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Essays in Corporate Governance and Innovation

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Essays in Corporate Governance and Innovation

A dissertation submitted in partial satisfaction
of the requirements for the degree
Doctor of Philosophy in Management

by

Shenje Hshieh

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ABSTRACT OF THE DISSERTATION

Essays in Corporate Governance and Innovation

by

Shenje Hshieh
Doctor of Philosophy in Management
University of California, Los Angeles, 2017
Professor Mark J. Garmaise, Chair

In the first chapter, I show that mature patent-practicing firms respond to windfall profits derived from exogenously extended patent protection time by engaging in external patent acquisitions that diversify their patent portfolios into new technologies. By exploiting the random timing of patent term expiry dates and their unexpected extensions due to the Uruguay Round Agreements Act, I find that a one standard deviation increase in the citation-weighted patent portfolio share of term-extended patents leads to an increase in cash flow by 1.5 percent of book assets. Given these windfall profits, I find evidence of physical capital investment, debt issuance reduction, and acquisitions of new external technologies. Internal investments in R&D, on the other hand, show no response, suggesting high R&D adjustment costs for large, mature firms. In the second chapter, I find that being connected to directors who are or had been board members at bankrupt firms at the time of bankruptcy filing limits the efficacy of business networks in searching for directorships. Assuming that corporate bankruptcies can weaken interpersonal ties among directors, I exploit a quasi-natural experiment to investigate the degree to which director turnover is dependent on professional connections forged from current and past board memberships. By comparing directors who are indirectly linked to bankruptcy-filing firms through their professional networks to those without this indirect link, I find that a director's chances of finding additional directorships within a 1-year period are lowered by over 10 percent on average after losing a set of connections due to corporate bankruptcies. This decline in director mobility is concentrated mostly among highly central directors and directors with board positions at firms with high

G-Index measures, suggesting that the dependency on personal ties is stronger among firms with weak shareholder rights. In the third chapter, we explore the proxy voting patterns of passive mutual funds. We find that passive funds disagree with management more frequently than active funds within fund family. Additionally, voter efficacy between passive and active funds are not equal across agenda item categories.

The dissertation of Shenje Hshieh is approved.

Moshe Buchinsky

William Giles Mann

Ivo I. Welch

Antonio E. Bernardo

Mark J. Garmaise, Committee Chair

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2017

To my mother, Man-ling, and two brothers, Shenche and Shenho

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CHAPTER 1

Profit Windfalls and Investments in Innovation: Evidence from Patent Term Extensions

While there is considerable evidence suggesting that young and small innovating firms experience financial constraints on investments, such evidence for large, mature firms is limited, particularly on R&D investments (Hall and Lerner 2010). Asymmetric information and moral hazard can prevent firms from obtaining external financing for all the investments that they would have pursued if they had sufficient internal funds (Fazzari, Hubbard, and Petersen 1988). These impediments can be severe for firms that are considering engaging in innovative activities due to the intangible nature of R&D investments.[1] Do mature, patent-practicing firms face financial constraints on their capital expenditures and R&D investments?[2] How do they pursue investments in innovation? This paper examines the investment strategies and degree of financial constraints on investments for mature, patent-practicing firms through the Uruguay Round Agreements Act of 1994 (URAA), an event potentially resulting in windfall profits arising from term extensions on expiring patents. Further study of this event presents an opportunity not only to understand how changes in patent protection time can affect corporate profits but also how and why investments in physical capital and R&D differ for these firms when exogenously supplied with additional cash flow.

For corporations whose business depends on the enforcement of intellectual property rights, the primary function of patents is to guard the cash flow generated by product sales

[1] Information asymmetry could exist in the valuation of human capital. Moral hazard could manifest through the replacement costs of intangible assets (e.g., highly trained employees).

[2] "Patent-practicing" means a firm uses the underlying technology being protected as opposed to merely holding patents to generate income through infringement lawsuits or collecting licensing fees, which is usually done by "non-practicing entities" (NPE) or patent trolls.

against competition. With this in mind, I design a quasi-natural experiment using the URAA as a cash windfall event, which bestows upon some firms active in the U.S. patent system an extended period of profitability through patent protection, in order to study corporate investments in innovation and a range of corporate financing decisions. Specifically, URAA's transitional provision gives all utility and plant patents still in force by (or filed prior to) June 8, 1995 a maximum term of either 17 years from the grant date (the old policy) or 20 years from the filing date (the new policy).[3] This gave such patents up to 3 additional years of life. Patent expiration around this threshold is effectively exogenous as the policy date could not have been known 17 years in advance.[4]

In this paper I construct a continuous treatment variable that measures the fractional gain in term-extended patents from URAA's transitional provision on each firm. This continuous treatment is a function of the number of patents owned originally expiring within six months after June 7, 1995 that received term extensions ("term-extended" patents) and the number of patents owned that would have benefited from the transitional provision but expired at most six months prior to June 8, 1995 ("counterfactual" patents).[5] The continuous treatment is defined for each firm as the forward citation-weighted difference between the number of term-extended and counterfactual patents scaled by the firm's forward citation-weighted portfolio of patents that have not expired by the end of 1995.[6] The differencing captures the treatment intensity for a specific firm.[7] The scaling, on the other hand, makes

[3]U.S. utility patents protect the functionality of an invention. The term of design patents, on the other hand, was unaffected by URAA.

[4]I ignore patent ownership transfers after the approval of the Trade Related Aspects of Intellectual Property Rights (TRIPS) Agreement in 1994, which is the international trade agreement underlying URAA, to account for possible self-selection issues.

[5]The counterfactual patents are relevant here because I need to exclude technologies that systematically take longer to receive patent grants. Firms that strategically take longer to patent their inventions can operate very differently. The likelihood of treatment for each firm is therefore related to the counterfactual patents that they own.

[6]Forward citations of a patent is the number other patents citing it.

[7]The intuition is the following. The relevant pool of firms are those that own patents that can potentially benefit from URAA's transitional provision (i.e., patents that benefit from the new 20-year term). The exogeneity of patent term extensions on expiring patents comes from the unknown timing of the cutoff date. Firms in the relevant pool that were lucky enough to have some of their patents receive term extensions by expiring after this cutoff date are therefore "shifted out" of the pool of counterfactual firms. The degree of

the treatment intensity comparable across firms, since the impact is relative to the size of a firm's patent portfolio.[8] Alternatively expressed, given each firm's unexpired set of patents by the end of 1995, the continuous treatment variable is the citation-weighted difference between the patent portfolio share of expiring patents that received and did not receive term extensions.This setup identifies the exogenous effect of randomly assigning term extensions to expiring patents after the cutoff date of June 8, 1995 because of a firm's inability to time patent grants or expiration dates far in the past. This treatment variable therefore correlates with the immediate changes in (book asset-scaled) cash flow resulting from URAA's transitional provision.

I hypothesize that if R&D oriented firms are financially constrained, they will invest in innovative activities or assets conducive to future innovation, increase capital expenditure, and reduce levels of borrowing in response to this profit windfall (Farre-Mensa and Ljungqvist 2016). If agency problems exists within these firms, windfall profits may spill over into executive compensation. Furthermore, while there is no general consensus on whether internal R&D expense is sensitive to cash flow for mature innovating firms, I emphasize that there may be several other channels through which these firms may still exhibit some form of investment in innovation (e.g., patenting activities, etc.).

Under a reduced form difference-in-differences framework, I find strong evidence that URAA's transitional provision allowed treated firms to continue to exclusively profit from their inventions. Using the treatment definition described above, I find that a one standard deviation increase (15 percentage points) in the citation-weighted patent portfolio share of term-extended patents owned that would have expired if not for the transitional provision leads to an increase in cash flow by 1.5 percent of book assets. For the mean treated firm with \$6.5 billion in book assets, a one standard deviation increase (15 percentage points) in the treatment variable translates into roughly \$98 million. The estimated treatment effect is statistically significant across several measures of income: a one standard deviation in-

the shift is captured by this differencing.

[8]Most firm-level outcome variables will be scaled by a size-related variable. Cash flow, for example, is scaled by book assets.

crease (15 percentage points) in the citation-weighted share of term-extended patents owned increases EBIT (scaled by book assets), return on sales (ROS), and return on net operating assets (RNOA) by 1.35, 0.75, and 4.05 percentage points, respectively.

The main finding of this paper is that patent-practicing firms acquire more external patents as a result of the additional cash flow generated by URAA's term extensions. This is observed in both the likelihood and quality (via citation weighting) of patent acquisitions. These acquired external patents are on average categorized in patent class/subclasses that do not already exist within the acquiring firms' historical patent portfolios.[9] This is evidence that firms are diversifying in technologies that are different from their own previous patent portfolios. I also find that these acquired patents originate from private firms (i.e., private at the time of patent issuance) and have proportionally fewer outside patent citations.[10] A one standard deviation increase (15 percentage points) in the citation-weighted share of term-extended patents leads to an increase in the probability of acquiring patents by 1.8 percent, an increase of 2.25 percentage points in net patent transfers or the net citation-weighted patents acquired as a share of current citation-weighted patent portfolio size, and an increase of 1.83 percentage points in the proportion of new class/subclasses of newly acquired patents. Estimating the direct cash flow effect by combining the difference-in-differences and instrumental variable methods (i.e., using the continuous treatment variable as the instrument), I find that a one percentage point increase in book asset-scaled cash flow yields an increase of 0.9 percentage points in net patent transfers and an increase of 0.98 percentage points in the proportion of new class/subclasses of newly acquired patents.[11]

I also find strong evidence that URAA's patent term extensions have a significant influence on capital structure and investment decisions. A one standard deviation increase (15 percentage points) in the citation-weighted share of term-extended patents leads to an increase in capital expenditures by 0.3 percent of book assets and a decrease in debt is-

[9]Historical patent portfolios consider all patents that are acquired or generated.

