TWO ESSAYS ON CORPORATE INNOVATION

A DISSERTATION SUBMITTED TO THE GRADUATE DIVISION OF THE

UNIVERSITY OF HAWAIʻI AT MĀNOA IN PARTIAL FULFILLMENT OF THE

REQUIREMENTS FOR THE DEGREE OF

DOCTOR OF PHILOSOPHY

IN

BUSINESS ADMINISTRATION

JULY 2017

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Keywords: corporate innovation, pension, institutional ownership, common ownership

DEDICATION

To my father and to the memory of my mother

ACKNOWLEDGMENTS

I am indebted and grateful to so many people who have positively influenced my career and enabled me to achieve my academic aspirations.

My deepest gratitude is extended to my committee chair, Professor S. Ghon Rhee, for his guidance and encouragement. During the past four years, he served as an excellent role model by focusing my efforts and challenging me intellectually. I am very appreciative of his time and commitment. I have learned a great deal from him about finance and academic research in general. I also want to thank Professors Rosita Chang, Wei Huang, Boochun Jung, Joonho Kim, and Inessa Love for their willingness to serve on my committee, support, and positive feedback. I am very grateful for their generosity, time, and valuable contributions. They developed my critical thinking skills and allowed me to achieve a higher level of understanding.

I want to especially acknowledge my parents-in-law. They supported me to pursue a doctoral education emotionally and physically.

My children, Jasmine and Michael, are my inspiration. They have provided me with joy and purpose. In many ways, they have taught me how to become a better educator. I love them and hope to inspire them as much as they have inspired me.

Finally, I want to thank my wife, Xianghong Liu, for her constant patience, support, and commitment. Without her, I could not achieve balance in my life.

ABSTRACT

In Part I of this dissertation, I exploit a natural experiment of tax-qualified 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. Consistent with the worker-firm bonding theory, my findings suggest the bright side of DB plans despite recent pension freezes. Further analysis reveals that non-qualified executive pensions weaken the above effect. Overall, I provide a positive answer to an important economic question: whether secured deferred compensation promotes corporate innovation among the rank and file employees. Part II tests how ownership structure affects corporate innovation. The prior literature documents a positive effect that the fraction of the firm held by institutional investors has on corporate innovation. I focus on the fraction of the institution's portfolio represented by the firm and find that institutions' portfolio weights positively affect patent success. Yet, it is important to distinguish between cross-industry diversification and same-industry diversification of monitoring institutions. I provide evidence that the former fosters innovation, while the latter, if it creates common ownership, impedes innovation. I address endogeneity issues with multiple methods, including regression discontinuity design, instrumental variable approach, and difference-in-differences analysis.

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PART I

Golden Handcuffs and Corporate Innovation:

Evidence from Defined Benefit Pension Plans

Chapter I-1: Introduction

"It would be appealing to have an old-fashioned (defined-benefit) pension. A pension is pretty valuable."

Herbert Whitehouse, one of the champions of the 401(k)

"The great lie is that the 401(k) was capable of replacing the old system of pensions."

Gerald Facciani, former American Society of Pension Actuaries head

Both statements were quoted in The Wall Street Journal (January 2, 2017) – "The Champions of the 401(k) Lament the Revolution They Started"

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, we examine the impact of another incentive scheme on corporate innovation. 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, including the 401(k), 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 final 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), we mainly focus on DB plans in this paper[1]. 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))[2]. 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.

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,

[1] In Section VIII, we add DC firms to our sample and find qualitatively similar results.
[2] 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.

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 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)[3]. 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, we examine one of the potential benefits associated with DB plans—their capacity for promoting technological innovation, a crucial competitive advantage for firms.

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, we find that DB pension plans foster corporate innovation[4]. Our 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[5]. The association is both economically and statistically significant. To ensure the robustness of these results, we perform a number of analyses using alternative model specifications and variable definitions. Furthermore, we employ the instrumental variable

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[3] 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.

[4] 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.

[5] We also use the number of citations per patent to measure innovation quality in our empirical analysis and find similar results.

approach to address the possibility of reverse causality and the problem of omitted variables, which could drive both innovation and DB pension contributions. Specifically, we 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. We 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 pension contributions capture a direct response of innovation to total pension contributions. In other words, funding status adequately controls for capital investment in innovation. Our 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. The results remain unchanged when we use the two-step Heckman model to address self-selection bias in the cases of pension freezes and of adding DC firms to our sample.

This paper contributes to the extant literature on multiple fronts. First and foremost, our findings identify another determinant of corporate innovation. In the current knowledge economy, decision-makers are keenly interested in knowing what factors drive innovation. We 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, we 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, we demonstrate that DB pension plans can be another lever to pull for innovative firms. Third, we 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, we 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 we 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, our 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 that employees play in the process of innovation. Mayer et al. (2015), Mao and Weathers (2015), and Chen et al. (2016) 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) illustrate 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. We add to this literature by focusing on a particular (different) incentive scheme—DB plans.

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. Finally, Section 9 concludes the paper.

Chapter I-2: Institutional background of pension plans

2.1 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 -0.60)]}. The calculation of the required contribution during the sample period for this study is discussed in detail in Section 4.3.

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. We take this into consideration where necessary.

2.2 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, we discuss the computation of the DB plan assets and liabilities in Section 4.3 as well.

2.3 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 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[6]. 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, employers having an obligation to contribute under the

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

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.

Chapter I-3: 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, we posit that compensation systems can influence firm innovation. Specifically, we 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, we 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[7]. Therefore, DB plan

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

contributions may be associated with the reduced likelihood of innovative success. This assumption serves as the basis for the first hypothesis, which we 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 we 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 salient to our 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[8]. Because our data are from the IRS Form 5500, SERPs are excluded from our 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. From the firm's perspective, DB pensions substantially increase firm leverage ratios (Shivdasani and Stefanescu (2010)). The incentive effects associated with debt encourage firms to engage in risky investments (Jensen and Meckling (1976)). The reason is that equity holders benefit from successful outcomes of high-risk projects, while losses from unsuccessful outcomes are borne by debt holders. This asymmetry between who receives the gains and losses from a project could make it optimal for equity holders to undertake highly risky investments such as innovation, thereby increasing innovation output.

Moreover, Ippolito (1985) show that DB plans increase productivity by backloading a firm's 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

[8] 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)).

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. 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[9]. 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,

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

delayed compensation is 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, we predict that DB plans should be associated with a higher likelihood of innovative success. This rationale leads to the second hypothesis, which we 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.*

We find overall support for the deferred compensation hypothesis by showing that the value of DB plans enhances innovation. Using DB plan and patenting data, we 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.

Chapter I-4: Data, variables, and summary statistics

4.1 Data and sample

We 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. We 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[10]. 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, we obtain data on stock prices and returns from the Center for Research in Security Prices (CRSP) files.

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

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

partially remedies this shortcoming[11]. We 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, we 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[12]. Following Hirshleifer et al. (2012), we 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), we 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. We 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), we use a one-year lag of the DB plan value when predicting innovation output.

4.2 Measuring innovation output

Our 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. Our sample period ends three years prior to the last year for which patent information is available. Therefore, we 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)). We therefore follow

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

[12] 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).

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. We correct for these truncation errors by adjusting fixed effects in a manner consistent with Hall et al. (2001) and Seru (2014). Specifically, we 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)[13]. In later analyses, we also use citations per patent as the dependent variable for regression analysis.

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

4.3 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, we include firm-level funding status and pension contributions as explanatory variables in the model. Moreover, we use an alternative measure of DB plan value on a projected basis for the regressions in Appendix C. Using data from Compustat, we 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.

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

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, we use PBO as the main measure of DB plan liabilities and as an alternative measure of DB plan value[14]. 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, we 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, we use pbpro as PBO. We follow the same practice when calculating pension plan assets. See Appendix B for variable definitions.

[Insert Figure I-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 our final sample is representative of the Compustat Pension universe. TCs increased sharply starting in 2001,

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

possibly triggered by the deterioration in plan funding (see Figure 1) due to the burst of the dot com bubble.

[Insert Figure I-2 here]

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), we 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, we argue that MCs are exogenous to a firm's innovation. To mitigate heteroskedasticity, we 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 our interest in the regression analyses in this study.

[Insert Figure I-3 here]

4.4 Control variables

To isolate the effect of DB plans on innovation output, we 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, we use the natural logarithm of total assets (Ln(Assets)) in our analyses to control for firm size. Our results are robust to the use of net sales or the number of employees as proxies for firm size. We 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, we 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, we 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), we 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 our 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.

4.5 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 our 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.

We 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. We 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[15]. 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 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 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, we will use both measures in our regressions to check the robustness of our results.

[Insert Table I-1 here]

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

Chapter I-5: Main results

5.1 The baseline model

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

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

where Innovation refers to Our 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 our innovation measures and (b) include zero values of innovation, we 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. We also include two-digit SIC industry and year fixed effects in the model.

Columns 1 and 5 in Table 2 report the results of our 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[16]. 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 our previous argument that employees consider how well plans are funded. The coefficients of other control variables are generally consistent with prior literature. For example, we find that firms with higher R&D intensity are associated

[16] Calculated as (1+55)× [exp(0.0091×13.166)-1]=7.13 and (1+59)×[exp(0.0091×13.337)-1]=7.74, respectively.

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, we use a quantile regression specification to alleviate concerns related to outlier effects. Specifically, we 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, we 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. 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 I-2 here]

We also perform an additional test to ensure that our 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, we 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.

5.2 Industry Innovativeness

We expect the effect of DB plan value on innovative outcomes to be greater in industries in which innovation is more important and better fostered. We 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 our evidence that DB plans have an effect on innovation. To conserve space, we 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), we 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 we alternatively use the ratio of the PBO to the number of employees as the DB plan value. These results suggest, upholding our hypothesis, that the DB plan value has a greater effect on a firm's innovation output in innovative industries.

[Insert Table I-3 here]

5.3 Endogeneity issues

Although our 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 we 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 our 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, we 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, we 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, our 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 our sample. We 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)[17]. These results suggest that MCs do not directly affect innovation by siphoning off funds for R&D. Furthermore, MCs are a discontinuous and kinked function of

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

funding status. There is no reason that corporate innovation makes a discrete jump at the point of full pension funding or changes in slope at the point at which the MCs function changes slope. Other than a direct response of corporate innovation to incentives provided by total pension contributions, it is unlikely that innovation should be affected by MCs when the funding status is controlled for. Therefore, our instrument is likely to meet the exclusion restriction condition as well[18]. 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).

We 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, we 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). We 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 our use of the IV method. The dependent 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 I-4 here]

[18] 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.

Chapter I-6: 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, we 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, we 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, we 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, we use the alternative measure, PBO (specifically, the natural logarithm of one plus per-employee PBO), to gauge the DB plan value[19]. 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. We then conduct OLS and IV analyses by using patent counts

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

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 sponsors’ innovation output (significant at 5% or better).

[Insert Table I-5 here]

Chapter I-7: 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, we collect DB pension freeze data from Form 5500 for the years 2002 to 2007. Our 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 so in that year. We 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 our 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, we are left with 175 firms that instituted a hard freeze on their DB pension plans during our 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, we follow the Heckman (1976) two-stage estimation procedure to adjust for this selection bias. In the first stage, we analyze the determinants of a firm's decision to freeze its DB plan using the model proposed by Choy et al. (2014). Specifically, we 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 that is equal to one if the firm's DB plans are subject to a collective-bargaining agreement, and zero otherwise. We also include year and industry fixed effects to control for the effect of changes in macroeconomic or industry conditions on pension freeze decisions. We 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, we regress innovation on the inverse Mills ratio and the set of control variable included in Equation (1). We are 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 our freeze sample, while the control group is the non-freeze DB firms. Following Bertrand and Mullainathan (2003) and Choy et al. (2014), we estimate the following model:

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

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 count. 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, we conclude that there is a significant decrease in corporate innovation after DB-plan freezes, consistent with our 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. There are two possible explanations for reconciling this contradiction. One is that Choy et al. (2014) include SERPs in DB plans and find that the reduction of this unsecured “inside debt” aligns senior executives’ incentives more closely with those of shareholders rather than debtholders. In contrast, this paper only considers qualified and secured DB plans, in which the above incentive effect may not exist. The other reason could be that R&D investment is only part of the input 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, when a firm increases R&D expenditures but simultaneously withdraws an important incentive scheme, corporate innovation will still suffer and experience a decline. This possibility 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 I-6 here]

Chapter I-8: Full sample analysis

To address sample selection bias, we now augment our 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, we here refer to DC firms strictly as those with DC plans only and without any DB plan[20]. We do so by adding the Compustat firms not matched to our DB sample above. We then set all the DB-related variables to be zeros for DC firms and rerun the above OLS and IV regressions. Results are reported in Table 7.

Columns 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. Column 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 We use citations per patent as dependent variable, untabulated results (to 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, we conclude that after including DC firms, there is still possibly a causal effect running from DB pension contributions to corporate innovation.

[Insert Table I-7 here]

As a robustness check, we 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,

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

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.

We 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), we 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, we include two variables in the probit model that we 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. We 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, we 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 our sample, however, we 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. These results indicate that DB plans promote corporate innovation.

[Insert Table I-8 here]

Chapter I-9: Moderating effect of CEO's inside debt

Although qualified pension plans are guaranteed by the PBGC and funded, non-qualified executive pensions (i.e., SERPs) and other deferred compensation represent unsecured, unfunded debt claims against the firm. These are the so-called "inside debt" (Sundaram and Yermack, 2007). The higher the relative importance of debt- versus equity-based compensation in an executive's pay, the more closely her incentives are aligned with debt holders vis-à-vis stockholders and the lesser the degree to which she engages in risk taking to the detriment of debtholders (Sundaram and Yermack 2007, Edmans and Liu 2011). Therefore, the effect of rank-and-file plans on corporate innovation is weaker at higher level of inside debt.

To test whether managers' inside debt holdings in the form of pensions and other deferred compensation have a moderating effect on the relation of rank-and-file plans and corporate innovation, we retrieve data on CEO's debt-like and other compensation from the ExecuComp database for fiscal years 2006–2007. On August 29, 2006, the SEC issued a new rule requiring tabular disclosure of the present value of benefits accrued under pension and other deferred compensation plans. Prior to 2006, firms were not required to disclose the present value of accumulated benefits. Disclosure requirements for other deferred compensation balances were also almost nonexistent.

Edmans and Liu propose the statistic *k*:

$$k=(D_{CEO}/D_{FIRM})\div(E_{CEO}/E_{FIRM})$$

$$=(D_{CEO}/E_{CEO})\div(D_{FIRM}/E_{FIRM})$$

where D_{CEO} and E_{CEO} are the manager's inside debt and inside equity, and D_{FIRM} and E_{FIRM} are the total debt and equity claims against the company, including those held internally by the CEO. We call *k* the "CEO's relative debt-equity ratio." If k=1, the manager should have no incentive to engage in risk shifting strategies that transfer value from debt to equity or vice versa. A limitation of the CEO's relative debt-equity ratio is that it captures levels but not changes in the values of debt and equity. Following Wei and Yermack (2011), we measure executive incentive by the marginal change in the CEO's inside debt over the marginal change in her inside equity holdings, given a unit change in the overall value of the firm, scaled by the ratio of the marginal change in the firm's external debt over the marginal change in its external equity, given the same unit change in the overall value of the firm. In other words, we are interested in the following statistic:

$$k^{*} = (\Delta D_{CEO}/\Delta D_{FIRM}) \div (\Delta E_{CEO}/\Delta E_{FIRM}) \approx (D_{CEO}/D_{FIRM}) \div (\Delta E_{CEO}/\Delta E_{FIRM})$$

Wei and Yermack call k^* the "CEO's relative incentive ratio." We obtain inside debt data from ExecuComp and inside equity data from Lalitha Naveen's website[21]. Untabulated results show that k^* has a mean of 0.807, a median of 0.926, the 25th percentile of 0.698, and the 75th percentile of 1.037. Because the last year for patent data is 2008 (cutting two years from 2010 to mitigate truncation bias) and the inside debt data starts from 2006, we use per-employee pension liabilities instead of total contribution ratios to retain more observations. We then run the baseline regression, Equation (1), by adding two more independent variables, CEO's relative incentive ratio and an interaction term between it and the per-employee pension liabilities. Regression results are reported in Table 9. The coefficients of the interaction terms in both the patent quantity and quality models (Columns 1, 2 and 3) are negative and significant (t = -2.08, -2.16, and -2.31, respectively). The results confirm our conjecture that in firms with higher inside debt, the effect of rank-and-file pensions on innovative success is weaker. To determine whether rank-and file pensions and inside debt affects corporate innovation positively or negatively, we can spotlight an average firm with the mean Ln(PBO/#employees) (i.e., ln56,000=11, Table 1) and the mean CEO's relative incentive ratio of 0.81 (untabulated). In the patent quantity model (Column 1), the coefficients on Ln(PBO/#employees), the CEO's relative incentive ratio, and their interaction term are 0.188 (t=1.85), 0.047 (t=1.90), and -0.038,

[21] http: //astro.temple.edu/~lnaveen/data.html. Starting from 2006, ExecuComp no longer reports the value of the option portfolio as of the fiscal year end using the BlackScholes formula.

respectively. The marginal effect of Ln(PBO/#employees) on patent quantity is 0.188 - $0.038\times0.807 = 0.157$. The result shows a positive effect of rank-and-file pension on innovation. In contrast, the marginal effect of the CEO's relative incentive ratio on patent quantity is 0.047 – $0.038 \times 11 = -0.371$, which means that inside debt affects patent quantity negatively. We can draw the same conclusions on the patent quality models (Column 2 and 3), although in Colum 3, the loadings on Ln(PBO/#employees) and the CEO's relative incentive ratio lose significance.

[Insert Table I-9 here]

Chapter I-10: 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. Our 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), we 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 our 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 firms to leverage 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. Given the opposite effects on innovation of average employee deferred compensation and executive deferred compensation, it is important to treat rank-and-file pensions and executive pensions differently.

Appendix I-A: A Detailed Example of a DB Plan[22]

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.

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

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

Appendix I-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.

