth	-0.537** (-4.14)	-0.487*** (-3.55)	-0.045 (-1.25)
ROA	2.170*** (3.45)	2.200*** (3.37)	0.376*** (2.78)
M/B	-0.018 (-0.34)	-0.006 (-0.11)	-0.002 (-0.15)
Leverage	-0.338 (-1.28)	-0.406 (-1.51)	-0.026 (-0.45)
Cash/Assets	0.345 (-0.62)	-0.407 (-0.72)	0.120 (0.88)
Stock return	0.046 (1.15)	0.077* (1.86)	0.010 (1.04)
Stock volatility	8.373*** (3.19)	8.622*** (3.14)	-0.815 (-1.29)
Herfindahl	0.629 (0.86)	0.628 (0.82)	0.031*** (0.19)
Herfindahl^2	-0.388 (-0.58)	-0.369 (-0.53)	-0.081 (-0.57)
Industry and year fixed effects	Yes	Yes	Yes
N/Adj. R-squared	4,106/0.59	4,106/0.57	4,106/0.31

Table 7
OLS and IV analyses for a sample including both DB and DC firms.
The sample consists of both DB and DC firms jointly covered in the Compustat Fundamentals, Compustat Pension, and UTPSO Patent and Citation databases from 1990 to 2007 TcAt is total pension contributions scaled by book value of total assets of the firm. McAt is mandatory contributions scaled by book value of total assets of the firm. Control variables are the same as those in Table 2. Variable definitions are provided in Appendix B. Columns 1–2 report the estimates of the OLS regressions. Column 3 reports the estimates of the first-stage regression and Columns 4–5 report the estimates of the second-stage regressions using the 2SLS model. Variable definitions are provided in Appendix B. The t-statistics in parentheses are calculated from the standard errors clustered at the firm level. The symbols ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	OLS		IV		
			1st Stage	2nd Stage	
	Ln(1+Patents) (1)	Ln(1+Citations) (2)	TcAt (3)	Ln(1+Patents) (4)	Ln(1+Citations) (5)
TcAt	16.992*** (3.23)	18.365** (3.31)	N/A	53.963*** (5.18)	53.103*** (4.84)
McAt	N/A	N/A	0.359*** (23.61)	N/A	N/A
Funding status	0.256 (0.40)	0.190 (0.29)	-0.030*** (-20.43)	2.297*** (4.33)	2.005*** (3.59)
R&D intensity	6.965*** (8.08)	7.030*** (7.68)	-0.001 (-0.11)	12.336*** (19.13)	12.827*** (18.87)
Ln(Assets)	0.672*** (25.86)	0.669*** (25.01)	-0.011** (-2.31)	0.737*** (52.54)	0.748*** (50.65)
Ln(Firm Age)	0.238*** (6.20)	0.248*** (6.28)	-0.001*** (0.10)	0.173*** (7.91)	0.172*** (7.46)
Ln(PPE/#employees)	0.029 (0.50)	0.013 (0.22)	0.001 (0.98)	0.027 (0.79)	0.003 (0.07)
Ln(Sales/#employees)	-0.056 (-0.78)	-0.068 (-0.90)	0.001 (1.37)	-0.060 (-1.16)	-0.077 (-1.41)
Sales growth	-0.163*** (-2.84)	-0.134** (-2.28)	-0.002*** (-4.43)	-0.266*** (-2.80)	-0.204** (-2.04)
ROA	0.439 (1.53)	0.394 (1.34)	0.005*** (3.79)	1.215*** (3.61)	1.275** (3.60)
M/B	0.061** (2.15)	0.077** (2.58)	0.001*** (0.62)	-0.046* (-1.67)	-0.044 (-1.53)
Leverage	-0.772*** (-4.05)	-0.772*** (-3.97)	-0.003*** (-6.91)	-0.416*** (-3.32)	-0.448*** (-3.39)
Cash/Assets	0.398 (1.17)	0.320 (0.92)	0.001 (0.01)	0.396* (1.67)	-0.278 (-0.88)
Stock return	0.019 (0.83)	0.040 (1.63)	-0.001 (-0.77)	0.031 (0.82)	0.048 (1.20)
Stock volatility	8.185*** (4.86)	8.313*** (4.65)	0.003 (0.00)	5.904** (3.57)	5.869*** (3.37)
Herfindahl	0.556 (1.01)	0.602 (1.04)	0.003** (2.23)	0.122 (0.39)	0.227 (0.69)
Herfindahl^2	-0.107 (-0.20)	-0.179 (-0.32)	-0.002 (-1.64)	0.173 (0.55)	0.066 (0.20)
Industry and year fixed effects	Yes	Yes	Yes	Yes	Yes
N/Adj. R-squared	25,392/0.58	25,392/0.56	21,348/0.50	21,348/0.62	21,348/0.60

Table 8

Treatment effects model: Effects of DB plan contributions on corporate innovation.