[10]"Private" here means not publicly traded on a U.S. stock exchange. "Private firms" therefore may include foreign firms that are publicly traded elsewhere.

[11]Intra-firm patent transfers are ignored. Patents purchased outright or indirectly through mergers or acquisitions are used in the construction of the "net patent transfers" variable.

suance by 1.65 percent of book assets. These results, as suggested by the capital structure and investment-cash flow literature, can be explained by differences between internal and external costs of capital, resulting from asymmetric information between firm managers and investors. The increase in investment implies costly external financing or underinvestment (Fazzari, Hubbard, and Petersen 1988). Estimating the investment-cash flow sensitivity can be accomplished by combining the instrumental variable and difference-in-differences methods. Using the aforementioned constructed treatment variable as an instrument for cash flow, I estimate that a one percentage point increase in book asset-scaled cash flow increases capital expenditure by 0.13 percent of book assets and reduces debt issuance by 0.54 percent of book assets.

Interestingly, I find no changes in R&D spending, which is not inconsistent with the current literature on the relationship between R&D expense and the availability of internal financing for large firms (Brown and Petersen 2011). This could be attributed to high current and future adjustment costs in hiring and training new researchers, for example (Hall and Lerner 2010). Notwithstanding this finding, there is evidence of external investments in innovation through patent acquisitions, as mentioned above.

Lastly, if agency issues are severe within innovating firms, executive compensation could react positively to this event, implying that treated executives were rewarded for luck (Bertrand and Mullainathan 2001). I find no significant changes in salary, bonuses, or options and stock grants to executives in response to URAA's transitional provision, after controlling for both firm and executive characteristics.

In summary, the findings of this paper contribute to the finance literature in two distinct dimensions. Firstly, by identifying an *unexpected* profit windfall event, my findings address endogeneity issues when testing various theories on capital structure and investment decisions.[12] Using patenting decisions made in the past that extended the protection period of expiring patents as an exogenous source of cash flow, my findings allow testing for whether financial frictions exist within innovating firms. Secondly, my findings provide insight into

[12]See Figure 1.1 for evidence of URAA being unanticipated.

firm investment channels for R&D. In this paper, I observe that internal R&D investment is insensitive to exogenous cash flow. Rather, I find that firms prefer to acquire innovation externally via patents.

The rest of the paper is organized as follows. Section 1 summarizes the relevant literature. Section 2 gives relevant background on U.S. patent law and the legislation timeline of URAA. Section 3 provides a description of the constructed dataset and the experimental setup. Section 4 presents the empirical results. Section 5 provides extensions. Section 6 concludes.

1.1 Related Literature

This paper contributes to many aspects of the growing research in the relationship between finance and firm innovation. While patents have been increasingly used as a measurement of both quantity (e.g., patent count) and quality (e.g., forward citations) of firm R&D output, the current empirical understanding on their relationship with cash flow and subsequent R&D investments are, to the best of my knowledge, limited at best within the literature, thus needing further investigation.

1.1.1 Financial Constraints and Investment-Cash Flow Sensitivity

Under strict assumptions, Modigliani and Miller (1958) conclude that capital structure is irrelevant and therefore a firm's investment choice should be independent of the availability of internal financing sources. However, when considering financial frictions manifesting from adverse selection costs, investment and capital structure decisions can respond to exogenous changes to cash flow. Financial constraints arise from frictions in the supply of capital, primarily due to asymmetric information between investors and the firm (Tirole 2006).

There are two prevailing ways of defining financial constraints in the literature. The first way is based on supply frictions that have an effect on the supply elasticity of external capital. Stiglitz and Weiss (1981), Almeida and Campello (2001), and Whited and Wu (2006) view a firm as financially constrained if it is unable to raise an additional dollar of external capital due to a vertical (inelastic) supply of external capital curve (i.e., credit rationing). The second way defines financial constraints as the difference between the cost of new debt and equity and the opportunity cost of internal finance (e.g., retained earnings or cash flow). Fazzari, Hubbard, and Petersen (1988) claim that a firm is constrained if it has access to external capital at a higher price than the price that would reflect its actual risk. While both versions of financial constraints can exist simultaneously for each firm, the predicted observable outcomes on investments when imparted an exogenous cash flow shock should be the same. We should expect more constrained firms, on the margin, to possibly rely less on debt and equity and to increase investments in response to a positive cash flow shock.

From an investor's perspective, firms that depend on technological innovation are extremely risky; not only could R&D produce no viable products, but also profits could erode if the underlying technologies of their products are not properly protected against infringement.[13] The valuation of this risk requires a deep understanding of the firm's R&D strategy, which may differ between managers and investors. Given this adverse selection cost, Myers (1977) and Meyers and Majluf (1984) predict that a cash windfall could reduce the reliance on debt and equity and increase levels of investment.

This paper follows the efforts of Blanchard, Silanes, and Shleifer (1994), Calomiris and Hubbard (1995), and Lamont (1997) in testing the predictions above while addressing endogeneity issues via quasi-natural experiments. Blanchard, Silanes, and Shleifer (1994) finds that managers of firms receiving cash awards from corporate litigation pursue empire building behavior through bad acquisitions. Calomiris and Hubbard (1995) estimates the cost of external finance directly using the unanticipated surtax on undistributed profits of 1936–1937. Many firms actually preferred paying higher tax rates than paying out dividends. Lastly, Lamont (1997) discovers that in multi-segmented firms, a sudden decline in oil prices in 1986 caused not only the non-oil segments to become more profitable than before, but also to cut more capital expenditure than the industry median and mean. This provides

[13] Surveys from Mansfield (1986), Levin et al. (1987), and Cohen, Nelson, and Walsh (2000) revealed that most high-tech industry executives believes that many inventions would not have been introduced without patent production. Mansfield, Schwartz, and Wagner (1981) and Levin et al. (1987) found patents raised imitation costs immensely for chemical and petroleum industries and slightly for electronics.

evidence of over-investment in the non-oil segments from oil profits prior to the negative oil price shock. The quasi-natural experiment presented here adds to the list of events where cash flow is plausibly exogenous.

1.1.2 R&D as Investments

The rationale for considering cash flow as a determinant of R&D investment is the same for that of physical investment; capital markets are imperfect, and the aforementioned imperfections put constraints on external financing. However, R&D expenses (i.e., accounting based measures of R&D) are known to exhibit higher serial correlation and smoothing over time (Brown and Petersen 2011), which are often attributed to high adjustment costs (Hall and Lerner 2010). Because an innovating firm needs to devote much of its R&D resources to train its researchers, the firm's cost of employee turnover is extremely high. The additional risk of transmitting valuable knowledge and trade secrets to competitors also raises the overall costs (Pakes and Nitzan 1983). As a result, research workers are not "perfectly elastic in supply" (Grabowski 1968). Innovating firms are therefore expected to minimize both current and future adjustment costs, implying that the level of R&D investment should only respond to permanent changes in cash flow rather transitory ones.

Empirical findings on the cash flow sensitivity of R&D investments, however, are mixed. Many early studies such as Scherer (1965) and Mueller (1967) find little evidence of a relationship between internal finance and R&D. R&D is more responsive to internal finance when restricted to small firms, as confirmed by Hao and Jaffe (1993) and Himmelberg and Petersen (1994). Likewise, Harhoff (1998) and Bond, Harhoff, and Reenen (2005) provide some evidence that R&D investment in small German firms may be financially constrained. More recently, Brown, Martinsson, and Petersen (2012) shows that both cash flow and public equity issuance highly influence younger U.S. firms between 1990 and 2004 but have little impact on R&D for large and mature firms.

Based on the empirical evidence thus far, it is difficult to tell whether cash flow encourages R&D or if they are in fact co-determined by some common unobserved factor (e.g., firm's underlying ability). Reverse causality could also occur since cash flow may just be a reflection of past R&D expenditures (Branch 1974).[14] This paper presents a quasi-natural experiment to test the sensitivity of R&D investments to cash flow for innovating firms directly.

1.1.3 Patents as a Measurement of Firm Innovation

Several papers such as Hall, Jaffe, and Trajtenberg (2005) have shown that patents contain significant information on the market value of firms. Both raw and (forward) citation-weighted patent counts (application, grant, or aggregated portfolio) are now used as alternative measures of firm innovativeness (as opposed to accounting-based measures such as R&D expense to market cap or R&D expense to sales ratios). The purpose of citation weighting is to adjust for a patent's relevance in the technology space (Munari and Oriani 2011). Harhoff et al. (1999) and Abrams, Akcigit, and Popadak (2013) provide evidence of a strong link between patent value and forward citation counts. The compilation of USPTO patent data matched to Compustat firms made available by Hall, Jaffe, and Trajtenberg (2001) spurred a wave of papers that shed light on finance-related determinants of firm innovation.