Appendix I-B (Continued): Variable Definitions

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 $(\text{firm assets/industry assets})^2$; computed on the basis of three-digit SIC codes and fiscal years.
CEO’s relative incentive ratio	CEO’s inside debt over the marginal change in her inside equity holdings, given a unit change in the overall value of the firm, scaled by the ratio of the firm’s external debt over the marginal change in its external equity, given the same unit change in the overall value of the firm

Appendix I-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)

Appendix I-C (Continued): Robustness Check on Alternative Measure of DB Pension Plan Value

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

Appendix I-D (Continued): Robustness Check on Alternative Measure of Patent Quality—Citations per Patent

	Ln(1+CPP)					
	OLS	25th Quan	50th Quan	75th Quan	IV	OLS
	(1)	(2)	(3)	(4)	(5)	(6)
Herfindahl	0.041	-0.072	0.032	0.037	0.040	0.014
	(0.47)	(-0.69)	(0.33)	(0.34)	(0.45)	(0.16)
Herfindahl^2	-0.083	0.074	-0.093	-0.099	-0.084	-0.061
	(-1.04)	(0.81)	(-1.02)	(-0.98)	(-1.05)	(-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

Table I-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**

Table I-1 (Continued). Summary Statistics

	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）
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 I-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)

Table I-2 (Continued). Effects of DB Plan Contributions on Innovation Output

	Ln(1+Patents)				Ln(1+Citations)			
	OLS	25th Quan	50th Quan	75th Quan	OLS	25th Quan	50th Quan	75th Quan
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
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 I-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 I-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	Ln(1+Patents)	Ln(1+Citations)
	(1)	(2)	(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)

Table I-4 (Continued). Instrumental Variable Approach

	1st Stage	2nd Stage	
	TcAt	Ln(1+Patents)	Ln(1+Citations)
	(1)	(2)	(3)
Stock volatility	-0.004	6.337**	6.495**
	(-0.35)	(2.28)	(2.22)
Herfindahl	0.002	0.536	0.556
	(0.83)	(0.76)	(0.75)
Herfindahl^2	-0.001	-0.286	-0.283
	(-0.57)	(-0.46)	(-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 I-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)

Table I-5 (Continued). OLS and IV Analyses Based on Per-employee-PBO DB Plan Value and Moody's Measure of MCs

	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)
Stock return	0.002	0.027	-0.001	0.013	0.040
	(0.08)	(0.92)	(-0.04)	(0.37)	(1.07)
Stock volatility	9.316***	9.338***	-5.082***	10.696**	11.114***
	(5.02)	(4.78)	(-5.28)	(7.73)	(7.71)
Herfindahl	0.670	0.713	1.439***	0.498*	0.431
	(1.16)	(1.18)	(6.79)	(1.61)	(1.34)
Herfindahl^2	-0.245	-0.276	-1.349***	-0.198	-0.112
	(-0.48)	(-0.52)	(-6.79)	(-0.68)	(-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 I-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)	Ln(1+Citations)	Ln(1+CPP)
	(1)	(2)	(3)
Post freeze	-0.513***	-0.519***	-0.076**
	(-3.16)	(-3.10)	(-2.06)
Inverse Mills ratio	0.667***	0.651***	0.138***
	(3.94)	(3.72)	(3.80)
McAt	11.009***	11.291***	0.745
	(2.79)	(2.84)	(0.87)
Funding status	2.194***	2.189***	0.276*
	(3.27)	(3.24)	(1.77)
R&D intensity	11.492***	11.505***	1.310***
	(7.13)	(6.93)	(4.21)
Ln(Assets)	0.781***	0.789***	0.093***
	(18.43)	(18.10)	(11.06)
Ln(Firm Age)	0.121**	0.120**	0.005
	(2.47)	(2.40)	(0.45)
Ln(PPE/#employees)	0.072	0.059	-0.009
	(0.86)	(0.67)	(-0.41)
Ln(Sales/#employees)	-0.525***	-0.557***	-0.081***
	(-4.21)	(-4.18)	(-2.76)
Sales growth	-0.537**	-0.487***	-0.045
	(-4.14)	(-3.55)	(-1.25)
ROA	2.170***	2.200***	0.376***
	(3.45)	(3.37)	(2.78)
M/B	-0.018	-0.006	-0.002
	(-0.34)	(-0.11)	(-0.15)
Leverage	-0.338	-0.406	-0.026
	(-1.28)	(-1.51)	(-0.45)
Cash/Assets	0.345	-0.407	0.120
	(-0.62)	(-0.72)	(0.88)

Table I-6 (Continued). Impact of Pension Freezes on Corporate Innovation

	Ln(1+Patents)	Ln(1+Citations)	Ln(1+CPP)
	(1)	(2)	(3)
Stock return	0.046	0.077*	0.010
	(1.15)	(1.86)	(1.04)
Stock volatility	8.373***	8.622***	-0.815
	(3.19)	(3.14)	(-1.29)
Herfindahl	0.629	0.628	0.031***
	(0.86)	(0.82)	(0.19)
Herfindahl^2	-0.388	-0.369	-0.081
	(-0.58)	(-0.53)	(-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 I-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)	Ln(1+Citations)	TcAt	Ln(1+Patents)	Ln(1+Citations)
	(1)	(2)	(3)	(4)	(5)
TcAt	16.992***	18.365**	N/A	53.963***	53.103***
	(3.23)	(3.31)		(5.18)	(4.84)
McAt	N/A	N/A	0.359***	N/A	N/A
			(23.61)		
Funding status	0.256	0.190	-0.030***	2.297***	2.005***
	(0.40)	(0.29)	(-20.43)	(4.33)	(3.59)
R&D intensity	6.965***	7.030***	-0.001	12.336***	12.827***
	(8.08)	(7.68)	(-0.11)	(19.13)	(18.87)
Ln(Assets)	0.672***	0.669***	-0.011**	0.737***	0.748***
	(25.86)	(25.01)	(-2.31)	(52.54)	(50.65)
Ln(Firm Age)	0.238***	0.248***	-0.001***	0.173***	0.172***
	(6.20)	(6.28)	(0.10)	(7.91)	(7.46)
Ln(PPE/#employees)	0.029	0.013	0.001	0.027	0.003
	(0.50)	(0.22)	(0.98)	(0.79)	(0.07)
Ln(Sales/#employees)	-0.056	-0.068	0.001	-0.060	-0.077
	(-0.78)	(-0.90)	(1.37)	(-1.16)	(-1.41)
Sales growth	-0.163***	-0.134**	-0.002***	-0.266***	-0.204**
	(-2.84)	(-2.28)	(-4.43)	(-2.80)	(-2.04)
ROA	0.439	0.394	0.005***	1.215***	1.275**
	(1.53)	(1.34)	(3.79)	(3.61)	(3.60)
M/B	0.061**	0.077**	0.001***	-0.046*	-0.044
	(2.15)	(2.58)	(0.62)	(-1.67)	(-1.53)
Leverage	-0.772***	-0.772***	-0.003***	-0.416***	-0.448***
	(-4.05)	(-3.97)	(-6.91)	(-3.32)	(-3.39)
Cash/Assets	0.398	0.320	0.001	0.396*	-0.278
	(1.17)	(0.92)	(0.01)	(1.67)	(-0.88)

Table I-7 (Continued). OLS and IV Analyses for a Sample Including Both DB and DC Firms

	OLS		IV		
			1st Stage	2nd Stage	
	Ln(1+Patents)	Ln(1+Citations)	TcAt	Ln(1+Patents)	Ln(1+Citations)
	(1)	(2)	(3)	(4)	(5)
Stock return	0.019	0.040	-0.001	0.031	0.048
	(0.83)	(1.63)	(-0.77)	(0.82)	(1.20)
Stock volatility	8.185***	8.313***	0.003	5.904**	5.869***
	(4.86)	(4.65)	(0.00)	(3.57)	(3.37)
Herfindahl	0.556	0.602	0.003**	0.122	0.227
	(1.01)	(1.04)	(2.23)	(0.39)	(0.69)
Herfindahl^2	-0.107	-0.179	-0.002	0.173	0.066
	(-0.20)	(-0.32)	(-1.64)	(0.55)	(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 I-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	Ln(1+Patents)	Ln(1+Citations)	Ln(1+CPP)
	(1)	(2)	(3)	(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)

Table I-8 (Continued). Treatment Effects Model: Effects of DB Plan Contributions on Corporate Innovation

	Pension choice	Ln(1+Patents)	Ln(1+Citations)	Ln(1+CPP)
	(1)	(2)	(3)	(4)
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 I-9. Moderating Effect of Inside Debt

This table presents the parameter estimates of interaction effects models. PBO/#employees is projected benefit obligation (PBO) scaled by the number of employees. CEO's relative incentive ratio is the CEO's inside debt over the marginal change in her inside equity holdings, given a unit change in the overall value of the firm, scaled by the ratio of the firm's external debt over the marginal change in its external equity, given the same unit change in the overall value of the firm. CPP stands for citations per patent. Other variable definitions are provided in Appendix B. Robust t-statistics with standard errors clustered at the firm level are reported in parentheses. The symbols ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	Ln(1+Patents)	Ln(1+Citations)	Ln(1+CPP)
	(1)	(2)	(3)
Ln(1+PBO/#employees)	0.188* (1.85)	0.196** (2.04)	0.037 (1.44)
Ln(1+PBO/#employees) × CEO's relative incentive ratio	-0.038** (-2.09)	-0.039** (-2.16)	-0.010** (-2.31)
CEO's relative incentive ratio	0.047* (1.90)	0.048* (1.87)	0.004 (0.52)
Funding status	-0.590 (-0.21)	0.160 (0.07)	-0.435 (-1.01)
R&D intensity	4.078** (2.18)	3.489* (1.90)	1.068** (2.12)
Ln(Assets)	0.394*** (6.17)	0.381*** (6.03)	0.095*** (6.83)
Ln(Firm Age)	0.026 (0.33)	0.042 (0.52)	-0.007 (-0.27)
Ln(PPE/#employees)	-0.178 (-1.52)	-0.189 (-1.61)	-0.064** (-2.07)
Ln(Sales/#employees)	-0.255* (-1.81)	-0.252* (-1.81)	-0.036 (-0.96)
Sales growth	0.035 (0.08)	-0.010 (-0.02)	0.010 (0.11)
ROA	1.737 (1.07)	1.711 (1.08)	0.341 (0.69)
M/B	-0.106 (-0.92)	-0.101 (-0.89)	-0.026 (-0.66)
Leverage	0.649 (1.48)	0.749* (1.71)	0.161 (1.50)
Cash/Assets	2.012** (2.00)	2.063** (2.05)	0.685** (1.99)
Stock return	0.193 (1.46)	0.172 (1.31)	0.035 (1.01)
Stock volatility	-2.905 (-0.91)	-2.964 (-0.95)	-1.017 (-0.98)
Herfindahl	-0.200 (-0.16)	0.218 (0.18)	-0.142 (-0.36)
Herfindahl^2	0.340 (0.30)	-0.028 (-0.03)	-0.207 (0.59)
Industry and year fixed effects	Yes	Yes	Yes
N/R-squared	223/0.48	223/0.47	223/0.40

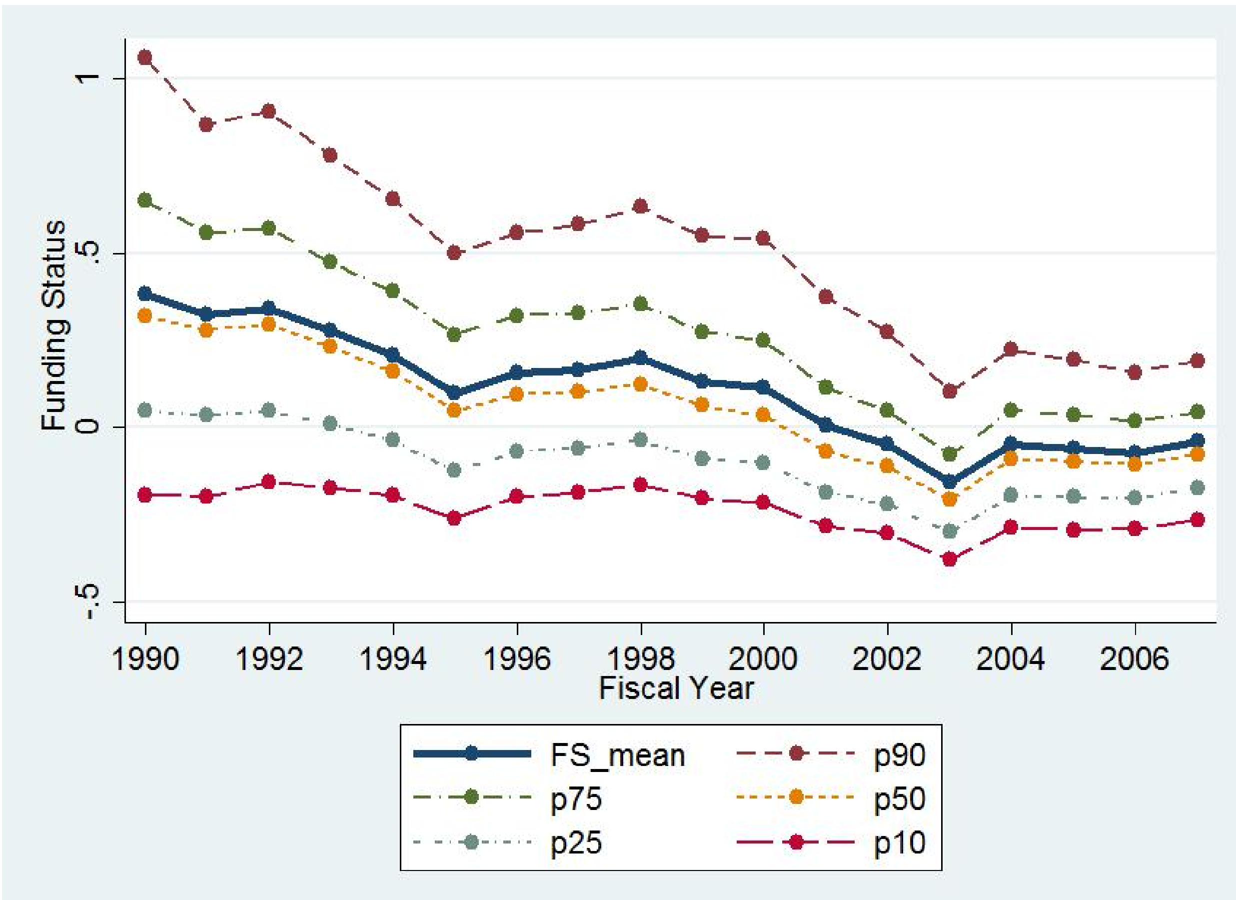

Figure I-1. Distribution of beginning-of-year funding status (FS). This figure depicts the distribution of firm-level pension funding status of Compustat firms at the start of fiscal years from 1990 to 2007. Funding status is defined as pension assets minus pension liabilities divided by firm assets.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

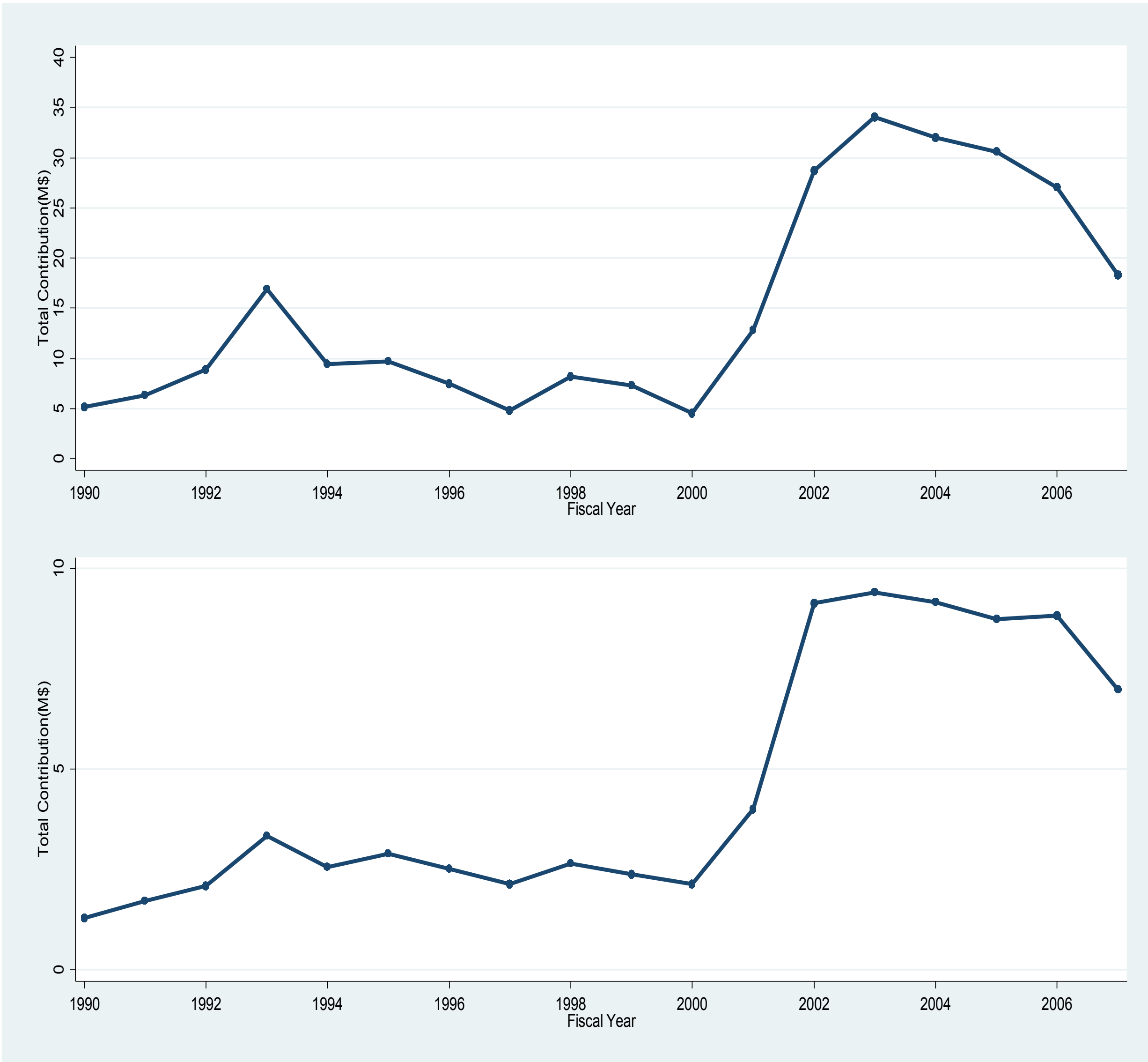

Figure I-2. Distributions of mean total contributions in dollar terms. The top graph depicts firms in our final sample, jointly covered by the 5500-CRR, Compustat, and UTPSO patent databases. The bottom graph depicts a larger sample of firms jointly covered by the 5500-CRR and Compustat databases from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