This table presents the parameter estimates of the two-step treatment effects models. The sample consists of both DB and DC firms. Column 1 reports estimates from the pension choice model. ROA Vol is the standard deviation of the historical operating income based on the prior ten years. Collateral is net PPE divided by book assets. Unionization is the percentage of employed workers in an industry represented by a union as reported in the Current Population Survey of the Department of Labor. Tenure is the median employee tenure by industry. Other variable definitions are provided in Appendix B. Robust t-statistics are reported in parentheses. The symbols ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	Pension choice (1)	Ln(1+Patents) (2)	Ln(1+Citations) (3)	Ln(1+CPP) (4)
ROA Vol	0.001*** (4.01)			
Collateral	1.012*** (10.12)			
Tenure	0.161*** (23.00)			
Unionization	0.106*** (18.41)			
TcAt		12.922*** (3.89)	11.585*** (3.33)	2.497*** (2.90)
Inverse Mills ratio		0.258*** (12.36)	0.260*** (11.67)	0.022*** (3.08)
Funding status		3.638*** (7.27)	3.530*** (6.88)	0.580*** (4.53)
R&D intensity		2.018*** (17.31)	2.080*** (16.33)	0.494*** (11.57)
Ln(Assets)	0.256*** (36.12)	0.579*** (60.38)	0.582*** (57.98)	0.077*** (30.36)
Ln(Firm Age)		0.193** (11.29)	0.187*** (10.53)	0.007 (1.51)
Ln(PPE/#employees)		0.108 (8.97)	0.112*** (8.74)	0.033*** (8.49)
Ln(Sales/#employees)		0.046*** (2.92)	0.044*** (2.64)	-0.001 (-0.25)
Sales growth		-0.072*** (-3.64)	-0.063*** (-2.89)	-0.004 (-0.55)
ROA	-.1313*** (-2.51)	0.601*** (8.37)	0.646*** (8.48)	0.109*** (4.53)
M/B	-0.265*** (-19.24)	0.055 (8.28)	0.062*** (8.67)	0.016*** (7.06)
Leverage		-0.436 (-7.79)	-0.500*** (-8.49)	-0.080*** (-4.54)
Cash/Assets		-0.083 (-1.20)	-0.057 (-0.77)	0.052** (2.01)
Stock return		0.038*** (2.94)	0.043*** (3.11)	0.015*** (3.25)
Stock volatility		4.566*** (8.98)	4.859*** (9.10)	-0.351** (-2.15)
Herfindahl		-0.767*** (-4.60)	-0.727*** (-4.08)	-0.056 (-1.04)
Herfindahl^2		0.823*** (4.66)	0.792*** (4.23)	0.035 (0.62)
Industry and year fixed effects	Yes	Yes	Yes	Yes
N/(Pseudo) R-squared	17,056 /0.59	14,277/0.55	14,277/0.52	14,277/0.30
Diagnostic tests				
Wald test: all coefficient=0		2638***	2308***	2596****
Heckman's lambda		0.984**	-1.118***	-0.059***
Wald/Likelihood ratio test of independent equations (ρ=0)		165.71***	51.31****	11.84****

Table 9
T-tests for potential underlying mechanisms.

Panel A: Inventor tenure

The sample consists of 137,152 inventor-years jointly covered in the Compustat Fundamentals, Compustat Pension, and HBS Patent and Inventor databases from 1990 to 2007. The t-test is conducted to test for differences in mean values between the High- and Low-TcAt subsamples, using median as the dividing line. The t-statistic is in parentheses. The symbol *** indicates that subsample means are significantly different from each other at the 1% level.