CEO overconfidence (Galasso and Simcoe 2011 and Hirshleifer, Low, and Teoh 2012), institutional ownership (Aghion, Reenen, and Zingales 2009), private ownership (Bernstein 2015), mergers (Bena and Li 2014), and the strength of creditor rights (Mann 2015) have all been positively linked with firm patenting output. Galasso and Simcoe (2011) finds that overconfident CEOs not only help firms obtain more patents but also become more efficient at producing relevant inventions (measured by citations per dollar of R&D). Hirshleifer, Low, and Teoh (2012) produces similar findings using both option-based and press-based measures of CEO overconfidence.[15] In Aghion, Reenen, and Zingales (2009), institutional ownership is found to encourage innovation (as measured by aggregate forward citations) by reducing the likelihood of CEO turnover. Mann (2015) shows that when certain U.S. state court decisions

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[14] See Mansfield, Rapoport, and Schnee (1972) and Ravenscraft and Scherer (1982) for case studies and econometric evidence.

[15] Options-based and press-based measures of CEO overconfidence described in Malmendier and Tate (2005a, 2005b, 2008).

strengthened creditor rights governing the use of patents as collateral, making external financing possibly more accessible, innovating firms invested more in R&D, filed more patents, and borrowed more through pledging patents as collateral. In Bernstein (2015), firms reduce the "quality" of internally generated patents (e.g., lower forward/backward citations) and pursue acquisitions of patents produced outside the firm after going IPO. Lastly, Bena and Li (2014) show that acquirer and target firms produce more patents in aggregate after a merger. With respect to financial markets, Fang, Tian, and Tice (2014) provide evidence that an increase in stock liquidity may pressure managers to reduce patenting activity (measured by citation and patent count) in order to produce short-term earnings. As argued in their paper, stock liquidity can increase exposure to hostile takeovers and poor monitoring by institutional investors.

This paper also explores investments in external patent acquisitions through the use of patent assignment data (i.e., patent ownership and transfers) provided by the Patent and Trademark Office (USPTO). Similar to the aforementioned papers, I use citation weights on patent counts to factor in a patent's technological relevance. We expect a more technologically relevant invention to have a larger impact on a firm's profits, especially when it is strongly linked to a successful product. Additionally, I study the value of patents acquired by innovating firms using data from Kogan et al. (2016), which relies on event studies on stock prices around patent grant dates.

1.1.4 Executive Compensation and Luck

The quasi-natural experiment in this paper also gives us an opportunity to investigate possible principal-agent problems within innovating firms. As demonstrated in Bertrand and Mullainathan (2001) and Garvey and Milbourn (2006), executives can be rewarded for firm performance beyond their control. That is, executives can receive higher compensation for better-than-expected firm performance even though the cause of better performance is completely independent to their efforts. The transitional provision in URAA, which will be discussed in detail in the next section of this paper, was essentially a profit windfall if the pricing of a firm's products is also a function of whether the underlying patents are still in force. Here, we are able to test for possible spillovers of cash flow into executive compensation.

1.2 Institutional Setting

1.2.1 Brief Historical Background in U.S. Patent Law

The Patent Act of 1952 lays the foundation for modern patent laws in the United States; it outlines the duties of the USPTO, when and how patents may be obtained, and the protection of rights under patents. Until the establishment of the World Trade Organization (WTO) in 1994, U.S. patent law experienced little change or modification. The term of patents, for example, remained unchanged since 1861.

The WTO was created during the Uruguay Round, a set of multilateral trade negotiations that spanned from 1986 to 1994. While the purpose of these negotiations was to enhance international trade since the General Agreement on Tariffs and Trade (GATT) of 1948, the WTO also negotiated the agreement on Trade-Related Aspects of Intellectual Property Rights (TRIPS), which unified intellectual property rights across WTO member countries. In order to abide by the minimum standards set out by TRIPS, the U.S. enacted the Uruguay Round Agreements Act (URAA) on December 8, 1994 (see Public Law 103-465). URAA, which took effect on January 1, 1995, made several changes to the patent system. What received the most attention, however, was the change in the patent term from 17 years from the issue or grant date to 20 years from the filing date.[16]

1.2.2 Transitioning from a Fixed 17-year to a Variable 20-year Patent Term

TRIPS required patents granted by WTO member countries to be enforceable for at least 20 years. Under URAA, patents filed on or after June 8, 1995 in the U.S. would expire 20 years after the first application date. However, URAA was controversial at the time because it

[16]This excludes design patents.

potentially permitted term extensions on pending patents and patents in force. For patents filed before June 8, 1995 and for patents that were still in force on June 8, 1995, the term of protection is equal to the greater of 17 years from the issue date or 20 years from the filing date. This automatic extension allows a patent filed prior to June 8, 1995 that was previously bound to a 17-year term to add up to 3 years to the patent term.

One of the most controversial extensions given resulting immediately after the enactment of URAA was for U.S. Patent No. 4,128,658, a patent on the chemical compound ranitidine hydrochloride. This is the main ingredient for the anti-ulcer drug Zantac, the world's best selling drug at the time ($10.09 billion and $2 billion in sales worldwide and U.S., respectively, in 1995). Under URAA, the patent, owned by Glaxo Plc. (now GlaxoSmithKline), would expire on July 25, 1997 rather than on December 5, 1995, an extension that was estimated to be worth about $1 billion. This extension jeopardized generic drug companies' plans to sell generic versions of Zantac. On April 21, 1995, Glaxo successfully defended its patent term extension in court against generic competitor Novopharm from making a generic version of Zantac until patent expiry. The FDA further officially approved the 18-month extension for Zantac on May 25, 1995. The U.S. Senate defeated efforts to close this legal loophole on December 7, 1995.

1.2.3 Patent Expiration and Corporate Profits

Do patents near expiry have value? Note that the 17 or 20 year patent term discussed above is merely the maximal duration of a patent and only a minority extends to the full length. In the U.S., for utility patents issued on or after December 12, 1980, renewal or maintenance fees are due after 3.5, 7.5, and 11.5 years.[17] If maintenance fees are not paid within a certain time period, the patent lapses (i.e., expires) automatically. The decision not to pay maintenance fees can be influenced by a number of circumstances: whether market approval has been obtained for a drug whose chemical ingredients are patented, whether a close substitute or improvement has effectively ended a patent's life, etc. In aggregate for

[17] Plant and design patents are exempt.

the U.S., about half of the patents issued are maintained for approximately 12 years (Weiss 2010). However, the large amount of abandonment of patents are mainly from small entities (e.g., universities, non-profit organizations, and businesses with fewer than 500 employees).[18] Large entities, on the other hand, are less likely to abandon their patents after issuance.

The fundamental premise of this paper is that a patent near the end of its life can still add value to firms through pricing power in the product market or revenue from licensing arrangements. In order to test this premise, I estimate the following two-way fixed effects regression model (i.e., year and firm) over a 10-year period (1992–2002):

$$y_{it} = \alpha_i + \alpha_t + \beta X_{it} + \gamma' C_{it} + \epsilon_{it} \tag{1.1}$$

where i and t are firm and year indicators, respectively, y is a measure of corporate profits, α is a firm or year fixed effect, X is the percentage of patents that expired in the previous year, C is a vector of control variables, and ϵ is an error term. Note that X_{it} excludes patents that expired resulting from failure to pay maintenance fees. This is so that we are only concerned about patents that are strategically important enough for firms to continue to keep in place. Controlling for patent portfolio size, book assets, investment opportunities (Tobin's Q), book leverage, capital intensity, number of employees, and firm age (all included in C_{it} in Equation 1.1), I find that patent expiration is economically and statistically related to firm profitability across various measures. Table 1.4 documents the regression estimation results of the aforementioned fixed effects model. On average, a one percentage point increase in the portfolio share of patents expired in the previous period decreases firm profitability by 0.05 percent of book assets (see Columns 5 and 6 in Table 1.4). With standard errors clustered at the firm level, this effect is statistically significant at the 1 percent level for return on sales (ROS), cash flow (scaled by book assets), and EBIT (scaled by book assets).

[Insert Table 1.4]

However, the choice to pay maintenance fees (i.e., keeping patents in force) until expiry

[18] Small entities receive a 50 percent reduction in fees as well.

is endogenous (i.e., expiration is not exogenous). The key take away from this is that we should expect patent expiration to negatively affect firm profitability.[19] If firms were to receive an exogenous extension, we should observe a brief period of extended profitability with an eventual decline thereafter.

1.2.4 Determining Patent Expiration Dates

Determining the expiration date for most patents is straightforward. For most utility and plant patents, if the patent is filed prior to June 8, 1995 or is still in force by that cut off date, the expiration date is precisely the greater term of 17 years from the grant date and 20 years from the filing date.[20] If the patent was filed on or after June 8, 1995, the expiration date is the filing date plus 20 years (see Figure 1.4 for visual depictions of a typical utility patent's timeline). Design patents expire 14 years from the grant date regardless of when it was filed. However, of course, there are multiple exceptions to the general rule. I do my best to calculate patent expiration dates as precisely as possible in my dataset. Notable exceptions and adjustments are discussed in the Appendix.

[Insert Figure 1.4]

1.2.5 Other Studies on the Uruguay Round Agreements Act and TRIPS

As of writing, I am only aware of four other papers that have designed quasi-natural experiments using URAA. Abrams (2009) evaluates the impact of the expected patent term extension gained (or lost) due to the enactment of URAA on subsequent innovation as measured by forward citation counts in a patent class. Expected extension for a given patent class is defined as the mean processing time averaged over a two-year period subtracted

[19]This is often called patent cliffs. Patent cliffs denotes a sharp decline in revenues upon patent expiring of key products of a firm. Identifying patents linked to those products is extremely difficult, since relevant patents could not only be used to prevent others from duplicating the product exactly, but also to block the creation of near substitutes.