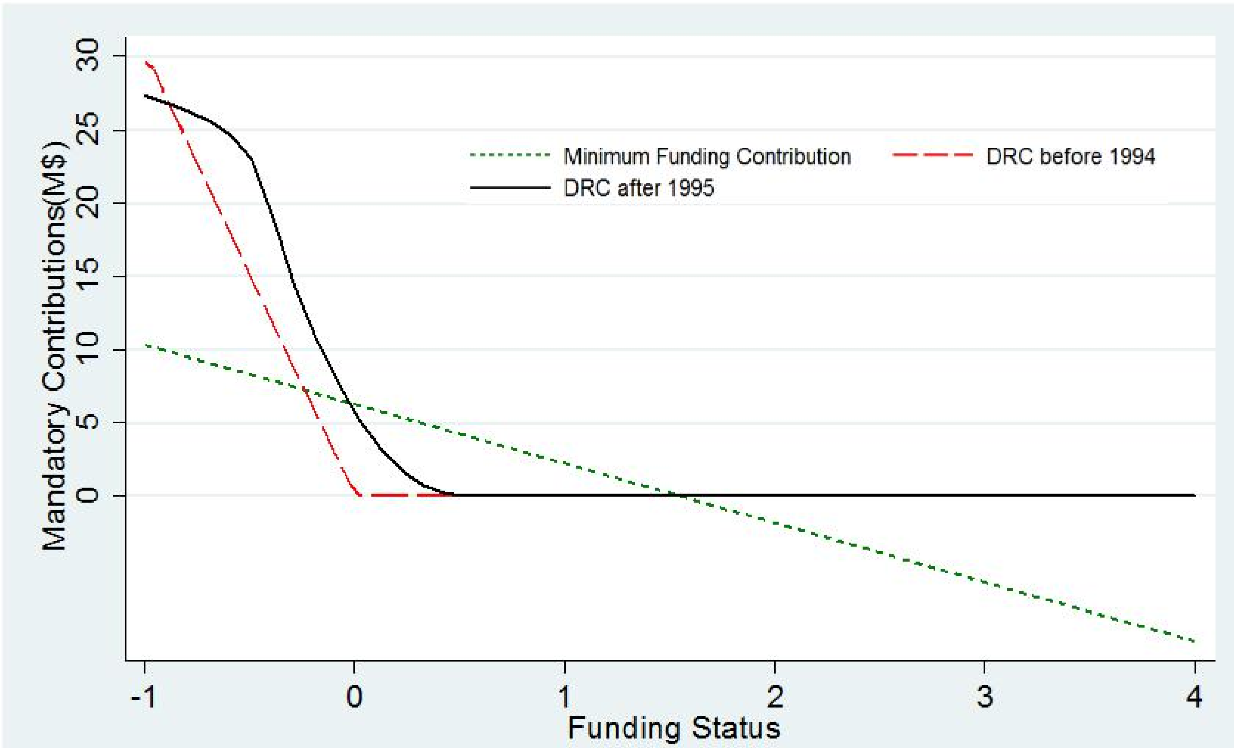

Figure I-3. Mandatory pension contributions. A firm's mandatory contribution is the maximum of two elements: the minimum funding contribution (MFC) and the deficit reduction contribution (DRC). The graph shows mandatory contributions in dollar terms for a firm with characteristics equivalent to the sample 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.

REFERENCES I

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.

Edmans A, and Q Liu. Inside debt. Review of Finance, 15(2011), 75–102.

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.

Jensen, M. C., and W. H. Meckling. Theory of the Firm: Managerial Behavior, Agency Costs, and Ownership Structure. Journal of Financial Economics 3 (1976), 305–360.

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).

Wei, C., and D. Yermack. Investor Reactions to CEOs' Inside Debt Incentives. Review of Financial Studies, 24 (1201), 3813-3840.

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

Chapter II

Institutional Multiple Holdings and Corporate Innovation

Chapter II-1: Introduction

Institutional ownership of US equities had experienced a rapid increase before it settled down to a stable rate in the most recent decade. According to the Federal Reserve Board's Flow of Funds report, institutions owned approximately 7% of American common stocks in 1950, 51% by the end of 2004, 47% by the end of 2012, and 46% by the end of 2015. Given this predominant firm ownership, our understanding of how institutional investors intervene in or affect their invested firms is still limited.

There is a long-standing debate between active versus passive investing. Accordingly, institutional investors exhibit heterogeneity in their investment strategy. On the one hand, some institutions pick stocks and allocate disproportional portfolio weights to different stocks. On the other hand, other institutions tend to diversify by indexing, creating multiple holdings in both cross-industry and same-industry firms. In other words, along with diversification comes ownership both across industries and in the same industry. I ask how these different strategies and resulting ownership affect corporate innovation as a potential channel to realize these investors' investment performance.

Institutional investors typically have multiple stock holdings across firms, thereby creating different ownership structures from the perspective of the institutions. Prior literature measures the impact of institutional ownership by the relative importance of the institution's holdings in the firm's outstanding shares (Officer, Ozbas, and Sensoy, 2010; Aghion, Van Reenen, and Zingales, 2013; Crane, Michenaud, and Weston, 2016). In contrast, Ekholm and Maury (2014) and Fich, Harford and Tran (2015) show that the fraction of the institution's portfolio represented by the firm is a cleaner institutional ownership proxy than traditional ones (measured relative to the invested firm's outstanding shares). I utilize this angle (i.e., from the investor perspective) and expand the measure of institutional ownership structure to three dimensions: concentration, diversification across industries, and common ownership within industries. I then use them to scrutinize the effects of institutional ownership on corporate innovation. First, an institutional investor with multiple holdings focuses its monitoring efforts on its largest/concentrated holdings to accrue the most benefits. Accordingly, I find the relative importance of a firm's stock in the institution's portfolio positively affects firm innovation. Second, firms with more diversified shareholders undertake riskier investments (Faccio, Marchica, and Mura, 2011). Consistent with this finding, I detect a positive correlation between patent success and institution diversification across industries. Third, common ownership by a small set of large diversified institutional investors reduces product market competition and enhances market power (He and Huang, 2014; Azar, Schmalz, and Tecu, 2016). Firms could reduce R&D expenditures as a result of attenuated competition. My empirical analysis confirms this conjecture and documents a negative relation between same-industry common ownership and corporate innovative performance.

To address endogeneity concerns in each analysis, I apply different techniques. First, I use regression discontinuity design to tackle the endogeneity of the shares owned by monitoring institutions. Specifically, I use plausibly exogenous changes in institutional holdings generated by Russell index reconstitutions to establish causality. Second, I use instrumental variable approach to deal with the endogeneity of portfolio diversification by institutional investors. Specifically, I take the average portfolio diversification of monitoring institutions across all other industries as an instrumental variable to capture the "natural" tendency to diversify across all monitoring institutions who are involved in similar types of activities. Third, I employ the difference-in-differences analysis to establish the causal effect of joint ownership on corporate innovation. Specifically, the acquisition of the Citi Group's Asset Management division by Legg Mason in 2005 generated variation across firms in common ownership. I exploit this event to study the "before" and "after" treatment effect.

This paper is closely related to the literature studying institutional investors' impact on corporate innovation. Aghion, Van Reenen, and Zingales (2013) argue that a large share of institutional shareholders is instrumental in facilitating corporate innovation as these shareholders tend to pursue a long-run objective. Bena, Ferreira, and Matos (2014) find that foreign ownership increases firm innovation output. Brav, Jiang, and Tian (2014) show that hedge fund activism leads to more efficient use of innovative resources and human capital. Yang (2016) establishes that institutional dual ownership of a firm's debt and equity lead to fewer but more valuable patents. Geng, Hau, and Lai (2016) provide evidence that institutional ownership overlaps across firms with patent complementarities help mitigate holdup and correlate with more innovative success.

This paper differs from Geng, Hau, and Lai (2016) in that they look at common ownership across firms in the same technology space (i.e., firms with upstream and downstream patents), while I examine common ownership across firms in the same product market space (i.e., same industry). A firm's position in technology space and product market space are typically different. For example, IBM, Apple, Motorola, and Intel are close to each other in technology space as revealed by their patenting. However, they are in different product markets. Specifically, IBM and Apple produce PC desktops, while Intel and Motorola mainly produce semi-conductor chips not computer hardware (Bloom, Schankerman, and Reeman, 2013). Therefore, although Geng, Hau, and Lai (2016) find a positive effect of technology-complementary common ownership on patent success, I observe a negative effect of same-industry common ownership on corporate innovation. Furthermore, I examine two other dimensions (i.e., portfolio concentration and cross-industry diversification), thereby providing a more comprehensive understanding of the effect of ownership structure on corporate innovation.

A related line of research explores the effect of an investor owning multiple firms on corporate governance. Edmans, Levit, and Reilly (2016) find that common ownership strengthens governance through both voice and exit. Although my findings about the effect of multiple holdings on corporate innovation do not always require shareholder intervention, it is consistent in spirit with the conclusion of Edmans, Levit, and Reilly (2016). Firms reduce innovation to ease competition with their natural competitors that are also owned by the firms' institutional investors. This anti-competitive effect of common ownership benefit the shareholders at the expense of consumers. However, a comprehensive look into the three dimensions of ownership (i.e., portfolio concentration, cross-industry diversification, and same-industry common ownership) is missing from previous research. This paper aims to fill this gap.

The remainder of the paper proceeds as follows. Section 2 reviews the literature and develops hypotheses. Section 3 describes the data and presents summary statistics. Section 4 details the methodology used and discusses the results. Finally, Section 5 concludes the paper.

Chapter II-2: Literature and hypotheses

Not all institutional investors are equal. Bushee (1998)'s seminal paper classifies institutional investors based on their past investment behaviors. He finds that the less frequently an institutional investor trades, the more effective it is in alleviating managerial myopia. By examining business relationships and investment horizons, Chen, Harford, and Li (2007) conclude that independent institutions with long-term investments engage in monitoring. Appel, Gormley, and Keim (2015) show that passive institutional investors influence firms' governance choices through their large voting blocs. Appel, Gormley, and Keim (2016) establish that the increasingly large ownership stakes of passive institutional investors facilitate shareholder activism due to easier coordination and higher reputation.

Surprisingly, no research, so far, has focused on how the dimension of portfolio diversification/concentration on the part of institutional investors affects firms' behaviors, such as risk-taking. On the one hand, many institutions (e.g. passive funds) are typically well-diversified; on the other hand, other institutional investors deviate from holding the market portfolio (Brown and Goetzmann, 1997; Daniel, Titman, and Wermers, 1997). Institutions have incentives to systematically hold concentrated portfolios when they shoulder fiduciary responsibilities (Del Guercio, 1996), or when they adopt investment styles (O'Barr and Conley, 1992), or when they have information advantage from specialization and economies of scale (Choi, Fedenia, Skiba, and Sokolyk, 2015). Given the heterogeneity of their portfolio diversification, institutional investors should have different attitudes of encouraging firms to take risks, especially high risks. I thus examine the impact of institutional investor diversification on firms' key risk-taking behavior – innovation. Another reason why I focus on innovation is that if institutions monitor, they should monitor innovation because a long-term orientation of the monitors can clearly benefit from this core competency that also needs to be fostered over an extended period of time. My overarching hypothesis is that both portfolio concentration and diversification can affect firm's innovation through different channels.

Aghion, Van Reenen, and Zingales (2013) find that institutional ownership positively affects corporate innovation through reducing managers' career risk to increase their innovative incentives. They measure institutional ownership by the fraction of the firm held by institutions. In contrast, Fich, Harford, and Tran (2015) measure institutional ownership by the fraction of the institution's portfolio represented by the firm. The latter finds that institutional monitoring is greater when the firm represents a higher allocation of funds in the institution's portfolio. That is, an institution focuses its effort on its largest (concentrated) holdings to accrue the most benefits to their monitoring. Ekholm and Maury (2014) compare the portfolio concentration to the traditional measure of ownership concentration, and find that their measure considering the portfolio dimension is more reliably related to firm performance than the traditional ownership concentration measure. A natural question to ask then is how institutional investors' portfolio weights affect corporate innovation. This rationale leads to my first hypothesis:

H1) Institutional investors' portfolio weights positively affect corporate innovation due to more intervention exerted by the institutional investors.

However, since innovation is inherent with high risks, the dimension of diversification may play a crucial role in encouraging innovation. Indeed, Faccio, Marchica, and Mura (2011) document that in Europe firms controlled by diversified large shareholders undertake riskier investments than firms controlled by nondiversified large shareholders. Their argument is that the expected utility of a risk-averse decreases in variance of her wealth. If a controlling shareholder is risk-averse and poorly-diversified, an increase in firm-specific risk will decrease her expected utility. Thus, she will prefer to keep firm risk-taking in check. By contrast, a well-diversified controlling shareholder is unaffected by firm-specific risk because it has been diversified away. Following this logic, she should allow her firm to take risky projects including R&D, thereby enhancing innovation. Yet, Azar, Schmalz, and Tecu (2016) find that common ownership across firms in the same industry resulted from portfolio diversification impairs competition. Furthermore, Schumpeter (1912) and Knott and Posen (2003) show that innovation increases with the degree of industry competition. These findings lead to my second and third hypotheses:

H2) The average degree of cross-industry diversification of the monitoring institutions in a firm is positively correlated with corporate innovation due to the encouragement of more risk-taking.

H3) Due to its anti-competitive effect, same-industry common ownership reduces corporate innovation.

Following Fich, Harford, and Tran (2015), I define the monitoring institutions as those whose holding value in the invested firm is in the top 10% of their portfolio. As in Faccio, Marchica, and Mura (2011), I use three proxies to measure diversification of the monitoring institutions in a firm: (i) the (natural logarithm of the) number of four-digit industries in which the monitoring institutions holds shares; (ii) the Herfindhal Index of stockholding concentration; and (iii) the correlation of the stock returns of a firm's industry with the largest institutional investor's overall portfolio returns. The same caveat as theirs follows: I capture US equity investments, but I miss other significant investments, such as bonds, real estate, and international investments, due to data unavailability.

My major measure of common ownership is the difference between the modified Herfindahl-Hirschman Index (MHHI), derived in O'Brien and Salop (2000), and the market share-based Herfindahl-Hirschman Index (HHI, or H(market shares)), following Azar, Schmalz, and Tecu (2016). The traditional HHI does not consider common ownership. To allow for this component, O'Brien and Salop (2000) propose using the MHHI, defined as

$$MHHI = \sum_{j}\sum_{k} s_j s_k \frac{\sum_i \gamma_{ij}\beta_{ik}}{\sum_i \gamma_{ij}\beta_{ij}}, \tag{1}$$

as a measure of market power, where s_j and s_k are market shares of firm j and k in the same industry with N firms and M owners, γ_{ij} is the control share of firm j held by owner i, and β_{ij} (β_{ik}) is the ownership shares of firm j (k) accruing to investor i. Control rights and ownership rights differ in many cases and thus need to be treated separately. Using simple algebra, we can rewrite MHHI as

$$MHHI = HHI + \sum_{\mathrm{j}} \sum_{k \neq j} s_j s_k \frac{\sum_i \gamma_{ij} \beta_{ik}}{\sum_i \gamma_{ij} \beta_{ij}} \qquad (2)$$

The second term in the Equation (2) is the difference between the MHHI and the HHI, denoted as the MHHI delta. It is a measure of the anti-competitive incentives due to interlocking shareholdings[23].

As a robustness check, I also follow He and Huang (2014) by constructing seven measures of common ownership[24]. The first one, CommonDummy, is a dummy variable that equals one if the firm is commonly-held in any of the four quarters prior to the fiscal year end, and zero otherwise. The second measure, LnNumCommon, is the natural logarithm of one plus the average number of unique institutions that cross-hold the firm in the four quarters prior to the fiscal year end. This measure captures the extent to which a firm is connected to other same-industry peers through common ownership. The third measure, AvgPercent, is the average percentage holding in same-industry peers block-held by the average common-holding institution. More specifically, I first calculate the average percentage holding in same-industry firms (other than the one in question) block-held by each common-holding institution during the four quarters prior to the fiscal year end and then averaged across all such institutions. This measure captures the intensity of common-holding activities for an average institution. The fourth measure, AvgNum, is similarly defined. It is the average number of same-industry peers block-held by the average common-holding institution. The fifth measure, TotalCommonOwn, is the sum of all common-holding institutions' average percentage holdings in the firm itself. This measure captures the total power of common-holding institutions to influence firm management if they have similar goals. The sixth measure, FracPosChgPt, is the fraction of the firm's common-holding institutions whose average percentage block holding in other same-industry peers is higher than that in the previous year. The last measure, FracPosChgNum, is similarly defined. It is the fraction of the firm's common-holding institutions whose average number of

[23] Please refer to Azar, Schmalz, and Tecu (2016) for examples of MHHI computations to aid with intuition.
[24] He and Huang (2014) use the term "cross ownership" to refer to common ownership. To avoid confusion with corporate equity ownership across one another, I stick to the term "common ownership."

other same-industry common-holdings is higher than that in the previous year. The last two measures capture the incentives of an average common-holding institution to exert influence.