	High-TcAt firms	Low-TcAt firms	Difference
Mean inventor tenure	4.54	4.30	0.24*** (10.12)
Number of observations	74,238	62,914	

Panel B: Inventor productivity and risk-taking

The sample consists of inventor-firms jointly covered in the Compustat Fundamentals, Compustat Pension, and HBS Patent and Inventor databases as well as Boston College 5500-CRR data from 1990 to 2007. Patents is the number of patents applied for (and eventually granted) during the year. Citations is number of citations in a given year divided by the mean number of citations in that year and within the same patent technology class as defined by USPTO. Citations per patent (CPP) is Citations scaled by Patents. Citation variance is the variance in citations of granted patents for individual investors in a given year. T-tests are conducted to test for differences in mean values between the High-TcAt and low-TcAt subsamples, using median as the dividing line. The t-statistics are in parentheses. The symbol *** indicates that subsample means are significantly different from each other at the 1% level.

	High-TcAt firms	Low-TcAt firms	Difference
Mean patents	1.87	1.82	0.05*** (3.70)
Mean citations	25.40	23.70	1.70*** (3.82)
Mean citations/patents	12.54	11.67	0.87*** (6.76)
Number of observations	49,489	46,947	
Citation variance	0.950	0.847	0.103* (1.94)
Number of observations	17, 538	15,679	

Table 10

Effects of DB plan contributions on inventor tenure, productivity, and risk-taking.

The sample consists of observations jointly covered in the Compustat Fundamentals, Compustat Pension, and UTPSO Patent and Citation databases as well as Boston College 5500-CRR and HBS inventor data from 1990 to 2007. Average tenure is the average number of years that an inventor stays with a particular firm during the sample period. Patents is the number of patents applied for (and eventually granted) during the year. Citations is the number of citations in a given year divided by the mean number of citations in that year and within the same patent technology class as defined by USPTO. Citations per patent (CPP) is Citations scaled by Patents. Citation variance is the variance in citations of granted patents for individual investors in a given year. TcAt is total pension contributions scaled by book value of total assets of the firm. Control variables are the same as those in Table 2. Variable definitions are provided in Appendix B. All models are estimated using 2SLS. Constant terms are included but not reported here. The t-statistics in parentheses are calculated from standard errors clustered at the inventor level, except for Column 1, where t-statistics are calculated from standard errors clustered at the firm level. The symbols ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	Average Tenure (1)	Ln(1+Patents) (2)	Ln(1+Citations) (3)	Ln(1+CPP) (4)	Citation Variance (5)
TcAt	35.136** (2.32)	-0.098 (-0.22)	2.565* (1.90)	2.663** (2.15)	14.535* (1.95)
Funding status	0.355 (0.43)	-0.073** (-2.52)	-0.327*** (-3.58)	-0.253*** (-3.04)	-0.506 (-1.00)
R&D intensity	2.786** (2.26)	0.121*** (2.80)	-0.523*** (-3.86)	-0.644*** (-5.23)	1.436 (1.56)
Ln(Assets)	-0.027 (-1.09)	0.005*** (3.74)	0.013*** (3.06)	0.007** (1.95)	-0.001 (-0.02)
Ln(Firm Age)	0.147*** (3.87)	-0.001 (-0.29)	-0.021*** (-3.84)	-0.021*** (-4.16)	0.008 (0.31)
Ln(PPE/#employees)	0.110 (1.45)	0.011** (3.35)	0.032*** (3.20)	0.021** (2.36)	0.087* (1.90)
Ln(Sales/#employees)	-0.020 (-0.16)	-0.010** (-2.11)	-0.065*** (-4.25)	-0.055** (-3.98)	-0.045 (-0.31)
Sales growth	0.425 (0.95)	0.017** (2.02)	0.123*** (4.66)	0.106*** (4.40)	-0.147 (-1.30)
ROA	0.972 (1.36)	0.017 (0.61)	0.472*** (5.64)	0.455*** (6.03)	0.710* (1.73)
M/B	-0.052 (-0.89)	0.001 (0.65)	-0.005** (-1.03)	-0.006 (-1.37)	0.083* (1.72)
Leverage	0.219 (0.73)	-0.015 (-1.37)	-0.108*** (-3.16)	-0.093*** (-3.02)	0.093 (-0.45)
Cash/Assets	0.776 (1.13)	0.040 (1.63)	0.258*** (3.43)	0.218*** (3.22)	0.561 (1.11)
Stock return	0.390* (1.71)	0.010*** (3.44)	0.085*** (7.66)	0.075*** (7.46)	0.209*** (3.04)
Stock volatility	-2.431 (-0.48)	-0.133 (-0.60)	2.581*** (3.67)	2.714*** (4.29)	17.525*** (4.70)
Herfindahl	0.183 (0.29)	-0.021 (-0.88)	0.227*** (3.11)	0.247*** (3.76)	1.069* (1.95)
Herfindahl^2	-0.036 (-0.06)	0.019 (0.91)	-0.178*** (-2.83)	-0.196*** (-3.48)	-1.108** (-2.53)
Industry and year fixed effects	Yes	Yes	Yes	Yes	No
N/R-squared	270/0.219	92,436/0.004	92,436/0.015	92,436/0.015	33,217/0.003