[20]Patents that are not in force by the cut off date of June 8, 1995 expire by the end of the old 17 year term.

from the 3-year possible gain in patent protection. The paper finds that there is a statistically significant change in the number of patents applied following URAA, but no significant difference in mean citations per patent. Dass, Nanda, and Xiao (2015) shows that URAA strengthened patent rights in general, which led to lower stock volatility. The treatment group in their paper includes firms that applied for patents in the two-year period prior to the implementation of URAA. In Lemus and Marshall (2016) and Sukhatme and Cramer (2015), the authors provide evidence that URAA created incentives to decrease the patent prosecution time to take advantage of the new 20-years from filing date patent term policy. For each firm, Sukhatme and Cramer (2015) uses the number of patent filings 1 month prior to URAA divided by the number of patent filings 1 year prior over the same month as a continuous treatment variable, which measures a patentee's sensitivity to the new patent policy (i.e., a higher ratio means the patentee benefited more from the old fixed 17-year term from grant date and therefore had more incentive to reduce application delay). Lemus and Marshall (2016) studies the patent filings behavior (e.g., word count, etc.) resulting from TRIPS using patents filed months before June 8, 1995 as counterfactuals for those filed after TRIPS came into force.

1.3 Data and Experimental Setup

1.3.1 Data

My overall dataset is constructed from six sources: (1) U.S. patent data granted from 1975 to 2006 (Hall, Jaffe, and Trajtenberg 2001), (2) U.S. patent data granted from 1975 to 2010 with inventor information (Lia et al. 2014), (3) U.S. patent maintenance fee payment history (USPTO), (4) U.S. patent assignment database (USPTO), (5) annual corporate accounting data from Compustat, and (6) executive compensation data from Standard and Poor's ExecuComp (1992–1994). Datasets generated by Hall, Jaffe, and Trajtenberg (2001) and Lia et al. (2014) provide identification keys that match patents to Compustat firms (via `GVKEY`) depending on grant date. The patent assignment data, on the other hand, is raw and is not matched to Compustat firms (Marco et al. 2015). I use fuzzy string matching techniques to match the distinct parties of each transaction to Compustat firms by name. First, I use the Trigram algorithm to match assignees (firms acquiring patents) and assignors (firms relinquishing patents) to the set of Compustat firms identified in Hall, Jaffe, and Trajtenberg (2001) and Lia et al. (2014). Then, I manually inspect the integrity of the match.

With the dataset created by Hall, Jaffe, and Trajtenberg (2001) and the patent assignment database, I construct measurements of patent ownership over time for each firm. While Hall, Jaffe, and Trajtenberg (2001) accounts for patent transfers resulting from mergers and acquisitions, it does not account for patent sales or purchases beyond M&A. The patent assignment database allows me to make proper adjustments to these patent ownership measurements. However, one limitation to the patent assignment database is that reporting patent assignments is voluntary. Nonetheless, utilizing the patent assignment database ultimately gives us a more accurate representation of corporate ownership of patents.

Each patent's expiration date is computed based on the rules discussed in the previous sections. I incorporate patent maintenance fees and terminal disclaimer information manually to modify patent expiry dates to account for failure to pay fees or avoidance of double patenting. Hatch-Waxman term adjustment data is pulled from the USPTO website.[21] I ignore patent reissuances when constructing the treatment variable since they consist merely of updates to previously granted patents.[22]

1.3.2 Treatment Definition

In order to estimate the impact of URAA's term extensions of expiring patents for each firm, I construct a continuous treatment variable in three steps. Firstly, I identify patents expiring six months before and after the policy cutoff date of June 8, 1995 according the pre-URAA 17-

[21]See `http://www.uspto.gov/patent/laws-and-regulations/patent-term-extension/patent-terms-extended-under-35-usc-156`.

[22]Patent identifications beginning with "RE" are not used. In fact, including reissued patents in the construction of forward citations could result in double counting since citing reissued patent requires one to also cite the original patent as well.

years patent term.[23] Patents that expire between June 8 and December 31, 1995, but qualify for term extensions greater than zero are denoted as "term-extended" patents. Patents that expire between January 1 and June 7, 1995, but would have received term extensions greater than zero if they had expired slightly later are denoted as "counterfactual" patents. The average extension of patents expiring between June 8, 1995 and December 31, 1995 owned by Compustat firms is 531 days (standard deviation of 170), which is roughly 1.5 years. Figure 1.2 visually depicts the identification of patents in this step. Each rectangular bar in the figure represents the length of a patent's protection period under the pre-URAA rule of 17-years from the grant date. In order for a patent to be considered in the construction of the treatment variable, it must hypothetically or actually benefit from the new 20-years from application date criteria. The solid vertical line represents the threshold date for which patents must be in-force to qualify for the transitional provision. That is, the patent must expire on or after the cutoff date to receive a term extension. The dashed vertical lines encompass a small 1-year window restriction to mitigate the residual term effects (i.e., time left to expiry under the 17-year term policy) from confounding the windfall profit estimates. This means we only consider patents expiring within this 1-year window (solid rectangular bars) and ignore patents that expire outside this window (shaded rectangular bars).

[Insert Figure 1.2]

Secondly, I group each set of term-extended and counterfactual patents by firm. Figure 1.3 illustrates three scenarios of patent ownership as a result from grouping these patents by firm. Firms could (1) exclusively own term-extended patents ("treated" firms), (2) exclusively own counterfactual patents ("control" firms), and (3) own a mixture of term-extended and counterfactual patents ("partially treated" firms). In Figure 1.3, each point represents the time at which a patent expires under the pre-URAA rule of 17-years from the grant date. Solid circles and red x's are term-extended and counterfactual patents, respectively. The solid black and dashed gray ellipses represent the treated and control firms, respectively,

[23]From this point on, we only concern ourselves with utility and plant patents and ignore design patents since they are not affected by URAA's new term policies.

that own the patents enclosed by the ellipses. The black dashed ellipse is a firm that own both counterfactual and term-extended patents.[24]

[Insert Figure 1.3]

In the third and final step, I construct the continuous treatment variable, which is interpreted as a measurement of treatment intensity of patent term extensions on patents expiring within a 1-year window around the cutoff date of June 7, 1995. I define the following continuous treatment variable for each firm i:

$$\begin{aligned} D_i &\equiv \frac{\sum_{t \in T_i} f_{t,i} - \sum_{c \in C_i} f_{c,i}}{\sum_{p \in P_{95}} f_{p,i}} \\ &= \text{\% Term-extended Patents} \; - \; \text{\% Counterfactual Patents}, \end{aligned} \tag{1.2}$$

where $f_{j,i}$ is the forward citations of patent j owned by firm i and P_{95} is firm i's patent portfolio or set of patents owned that have not expired yet by December 31, 1995. Because I am scaling by firm i's aggregate patent portfolio, the continuous treatment variable captures the net policy impact relative to the size or strength of its technological influence in 1995. Forward citations account for a patent's technological relevance.[25] The differencing captures the treatment intensity for a specific firm. The scaling makes the treatment intensity comparable across firms, since the impact is relative to the size of a firm's patent portfolio.

1.3.3 Concerns of Self-Selection

Because the treatment variable is determined by patents granted in the *past* (i.e., 17 years ago), self-selection can only come from (1) purposely reviving lapsed patents, (2) acquiring patents externally with prior knowledge of the transitional provision, or (3) manipulating

[24]The categorization into treated, control, and partially treated firms is not used explicitly in the construction of the continuous treatment variable.

[25]See Harhoff et al. (1999) and Abrams, Akcigit, and Popadak (2013) on the link between patent value and forward citation count.

the cutoff date. The first scenario does not apply since the patents I use to construct the treatment variable were granted in 1978 or earlier.[26] However, being unable to distinguish between active and inactive patents could produce a downward bias in the profit windfall estimation as we are unable to observe if those patents are actually protecting existing products — drug patents aside. The second scenario can be accounted for by excluding patents that were externally acquired or sold between 1994 and 1995 when constructing the continuous treatment variable. My results are robust with or without this adjustment.[27] The third scenario could arise through corporate lobbying to influence Congress on setting the cutoff date that maximally benefited the firms being lobbied (e.g., a firm may own a cluster of expiring patents it would like extended). I argue that this scenario is unlikely for three reasons. First, the bill for URAA was submitted under special fast-track procedures that precluded modifications by either the House of Representatives or the Senate.[28] This effectively eliminated the possibility of lobbyist intervention of the bill after it was introduced to the House. Secondly, after realizing that the profit windfall gained by some pharmaceutical companies came with a social cost of delaying generic versions of key drugs for consumers, Congress attempted and failed to close this "loophole" *after* signing URAA into law. This implies that Congress most likely was unaware of the consequences when the bill was introduced. Thirdly, the URAA was based on the TRIPS Agreement, which was negotiated by trade negotiators and not corporate lawyers (Carvalho 2005). This fact also reduces the likelihood that the cutoff date was subject to manipulation.

[26]Maintenance fees are only enforced on patents filed on or after December 12, 1980.

[27]Results shown in this paper account for this adjustment.