Chapter II-3: Data

3.1 Sample selection

My sample combines institutional ownership data with patenting data for U.S. listed firms. The ownership data is from the Thomson Reuters 13F database. Aghion, Van Reenen, and Zingales (2013) document reporting inconsistencies in the 13F data prior to 1991, therefore I only retain ownership data from 1991 and thereafter. I retrieve patent and citation information from data compiled by Kogan, Papanikolaou, Seru, and Stoffman (2015) (henceforth KPSS). The KPSS patent data set contains detailed information for all patents that are granted by the United States and Trademark Office (USPTO) from 1926 till 2010. On average, the granting of patents lagged patent application by two years. Thus, I only use the patent portfolios of the firms that filed application up to 2008. I do not use the NBER data set because it only contains patents that are granted up to 2006. I obtain accounting data from Compustat and the stock price and shares outstanding data from CRSP. My final sample covers firms from 1991 to 2008.

3.2 Measures of innovation

Following the extant literature (e.g., KPSS (2014); Seru (2014)), I use patent-based metrics to capture corporate innovation. Patent-based measures are widely used proxies of innovation output. I obtain patent data from the database created by KPSS, who have matched assignees in the patent data set with CRSP PERMNOs if the assignee is a public corporation or a subsidiary of a public corporation. Patent data are subject to two types of truncation biases. First, patents are recorded in the data set only after they are granted and the lag between patent applications and patent grants is significant (about two years on average). As we approach the last few years for which there are patent data available, we observe a smaller number of patent applications that are eventually granted. Many patent applications filed during these years were still under review and had not been granted by 2010. I partially mitigate this bias by restricting our analyses to two years before the patent data ends (i.e., in 2009). Further, following Hall, Jaffe, and Trajtenberg (2001) and Seru (2014), I correct this bias by dividing each patent for each firm-year by the mean number of patents for all firms for that year in the same 3-digit technology class as the patent. The second type of truncation problem stems from citation counts. Patents tend to receive citations over a long period of time, so the citation counts of more recent patents are significantly downward biased. Following Hall, Jaffe, and Trajtenberg (2001) and Seru (2014), this bias is accounted for by scaling citations of a given patent by the total number of citations received by all patents in that year in the same 3-digit technology class as the patent. Note that the above methodology gives us fixed-effect-adjusted measures of patents and citations, which adjust for trends in innovative activity in particular industries in the overall economy.

I construct three measures for a firm's annual innovative output based on the patent application year. The first measure, Ln(Patents), is the natural logarithm of one plus the fixed-effect-adjusted patent count for a firm in a given year. Specifically, this variable counts the total number of (fixed-effect-adjusted) patent applications filed that year that were eventually granted. However, a simple count of patents may not distinguish breakthrough innovations from incremental technological discoveries. Therefore, I consider two additional measures. The second measure, Ln(Citations), is the natural logarithm of one plus the fixed-effect-adjusted total number of citations received on the firm's patents filed in a given year. The third measure, Ln(Citations/Patent), is constructed by taking natural logarithm of one plus the total number of fixed-effect-adjusted citations a firms receives on all the patents it applies for in a given year and normalizing it by one plus the total number of fixed-effect-adjusted patents applied for in that year. I take the natural logarithm because the distribution of patents and citations are right skewed. To avoid losing observations with zero patents or zero citations, I add one to the actual values.

3.3 Summary statistics

Table 1 reports the summary statistics. An average firm in my sample has 27 granted patents and the average firm's patents receive 32 fixed-effect-adjusted citations in total. In terms of innovation efficiency, every million dollars spent on R&D generate 0.743 patents and 0.915 citations, respectively. On average, 22% of a firm's outstanding shares are owned by monitoring institutions, 6% of institutional owners of a firm are monitoring institutions, and a firm has 17 monitoring institutions. In terms of the cross-industry diversification measures, the mean value of the number of four-digit industries that the monitoring institutions at a firm hold is 66,052. For (1-Herfindhal Index), the highest possible value, 1, denotes perfect diversification, and the lowest possible value, 0, denotes no diversification at all. In my sample, the mean value of (1-Herfindhal Index) is 0.153 and of -Correlation is -0.496, both indicating that institutions are relatively undiversified. In terms of the same-industry common ownership measures, the mean value of MHHI delta is 12.531. On average, about 56% of the firm-years in my sample are commonly held by more than one institution (untabulated). The rest of the table summarizes my control variables. An average firm in my sample spends 6% of its total assets on R&D, has a book value of assets of $810.78 million (the log of which is 6.698 million), a firm age of 14.60 years since it first entered the CRSP, per-employee PP&E of $40 thousand, per-employee sales of $211 thousand, sales growth of 12.90%, ROA of 11.91%, leverage of 18.44%, Tobin's q of 1.73, cash-to-asset ratio of 12.60%, stock return of 19.63%, and stock volatility of 3.07%.

[Insert Table 1 here]

Chapter II-4: Empirical results on the relation between ownership structure and corporate innovation

I measure (institutional) ownership structure from the three dimensions: portfolio concentration, diversification across industries, and diversification within industries. In this section, I test how the three dimensions affect patent success respectively.

4.1 Institutional portfolio weights and corporate innovation

4.1.1 Baseline regression results

Since shareholders tend to focus their monitoring efforts on their largest holdings, I examine the role of monitoring institutions in corporate innovation. To assess how institutional investors' portfolio weights affect their invested firms' innovation output, I estimate various forms of the following model using the ordinary least squares (OLS):

$$\mathrm{Ln}(1+Innovation)_{i,t+1} = \alpha + \beta \times \mathrm{Portfolio\ \ Weight}_{i,t} + \gamma \times X_{i,t} + \mu_i + \eta_t + \varepsilon_{i,t} \qquad (3)$$

where i indexes firm and t indexes time. The dependent variable is a firm's one-year-ahead innovation measures as defined in the previous section. Following Fitch, Harford, and Tran (2015), the Portfolio Weight is one of the following three measures based on the size of holdings by monitoring institutions for firm i in year t: (1) Number of monitoring institutions, i.e., the number of institutions whose holding value in the firm is in the top 10% of the institution's portfolio; (2) Proportion of monitoring institutions, namely, the proportion of monitoring institutions among all institutions holding the firm's shares; (3) Total ownership of monitoring institutions, i.e., the total ownership of monitoring institutions as a proportion of the firm's total shares outstanding. X is a vector of time-varying firm characteristics that may affect a firm's innovation performance. X includes a traditional institutional ownership proxy (measured relative to a firms' outstanding shares), such as the number of (or the ownership by) blockholders. μ captures industry fixed effects and η captures year fixed effects.

In Table 2, I report the estimation of three variants of an OLS model in which the dependent variable is one of my three measures of innovation. Chang, Fu, Low and Zhang (2015) estimate a similar model. Therefore, except for the controls for institutional ownership and industry concentration (HHI) that will be explained later, all independent variables in my regressions are similar to theirs. To account for the institutional investors' impact, all the tests in Table 2 control for total institutional blockholder ownership of the firm. Additionally, in models 1, 2, and 3, I respectively add the total ownership of monitoring institutions, the proportion of monitoring institutions, and the number of monitoring institutions as an explanatory variable. The blockholder variable, a traditional proxy for institutional ownership in the literature, does not attain statistical significance in all the tests except one reported in Table 2. In contrast, all of my measures for monitoring institutions exhibit positive and significant coefficients, except in Model 3 for the citations per patent specification. This is generally consistent with Ekholm and Maury (2014) and Fich, Harford, and Tran (2015). According to the marginal effect in Model 1, an interquartile-range increase in total ownership of monitoring institutions is associated with a 13 percent point increase in patent counts and a 15 percent point increase in adjusted patent citations[25].

I control for a vector of variables that have been shown by the literature to affect innovation. 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

[25] The increases in patent counts and citations are calculated as $(1+27)\times(\exp(0.492\times0.2386)-1)/27$ and $(1+32)\times(\exp(0.556\times0.2386)-1)/32$, respectively.

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, Lakonishok, and Sougiannis (2001) find that stock volatility positively affects R&D investments. Results for the other control variables in Table 2 are generally consistent with those in the extant innovation literature. For instance, firms with higher R&D intensity, larger size, older age, higher growth opportunities, higher per-employee PPE, lower leverage, higher stock returns, and higher stock volatility tend to secure more and better-quality patents.

[Insert Table 2 here]

4.1.2 Institutional monitoring and innovation efficiency

I expect firms with higher ownership of monitoring institutions to experience higher innovation efficiency. Two measures of innovative efficiency are employed: patent counts scaled by R&D capital (Prd) and patent citations scaled by R&D capital (Crd). R&D capital is defined as the weighted average of R&D expenditures over the last five years with an annual depreciation rate of 20% (Chan, Lakonishok, and Sougiannis, 2001). Specifically, R&D capital for firm i in year t is calculated as

$$R\&D\,Capital_{it} = R\&D_{it} + 0.8R\&D_{it-1} + 0.6R\&D_{it-2} + 0.4R\&D_{it-3} + 0.2R\&D_{it-4} \tag{4}$$

Missing R&D has been set to zero. I scale innovative outputs by cumulative R&D expenses because Hirshleifer, Hsu, and Li (2013) find that R&D expenses over the preceding five years all contribute to successful patent applications filed in year t. I then regress Prd (Crd) on total ownership of monitoring institutions and other control variables in Equation (3). Table 3 reports the OLS regression results. The loadings of total ownership of monitoring institutions are 0.709 (t=2.18) and 1.119 (t=2.58) when using Crd and Prd as the innovation efficiency measures, respectively. The results suggest that firms with higher ownership of monitoring institutions are more efficient in innovation.

[Insert Table 3 here]

4.1.3 Identification

Giannetti and Simonov (2006) argue that investors select stocks not only on the basis of corporate risk and return, but they also take into account other company characteristics, such as growth prospects, corporate governance, and their own familiarity with the nature of the business. Using a similar line of reasoning, in my setting, institutions could select into firms that are likely to be more innovative. Under this circumstance, causality runs in the opposite direction and my assertion that institutional monitoring fosters corporate innovation would be incorrect.

To address the endogeneity problem, I employ a fuzzy regression discontinuity design (RDD) approach in the context of an instrumental variable (IV) estimation similar to that in Fich, Harford, and Tran (2015) and in Crane, Michenaud, and Weston (2016). Following their empirical design, my identification strategy exploits the discontinuity in Russell index weights. Every year in June, the largest one thousand firms based on market capitalization are selected to comprise the Russell 1000 Index and the next two thousand firms are included in the Russell 2000 index. These two market indexes are widely used as benchmarks. According to Chang, Hong, and Liskovich (2015), in 2005, the amount of institutional assets benchmarked to the Russell 2000 index was in excess of \$200 billion, and \$90 billion tracked the Russell 1000. Because both indexes are value-weighted, institutions tracking them will have to adjust their holdings accordingly every year. I use Russell index inclusion as a source of plausibly exogenous variation in a firm's ownership structure.

My sample for the RDD analysis consists of the Russell 1000 and Russell 2000 index constituents from 1997 until 2006. I obtain these data from Russell and merge them with firm-level accounting data from Compustat, institutional holdings data from 13F filings, and stock return data from CRSP. I end the sample period in 2006 because in 2007, Russell instituted its banding policy to minimize the number of stocks that switch indexes each year. For instance, if two firms on the edge of the threshold switch places in a given year, Russell may leave those firms in their prior year index provided the market value differential is small. That is, a stock would not change indices unless it moved far enough beyond the 1000 cutoff. Figure 1 depicts the discontinuity of institutional ownership generated by the index reconstitution from 1997 to 2006.

[Insert Figure 1 here]

My underlying assumption is that (monitoring) institutional ownership varies around the Russell index threshold because of mechanical weighting differences that are orthogonal to firm characteristics. To satisfy this assumption, assignment to an index cannot be based on innovation or any determinant of corporate innovation outside of its effect on index inclusion. However, it is clear that large firms have corporate policies different from small firms, and index assignment is based on firm size. Thus, we need to focus only on variation in a neighborhood close to the threshold in which firms are similar enough so that the variation in institutional ownership is plausibly exogenous to the innovation variables under study. Essentially, I am employing an IV estimation using firms around the Russell 1000/2000 cutoff. Specifically, I use as an instrument a binary treatment variable, Russell 2000, that represents inclusion in the Russell 2000. Being included in the Russell 2000 could affect all firms' weights and relative importance to the institutions that hold them. Hence, my instrument satisfies the relevance condition because index inclusion is correlated with changes in monitoring institutions. Moreover, variations in index membership are random at the threshold when controlling for differences in the control variables in Equation (3). In this setting, my instrument satisfies the exclusion restriction because the change in total ownership of monitoring institutions is random conditional on changes in market capitalization. Table 4 reports the instrumental variable analysis results. Panel A — D respectively reports estimation results for one of the bandwidths (±600, ±500, ±400, and ±350). As shown in the first stage of each panel, R2000 is significantly and negatively associated with total ownership of monitoring institutions. That is, being included in R2000 (instead of R1000) reduces monitoring ownership, or in other words, more institutions monitor the R1000 firms than the R2000 firms. This finding is consistent with Fich, Harford, and Tran (2015), who find that a firm exhibits a decline of about one monitoring institution upon switching from the Russell 1000 in year t-1 to the Russell 2000 in year t.

In the second stage of each panel (except Panel D), the coefficients for total ownership of monitoring institutions are all positive and statistically significant. This finding suggests that firms that become a top holding in an institution's portfolio (due to the Russell index reconstitution) secure more and higher quality innovation outputs. This result also indicates that these monitoring investors are responsible for the higher levels of patent success and, therefore, mitigates the concern of reverse causality. My IV analyses suggest that an exogenous shock to an institution's portfolio weights possibly induce the institutions to monitor portfolio positions that experience an increase in weight. I apply a similar empirical procedure to instrument for the proportion of monitoring institutions as well as for the number of monitoring institutions, and find similar results (untabulated). Taken together, the results uphold the hypothesis that institutional monitoring, and thus innovation, increases in portfolio weights.

[Insert Table 4 here]

4.2 Cross-industry diversification and corporate innovation

As shown above, portfolio concentration could enhance invested firms' innovation performance through institutional monitoring. On the other hand, portfolio diversification may also foster corporate innovation by encouraging risk-taking. Indeed, Faccio, Marchica, and Mura (2011) find strong statistical evidence that firms controlled by well-diversified large shareholders pursue riskier investment opportunities than firms controlled by nondiversified large shareholders. However, same-industry diversification does not reduce portfolio risk by too much because of the high correlation between returns of stocks in the same industry. In fact, same-industry diversification could generate anti-competitive common ownership (Azar, Schmalz, and Tecu, 2016), which might hurt innovation, a key lever that firms pull to compete. Therefore, it is necessary to investigate cross-industry diversification and same-industry diversification separately. As such, this section examines the effect of cross-industry diversification on corporate innovation, while next section looks into the relation of same-industry diversification and patent success.

4.2.1 Baseline regression results

To analyze the impact of monitoring institutions' portfolio diversification across industries on corporate innovation, I use the following model specification.

$$Ln(1 + Innovation_{i,t}) = \alpha + \beta Monitor\ Diversification_{i,t-1} + \gamma X_{i,t-1} + \delta Industry_{i,t} + \theta Year_t + \varepsilon_{i,t} \quad (5)$$

Monitor Diversification is one of the three proxies for cross-industry diversification of the monitoring institutions in a firm defined above in Section 3, similar to the proxies used in Faccio, Marchica, and Mura (2011). I make the following adjustments to suit my setting: (1) They look at the diversification of the largest shareholder of a firm, while I study the diversification of the monitoring institutions of a firm; (2) those authors define diversification in terms of stock holdings at the firm level, while I define diversification in terms of stock holdings at the industry level, considering possible common ownership within industries. Specifically, *Ln No. Industries* is the natural log of the average number of four-digit SIC industries in which a company's monitoring institutions hold shares in a given year. *The Herfindhal Index* is the averaged sum of the squared values of the weight that each investment has in a monitoring institution's portfolio, $\frac{1}{M}\sum_{j=1}^{J}\omega_{ij}^{2}$. *-Correlation* is the averaged correlation of the stock returns of a firm's industry with the shareholder's overall portfolio returns multiplied by -1. All other variables are the same as those in regression equation (3).

Table 5 reports the regression results. For all specifications, the results indicate that cross-industry diversification is positively and significantly related to firm innovation. All coefficients on the cross-industry diversification variables are positive, with p-values of less than 10%. These results suggest that well-diversified monitoring institutions are able to increase the quantity and quality of firm innovation outputs.

The economic impact of institutional cross-industry diversification on corporate innovation is important. Take the number of patents as an example. On average, an increase of Ln No. Industries from the first to the second quartile of the distribution results in a 14.4% increase in patent counts relative to its mean. To compute this economic impact, I first multiply the interquartile range, 0.058, of Ln No. Industries (from Table 1) by the coefficient, 2.245, of Ln No. Industries in regression (4). Because the dependent variable is in logarithm, I use the calculation, (1+27)×(exp(0.058×2.245)-1)=3.89, to obtain the increase in the dependent variable, patent count (raw), associated with an increase in Ln No. Industries from the first to the second quartile of the distribution. I then compare this increase in patent count to the average patent count across firms, 27. This comparison indicates that an increase in Ln. No. Firms from the first to the second quartile of the distribution results in a 14.4% (3.89/27) increase in patent count relative to the cross-sectional mean of patent counts. Similarly, an increase in (1-Herfindhal Index) and -Correlation from the first to the second quartile is associated with a 1.2% and 122%, respectively, increase in the patent citation (adjusted) and citations per patent (adjusted) relative to their means.

[Insert Table 5 here]

4.2.2 Identification

An endogeneity concern is self-selection. More diversified institutions could select innovative industries because they are more immune to industry-specific risks inherent in R&D projects, rather than directly affecting these firms' innovation. Another possible endogeneity concern relates to the direction of causality in my results. For example, institutions planning to invest in innovative firms would, as a result, adjust the structure of their holdings in order to increase portfolio diversification. To address these issues, I utilize an instrumental variables technique. In this test, I extract the exogenous component of institutional diversification by constructing an instrumental variable (IV) that captures the "natural" tendency to diversify across all monitoring institutions who are involved in similar types of activities. For this purpose, I follow Laeven and Levine (2007, 2009) and Faccio, Marchica, and Mura (2011) and calculate, for each firm, the average portfolio diversification of monitoring institutions across all other industries than the one to which the firm belongs. This variable is then employed as an IV for each monitoring institution's degree of cross-industry portfolio diversification.