Appendix A: A Detailed Example of a DB Plan[24]

In order to understand the incentives in defined benefit plans, assume a worker takes her first job on her 25th birthday at an annual salary of $20,000. Assume further that this worker receives pay increases of 5% per year throughout her career up through her 64th birthday, regardless of whether she stays with first employer or moves on to other employers at various times during her career. Next, assume that she will retire on her 65th birthday at the end of a 40-year career. Finally, assume this woman's first employer has a pension plan in which she earns a vested benefit after five years of service under the plan, and beginning at age 65, the plan pays retirement benefits equal to 1 percent of her final annual salary under the plan for each year in the plan sponsor's employment.

Table A.1 reflects this worker's prospects in the pension plan offered by her initial employer. If she stays with her employer for only one year, the value of her benefit will be zero because she must work for the employer five years to be vested in the plan. If she stays with her first employer until retirement, however, she will receive a benefit of $1,340.95 per year based on her first year of employment, or 1 percent of her final salary during the year immediately prior to her retirement. In actuality, the worker would not consider the current value of the benefit to be the full $1,340.95 because the benefit will not be paid for many years, and her job might not last until retirement or she might die before attaining retirement eligibility. But even after discounting the value of the benefit, there is clearly some economic value to remaining covered under the plan.

Continuing with the example, if the worker takes a new job on her 35th birthday, she will ultimately be paid $3,102.66 per year out of her first employer's retirement plan—that is, 1 percent of her terminal salary with that employer, as shown in Table A.1. If she stays until retirement, however, she will receive an annual benefit of $13,409.50 because she will receive 1 percent of her career terminal earnings for each of her first ten years of service rather than 10 percent of her earnings at age 35.

Looking at the difference between the two benefits from the perspective of a 35-year-old worker deciding whether to change jobs, the prospect of receiving roughly an additional $10,000 per year in retirement income 30 years into the future would be discounted somewhat. At an 8 percent discount rate, the difference in the annual benefit values would be only about $1,000 per year, but over a normal life expectancy, it would be valued at more than three times the difference at age 35. Thus the plan imposes significant penalties on workers who terminate their jobs before becoming eligible for retirement.

Table A.1 Pay Levels and Retirement Benefits Based on Current and Career Terminal Salary for Hypothetical Worker at Selected Ages

Age at End of Year Worked	Salary for Year	Benefit Based on Current Salary	Benefit Based on Terminal Salary
25	$20,000.00	$0.00	$1,340.95
35	31,026.56	3,102.66	13,409.50
45	50,539.00	10,107.80	26,819.00
55	82,322.71	24,696.81	40,228.51
65	134,095.02	53,638.01	53,638.01

[24] This example is directly drawn from Fundamentals of Private Pensions, McGill et al., 2010, Oxford University Press, p147.