[28]"Fast track authority" is the authority of the President of the U.S. to negotiate international agreements that Congress can approve or deny, but cannot amend or filibuster.

1.3.4 Identification Strategy

1.3.4.1 Multi-Period Difference-in-Differences Model

To estimate the average treatment effect of patent term extensions from URAA, I work in a difference-in-differences framework. I estimate the following general multi-period model:

$$y_{it} = \alpha_i + \alpha_t + \tau(D_i \times Post) + \gamma' C_{it} + \epsilon_{it} \tag{1.3}$$

where i and t are group (i.e., firm or executive-firm) and time (i.e., year) indicators, respectively, α is a fixed effect (for firm/executive-firm or time), D_i is the treatment variable, $Post$ is an indicator variable for post-treatment time (i.e., $Post = 1$ if $t \geq 1995$), C is a vector of control variables, τ is the average treatment effect, y_{it} is the outcome variable, and ϵ is the error term.[29] At the firm level, the control variables included in Equation 2.9 are the percentage of patents owned that expired in the previous year, the natural logarithm of patent portfolio size (i.e., count of unexpired patents), the natural logarithm of total book assets, Tobin's Q, book leverage, capital intensity, the natural logarithm of the number of employees, and the natural logarithm of the firm's age. At the executive level, control variables also included in Equation 2.9 are executive's age, an indicator variable for whether the executive is the CEO, an indicator variable for whether an executive is a director, and an indicator variable for whether an executive is listed in the Compensation Committee Interlocks section of an annual proxy statement.[30] See Table 1.15 for explicit variable definitions and construction. I control for within-cluster (i.e., cluster at the firm level) error correlation by first estimating Equation 2.9 and then obtaining cluster-robust standard errors (White 2014 and Arellano 1987).

[29] I trim the 1% tails of all regression variables.

[30] This indicates that the named officer is generally involved in one of the following situations: (1) The officer serves on the board committee that makes his compensation decisions, (2) the officer serves on the board (and possibly compensation committee) of another company that has an executive officer serving on the compensation committee of the indicated officer's company, or (3) the officer serves on the compensation committee of another company that has an executive officer serving on the board (and possibly compensation committee) of the indicated offier's company

[Insert Table 1.15]

There are two other concerns that could bias my treatment effect estimation under a difference-in-differences framework. The first concern assumes that firms with different treatment intensities must have the same pre-treatment trends in the outcome variables of interest. Including time-varying control variables and time fixed effects may capture some differences in trends between groups. As done in Autor (2003), a formal inspection of parallel trends can be achieved by estimating the following fixed effects model:

$$y_{it} = \alpha_i + \alpha_t + \sum_{\tau=1990}^{1993} \beta_\tau (D_i^b \times \mathbb{1}_{t=\tau}) + \sum_{\tau=1995}^{1998} \beta_\tau (D_i^b \times \mathbb{1}_{t=\tau}) + \gamma' C_{it} + \epsilon_{it} \tag{1.4}$$

where α_i and α_t are time and group fixed effects, respectively, $\mathbb{1}_{t=\tau}$ is a period indicator or dummy, C is a vector of control variables, y_{it} is the outcome variable of interest, and D_i^b is a binary variable equaling to 1 if a firm is among the "most" treated and 0 if a firm is among the "least" treated. Construction of D_i^b is explained below. I include the interactions of the time dummies and the treatment indicator D_i^b for the pre-treatment years 1990 through 1993 and leave out one interaction for the last pre-treatment period 1994 due to the dummy variable trap (i.e., multicollinearity problem). This means that all other interactions are expressed relative to the omitted period, which serves as the baseline. If the pre-treatment outcome variable trends are the same, then β_{1990}, β_{1991}, β_{1992}, and β_{1993} should be statistically insignificant (i.e., the trends are not significantly different between the two groups in the pre-treatment period). Additionally, β_{1995}, β_{1996}, β_{1997}, and β_{1998} can inform us of whether the treatment effect fades out over time.

The purpose of constructing D_i^b is to be able to compare the pre-treatment outcome variable trends between high and low treatment firms. I do this by assigning firms with treatment values above the 75th percentile into the "high treatment" group and firms with treatment values below the 25th percentile into the "low treatment" group. In other words, I construct the following binary variable:

$$D_i^b \equiv \begin{cases} 1 \text{ if } D_i > D_{75\text{th-\%ile}} \\ 0 \text{ if } D_i < D_{25\text{th-\%ile}} \end{cases} \tag{1.5}$$

As shown in Table 1.1, I obtain a sample size of 410 (for the year 1995), with 205 firms each in the control and treatment groups. The distribution of firms by industry (Fama-French 12 industry categories) is also shown. The industry distribution between the experimental groups are quite similar, which suggests that my results are not likely driven by a relative over-representation of any one particular industry for any one group. The top four industries with the largest representation in my sample are manufacturing (32 percent), computer/software/electronics (18 percent), consumer non-durables (8 percent), and drugs/medical equipment (6 percent).

[Insert Table 1.1]

The second concern—although one could say it is the same as the first—refers to the choice of the outcome variables to analyze. As observed in the labor economics literature (e.g., Meyer, Viscusi, and Durbin 1995), the difference-in-differences framework is scale dependent. If the assumptions of parallel trends hold for y_{it}, the same assumptions may not necessarily hold for a monotone transformation of y_{it}. The plausibility of my treatment therefore hinges on the scaling of variables that I choose to study. In this paper, the majority of the outcome variables constructed have been used before in the finance literature.

1.3.4.2 Combining Instrumental Variable with Difference-in-Differences Methods

In order to estimate the cash flow sensitivities of investment and capital structure variables, I need to remove any sources of endogeneity that may bias the cash flow effect. In this paper, I do this by instrumenting cash flow with my continuous treatment variable, which I believe is plausibly exogenous. Following Waldinger (2010), I estimate my combined instrumental variable and difference-in-differences regression model in two stages:

$$
\begin{aligned}
F_{it} &= \alpha_i + \alpha_t + \tau(D_i \times Post) + \gamma' C_{it} + \epsilon_{it} \\
y_{it} &= \beta_i + \beta_t + \theta \hat{F}_{it} + \omega' C_{it} + u_{it}
\end{aligned} \tag{1.6}
$$

α and β represent fixed effects (time or group), D_i is the continuous treatment variable defined in Equation 1.2, $Post$ is a dummy for years after 1994, C is a vector of control variables (the same set used in Equations 2.9 and 1.4), ϵ and u are error terms, F is cash flow (scaled by book assets), and $\hat{F}$ is the instrumented cash flow. The parameter of interest is θ, the two-stage least squares estimator. This parameter is the unbiased measurement of cash flow sensitivity for y_{it}. As discussed in Bound, Jaeger, and Baker (1995), however, instrumental variable estimates can be biased and inconsistent when instruments are only weakly correlated with the endogenous variable. I test for weak identification by computing the Cragg-Donald Wald and the Kleibergen-Paap Wald rk F statistics.[31]

1.4 Results

1.4.1 Treatment Dynamics on Profits between Firms with High and Low Treatment Values

The key assumption in the difference-in-differences framework is that the average change in the outcome variable for the comparison group (i.e., firms with lower treatment intensity values) represents the counterfactual change for the treatment group (i.e., firms with higher treatment intensity values) in the absence of treatment. If something other than the treatment changes in one group but not the other at the same time as the treatment, a violation of the parallel trend assumption would occur. For a given outcome variable, estimating Equation 1.4 allows us to inspect whether there are any differences in pre-treatment period trends across firms of different treatment intensity values. Given the limited sample size, I compare firms with the highest treatment values (top 25 percentile) to firms with the lowest

[31] See Cragg and Donald (1993) and Kleibergen and Paap (2006) for more details.

treatment values (bottom 25 percentile), as specified in Equation 1.5 (i.e., the construction of D_i^b), over time to understand the treatment dynamics on cash flow, investments, and capital structure variables.

Table 1.1 and 2.2 show that firms with the highest treatment values are very similar to firms with the lowest treatment values across several firm-level observables, which reassures us that differences in group characteristics most likely are not driving the results. Table 1.1 documents that industry representation across these two firm groups defined by D_i^b are almost the same if one partitions these firms in each group by Fama-French 12 industry classifications. Differences in firm count across these industry classifications between these two groups range from only 1 to 7. Table 2.2, on the other hand, compares the lowest and highest treatment value firms across key accounting variables averaged over 1993 and 1994 (i.e., the pre-treatment period). There are no salient differences (not statistically significant) in several measures of firm size such as book leverage, capital intensity, number of employees, or book assets, for example. EBIT and Tobin's Q are slightly different, but only statistically significant at the 10% level. Firm age and patent portfolio size, conversely, are statistically different (at the 1% level) between high vs. low treatment firms. However, the magnitudes are not large; highly treated firms are older by about 3 years and own 4 more patents on average (each group own on average about 70 patents).

[Insert Table 2.2]

Since the average treatment effects for the capital structure and investment variables will be discussed separately later, I focus here on just cash flow, which should be the most important variable that responds to URAA's term extensions on expiring patents.[32] Table 1.6 documents the coefficient estimates of Equation 1.4 on cash flow, EBIT, ROS, and RNOA. Figures 1.5 and 1.6 plot the estimated β_τ coefficients along with their 90 percent confidence intervals.[33]

[32]Equation 1.4 is also estimated for all dependent variables listed in the column headers of Table 1.8. I find no statistically significant differences in pre-treatment trends for them as well.