In the first-stage regressions, I use all exogenous variables along with the "natural" degree of portfolio diversification for each company's monitoring institutions' average diversification choice. In Table 6, I only report the coefficient and the p-value for the IV. In the second stage, I employ the predicted value of an average monitoring institution's degree of cross-industry portfolio diversification. The IV estimates are consistent under the assumption that the IVs are correlated with the endogenous variable but have no direct or indirect effect on the outcome in question. To evaluate the relevance of my IV, I calculate the F-statistic and the partial R^2 on the instruments in the first-stage regression. As shown in the first column of Table 6, the "natural" degree of cross-industry portfolio diversification is highly correlated with the endogenous variable with an F-statistic of 509 and a partial R^2 of 0.78[26]. In the second and third IV specifications, I report an F-statistic of 29 and 1,153, respectively, and a partial R^2 of 0.09 and 0.80, respectively. These results mitigate possible concerns that my coefficient estimators suffer from biases partly due to weak instruments. Moreover, with each IV, the (second-stage)

[26] As a rule of thumb, an F-statistic below 10 is suggestive of a weak instrument (Staiger and Stock, 1997).

regression results continue to indicate more innovation among firms monitored by well-diversified institutional investors.

[Insert Table 6 here]

4.3 Same-industry common ownership and corporate innovation

The pro-innovation effect of cross-industry portfolio diversification may not apply to same-industry portfolio diversification. The reason is that pervasive diversification within industries often creates common ownership, which refers to the phenomenon that firms are commonly owned by the same set of investors. Common ownership of natural competitors reduces incentives to compete since the market share gains from aggressive competition come at the expense of the same investors' other commonly owned firms (Azar, Schmalz, and Tecu, 2016)[27]. In fact, same-industry common ownership could impede corporate innovation due to less needs for market competition. Empirical evidence from recent literature shows a negative relation between industry concentration and corporate innovation (Hou and Robinson, 2006). Hence, it warrants an investigation into common ownership. I first use OLS to test the effect of common ownership on patenting success and then address endogeneity issues.

4.3.1 Baseline regression results

Following Azar, Schmalz, and Tecu (2016), I use the MHHI delta, as defined in Chapter II-2, to measure common ownership and run first-difference models by using the same set of control variables in the Equation (3). Table 7 reports the results. The first three columns use innovation output measures as dependent variables. Results show that the change of common ownership is negatively and statistically significantly related with changes of patent counts, patent citations, and citations per patent. The loadings are -0.006 (t=-3.30), -0.006 (-2.69), and -0.002 (-2.32), respectively. The fourth column tests how innovation input (R&D intensity)

[27] By examining the US airline industry, those authors find that common ownership increases ticket prices through reducing product market competition.

changes with common ownership. Commonly-owned firms could cut R&D due to less threat from product market competition. And this decline of R&D can in turn reduce product market competition. It is known that R&D generates at least two distinct types of “spillover” effects. The first is technology (or knowledge) spillovers, which may increase the productivity of other firms that operate in similar technology areas. The second type of spillover is the product market rivalry effect of R&D, which has a negative effect on a firm’s value due to business stealing. So, commonly-owned firms may see a negative relation between common ownership and R&D expenditure. Consistent with this prediction, I find a negative and statistically significant relation in the fourth test, with a coefficient estimate of -0.001 (t=-2.80). So far, the evidence suggests that commonly-owned firms secure less and lower-quality patents and cut R&D expenditures due to less market competition.

[Insert Table 7here]

As a robustness test, I consider alternative measures of common ownership proposed by He and Huang (2014). Specifically, I construct seven measures of common ownership, as defined again in Chapter II-2. I then run OLS regressions to test their effects on corporate innovation output measures. Results are reported in Table 8. The results are generally consistent with those in Table 7 and confirm that common ownership is negatively associated with firm patent success.

[Insert Table 8 here]

4.3.2 Identification

To address reverse causality and other endogeneity concerns, I exploit a plausibly exogenous change in MHHIs. On June 23, 2005, Legg Mason agreed to acquire Citi Group's asset management business for $3.7 billion. This helped the transition of the Baltimore-based Legg Mason from a small regional brokerage firm into a money-management giant, making it the world's fifth-largest. The acquisition was announced on June 24, 2005 and was formally completed on December 1, 2005. This event changed common ownership across firms, but happened for reasons unrelated to developments in corporate innovation, and therefore can be used for the difference-in-differences (DiD) analyses. I use 2002-2004 as the pre-period and 2006-2008 as the post-period.

I start by calculating the MHHI delta in the pre-period. I then calculate a counterfactual MHHI delta for the same period with the only difference being that I treat the holdings of Legg Mason and Citi Asset Management as if they had been held by a single entity already. Notice that neither a hypothetical merger of two equity portfolios nor any other transfer of ownership affects market shares and thus the traditional HHI measure of market concentration. I call the difference between the latter MHHI delta and the former MHHI delta the "implied change in the MHHI delta." I conduct a DiD analysis based on this implied change in MHHI delta. The reason for doing this is that between the pre- and post-periods, many changes can occur in portfolios and market shares, some of which might be endogenous. The sum of these changes constitutes the actual change in the MHHI delta. I intend to use only variation that is not endogenous. If the Legg Mason acquisition were the only change, the actual change in the MHHI delta would be exactly the same as the implied change. If other changes are small relative to the Legg Mason acquisition, it will not be exactly the same, but the correlation between the two will be high, resulting in a strong instrument. Untabulated results show that the implied change in the MHHI delta is in fact a strong predictor of the actual changes in the MHHI delta. Thus, we can think of the implied change in the MHHI delta as a "treatment" variable, which measures a given firm's level of exposure to the acquisition event.

In a discrete-treatment version, I divide firms into terciles according to their implied changes in their MHHI deltas. I assign firms in the top tercile to the treatment group, and firms in the bottom tercile to the control group. In a continuous-treatment version, I use the implied change in MHHI delta as a continuous treatment variable. The relative benefit of the discrete-treatment specification is that it might alleviate concerns related to measurement error and is easier to understand and graphically illustrate, whereas the benefit of the continuous-treatment version is that it makes use of more variation. I use the treatment status interacted with a post-period indicator as the key explanatory variable to run OLS regressions.

Table 9 reports the DiD analyses results. In both the discrete and continuous treatment versions, the coefficients on the interaction terms are negative and statistically significant. Along with the OLS regressions, the DiD analyses support a negative causal relation running from common ownership to corporate innovation.

The DiD methodology is based on the assumption of a parallel trend. That is, the difference between treated and controls (i.e. unobserved characteristics that create the gap) stays stable over time. In other words, unobserved characteristics do not vary over time with treatment status. To test for a parallel pre-event trend in outcome variables, I run regressions of the innovation output measures on the treatment variable, time dummies for all pre-event periods except the event year, their interactions, and all the control variables used in my baseline regressions, using pre-event data only. If the trends do not parallel, at least one of the coefficients on the interaction terms would be statistically significant in these placebo tests. Table 10 reports the results. All estimates on the interaction terms are not significantly different from zero. While the identification assumption is fundamentally untestable since we do not observe the counterfactual of Citi Asset Management not having been acquired, my test results suggest that the parallel trend assumption is likely to hold.

[Insert Table 9 here]

Chapter II-5: Conclusion

Certain ownership structure could provide incentives or disincentives for managers to take risks and compete. This paper tests how ownership structure affects corporate innovation. Prior literature documents a positive effect that the fraction of the firm held by institutional investors have on corporate innovation. I focus on the fraction of the institution's portfolio represented by the firm and find that institutions' portfolio weights positively affect patent success. Nonetheless, it is important to distinguish between cross-industry and same-industry institutional multiple holdings. I provide evidence that the former fuels innovation, while the latter, if they create common ownership, impedes innovation. This is consistent with the anti-competitive consequence of common ownership documented by recent literature.

The findings above suggest that it is important to not generalize the impact of ownership structure on corporate innovation. Portfolio concentration and diversification can both foster innovation through different channels. More concentrated holdings deserve more attention and monitoring from the institutional investors, thereby helping the portfolio companies overcome managerial myopia and agency problems that are detrimental to corporate innovation. In contrast, portfolio diversification makes it possible for institutional owners to acquiesce in the risk-taking that is crucial for innovative success. However, this is true only for cross-industry diversification. When it comes to same-industry diversification, the anti-competitive and anti-innovative effect of common ownership often dominates, leading to less innovation.

These conclusions have important policy implications. Based on their finding of the anti-competition nature of common ownership, Azar, Schmalz, and Tecu (2016) argue that there exists a policy "trilemma." That is, the three goals of (i) perfect shareholder diversification, (ii) firms' maximization of shareholder interests, and (iii) preservation of competitive product markets cannot be simultaneously achieved. This paper echoes their argument by showing that as long as the diversification is across industries, product market competition will not be subotaged; on the contrary, such diversification is instrumental in facilitating firm innovation, which presumably can in turn enhance product market competition. What policy makers, i.e., the Federal Trade Commission and the U.S. Department of Justice (DOJ) Antitrust Division, need to guard against is the same-industry diversification because it could suppress benign competition and thus corporate innovation.

Appendix. Variable Definitions

Variable	Definition
Innovation Variables:	
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 (CPP)	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.
Portfolio Concentration Variables:	
Number of monitoring institutions	Number of monitoring institutions, i.e., the number of institutions whose holding value in the firm is in the top 10% of the institution's portfolio.
Total ownership of monitoring institutions	Total ownership of monitoring institutions, i.e., the total ownership of monitoring institutions as a proportion of the firm's total shares outstanding.
Proportion of monitoring institutions	The proportion of monitoring institutions among all institutions holding the firm's shares.
Innovation Efficiency Variables:	
Prd	Number of patent counts scaled by R&D capital (Prd). R&D capital is defined as the weighted average of R&D expenditures over the last five years with an annual depreciation rate of 20%.

Appendix. (Continued) Variable Definitions

Variable	Definition
Crd	Number of patent citations scaled by R&D capital (Crd). R&D capital is defined as the weighted average of R&D expenditures over the last five years with an annual depreciation rate of 20%. See Equation (4).
Cross-Industry Diversification Measures:	
Ln No.Industries -	The (natural log of the) number of four-digit industries in which the monitoring institutions holds shares.
H(Holdings)	The Herfindhal Index of stockholding concentration, computed as the sum of (holding of a particular stock/total holdings of the portfolio)^2, with holdings measured in dollar value.
Correlation	The correlation of the stock returns of a firm's industry with the largest institutional investor's overall portfolio returns.
Same-Industry Common Ownership Variables:	
H(Market Shares)	The Herfindhal Index of market shares.
MHHI delta	A measure of the anti-competitive incentives due to interlocking shareholdings, computed based on Equation (2).
Implied change of MHHI delta	The difference between a counterfactual MHHI delta and the actual MHHI delta. The counterfactual MHHI delta was calculated as if two merged firms had been held by a single entity already before the merger.
CommonDummy	A dummy variable that equals 1 if the firm is commonly-held in any of the four quarters prior to the fiscal year end, and 0 otherwise.
Ln NumCommon	The natural logarithm of one plus the average number of unique institutions that cross-hold the firm in the four quarters prior to the fiscal year end. This measure captures the extent to which a firm is connected to other same-industry peers through common ownership.

Appendix. (Continued) Variable Definitions

Variable	Definition
AvgNum	The average percentage holding in same-industry peers block-held by the average common-holding institution. More specifically, I first calculate the average percentage holding in same-industry firms (other than the one under consideration) block-held by each common-holding institution during the four quarters prior to the fiscal year end and then average across all such institutions. This measure captures the intensity of common-holding activities for the average institution.
AvgPercent	The average number of same-industry peers block-held by the average common-holding institution.
Total Common Ownership	The sum of all common-holding institutions' average percentage holdings in the firm itself. This measure captures the total power of common-holding institutions to influence firm management if they have similar goals.
FracPosChgPercent	The fraction of the firm's common-holding institutions whose average percentage block holding in other same-industry peers is higher than that in the previous year.
FracPosChgNum	The fraction of the firm's common-holding institutions whose average number of other same-industry common-holdings is higher than that in the previous year. The last two measures capture the incentives of the average common-holding institution to exert influence.
Control Variables:	
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.

Appendix. (Continued) Variable Definitions

Variable	Definition
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.

Table II-1. Summary Statistics

This table presents the summary statistics for firms that belong to the samples. Variables are defined in Appendix.

Variable	Mean	Median	Interquartile range	Min.	Max.	N
Innovation Variables:						
Patent counts (raw)	27	0	11	0	5,020	11,007
Patent citations (adj.)	32	0	11	0	5772	11,007
Cites per patent	1	0	1	0	14	11,007
logNPAT	1.345	0	2.485	0	8.521	11,007
logCites	1.341	0	2.521	0	8.661	11,007
logCitesPerPatent	0.349	0	0.662	0	2.692	11,007
Innovation Efficiency Variables:						
Prd	0.743	0.131	0.805	0	75.855	6,859
Crd	0.915	0.095	0.810	0	104.758	6,859
Portfolio Concentration Variables:						
Total ownership of monitoring institutions	0.2229	0.1723	0.2386	0.0001	0.9998	9,609
Proportion of monitoring institutions	0.06	0.04	0.06	0	1	11,007
Number of monitoring institutions	17	4	12	0	709	11,007
Cross-Industry Diversification Measures:						
No.Industries	66,052	19,074	53,532	12	1,326,600	9,514
Ln No.Industries	9.849	9.856	2.245	2.485	14.098	9,514
1-H(Holdings)	-0.153	0.239	0.874	-132.957	0.968	9,154
-Correlation	-0.496	-0.495	0.173	-1.000	0.130	9,514

Table II-1. (Continued) Summary Statistics

Variable	Mean	Median	Interquartile range	Min.	Max.	N
Same-Industry Common Ownership Variables:						
H(Market Shares)	0.014	0.007	0.011	0	1	58,867
MHHI delta (%)	12.531	12.501	6.876	0	60.821	58,867
Implied change of MHHI delta	0.077	0.026	0.031	-0.027	1.306	5,015
CommonDummy	0.557	1	1	0	1	10,778
Ln NumCommon	0.741	0.875	1.386	0	4.615	10,778
AvgNum	2.261	1.143	3.450	0	40.281	10,778
AvgPercent	0.057	0.076	0.089	0	15.998	10,778
Total Common Ownership	0.208	0.135	0.337	0	55.955	10,778
FracPosChgPercent	0.105	0	0	0	1	10,294
FracPosChgNum	0.134	0	0	0	1	10,778
Control Variables:						
Total ownership of blockholders	0.225	0.205	0.171	0.050	0.994	10,268
R&D intensity	0.06	0.03	0.08	0	0.64	10,931
Ln(Assets)	6.698	6.617	2.117	1.410	11.401	11,007
Ln(Firm Age)	2.681	2.639	1.217	0.693	4.357	11,007
Ln(PPE/#employees)	3.690	3.606	1.188	0.914	6.558	10,963
Ln(Sales/#employees)	5.3534	5.3533	0.7675	2.9039	7.4108	10,956
Sales growth	0.1290	0.0896	0.2031	-0.6341	2.0265	11,005
ROA	0.1191	0.1337	0.1046	-0.9331	0.3816	10,997
M/B	1.732	1.276	1.380	0.089	9.591	11,007
Leverage	0.1844	0.1555	0.2792	0	0.8751	10,982
Cash/Assets	0.1260	0.0836	0.1486	0.0005	0.7090	10,981
Stock return	0.1963	0.1009	0.5551	-0.7967	4.0877	11,007
Stock volatility	0.0307	0.0274	0.0099	0.0102	0.1212	11,007

Table II-2. Institutional Monitoring and Corporate Innovation

This table reports the effect of firms' institutional monitoring on corporate innovation output by running OLS regressions. Models 1-3 correspond to a different measure of institutional ownership of monitoring institutions. Variable definitions are in Appendix. Coefficients are reported with the t-statistics in parentheses. The symbols ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	Ln(1+Patents)			Ln(1+Citations)			Ln(1+CitationsPerPatent)		
	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
Total ownership of monitoring institutions	0.492*** (2.59)			0.556*** (2.82)			0.054* (1.89)		
Proportion of monitoring institutions		2.033*** (4.03)			2.167*** (4.14)			0.315*** (3.27)	
Number of monitoring institutions			0.003*** (3.40)			0.003*** (3.46)			-0.001 (-1.08)
Total ownership of blockholders	-0.177 (-1.14)	-0.124 (-1.11)	-0.051 (-0.46)	-0.227 (-1.41)	-0.150 (-1.27)	-0.075 (-0.64)	-0.017 (-0.59)	-0.195*** (-6.05)	0.026 (0.82)
R&D intensity	3.614*** (9.01)	2.466*** (10.07)	2.424*** (9.87)	3.651*** (8.56)	2.543*** (9.56)	2.500*** (9.38)	0.651*** (9.21)	0.693*** (9.10)	0.603*** (8.52)
Ln(Assets)	0.515*** (19.71)	0.429*** (22.47)	0.440*** (21.56)	0.513*** (18.70)	0.429*** (21.48)	0.442*** (20.75)	0.064*** (17.22)	0.047*** (11.37)	0.072*** (18.33)
Ln(Firm Age)	0.119*** (3.57)	0.118*** (4.65)	0.115*** (4.53)	0.102*** (2.93)	0.106*** (3.99)	0.103*** (3.89)	0.004 (0.89)	-0.017*** (-2.67)	0.007 (1.15)
Ln(PPE/#employees)	0.117*** (3.06)	0.105*** (3.95)	0.106*** (3.95)	0.117*** (2.82)	0.109*** (3.74)	0.110*** (3.75)	0.027*** (5.09)	0.041*** (5.43)	0.033*** (4.50)
Ln(Sales/#employees)	0.001 (0.01)	0.027 (0.81)	0.028 (0.85)	0.008 (0.16)	0.027 (0.76)	0.028 (0.80)	0.005 (0.75)	-0.060*** (-6.74)	0.004 (0.48)
Sales growth	-0.169*** (-3.58)	-0.097*** (-3.00)	-0.083*** (-2.59)	-0.143*** (-2.76)	-0.061* (-1.72)	-0.047 (-1.31)	0.003 (0.22)	0.019* (1.67)	0.022** (2.06)