Appendix B: Variable Definitions

Variable	Definition
Patent counts (raw)	The numbers of patents applied for (and eventually granted) during the year. Replaced by zero if missing.
Patent citations (fixed-effects adjusted)	Citation counts in a given year divided by the mean number of citations in that year and within the same patent technology class as defined by USPTO. Replaced by zero if missing.
Citations per patent	The total number of citations received during the sample period on all patents filed (and eventually received) by a firm in a given year, scaled by the number of the patents filed (and eventually received) by the firm during the year. The number of citations is adjusted by year and technology class fixed effects. Replaced by zero if citation counts are missing.
Citation variance	Variance in citations of granted patents for individual investors in a given year.
Innovative industry	An indicator variable that equals one for 4-digit SIC industries whose citations per patent exceed the median for all industries in a given year; this value equals zero for other industries.
DB liabilities or Projected benefit obligation(PBO)	If 1987 ≤ fiscal year ≤ 1997, Pension benefit projected obligation (pbpro)) + Underfunded pension benefit projected obligation(pbpru); If fiscal year ≥ 1998, Pension benefit projected obligation (pbpro).
DB Assets	If 1987 ≤ fiscal year ≤ 1997, Pension plan assets (pplao) + Underfunded pension plan assets (pplau); If fiscal year ≥ 1998, Pension plan assets (pplao).
Funding status (FS)	(Firm-level actuarial plan assets - Firm-level projected plan liabilities)/Book value of assets.
Mandatory contributions (MCs, Rauh)	Max(MFC,DRC), where MFC is the minimum funding contribution and DRC is the deficit reduction contribution. MFC= the normal cost+10% of previous funding gap. DRC/Funding gap = min{0.30, [0.30-0.25*(Plan Assets/Plan Liabilities -0.35)]} up to 1994(inclusive); and min{0.30, [0.30-0.40*(Plan Assets/Plan Liabilities -0.6)]} from 1995 (inclusive). The change to the DRC in 1995 also exempted plans which are more than 90% funded from DRCs. It also exempted plans that were at least 80% funded and had a recent history of being overfunded.
Mandatory contributions (MCs, Moody's)	Service cost plus {[Accumulated Benefit Obligation (ABO) – Fair Value of Pension Plan Assets (FVPA)]/ 30}, if PBO > FVPA; and zero otherwise, where in terms of Compustat items service cost is ppsc, FVPA is pplao + pplau, and ABO is pbaco + pbacu.
TcAt (Total contribution ratio)	Total contributions/book value of assets.
McAt (Mandatory contribution ratio)	Mandatory contributions/book value of assets.
Assets	Book value of total assets.
PPE/#employees	Net Property, Plant, and Equipment (PPE) scaled by the number of employees.
Sales/#employees	Net sales scaled by the number of employees.
ROA	Earnings Before Interest, Taxes, and Depreciation and Amortization (EBITDA) over Assets.
Sales growth	Change in net sales scaled by lagged net sales.
Market-to-book ratio (M/B)	(Assets+Market value of equity-Book value of equity)/Assets.
Leverage	(Short-term debt+Long-term debt)/Assets.
Firm age	The number of years elapsed since a firm enters the CRSP database.
R&D intensity	R&D expenses scaled by the book value of total assets.

Stock return	Buy-and-hold stock returns computed over the fiscal year.
Stock volatility	Standard deviation of daily stock returns over the fiscal year.
Herfindahl index	Sum of (firm assets/industry assets)^2; computed on the basis of three-digit SIC codes and fiscal years.
Inventor tenure	The number of years that an inventor stays with a particular firm during the sample period. If she changes employers, her tenure starts over.

Appendix C: Robustness Check on Alternative Measure of DB Pension Plan Value

This table reports the results of linear regression of number of patents (citations) on projected benefit obligation (PBO) scaled by the number of employees (following Chang et al. (2015)), controlling for industry and year fixed effects. All control variables are the same as those used in Table 2. Constant terms are included but not reported. The t-statistics in parentheses are calculated from standard errors clustered at the firm level. The symbols ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	Ln(1+Patents)	Ln(1+Citations)
	OLS	OLS
	(1)	(2)
Ln(1+PBO/#employees)	0.248***	0.233***
	(4.00)	(3.68)
Funding status	1.112	0.979
	(1.63)	(1.43)
R&D intensity	11.708***	11.689***
	(8.29)	(7.92)
Ln(Assets)	0.714***	0.725***
	(20.93)	(20.26)
Ln(Firm Age)	0.113**	0.115**
	(2.43)	(2.41)
Ln(PPE/#employees)	-0.032	-0.045
	(-0.38)	(-0.51)
Ln(Sales/#employees)	-0.258**	-0.275**
	(-2.15)	(-2.11)
Sales growth	-0.293**	-0.248*
	(-2.36)	(-1.87)
ROA	2.080***	2.071***
	(3.51)	(3.36)
M/B	-0.014	-0.001
	(-0.28)	(-0.01)
Leverage	-0.641**	-0.711***
	(-2.47)	(-2.72)
Cash/Assets	-0.186	-0.205
	(-0.35)	(-0.38)
Stock return	0.012	0.037
	(0.30)	(0.88)
Stock volatility	7.136**	7.300**
	(2.55)	(2.47)
Herfindahl	0.426	0.442
	(0.60)	(0.60)
Herfindahl^2	-0.180	-0.176
	(-0.29)	(-0.27)
Industry and year fixed effects	Yes	Yes
N/R-squared	4,156/0.65	4,156/0.63