[33]Standard errors are clustered at the firm level.

[Insert Table 1.6]

The results shown in Table 1.6 confirm the prediction that the additional protection time on expiring patents provide the affected firms the means to exploit their technological monopoly. Once the patents reach the end of their extended new life, any excess profits arising from the patent protection should disappear through competitive pricing, retirement of products, or termination of licensing agreements. This is exactly what we see in the plots on Figures 1.5 and 1.6: we observe an initial positive discontinuity on profits for high treatment firms in 1995 with a steady subsequent decline, as expected when the term-extended patents owned by firms expired over the years.

[Insert Figures 1.5 and 1.6]

1.4.2 Average Treatment Effect on Profits

To estimate the average treatment effect of randomly assigned patent term extensions on expiring patents on corporate profits, I estimate Equation 2.9 over a 4-year window (2 years prior and after the effective cutoff date) using the continuous treatment variable over the full sample.[34] I find that a one standard deviation increase (15 percentage points) in the citation-weighted patent portfolio share of term-extended patents owned that would have expired if not for the transitional provision leads to an increase in cash flow by 1.5 percent of book assets (statistically significant at the 1% level), EBIT by 1.5 percent of book assets (statistically significant at the 1% level), ROS by 1.35 percentage points (statistically significant at the 5% level), and RNOA by 4.2 percentage points (statistically significant at the 1% level). Table 1.7 documents the full regression results for each profit measure mentioned above. There is strong evidence that URAA's transitional patent term provision allowed treated firms to sustain their profits for a longer period of time than firms that were not lucky enough to benefit from it. The profit effect is statistically significant, which should not be surprising for firms that are highly active in (dependent on) the U.S. patent system.

[34] See Table 1.2 for summary statistics.

[Insert Table 1.7]

1.4.3 Average Treatment Effect on Capital Expenditure

From estimating Equation 2.9 on capital expenditure, I find that a one standard deviation increase (15 percentage points) in the citation-weighted patent portfolio share of term-extended patents owned increases capital expenditure by 0.3 percent of book assets, as documented in Column 2 of Table 1.8. This point estimate is statistically significant at the 1% level. The strong statistical significance of capital expenditure suggests that innovating firms are financially constrained. This should not be surprising, particularly since patent-dependent firms are often believed to face the strongest degree of adverse selection costs. I formally test for whether financial constraints are driving this result in Section 5 by first sorting and partitioning my sample of firms by several measures of financial constraint and then estimating the average treatment effect on capital expenditure for each sub-sample of firms. The most financially constrained firms should be the most sensitive in capital investments to term extensions on their expiring patents, which is strongly linked to cash flow.

[Insert Table 1.8]

1.4.4 Average Treatment Effects on R&D Expense and Patent Acquisitions

R&D expense does not respond to patent term extensions on expiring patents, as reported in Column 1 of Table 1.8. While there is little support for *internal* investments in R&D, I find evidence of R&D investment through acquisitions of external patents.[35] A one standard deviation increase (15 percentage points) in the citation-weighted patent portfolio share of term-extended patents owned leads to an increase in the probability of acquiring patents by 1.8 percent (significant at the 10% level), an increase in citation-weighted patents acquired by 6 percent (significant at the 10% level), and an increase of 2.25 percentage points in net patent transfers (significant at the 5% level). Net patent transfers is defined as the

[35] Patent acquisitions do not show up under R&D expense since they are considered intangible assets and are therefore not expensed immediately.

citation-weighted difference in the number of patents acquired and sold scaled by a firm's citation-weighted patent portfolio size.

[Insert Table 1.9]

These externally acquired patents, interestingly, have traits that suggest that mature innovating firms, in response to exogenous cash flow, are taking on riskier investments in technologies that are potentially beyond their core expertise. As shown in Column 1 of Table 1.9, I find that a one standard deviation increase in the citation-weighted patent portfolio share of term-extended patents owned leads to an increase in the share of new class/subclasses of acquired patents by 1.83 percentage points (significant at the 5% level). These patents seem to originate from private firms. Column 2 of Table 1.9 shows that a one standard deviation increase in the continuous treatment variable leads to an increase in acquired patents originating from private firms by 0.3 percent of an average firm's patent portfolio (significant at the 10% level). Lastly, these externally acquired patents also cite relatively fewer patents that are not already owned by affected firms. A one standard deviation increase in the continuous treatment variable leads to a decrease in the share of external citations of acquired patents by 2.5 percentage points (significant at the 10% level). In summary, despite being limited in how they approach internal R&D investments, mature innovating firms have a preference to outsource their investments in innovation.

Given the age and size of these firms (as measured by book assets or number of employees), the findings here are not inconsistent with the current literature, as mentioned previously. While financial constraints may be present, direct investments in R&D that is done internally may have high adjustment costs (e.g., opportunity cost of highly specialized employees or the cost of training new ones), which can lead firms to aggressively buffer R&D from transitory volatility in cash flow (Brown, Martinsson, and Petersen 2012). This does not imply that these firms are not constrained in their internal R&D investments, as this "smoothing" does not change the long-run availability of financing. As discussed in Section 4.5, innovating firms may build up cash holdings to buffer future shocks to R&D financing. Additionally, this R&D insensitivity may also reflect the frequency and cost of defending intellectual property, which could be of first order importance (Lanjouw and Schankerman 2001). For example, Lerner (1995) finds that U.S. firms spent over $1 billion enforcing or defending against patent lawsuits filed in 1991 alone, an amount equal to almost one-third of these firms' investments in basic R&D that year. In other words, the increased patent acquisitions could be a symptom of "patent portfolio racing" observed in Hall and Ziedonis (2001), where firms seek to mitigate expropriation risk.

1.4.5 Average Treatment Effect on Capital Structure

I find that firms reduce the level of their debt issuance but make no changes to the level at which they issue equity in response to term extensions on expiring patents. As shown in Column 4 of Table 1.8, I find that a one standard deviation increase (15 percentage points) in the citation-weighted patent portfolio share of term-extended patents decreases debt issuance by 1.65 percent of book assets (statistically significant at the 5% level). The treatment effect on the natural logarithm of equity issuance (Column 3 of Table 1.8), on the other hand, is not statistically significant. The strong decrease in debt issuance supports the theory of costly external financing.

There is also some evidence of firms increasing their cash holdings. Column 5 of Table 1.8 notes that a one standard deviation increase (15 percentage points) in the citation-weighted patent portfolio share of term-extended patents increases cash holdings by 0.3 percent of book assets (significant at the 10% level). Retaining cash is a common strategy for innovating firms to buffer themselves against future negative cash flow shocks (e.g., poor product sales, competition, technological obsolescence, etc.). In other words, the increase in cash holdings suggests that firms may hold cash as a precautionary measure, whether used to mitigate the risk of a future negative cash flow shock (Bates, Kahle, and Stulz 2009), future costly external financing options, or for possible future strategic corporate actions (e.g., mergers, acquisitions, etc.) due to changes in product market competition (Lyandres and Palazzo 2015).

1.4.6 Cash Flow Sensitivity

I conduct cash flow sensitivity analysis by combining two econometric models that are frequently used in quasi-natural experiment papers: the difference-in-differences and the instrumental variable models (see Equation 1.6). The rationale for such an empirical strategy is to find an unbiased relationship between cash flow and investment or capital structure variables. Following the investment-cash flow literature, the variable I instrument is cash flow (see Table 1.15 for definition). The outcome variables of interest are capital expenditure, debt issuance, net patent transfers, and share of new patent class/subclasses acquired. The instrument that I use is the continuous treatment variable that I define in Equation 1.2. Table 1.10 reports the two-stage estimation results for capital expenditure, debt issuance, net patent transfers, and share of new patent class/subclasses acquired. I estimate the cash flow sensitivity parameter in two stages. In the first stage, I estimate a difference-in-differences model using the continuous treatment with cash flow as the dependent variable. Columns 1, 3, 5, and 7 of Table 1.10 report the first stage estimation results. Columns 2, 4, 6, and 8 of Table 1.10 report the second stage estimation results (i.e., estimation of the cash flow sensitivity coefficient).

[Insert Table 1.10]

The results on investment resemble my findings earlier when I regress the continuous treatment variable directly on the outcome variables of interest (i.e., reduced form regressions). I estimate that a one percentage point increase in book asset-scaled cash flow increases capital expenditure by 0.13 percent of book assets (statistically significant at the 5% level), reduces debt issuance by 0.54 percent of book assets (significant at the 10% level), increases net patent transfers by 0.9 percentage points (satistically significant at the 10% level), and increases the share of class/subclasses of externally acquired patents by 0.98 percentage points (significant at the 10% level).

1.5 Extensions and Robustness Checks

1.5.1 Measures of Financial Constraint

Are financial constraints really driving the capital investment result in Column 2 of Table 1.8? If a firm has sufficient amount of cash or unused debt capacity to finance all its investment projects, then term extensions on expiring patents (i.e., cash flow) may not affect the level of investment. If a firm must, on the other hand, access the debt or equity market for additional financing, term extensions on expiring patents should have an impact on investment.