Table II-2. (Continued) Institutional Monitoring and Corporate Innovation

	Ln(1+Patents)			Ln(1+Citations)			Ln(1+CitationsPerPatent)		
	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
ROA	0.169 (0.77)	0.026 (0.20)	0.029 (0.23)	0.203 (0.88)	0.046 (0.34)	0.049 (0.36)	0.040 (1.06)	0.203*** (5.57)	0.024 (0.69)
M/B	0.001*** (4.20)	0.001*** (6.41)	0.001*** (7.51)	0.001*** (4.44)	0.001*** (6.79)	0.001*** (7.94)	0.001*** (6.47)	0.001*** (7.36)	0.001*** (9.13)
Leverage	-0.565*** (-3.99)	-0.411*** (-4.15)	-0.402*** (-4.07)	-0.579*** (-3.94)	-0.405*** (-3.87)	-0.397*** (-3.80)	-0.079*** (-3.51)	-0.001 (-0.05)	-0.057** (-2.08)
Cash/Assets	0.201 (1.26)	0.164 (1.53)	0.171 (1.60)	0.203 (1.20)	0.185 (1.64)	0.192* (1.70)	0.066* (1.92)	-0.063* (-1.81)	0.062* (1.88)
Stock return	0.043** (2.18)	0.064*** (5.62)	0.062*** (5.49)	0.059*** (2.76)	0.077*** (6.08)	0.075*** (5.96)	0.013** (2.14)	0.009** (2.30)	0.020*** (4.94)
Stock volatility	6.052*** (3.59)	3.347*** (3.74)	3.238*** (3.58)	7.086*** (3.90)	3.750*** (3.88)	3.655*** (3.74)	0.655** (2.12)	-.0708*** (-3.26)	-0.022 (-0.09)
Industry fixed effects	Y	Y	Y	Y	Y	Y	Y	Y	Y
Year fixed effects	Y	Y	Y	Y	Y	Y	Y	Y	Y
Standard errors adjusted for heteroskedasticity	Y	Y	Y	Y	Y	Y	Y	Y	Y
Standard errors adjusted for clustering at the firm level	Y	Y	Y	Y	Y	Y	N	Y	Y
N/(Pseudo) R-squared	11,007/0.52	17,904/0.48	17,904/0.48	11,007/0.49	17,904/0.45	17,904/0.45	11,007/0.34	17,904/0.22	17,904/0.30

Table II-3. Effect of Institutional Monitoring on Innovation Efficiency

The table reports the OLS regression results of innovation efficiency on Institutional monitoring. Variable definitions are in Appendix. Coefficients are reported with the t-statistics in parentheses. The symbols ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	Prd	Crd
Total ownership of monitoring institutions	0.709** (2.18)	1.119** (2.58)
Total ownership of blockholders	0.120 (0.55)	0.223 (0.58)
Ln(Assets)	-0.121** (-1.97)	-0.198** (-2.42)
Ln(Firm Age)	-0.047 (-0.97)	-0.149** (-2.11)
Ln(PPE/#employees)	0.188*** (3.11)	0.329*** (2.64)
Ln(Sales/#employees)	-0.127* (-1.68)	-0.268** (-2.42)
Sales growth	0.054 (0.58)	0.200 (1.65)
ROA	0.394 (1.44)	0.502 (1.10)
M/B	-0.001 (-0.59)	0.001 (0.23)
Leverage	0.448 (1.51)	0.188 (0.53)
Cash/Assets	-0.558*** (-2.65)	-0.774** (-2.27)
Stock return	0.002 (0.03)	0.110 (1.43)
Stock volatility	-1.268 (-0.44)	-1.852 (-0.36)
Industry fixed effects	Y	Y
Year fixed effects	Y	Y
Standard errors adjusted for heteroskedasticity	Y	Y
Standard errors adjusted for clustering at the firm level	Y	Y
N/(Pseudo) R-squared	6,859/0.11	6,859/0.09

Table II-4. Regression Discontinuity Design

This table addresses the endogeneity of institutional monitoring and corporate innovation using a regression discontinuity approach in the context of an instrumental variable (IV) estimation around index reconstitutions. The first stage only reports the coefficients for the instrumental variable, Russell 2000; control variables are included but coefficients are not reported. Panel A/B/C/D presents estimates calculated over ±600/±500/±400/±350 ranks from the threshold, respectively. The estimation is performed using a two-stage least squares. First-stage control variable estimates are suppressed for brevity. Coefficients are reported with the t-statistics in parentheses. The symbols ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Panel A. Band=600

First stage	Total ownership of monitoring institutions		
Russell 2000	-0.023***		
	(-3.29)		
Second stage	Ln(1+Patents)	Ln(1+Citations)	Ln(1+CitationsPerPatent)
Total ownership of monitoring institutions	8.917*	9.840*	2.955**
	(1.91)	(1.96)	(2.19)
Total ownership of blockholders	-4.247*	-4.891**	-1.506**
	(-1.94)	(-2.08)	(-2.38)
R&D intensity	8.586***	7.992***	0.457
	(7.40)	(6.62)	(1.58)
Ln(Assets)	-0.391	-0.518	-0.295*
	(-0.72)	(-0.89)	(-1.90)
Ln(Firm Age)	0.145**	0.143**	0.037**
	(2.51)	(2.32)	(2.30)
Ln(PPE/#employees)	0.276***	0.308***	0.073***
	(3.11)	(3.19)	(2.67)
Ln(Sales/#employees)	-0.094	-0.053	0.015
	(-1.20)	(-0.62)	(0.66)

Table II-4. (Continued) Regression Discontinuity Design

Panel A (Continued): Band=600

Second stage	Ln(1+Patents)	Ln(1+Citations)	Ln(1+CitationsPerPatent)
Sales growth	-0.323*	-0.369*	-0.096*
	(-1.73)	(-1.86)	(-1.84)
ROA	-1.557	-1.906	-1.009***
	(-1.15)	(-1.32)	(-2.61)
M/B	-0.001	-0.001	-0.001
	(-1.59)	(-1.60)	(-1.63)
Leverage	-0.684**	-0.645**	-0.045
	(-2.24)	(-2.08)	(-0.59)
Cash/Assets	-0.550	-0.539	-0.190
	(-0.93)	(-0.85)	(-1.11)
Stock return	0.110	0.137	0.042
	(0.82)	(0.96)	(1.13)
Stock volatility	1.555	4.453	1.805
	(0.27)	(0.72)	(1.12)
Industry fixed effects	Y	Y	Y
Year fixed effects	Y	Y	Y
Standard errors adjusted for heteroskedasticity	Y	Y	Y
N/(Pseudo) R-squared	1,794/Omitted	1,794/0.15	1,794/Omitted

Panel B. Band=500

First stage	Total ownership of monitoring institutions		
Russell 2000	-0.026***		
	(-3.66)		
Second stage	Ln(1+Patents)	Ln(1+Citations)	Ln(1+CitationsPerPatent)
Total ownership of monitoring institutions	8.221**	8.783**	1.992**
	(2.01)	(2.02)	(2.19)
Total ownership of blockholders	-4.136**	-4.641**	-1.074**
	(-2.08)	(-2.20)	(-2.13)
R&D intensity	8.450***	7.928***	0.691**
	(7.44)	(6.69)	(2.58)

Table II-4. (Continued) Regression Discontinuity Design

Panel B (Continued): Band=500

Second stage	Ln(1+Patents)	Ln(1+Citations)	Ln(1+CitationsPerPatent)
Ln(Assets)	-0.255	-0.321	-0.150
	(-0.61)	(-0.72)	(-1.44)
Ln(Firm Age)	0.137**	0.136**	0.033**
	(2.24)	(2.12)	(2.25)
Ln(PPE/#employees)	0.243***	0.272***	0.049**
	(3.16)	(3.30)	(2.24)
Ln(Sales/#employees)	-0.081	-0.052	0.008
	(-1.01)	(-0.59)	(0.39)
Sales growth	-0.342*	-0.378*	-0.077
	(-1.78)	(-1.87)	(-1.59)
ROA	-1.193	-1.393	-0.658**
	(-1.04)	(-1.15)	(-2.28)
M/B	-0.001*	-0.001*	-0.001
	(-1.74)	(-1.70)	(-1.25)
Leverage	-0.574*	-0.531*	-0.037
	(-1.82)	(-1.68)	(-0.53)
Cash/Assets	-0.479	-0.345	-0.056
	(-0.79)	(-0.54)	(-0.36)
Stock return	0.104	0.138	0.034
	(0.78)	(0.98)	(1.03)
Stock volatility	5.303	7.341	1.713
	(0.95)	(1.21)	(1.20)
Industry fixed effects	Y	Y	Y
Year fixed effects	Y	Y	Y
Standard errors adjusted for heteroskedasticity	Y	Y	Y
N/Adj. R-squared	1,542/0.25	1,542/0.38	1,542/0.15

Panel C. Band=400

First stage	Total ownership of monitoring institutions
Russell 2000	-0.026***
	(-3.48)

Table II-4. (Continued) Regression Discontinuity Design

Panel C (Continued): Band=400

Second stage	Ln(1+Patents)	Ln(1+Citations)	Ln(1+CitationsPerPatent)
Total ownership of monitoring institutions	8.605*	9.927**	2.620**
	(1.90)	(2.01)	(2.12)
Total ownership of blockholders	-4.372**	-5.203**	-1.326**
	(-1.99)	(-2.18)	(-2.22)
R&D intensity	8.592***	8.171***	0.737**
	(6.95)	(6.19)	(2.42)
Ln(Assets)	-0.203	-0.314	-0.173*
	(-0.48)	(-0.69)	(-1.54)
Ln(Firm Age)	0.141*	0.135*	0.028
	(1.88)	(1.66)	(1.35)
Ln(PPE/#employees)	0.283***	0.318***	0.063**
	(3.30)	(3.40)	(2.43)
Ln(Sales/#employees)	-0.088	-0.062	0.005
	(-0.97)	(-0.61)	(0.19)
Sales growth	-0.307	-0.386*	-0.096*
	(-1.45)	(-1.69)	(-1.84)
ROA	-1.070	-1.346	-0.681**
	(-0.85)	(-0.99)	(-2.03)
M/B	-0.001	-0.001*	-0.001
	(-1.61)	(-1.68)	(-0.79)
Leverage	-0.731**	-0.684*	-0.069
	(-1.98)	(-1.81)	(-0.79)
Cash/Assets	-0.070	0.018	-0.023
	(-0.11)	(0.03)	(-0.13)
Stock return	0.171	0.224	0.056
	(1.15)	(1.41)	(1.42)
Stock volatility	5.126	7.408	1.758
	(0.80)	(1.05)	(1.03)
Industry fixed effects	Y	Y	Y
Year fixed effects	Y	Y	Y
Standard errors adjusted for heteroskedasticity	Y	Y	Y
N/Adj. R-squared	1,252/0.25	1,252/0.18	1,252/0.36

Table II-4. (Continued) Regression Discontinuity Design

Panel D. Band=350

First stage	Total ownership of monitoring institutions		
Russell 2000	-0.025***		
	(-3.25)		
Second stage	Ln(1+Patents)	Ln(1+Citations)	Ln(1+CitationsPerPatent)
Total ownership of monitoring institutions	8.879	8.071	2.620**
	(1.50)	(1.64)	(2.12)
Total ownership of blockholders	-3.540	-4.259*	-1.326**
	(-1.58)	(-1.76)	(-2.22)
R&D intensity	8.930***	8.444***	0.737**
	(7.13)	(6.19)	(2.42)
Ln(Assets)	-0.047	-0.156	-0.173
	(-0.12)	(-0.37)	(-1.54)
Ln(Firm Age)	0.123*	0.121	0.028
	(1.66)	(1.51)	(1.35)
Ln(PPE/#employees)	0.290***	0.333***	0.063**
	(3.36)	(3.56)	(2.43)
Ln(Sales/#employees)	-0.155*	-0.145	0.005
	(-1.72)	(-1.45)	(0.19)
Sales growth	-0.301	-0.386*	-0.096*
	(-1.32)	(-1.69)	(-1.84)
ROA	-0.847	-1.346	-0.681**
	(-0.67)	(-0.99)	(-2.03)
M/B	-0.001	-0.001*	-0.001
	(-1.26)	(-1.68)	(-0.79)
Leverage	-0.616	-0.684*	-0.069
	(-1.63)	(-1.81)	(-0.79)
Cash/Assets	0.294	0.018	-0.023
	(0.41)	(0.03)	(-0.13)
Stock return	0.173	0.224	0.056
	(1.19)	(1.41)	(1.42)
Stock volatility	7.886	7.408	1.758
	(1.22)	(1.05)	(1.03)
Industry fixed effects	Y	Y	Y

Table II-4. (Continued) Regression Discontinuity Design

Panel D (Continued): Band=350

Second stage	Ln(1+Patents)	Ln(1+Citations)	Ln(1+CitationsPerPatent)
Year fixed effects	Y	Y	Y
Standard errors adjusted for heteroskedasticity	Y	Y	Y
N/R-squared	1,079/0.34	1,079/0.29	1,079/0.07

Table II-5. The Effect of Cross-industry Diversification on Corporate Innovation

This table reports OLS regression results. The dependent variable is the natural log of one of the three innovation output proxies. Ln No. Industries is the natural log of the average number of four-digit SIC industries in which a company's monitoring institutions hold shares in a given year. The Herfindhal Index is the averaged sum of the squared values of the weight that each investment has in a monitoring institution's portfolio, $\frac{1}{M}\sum_{j=1}^{J}\omega_{ij}^{2}$. -Correlation is the averaged correlation of the stock returns of a firm's industry with the shareholder's overall portfolio returns multiplied by -1. Other variables are defined in Appendix Variable Definitions. All tests include year-fixed effects. t-values, adjusted for heteroskedasticity and clustering at the firm level, are reported in brackets below the coefficients. The symbols ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	Ln(1+Patents)			Ln(1+Citations)			Ln(1+CitationsPerPatent)		
	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
Ln No. Industries	0.058**			0.071***			0.019***		
	(2.22)			(2.64)			(2.94)		
1-H(Holdings)		0.013*			0.014*			0.007***	
		(1.89)			(1.89)			(3.60)	
-Correlation			2.757***			2.799***			0.490***
			(20.48)			(19.71)			(15.84)
Total ownership of monitors	0.266	0.385*	0.854***	0.297	0.443**	0.942***	0.004	0.216***	0.160***
	(1.03)	(1.95)	(4.15)	(1.12)	(2.16)	(4.40)	(0.08)	(4.81)	(3.64)
Total ownership of blockholders	-0.226	-0.159	-1.158***	-0.295	-0.231	-1.270***	-0.057	-0.319***	-0.237***
	(-1.11)	(-0.89)	(-6.57)	(-1.40)	(-1.25)	(-6.91)	(-1.15)	(-7.04)	(-5.32)
R&D intensity	7.205***	4.201***	4.581***	7.249***	4.236***	4.647***	1.442***	0.826***	0.821***
	(13.07)	(8.92)	(9.04)	(12.67)	(8.52)	(8.69)	(11.75)	(6.64)	(6.68)

Table II-5. (Continued) The Effect of Cross-industry Diversification on Corporate Innovation

	Ln(1+Patents)			Ln(1+Citations)			Ln(1+CitationsPerPatent)		
	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
Ln(Assets)	0.438***	0.562***	0.423***	0.428***	0.561***	0.416***	0.033***	0.030***	0.037***
	(11.00)	(18.81)	(14.86)	(10.48)	(17.86)	(14.03)	(3.90)	(4.81)	(6.10)
Ln(Firm Age)	0.238***	0.120***	0.062*	0.221***	0.104***	0.044	0.035***	-0.011	-0.007
	(5.51)	(3.26)	(1.65)	(4.94)	(2.70)	(1.12)	(3.70)	(-1.24)	(-0.87)
Ln(PPE/#employees)	0.202***	0.130***	0.174***	0.193***	0.129***	0.174***	0.047***	0.039***	0.033***
	(4.56)	(2.98)	(3.89)	(4.17)	(2.72)	(3.59)	(4.78)	(3.63)	(3.14)
Ln(Sales/#employees)	0.087	-0.020	-0.291***	0.093	-0.012	-0.290***	0.039***	-0.066***	-0.046***
	(1.54)	(-0.36)	(-5.10)	(1.61)	(-0.19)	(-4.79)	(3.06)	(-5.11)	(-3.59)
Sales growth	-0.182***	-0.206***	-0.180***	-0.167**	-0.188***	-0.158**	-0.005	-0.001	-0.001
	(-2.97)	(-3.79)	(-3.03)	(-2.51)	(-3.13)	(-2.45)	(-0.27)	(-0.04)	(-0.08)
ROA	0.708**	0.167	0.809***	0.782	0.219	0.888***	0.103	0.179***	0.141**
	(2.49)	(0.67)	(3.17)	(2.68)	(0.84)	(3.33)	(1.60)	(2.89)	(2.33)
M/B	0.001	0.001***	0.001***	0.001	0.001***	0.001***	0.001	0.001***	0.001***
	(0.28)	(4.18)	(3.02)	(0.36)	(4.35)	(7.94)	(0.57)	(3.47)	(3.42)
Leverage	-0.699***	-0.547***	-0.439**	-0.703***	-0.557***	-0.446**	-0.084**	-0.031	-0.050
	(-3.95)	(-3.41)	(-2.53)	(-3.83)	(-3.35)	(-2.48)	(-2.03)	(-0.07)	(-1.17)
Cash/Assets	0.515**	0.231	-0.265	0.508**	0.228	-0.278	0.120**	-0.081	-0.043
	(2.44)	(1.25)	(-1.38)	(2.30)	(1.17)	(-1.40)	(2.14)	(-1.53)	(-0.83)