Appendix D: Robustness Check on Alternative Measure of Patent Quality—Citations per Patent

Linear regression of citations per patent (CPP) on alternative DB plan value measures in different specifications, controlling for industry and year fixed effects. All control variables are the same as those used in Table 2. Variable definitions are provided in Appendix B. Constant terms are included but not reported. The t-statistics in parentheses are calculated from the Huber/White/Sandwich heteroskedasticity-consistent errors. The symbols ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	Ln(1+CPP)					
	OLS (1)	25th Quan (2)	50th Quan (3)	75th Quan (4)	IV (5)	OLS (6)
TcAt	1.170* (1.94)	2.560*** (3.13)	1.229* (1.42)	0.290 (0.42)	3..437** (2.15)	
Ln(1+PBO/#employees)						0.019*** (2.68)
Funding status	0.207** (1.99)	0.366*** (2.87)	0.138 (1.37)	0.073 (0.60)	0.350** (2.48)	0.160 (1.64)
R&D intensity	1.588*** (8.44)	1.900*** (8.68)	1.355*** (7.20)	0.991*** (3.90)	1.584*** (8.40)	1.540*** (8.15)
Ln(Assets)	0.080*** (21.49)	0.093*** (25.66)	0.090*** (29.03)	0.045*** (8.21)	0.081** (21.06)	0.079*** (20.78)
Ln(Firm Age)	0.011** (1.87)	0.028*** (4.34)	0.006 (0.94)	0.003* (0.61)	0.010* (1.71)	0.008 (1.26)
Ln(PPE/#employees)	-0.015 (-1.49)	-0.007 (-0.74)	-0.017* (-1.69)	-0.011 (-0.91)	-0.016* (-1.55)	-0.018* (-1.76)
Ln(Sales/#employees)	-0.023 (-1.46)	0.005** (0.29)	-0.025 (-1.59)	-0.019 (-1.15)	-0.025 (-1.51)	-0.032* (-1.95)
Sales growth	-0.026 (-0.82)	-0.065** (-2.42)	-0.065** (-2.19)	-0.019 (-0.42)	-0.018 (-0.56)	-0.018 (-0.54)
ROA	0.279*** (2.94)	0.236** (2.25)	0.453*** (4.37)	0.242* (1.88)	0.270*** (2.83)	0.331*** (3.44)
M/B	-0.005 (-0.66)	0.004 (0.44)	-0.012 (-1.46)	-0.006 (-0.58)	-0.006 (-0.82)	-0.004 (-0.58)
Leverage	-0.058* (-1.69)	-0.062 (-1.61)	-0.008 (-0.19)	-0.009 (-0.19)	-0.054 (-1.54)	-0.067** (-1.92)
Cash/Assets	0.127 (1.50)	0.083 (0.89)	0.165* (1.95)	0.217* (1.91)	0.114 (1.34)	0.118 (1.39)
Stock return	0.002 (0.16)	0.004 (0.31)	0.006 (0.58)	0.007 (0.55)	0.003* (0.29)	0.003 (0.25)
Stock volatility	-1.445*** (-3.31)	-0.178 (-0.37)	-1.764*** (-4.08)	-1.620*** (-2.57)	-1.479*** (-3.21)	-1.263*** (-2.74)
Herfindahl	0.041 (0.47)	-0.072 (-0.69)	0.032 (0.33)	0.037 (0.34)	0.040 (0.45)	0.014 (0.16)
Herfindahl^2	-0.083 (-1.04)	0.074 (0.81)	-0.093 (-1.02)	-0.099 (-0.98)	-0.084 (-1.05)	-0.061 (-0.77)
Industry and year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
N/Adj. R-squared	4,217/0.34	4,217/0.18	4,217/0.30	4,217/0.20	4,217/0.35	4,156/0.34