To show that capital investment responds more to patent term extensions when firms are financially constrained, I first sort firms in my sample into quartiles according to three different measures of financial constraints: the Kaplan-Zingales Index (Lamont, Polk, and Saá-Requejo 2001), the Size-Age Index (Hadlock and Pierce 2001), and the Whited-Wu Index (Whited and Wu 2006). Then, I estimate the average treatment effect on capital investment from Equation 2.9 for firms within each quartile. If financial constraints is of first order importance, the most financially constrained firms should respond most in capital investments to term extensions on their expiring patents. Details of the construction of each index mentioned above can be found in the Appendix.

[Insert Table 1.11]

Lamont, Polk, and Saá-Requejo (2001) estimates an ordered logit model to classify firms as either constrained or unconstrained on five accounting ratios: cash flow to total capital, Tobin's Q, debt to total capital, dividends to total capital, and cash holdings to capital. I apply the estimates of this ordered logit regression to my sample. Higher values of the linear combination of the five ratios imply a higher degree of financial constraint. I separate my sample of firms into quartiles based on the value of the Kaplan-Zingales Index in 1994 and estimate Equation 2.9 separately on firms in each quartile. As shown in Table 1.11, I find that the effect of term extensions on expiring patents is significant (1% level) only for the top quartile of the Kaplan-Zingales Index (Column 4 of Table 1.11).

[Insert Table 1.12]

Hadlock and Pierce (2001) also estimates an ordered logit model to classify firms as either constrained or unconstrained. However, rather than use accounting ratios, they use size and age. Table 1.12 shows that, again, the effect of term extensions on expiring patents is the most significant for the top quartile of the Size-Age Index (Column 4 of Table 1.12).

[Insert Table 1.13]

Lastly, Whited and Wu (2006), in order to avoid sample selection, simultaneity, and measurement-error issues, structurally estimates a standard intertemporal investment model augmented with financial frictions. Estimation of their investment Euler equation provides fitted values of the shadow value of scarce external funds that is used in the construction of the Whited-Wu Index. Constructing the Whited-Wu Index for firms in 1994 and performing the same sorts and regression estimations, I find that term extensions on expiring patents is significant on investments only for the most constrained firms (Column 4 of Table 1.13).

1.5.2 Executive Compensation

Do agency issues exist within mature, patent-practicing firms? While it is difficult to tell whether the subsequent investments made by these firms in response to URAA's patent term extensions were inefficient, we can examine whether executives of treated firms are able to extract rents from windfall profits. In order to study the treatment effects of URAA's patent term extensions on executive compensation, I estimate Equation 2.9 at the executive-firm level using the ExecuComp database. Table 1.14 documents the regression results on the natural logarithm of executive salary (Column 1), total compensation (Column 2), options award value (Column 3), and bonuses (Column 4). Overall, I find no significant impact on any measure of executive compensation from term extensions on expiring patents after controlling for both firm and executive characteristics and including year, executive-firm, and payment rank fixed effects. Standard errors are clustered at the firm (i.e., treatment) level.

[Insert Table 1.14]

Although there is no strong evidence of executives being rewarded for luck or positive firm performance that is independent of their skills and effort, this does not mean that these firms are devoid of agency problems. It is possible that the investments made in response to URAA's term extensions could be a symptom of empire building and excessive risk taking. Nonetheless, Table 1.14 suggests that financial frictions arising from agency costs are most likely not first order issues for mature innovating firms.

1.5.3 Placebo Difference-in-Differences

The treatment dynamics plotted in Figures 5 and 6 compare trends in income measures between the lowest and highest treatment value firms over time. The discontinuity in 1995, which is statistically significant at the 5 percent level, suggests that the constructed treatment variable has a joint effect only for the years 1995 and 1996. However, is the constructed treatment variable merely mechanically capturing the residual term effects left over from patents that have yet to expire? While the procedure for controlling for this explicitly is not straight-forward (e.g., should we take the average, maximum, or minimum of the additional protection term—before applying URAA's automatic term extensions—that term-extended patents have over the counterfactual patents that are owned by each firm?), we can run a simple placebo difference-in-differences experiment for an arbitrary date as a pseudo-cutoff date.

[Insert Table 1.19]

I estimate the same quasi-natural experiment specified in this paper using the pseudo-cutoff date of June 7, 1994 (one year before the actual cutoff date) in the construction of T_i and C_i for each firm to see if the treatment variable definition is just capturing the residual term of patents expiring later. If Equation 1.2 is mechanically capturing the residual term of patents expiring after the cutoff date, we should expect a possible discontinuity in firm outcome variables for this date as well. Table 1.19 in the Appendix shows us that this is not the case. For cash flow, investment, and capital structure variables, the treatment variable constructed from the pseudo-cutoff date does not yield any statistically significant effects.

1.5.4 Bias from Forward Citation Weighting

Could counterfactual and term-extended patents be treated differently in the way they are cited in the future due to URAA's automatic term extensions? Moreover, could expired patents in general be given too much weight by forward citations relative to unexpired ones? To test for these possibilities, I construct the treatment variable using only patent counts. That is, I ignore forward citation information for all patents used in the construction of the treatment variable defined in Section 3. Table 1.20 in the Appendix documents the results of estimating Equation 2.9 for investment and capital structure variables using this non-citation-weighted treatment variable. I find that the direction and statistical significance of each estimated average treatment effects, in general, to be no different from the results using the citation-weighted version of the treatment variable. The magnitude, for some outcome variables, such as cash flow, tended to be larger, which is not surprising, since we are dealing with patent counts rather than citation counts.

[Insert Table 1.20]

1.6 Conclusion and Policy Implications

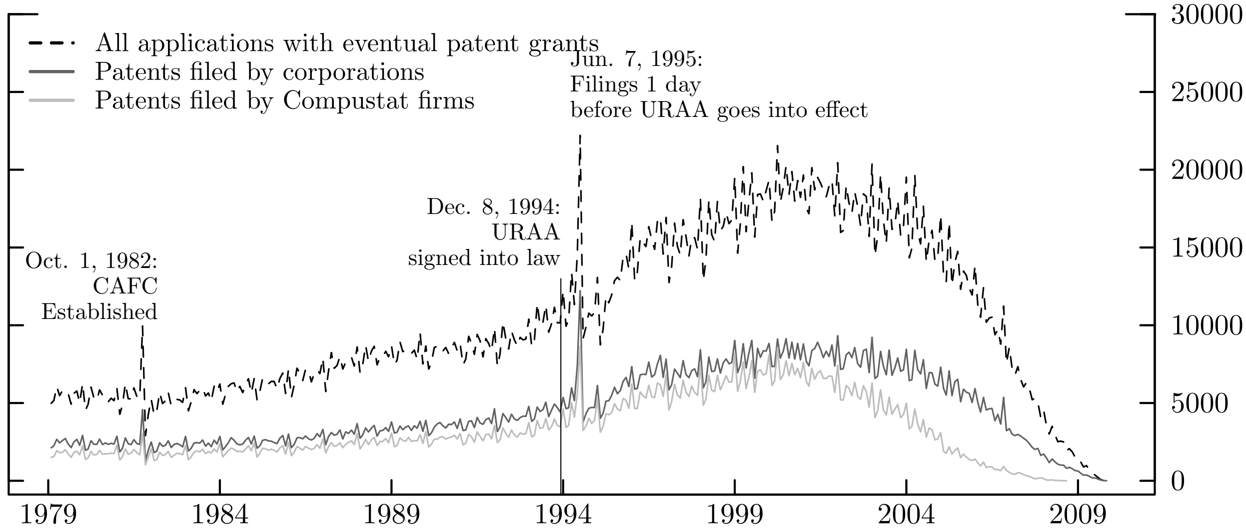
This paper investigates the effects of URAA, a major reform in U.S. patent law that changed the patent term from 17 years from the grant date to 20 years from the application date, on investments in corporate innovation and on corporate financing decisions. URAA imposed an unexpected and controversial transitional provision that extended the term of some existing patents in force depending on whether the patent was filed prior to or after the policy cutoff date (June 8, 1995). Because this threshold date was not known until the enactment of URAA on December 8, 1994, patent expiration around this threshold is as good as random. By exploiting the random timing of patent expiration 6-months before and after this policy cutoff date, I am able to compares firms that were lucky enough to have patents qualifying for term extensions to those that only had patents expire just before the threshold date.

I use two empirical strategies: difference-in-differences with the treatment variable defined in Equation 1.2 to study investments in corporate innovation, corporate financing decisions, and profits directly (i.e., reduced form) and the combination of difference-in-differences and instrumental variable methods, using the constructed treatment variable as the instrument, to study cash flow sensitivities of investments and capital structure. Under the reduced form difference-in-differences model, I find strong evidence that URAA induced an extra period of profits for treated firms. For firms with such windfall profits, we observe increases in capital expenditure, reductions in debt issuance, and increases in acquisitions of patents generated outside the firm. Estimating the combined difference-in-differences and instrumental variable model, I find that capital expenditure, debt issuance, and external patent acquisitions are sensitive to cash flow. These findings provide strong evidence that mature, patent-practicing firms do face financial constraints on both their R&D and physical capital investments.

More interesting, I find that innovating firms opt to acquire external patents rather than develop new technologies within themselves through internal R&D expenditure. These externally acquired patents on average originate from private firms, are of different technology classifications than the ones already represented in the acquiring firms' historical patent portfolios, and have relatively fewer external citations of patents not owned by the acquiring firms. Mature innovating firms essentially outsource their investments in innovation. The finding that internal R&D expense is insensitive to cash flow is not inconsistent with the current literature given the intangible nature of R&D investment, but it raises many policy related questions with regards to patenting strategy. For example, are the acquired patents used to facilitate future follow-on innovation or to block subsequent innovation by potential competitors (i.e., reduce expropriation risk)? This ultimately raises the question of whether there is actually underinvestment in R&D in aggregate due to possible hold-up issues produced by patent rights. Further research is needed on the relationship between corporate financing and patenting strategy.