Table II-5. (Continued) The Effect of Cross-industry Diversification on Corporate Innovation

	Ln(1+Patents)			Ln(1+Citations)			Ln(1+CitationsPerPatent)		
	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
Stock return	0.032	0.034	-0.038*	0.048	0.049**	0.021	0.006	-0.001	0.007
	(1.16)	(1.50)	(-1.67)	(1.63)	(1.99)	(-0.88)	(0.82)	(-0.22)	(-1.09)
Stock volatility	7.862***	6.741***	6.028***	10.182***	8.688***	7.601***	1.255**	-0.162	1.148***
	(2.87)	(2.98)	(3.50)	(3.50)	(3.57)	(4.14)	(2.06)	(0.37)	(2.65)
Industry fixed effects	N	Y	Y	N	Y	Y	N	Y	Y
Year fixed effects	Y	Y	N	Y	Y	N	Y	N	N
Standard errors adjusted for heteroskedasticity	Y	Y	Y	Y	Y	Y	Y	Y	Y
Standard errors adjusted for clustering at the firm level	Y	Y	Y	Y	Y	Y	Y	Y	Y
N/(Pseudo) R-squared	9,531/0.40	9,531/0.54	9,514/0.44	9,531/0.38	9,531/0.51	9,514/0.42	9,531/0.22	9,531/0.26	9,514/0.28

Table II-6. The Effect of Cross-industry Diversification on Corporate Innovation - Instrumental Variable Regressions

This table reports the results of instrumental variable analysis. In the second stage, each model (numbered 1, 2, and 3) uses the same set of independent variables, with one of the three innovation measures as the dependent variable. Variable definitions can be found in Appendix. In the first stage, Hausman test is the Hausman test of endogeneity for the difference between the OLS and the IV estimators. Coefficients are reported with the t-statistics in parentheses. The symbols ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	Second-stage Regressions								
	Ln(1+Patents)			Ln(1+Citations)			Ln(1+CitationsPerPatent)		
	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
Ln No. Industries (fitted)	1.248***			1.324***			0.307***		
	(3.38)			(3.42)			(3.32)		
1-H(Holdings) (fitted)		0.954***			1.028***			0.218***	
		(3.78)			(3.82)			(3.66)	
-Correlation (fitted)			22.512***			24.355***			2.4333***
			(3.56)			(7.29)			(4.12)
Total ownership of monitors	-2.238**	0.767***	1.126***	-2.353**	0.861***	1.251***	-0.626**	0.135***	0.133***
	(-2.20)	(3.08)	(3.21)	(-2.20)	(3.23)	(5.93)	(-2.45)	(2.29)	(3.32)
Total ownership of blockholders	-0.248	0.027	-0.290***	-0.281	-0.030	-0.374*	0.023	-0.005***	-0.077***
	(-0.57)	(0.13)	(-1.10)	(-0.61)	(-0.13)	(-1.81)	(0.21)	(-0.09)	(-2.06)
R&D intensity	3.375***	8.303***	5.824***	3.368***	8.443***	5.767***	0.526***	1.700***	1.309***
	(6.67)	(13.90)	(8.46)	(6.30)	(13.31)	(11.68)	(3.96)	(12.07)	(13.29)
Ln(Assets)	-0.516*	0.636***	0.593***	-0.578***	0.647***	0.601***	-0.190***	0.082***	0.059***
	(1.96)	(13.06)	(10.51)	(-2.10)	(12.48)	(17.83)	(-2.88)	(7.11)	(10.66)
Ln(Firm Age)	0.001	0.175***	0.2889***	-0.020	0.153***	0.276***	-0.021***	0.021***	0.041***
	(0.03)	(5.78)	(5.69)	(-0.69)	(4.76)	(9.68)	(-3.03)	(2.76)	(7.60)

Table II-6. (Continued) The Effect of Cross-industry Diversification on Corporate Innovation - Instrumental Variables Regressions

	Second-stage Regressions								
	Ln(1+Patents)			Ln(1+Citations)			Ln(1+CitationsPerPatent)		
	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
Ln(PPE/#employees)	0.209***	0.273***	0.285***	0.210***	0.268***	0.282***	0.040***	0.063***	0.055***
	(7.62)	(8.20)	(5.06)	(7.18)	(7.55)	(9.29)	(5.45)	(7.58)	(9.09)
Ln(Sales/#employees)	-0.331***	0.023	0.032	-0.327***	0.024	0.035*	-0.048***	0.025**	0.034***
	(-7.81)	(0.49)	(0.47)	(-7.27)	(0.49)	(0.92)	(-4.28)	(2.22)	(4.77)
Sales growth	-0.332***	-0.115	-0.542***	-0.320***	-0.095	-0.557***	-0.039	0.011	-0.042**
	(-3.93)	(-1.46)	(-3.89)	(-3.53)	(-1.11)	(-5.34)	(-1.71)	(0.54)	(-2.17)
ROA	-0.441	0.075	0.665*	-0.449	0.110	0.744***	-0.182	-0.034	0.116**
	(-0.91)	(0.67)	(1.88)	(-0.88)	(0.36)	(2.90)	(-1.47)	(-0.48)	(2.46)
M/B	-0.001***	0.001***	0.001**	-0.001***	0.001***	0.001***	0.001**	0.001***	0.001***
	(-2.69)	(4.28)	(2.30)	(-2.69)	(4.48)	(3.65)	(-2.53)	(4.21)	(3.13)
Leverage	0.030	-0.593***	-0.154	0.045	-0.593***	-0.114	-0.057	-0.062*	-0.030
	(0.18)	(-4.41)	(-0.60)	(0.26)	(-4.13)	(-0.71)	(1.37)	(-1.80)	(-0.97)
Cash/Assets	-0.619***	0.903***	0.261	-0.642***	0.927***	0.235	-0.113**	0.209***	0.096**
	(-3.73)	(4.72)	(0.88)	(-3.67)	(4.55)	(0.99)	(-2.39)	(4.05)	(2.20)
Stock return	0.082*	0.057	0.083**	0.105**	0.075	0.102**	0.021*	0.011	0.011
	(1.95)	(1.12)	(1.92)	(2.37)	(1.37)	(2.35)	(1.92)	(0.93)	(1.30)
Stock volatility	11.429***	8.760***	-8.897*	13.604***	11.119***	-7.978**	2.888**	1.439**	-0.600
	(2.96)	(3.99)	(-1.73)	(3.35)	(4.72)	(-2.34)	(2.97)	(2.58)	(-0.97)
Industry fixed effects	Y	N	N	Y	N	N	Y	N	N
Year fixed effects	N	Y	Y	N	Y	Y	N	Y	Y
Standard errors adjusted for heteroskedasticity	Y	Y	Y	Y	Y	Y	Y	Y	Y
N	9,531	9,531	9,510	9,531	9,531	9,510	9,531	9,531	9,510

Table II-6. (Continued) The Effect of Cross-industry Diversification on Corporate Innovation - Instrumental Variables Regressions

First-stage regressions:			
IV: Average Ln. No. Industries of other firms in the same four-digit industry	0.084*** (5.84)		
IV: Average wealth concentration of monitoring shareholders of other firms in the same four-digit industry		0.215*** (6.65)	
IV: Average -correlation of monitoring shareholders of other firms in the same four-digit industry			0.242*** (10.76)
Partial R^2 of excluded instruments	0.78	0.09	0.80
F-test of excluded instruments	509	29	1,153
Hausman test (p-values)	0.000	0.000	0.000

Table II-7. Effect of Same-industry Common Ownership (MHHI delta) on Corporate Innovation

This table reports the results of OLS regressions by using the first-difference models with the same set of control variables in the Equation (3). Variable definitions are in Appendix. Coefficients are reported with the t-statistics in parentheses. The symbols ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	Δ Ln(1+Patents)	Δ Ln(1+Citations)	Δ Ln(1+CPP)	Δ R&D Intensity
Δ MHHI_Delta	-0.006***	-0.006***	-0.002**	-0.001***
	(-3.30)	(-2.69)	(-2.32)	(-2.80)
Controls	Y	Y	Y	Y
Industry fixed effects	Y	Y	Y	Y
Year fixed effects	N	N	N	Y
Standard errors adjusted for heteroskedasticity	Y	Y	Y	Y
Standard errors adjusted for clustering at the four-digit industry level	N	N	Y	N
N/ R-squared	11,247/0.05	11,247/0.05	11,247/0.01	11,184/0.05

Table II-8. The Effect of Same-industry Common Ownership (seven alternative measures) on Corporate Innovation: OLS Regressions

To gauge a firm's common-ownership status in any given fiscal year, I construct seven measures, following He and Huang (2014). The first one, CommonDummy, is a dummy variable that equals one if the firm is commonly-held in any of the four quarters prior to the fiscal year end, and zero otherwise. The second measure, LnNumCommon, is the natural logarithm of one plus the average number of unique institutions that cross-hold the firm in the four quarters prior to the fiscal year end. This measure captures the extent to which a firm is connected to other same-industry peers through common ownership. The third measure, AvgPercent, is the average percentage holding in same-industry peers block-held by the average common-holding institution. More specifically, I first calculate the average percentage holding in same-industry firms (other than the one under consideration) block-held by each common-holding institution during the four quarters prior to the fiscal year end and then average across all such institutions. This measure captures the intensity of common-holding activities for the average institution. The fourth measure, AvgNum, is similarly defined. It is the average number of same-industry peers block-held by the average common-holding institution. The fifth measure, TotalCommonOwn, is the sum of all common-holding institutions' average percentage holdings in the firm itself. This measure captures the total power of common-holding institutions to influence firm management if they have similar goals. The sixth measure, FracPosChgPt, is the fraction of the firm's common-holding institutions whose average percentage block holding in other same-industry peers is higher than that in the previous year. The last measure, FracPosChgNum, is similarly defined. It is the fraction of the firm's common-holding institutions whose average number of other same-industry common-holdings is higher than that in the previous year. The last two measures capture the incentives of the average common-holding institution to exert influence. Coefficients are reported with the t-statistics in parentheses. The symbols ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. To avoid crowdedness, I separately report the effects on patent quantity and quality in two panels.

Panel A: Effect on Patent Quantity

	Dependent Variable						
	Ln(1+Patents)						
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model7
CommonDummy	-0.046*						
	(-1.70)						
LnNumCommon		-0.060**					
		(-2.21)					
AvgNum			-0.070***				
			(-9.84)				
AvgPercent				-0.059			
				(-0.62)			
TotalCommonOwn					-0.093*		
					(-1.92)		

Table II-8. (Continued) The Effect of Same-industry Common Ownership (seven alternative measures) on Corporate Innovation: OLS Regressions

Panel A (Continued): Effect on Patent Quantity

	Dependent Variable						
	Ln(1+Patents)						
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model7
FracPosChgPercent						-0.025	
						(-0.52)	
FracPosChgNum							-0.057
							(-1.17)
Total ownership of monitoring institutions	0.392***	0.373**	1.171***	0.402***	1.148***	0.377***	1.165***
	(3.65)	(2.15)	(5.77)	(3.76)	(9.67)	(3.44)	(9.85)
Total ownership of blockholders	-0.061	0.041	-1.372***	-0.094	-1.415***	-0.069	-1.492***
	(-0.60)	(0.26)	(-8.46)	（-0.95)	(-12.53)	(-067)	(-14.14)
R&D intensity	3.077***	3.082***	4.147***	3.076***	3.329***	3.128***	3.326***
	(12.46)	(7.65)	(9.25)	(12.44)	(12.15)	(12.27)	(12.15)
Ln(Assets)	0.533*	0.535***	0.387***	0.531***	0.358***	0.538***	0.356***
	(35.37)	(20.17)	(15.08)	(35.39)	(22.87)	(34.87)	(22.82)
Ln(Firm Age)	0.138***	0.138***	0.028	0.138***	0.022	0.144***	0.024
	(8.11)	(4.18)	(0.80)	(8.12)	(1.21)	(8.27)	(1.29)
Ln(PPE/#employees)		0.105***	0.186***	0.104***	0.191***	0.110***	0.192***
	0.105***	(2.78)	(4.63)	(5.36)	(8.68)	(5.47)	(8.70)
Ln(Sales/#employees)	-0.003	-0.002	-0.356***	-0.004	-0.525***	-0.004	-0.526***
	(-0.12)	(-0.04)	(-6.96)	(-0.15)	(-18.56)	(-0.15)	(-18.60)
Sales growth	-0.133***	-0.132***	-0.120**	-0.134***	-0.084*	-0.148***	-0.086*
	(-3.23)	(-2.88)	(-2.35)	(-3.23)	(-1.84)	(-3.50)	(-1.89)
ROA	-0.286**	-0.287	1.053***	-0.285**	0.789***	-0.325**	0.786***
	(-2.13)	(-1.26)	(4.52)	(-2.12)	(5.49)	(-2.37)	(5.49)
M/B	0.001***	0.001***	0.001**	0.001***	0.001***	0.001***	0.001***
	(7.85)	(5.12)	(3.48)	(7.81)	(8.79)	(7.85)	(8.82)
Leverage	-0.390***	-0.390***	-0.154	-0.389***	-0.063	-0.391***	-0.060
	(-4.83)	(-2.77)	(-0.60)	(-4.82)	(-0.63)	(-4.69)	(-0.64)
Cash/Assets	-0.619***	-0.018	-0.337*	-0.02	-0.759***	-0.047***	0.763***
	(-3.73)	(-0.12)	(-1.93)	(-0.19)	(-6.43)	(-0.43)	(-6.46)

Table II-8. (Continued) The Effect of Same-industry Common Ownership (seven alternative measures) on Corporate Innovation: OLS Regressions

Panel A (Continued): Effect on Patent Quantity

	Dependent Variable						
	Ln(1+Patents)						
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model7
Stock return	-0.020	0.046**	-0.010	0.045**	0.001	0.050**	0.001
	(-0.19)	(2.49)	(-0.52)	(2.33)	(0.01)	(2.50)	(0.04)
Stock volatility	4.391***	4.352***	-1.438	4.366***	-4.120***	4.607***	-4.195**
	(2.96)	(2.83)	(-1.12)	(4.08)	(-4.40)	(4.18)	(-4.48)
Industry fixed effects	Y	Y	Y	Y	Y	Y	Y
Year fixed effects	Y	Y	Y	Y	N	Y	N
Standard errors adjusted for heteroskedasticity	Y	Y	Y	Y	Y	Y	Y
Standard errors clustered at the firm level	N	N	Y	N	N	N	N
R-squared	0.59	0.59	0.40	0.59	0.47	0.59	0.47
N	10,778	10,778	10,778	10,778	10,778	10,326	10,778

Panel B: Effect on Patent Quality

	Dependent Variable													
	Ln(1+Citations)							Ln(1+CitationsPerPatent)						
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
CommonDummy	-0.096**							-0.013*						
	(-2.06)							(-1.68)						
LnNumCommon		-0.114***							-0.010*					
		(-3.37)							(-1.71)					
AvgNum			-0.073***							-0.002*				
			(-9.86)							(-1.84)				
AvgPercent				-0.146							-0.050*			
				(-1.10)							(-1.77)			

Table II-8. (Continued) The Effect of Same-industry Common Ownership (seven alternative measures) on Corporate Innovation: OLS Regressions

Panel B (Continued): Effect on Patent Quality

	Dependent Variable													
	Ln(1+Citations)							Ln(1+CitationsPerPatent)						
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
TotalCommonOwn					-0.056*							-0.019*		
					(-1.67)							(-1.91)		
FracPosChgPercent						-0.127**							-0.028**	
						(-2.23)							(-2.08)	
FracPosChgNum							-0.066							-0.024*
							(-1.29)							(-1.89)
Total ownership of monitoring institutions	1.366***	1.332***	1.527***	0.540***	0.534***	1.233***	1.267***	0.044	0.043	0.045	0.046	0.209***	0.055*	0.212***
	(6.39)	(6.21)	(5.96)	(2.72)	(4.65)	(6.05)	(10.21)	(1.54)	(1.48)	(1.55)	(1.60)	(6.95)	(1.86)	(7.08)
Total ownership of blockholders	-1.586***	-1.400***	-1.450***	-0.197	-0.163	-1.582***	-1.586***	-0.003	0.009	-0.010	-0.009	-0.287***	-0.010	-0.302***
	(-9.08)	(-7.42)	(-8.61)	(-1.21)	(-1.50)	(-9.68)	(-14.35)	(-0.09)	(0.29)	(-0.35)	(-0.31)	(-9.42)	(-0.34)	(-10.33)
R&D intensity	4.091***	4.097***	4.223***	3.619***	3.621***	3.381***	3.362***	0.658***	0.658***	0.657***	0.653***	0.725***	0.661***	0.724***
	(8.52)	(8.59)	(8.91)	(8.41)	(14.26)	(7.08)	(11.45)	(9.19)	(9.19)	(9.17)	(9.13)	(9.63)	(9.04)	(9.62)
Ln(Assets)	0.351***	0.355***	0.382***	0.510***	0.511***	0.354***	0.348***	0.065***	0.065***	0.065***	0.065***	0.033***	0.064***	0.033***
	(13.18)	(13.31)	(14.37)	(18.37)	(34.32)	(12.38)	(21.19)	(17.20)	(17.22)	(17.15)	(17.14)	(8.77)	(16.49)	(8.73)
Ln(Firm Age)	0.007	0.008	0.009	0.097***	0.097***	0.014	0.006	0.003	0.003	0.003	0.003	-0.015***	0.004	-0.015***
	(0.21)	(0.23)	(0.24)	(2.78)	(5.83)	(0.38)	(0.32)	(0.61)	(0.63)	(0.59)	(0.59)	(-3.27)	(0.80)	(-3.21)
Ln(PPE/#employees)	0.196***	0.196***	0.187***	0.122***	0.122***	0.202***	0.195***	0.028***	0.028***	0.028***	0.028***	0.043***	0.029***	0.043***
	(4.48)	(4.49)	(4.30)	(2.92)	(6.56)	(4.30)	(8.21)	(5.40)	(5.41)	(5.37)	(5.37)	(7.68)	(5.40)	(7.69)
Ln(Sales/#employees)	-0.385***	-0.382***	-0.355***	-0.002	-0.001	-0.523***	-0.523***	0.005	0.005	0.005	0.005	-0.073***	0.005	-0.074***
	(-7.12)	(-7.05)	(-6.58)	(-0.04)	(-0.06)	(-8.65)	(-17.51)	(0.71)	(0.73)	(0.69)	(0.69)	(-10.62)	(0.67)	(-10.65)
Sales growth	-0.105*	-0.103*	-0.092*	-0.140***	-0.139***	-0.078	-0.061	0.001	0.001	0.001	0.001	0.008	-0.002	0.007
	(-1.89)	(-1.85)	(-1.67)	(-2.71)	(-3.02)	(-1.41)	(-1.24)	(0.07)	(0.08)	(0.09)	(0.08)	(0.54)	(-0.11)	(0.51)
ROA	1.098***	1.089***	1.112**	0.190	0.189	0.787***	0.831***	0.033	0.032	0.035	0.033	0.218***	0.018	0.217***
	(4.44)	(4.40)	(4.54)	(0.81)	(1.39)	(3.06)	(5.44)	(0.83)	(0.83)	(0.90)	(0.84)	(5.40)	(0.46)	(5.39)
M/B	0.001**	0.001**	0.001***	0.001***	0.001***	0.001***	0.001***	0.001***	0.001***	0.001***	0.001***	0.001***	0.001***	0.001***
	(3.44)	(3.47)	(3.66)	(4.14)	(6.64)	(5.86)	(8.82)	(6.56)	(6.55)	(6.57)	(6.52)	(6.29)	(6.50)	(6.33)

Table II-8. (Continued) The Effect of Same-industry Common Ownership (seven alternative measures) on Corporate Innovation: OLS Regressions

Panel B (Continued): Effect on Patent Quality

	Dependent Variable													
	Ln(1+Citations)							Ln(1+CitationsPerPatent)						
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
Leverage	-0.327**	-0.333**	-0.345**	-0.578***	-0.578***	-0.045	-0.054	-0.078***	-0.078***	-0.077***	-0.078***	-0.028	-0.082***	-0.027
	(-2.00)	(-2.04)	(-2.15)	(3.93)	(-7.26)	(-0.27)	(-0.55)	(-3.46)	(-3.46)	(-3.41)	(-3.44)	(-1.14)	(-3.53)	(-1.13)
Cash/Assets	-0.448**	-0.436**	0.350*	0.220	0.223**	-0.813***	-0.802***	0.065*	0.065*	0.065*	0.063*	-0.080**	0.061*	-0.081**
	(-2.43)	(-2.38)	(-1.93)	(1.30)	(2.01)	(-4.43)	(-6.42)	(1.88)	(1.88)	(1.88)	(1.84)	(-2.21)	(1.72)	(-2.25)
Stock return	-0.002*	-0.002*	0.006	0.054***	0.054**	0.022	0.019	0.012**	0.012**	0.012**	0.012**	-0.002	0.012*	-0.002
	(-0.10)	(-0.09)	(0.30)	(2.51)	(2.47)	(1.05)	(0.88)	(1.99)	(1.98)	(1.97)	(1.97)	(-0.40)	(1.92)	(-0.37)
Stock volatility	-0.836	-0.858	-0.522	6.977***	6.970***	-3.127**	-3.431***	0.679**	0.668**	0.664**	0.672**	-0.713***	0.708**	-0.734***
	(-0.61)	(-0.63)	(-0.38)	(3.85)	(6.10)	(-2.37)	(-3.48)	(2.16)	(2.12)	(2.11)	(2.13)	(-2.70)	(2.18)	(-2.78)
Industry fixed effects	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Year fixed effects	N	N	N	Y	Y	N	N	Y	Y	Y	Y	N	Y	N
Standard errors adjusted for heteroskedasticity	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Standard errors clustered at the firm level	Y	Y	Y	Y	N	Y	N	N	N	N	N	N	N	N
R-squared	0.37	0.37	0.38	0.49	0.49	0.45	0.45	0.37	0.34	0.34	0.34	0.25	0.34	0.25
N	10,778	10,778	10,778	10,778	10,778	10,326	10,778	10,778	10,778	10,778	10,778	10,778	10,326	10,778

Table II-9. The Effect of Same-industry Common Ownership (MHHI delta) on Corporate Innovation: Difference-in-Differences Analysis

This table reports the DiD analyses results. Variable definitions are in Appendix. Coefficients are reported with the t-statistics in parentheses. The symbols ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	Discrete Treatment			Continuous Treatment		
	Ln(1+Patents)	Ln(1+Citations)	Ln(1+CPP)	Ln(1+Patents)	Ln(1+Citations)	Ln(1+CPP)
Treat × Post	-0.124**	-0.131**	-0.040***			
	(-2.09)	(-2.25)	(-3.05)			
Implied Change in MHHI delta × Post				-0.527***	-0.677***	-0.089*
				(-4.42)	(-6.69)	(-1.75)
Post	-0.755***	-0.737***	-0.137***	-1.285***	-1.275***	-0.241***
	(-4.70)	(-4.47)	(-3.60)	(-24.50)	(-24.04)	(-36.69)
Controls	Y	Y	Y	Y	Y	Y
Industry/Year fixed effects	N	N	N	Y	Y	Y
Standard errors adjusted for clustering at the firm-year level	Y	Y	Y	Y	Y	Y
N/(Pseudo) R-squared	5,345/0.33	5,345/0.31	11,247/0.01	9,393/0.54	9,393/0.52	9,393/0.33

Table II-10 Parallel Trend Test for the Difference-in-Differences Analysis

This table reports the placebo tests results for the DiD analyses, using pre-event data only. Treat is a dummy variable for treatment status. Time Dummy$_{-n}$ (n=1, 2, 3) is a dummy for the period that is n year(s) before the event, the Legg Mason - Citi Investment Management acquisition in 2005. Variable definitions are in Appendix. Coefficients are reported with the t-statistics in parentheses. Standard errors are clustered in two dimensions: firm and year. The symbols ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	Ln(1+Patents)	Ln(1+Citations)	Ln(1+CitationsPerPatent)
Treat × Time Dummy$_{-3}$	0.069 (0.94)	0.051 (0.65)	0.004 (0.18)
Treat × Time Dummy$_{-2}$	0.040 (0.59)	0.033 (0.44)	-0.018 (-0.91)
Treat × Time Dummy$_{-1}$	0.054 (0.82)	0.061 (0.84)	-0.013 (-0.63)
R&D intensity	2.412** (4.14)	2.328*** (4.00)	0.455** (2.24)
Ln(Assets)	0.632*** (14.27)	0.637** (13.41)	0.089*** (0.65)
Ln(Firm Age)	0.113** (2.35)	0.097* (1.90)	0.009 (0.65)
Ln(PPE/#employees)	0.091 (1.47)	0.120* (1.92)	0.045*** (2.96)
Ln(Sales/#employees)	-0.018 (-0.28)	-0.025 (-0.38)	-0.001 (-0.09)
Sales growth	0.053 (0.75)	0.123 (1.28)	0.079*** (4.53)
ROA	-0.715** (-2.22)	-0.804** (-1.97)	-0.235 (-1.30)
M/B	0.001*** (5.27)	0.001*** (4.57)	0.001*** (4.10)
Leverage	-0.615*** (-3.26)	-0.676*** (-3.20)	-0.118** (-2.13)
Cash/Assets	-0.363** (-1.98)	-0.409** (-2.25)	-0.027 (-0.58)
Stock return	0.011 (0.62)	0.118 (1.09)	0.021*** (2.62)
Stock volatility	5.625* (1.82)	4.783* (1.75)	-0.131 (-0.23)
Industry & year fixed effects	Y	Y	Y
N/(Pseudo) R-squared	2,233/0.59	2,233/0.57	2,233/0.38

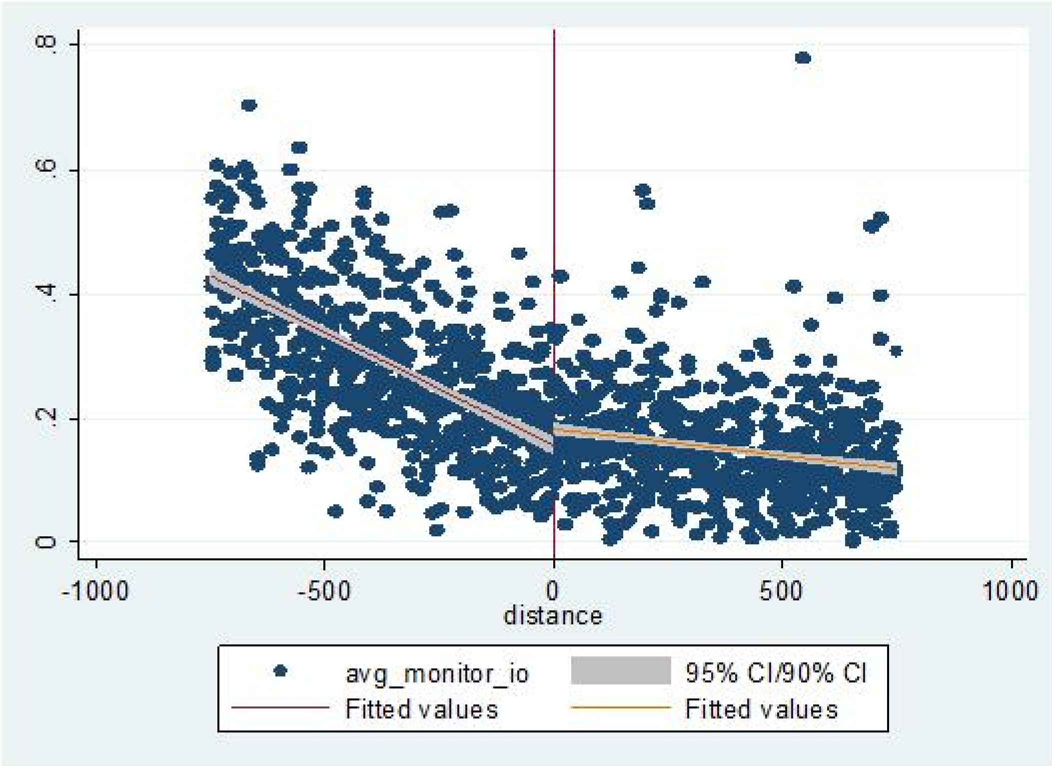

Figure II-1. Institutional ownership discontinuity

This figure shows the total ownership of monitoring institutions (scaled by total shares outstanding) for the first quarter ending after the reconstitution of the Russell indexes for the Russell 3000 firms from 1997-2006. The x-axis represents the distance from the Russell 1000/2000 thresholds using the actual Russell ranks in the indexes, with zero representing the last firm in the Russell 1000. The figure plots the average institutional monitoring ownership, adding regression discontinuity estimates and the associated 95% / 90% confidence bands to the left and right of the threshold, respectively.

REFERENCES II

Aghion, Philippe, John Van Reenen, and Luigi Zingales, 2013. Innovation and Institutional Ownership. American Economic Review 103, 277-304.

Appel, Ian, Todd Gormley, and Donald Keim, 2015. Passive Investors, Not Passive Owners. Journal of Financial Economics. Forthcoming.

Appel, Ian, Todd Gormley, and Donald Keim, 2016. Standing on the Shoulders of Giants: The Effect of Passive Investors on Activism. Working Paper.

Atanasov, Julian, 2013. Do Hostile Takeovers Stifle Innovation? Evidence from Antitakeover Legislation and Corporate Patenting. Journal of Finance 68, 1097–1131.

Azar, Jose, Martin C. Schmalz, and Isabel Tecu, 2016. Anti-Competitive Effects of Common Ownership. Working Paper.

Bloom, Nicholas, Mark Schankerman, and John Van Reeman, 2013. Identifying Technology Spillovers and Product Market Rivalry. Econometrica 81, 1347-1393.

Boone, Audra L., and Joshua T. White, 2015. The effect of institutional ownership on firm transparency and information production. Journal of Financial Economics 117, 508–533.

Brav, Alon, Wei Jiang, Song Ma, and Xuan Tian, 2017. How Does Hedge Fund Activism Reshape Corporate Innovation. Journal of Financial Economics, Forthcoming.

Brown, S., and W. Goetzmann, 1997. Mutual Fund Styles. Journal of Financial Economics 43, 373-399.

Bushee, Brian J., 1998. The Influence of Institutional Investors on Myopic R&D Investment Behavior. The Accounting Review 73, 305-333.

Bushee, Brian J., 2001. Do Institutional Investors Prefer Near-Term Eamings over Long-Run Value? Contemporary Accounting Research 18, 207-246.

Cassar, Alessandra, 2007. Coordination and Cooperation in Local, Random and Small World Networks: Experimental Evidence. Games and Economic Behavior 58, 209-230.

Chan, Louis K. C., Josef Lakonishok, and Theodore Sougiannis, 2001. The Stock Market Valuation of Research and Development Expenditures. Journal of Finance 56, 2431-2456.

Chang, Xin, Kangkang Fu, Angie Low, and Wenrui Zhang, 2015. Non-executive employee stock options and corporate innovation. Journal of Financial Economics 115, 168-188.

Chang, Yen-Cheng, Harrison Hong, and Inessa Liskovich, 2015. Regression Discontinuity and the Price Effects of Stock Market Indexing. Review of Financial Studies 28, 212-246.

Chen, Xia, Jarrad Harford, and Kai Li, 2007. Monitoring: Which Institutions Matter? Journal of Financial Economics 86, 279-305.

Choi, Nicole, Mark Fedenia, Hilla Skiba, and Tatyana Sokolyk, 2015. Portfolio Concentration and Performance of Institutional Investors Worldwide. Working Paper.

Crane, Alan, Andrew Koch, and Sebastien Michenaud, 2015. Institutional Investor Networks and Governance Mechanisms. Working Paper.

Crane, Alan D., Sébastien Michenaud, and James P. Weston, 2016. The Effect of Institutional Ownership on Payout Policy: Evidence from Index Thresholds. Review of Financial Studies 29, 1377-1408.

Daniel, K., M. Grinblatt, S. Titman, and R. Wermers, 1997. Measuring Mutual Fund Performance with Characteristics-base Benchmarks. Journal of Finance 52, 1035-1058.

Del Guercio, D., 1996. The Distorting Effect of the Prudent Man Law of Institutional Equity Investments. Journal of Financial Economics 40, 31-62.

Ekholm, Anders, and Benjamin Maury, 2014. Portfolio Concentration and Firm Performance. Journal of Financial and Quantitative Analysis 49, 903-931.

Faccio, Mara, Maria-Teresa Marchica, and Roberto Mura, 2011. Large Shareholder Diversification and Corporate Risk-Taking. Review of Financial Studies 24, 3601-3641.

Fich, Eliezer, Jarrad Harford, and Anh L. Tran, 2015. Motivated Monitors: The Importance of Institutional Investors' Portfolio Weights. Journal of Financial Economics 118, 21-48.

Geng, Heng, Harald Hau, and Sandy Lai, 2016. Technological Progress and Ownership Structure. Working Paper.

Giannetti, Mariassunta and Andrei Simonov, 2006. Which Investors Fear Expropriation? Evidence from Investors' Portfolio Choices. Journal of Finance 61, 1507-1547.

Hall, Bronwyn H., Adam B. Jaffe and Manuel Trajtenberg, 2001.The NBER Patent Citation Data File: Lessons, Insights and Methodological Tools. NBER Working Paper No. 8498.

Hall, Bronwyn H. And Rosemarie Ham Ziedonis, 2001. The Patent Paradox Revisited: An Empirical Study of Patenting in the U.S. Semiconductor Industry, 1979-1995. RAND

Journal of Economics 32, 101-128.

He, Jie, and Jiekun Huang, 2014. Product Market Competition in a World of Cross Ownership: Evidence from Institutional Blockholdings. Working Paper.

Hirshleifer, David A., Po-Hsuan Hsu, and Dongmei Li, 2013. Innovative Efficiency and Stock Returns. Journal of Financial Economics 107, 632-654.

Hou, Kewei and David T. Robinson, 2006. Industry Concentration and Average Stock Returns. Journal of Finance 61, 1927-1956.

Hsu, Po-Hsuan, Hsiao-Hui Lee, Alfred Zhu Liu, and Zhipeng Zhang, 2015. Corporate Innovation, Default Risk, and Bond Pricing. Journal of Corporate Finance 35, 329–344.

Knott, Anne Marie, and Hart Posen, 2003. Does Competition Increase Innovation? New Evidence from Old Industries? Working Paper, Mack Center for Technological Innovation.

Kogan, Leonid, Dimitris Papanikolaou, Amit Seru, and Noah Stoffman, 2015. Technological Innovation, Resource Allocation and Growth. Working Paper.

Laeven, Luc and Ross Levine, 2007. Is There a Diversification Discount in Financial Conglomerates? Journal of Financial Economics, 85, 331-367.

Laeven, Luc and Ross Levine, 2009. Bank Governance, Regulation and Risk-taking. Journal of Financial Economics, 93, 259-275.

O'Barr, W.M. and J.M. Conley, 1992. Managing Relationships: The Culture of Institutional Investing. Financial Analysts Journal 48, 21-27.

Officer, M., Ozbas, O., Sensoy, B., 2010. Club Deals in Leveraged Buyouts. Journal of Financial Economics 98, 214-240.

Seru, Amit, 2014. Firm Boundaries Matter: Evidence from Conglomerates and R&D Activity. Journal of Financial Economics 111, 381 – 405.

Schumpeter, Joseph, 1912. The Theory of Economic Development. Harvard University Press.

Shiller, Robert J. and Pound, John, 1989. Survey Evidence on Diffusion of Interest and Information among Investors. Journal of Economic Behavior & Organization 12, 47-66.

Staiger, Douglas O and James Harold Stock, 1997. Instrumental Variables Regression with Weak Instruments. Econometrica 65, 557-586.

Yang, Huan, 2016. Institutional Dual Holdings and Risk Shifting: Evidence from Corporate

Innovation. University of Georgia Working Paper.