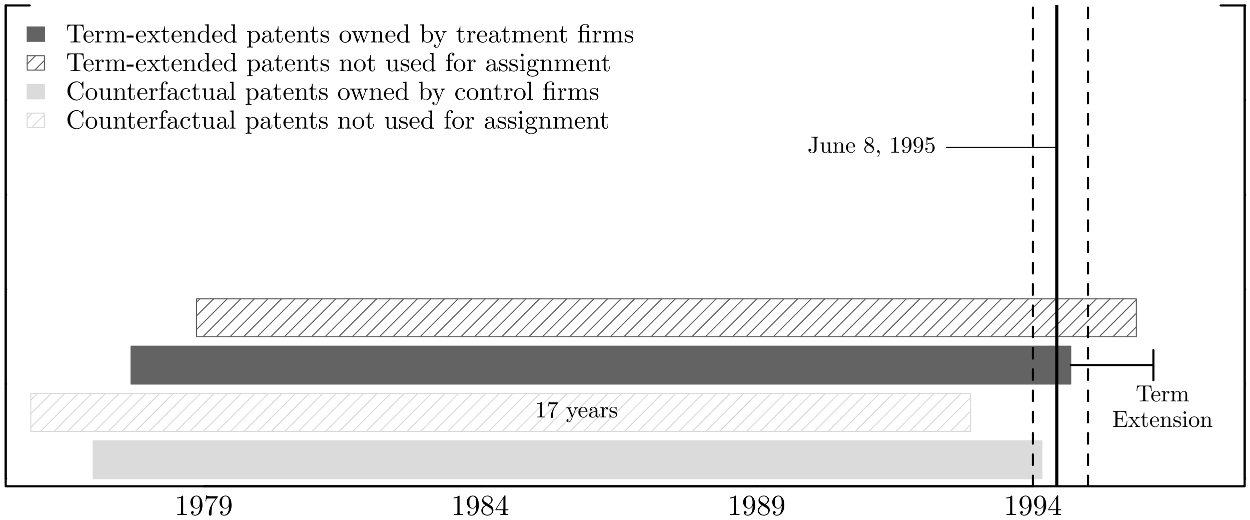
1.7 Figures

Figure 1.1: Monthly Patent Filings



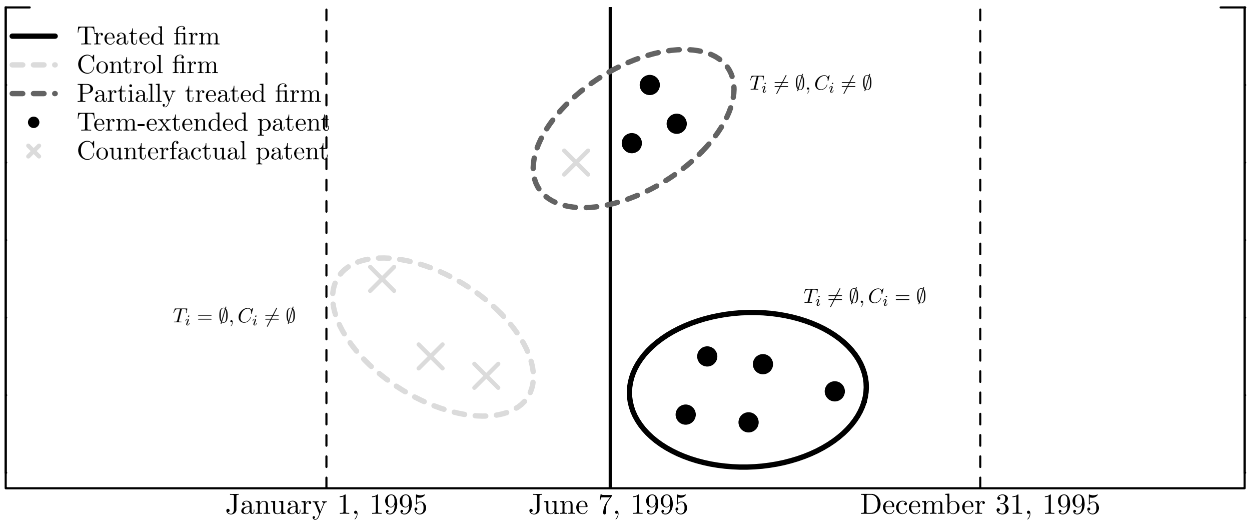
CAFC stands for the United States Court of Appeals for the Federal Circuit. The sharp increase in patent applications in June 1995 suggests that the new 20-year patent term policy and transitional provision was unanticipated.

Figure 1.2: Identifying Term-Extended and Counterfactual Patents



Each rectangular bar represents the length of a (utility or plant) patent's protection period (ignoring term restorations from the Hatch-Waxman Act for simplicity) under the pre-URAA rule of 17-years from the grant date. In order for an expiring patent to be used in the construction of the treatment variable, it must hypothetically or actually benefit from the new 20-years from application date criteria. The solid vertical line represents the cutoff date (June 8, 1995) for patents in-force to qualify for the term-extension transitional provision. The patent must expire on or after the cutoff date in order to receive a term extension. Counterfactual patents expire prior to this cutoff date. The dotted vertical lines encompass the small 1-year window used to construct the treatment variable.

Figure 1.3: Types of Firms by Ownership of Expiring Patents

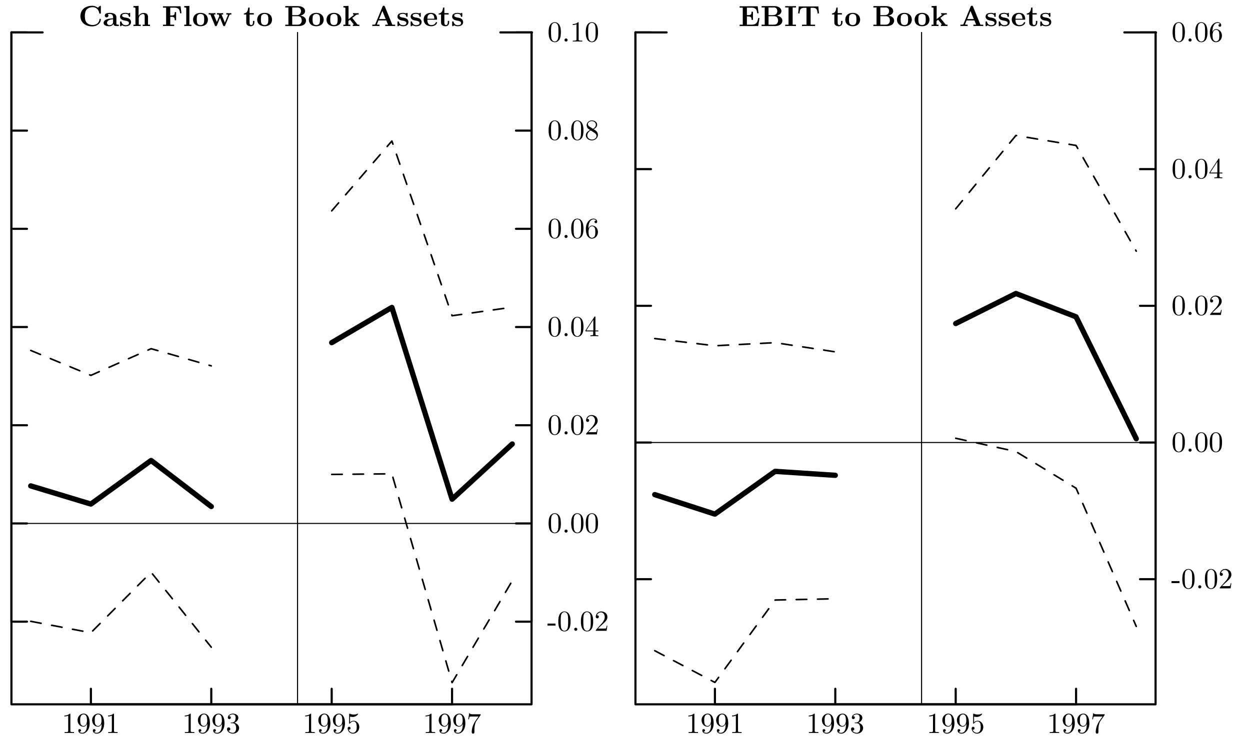


The figure above shows three possible firm types based on its ownership of expiring patents around a 1-year threshold window around June 8, 1995. Each point represents the time at which a patent expires under the pre-URAA rule of 17-years from grant date. Each ellipse (dashed or solid), which represents a firm, enclose a set of expiring patents owned by that firm. The continuous treatment variable is defined for each firm as the citation weighted difference between the number of term-extended and counterfactual patents scaled by the number of patents owned that have not expired by Dec. 31, 1995 (also citation weighted). C_i and T_i are the sets of patents expiring prior to and after the cutoff date (June 8, 1995), respectively, owned by firm i.

Figure 1.4: URAA Patent Term Extension (Patents filed prior to and in force on June 8, 1995)

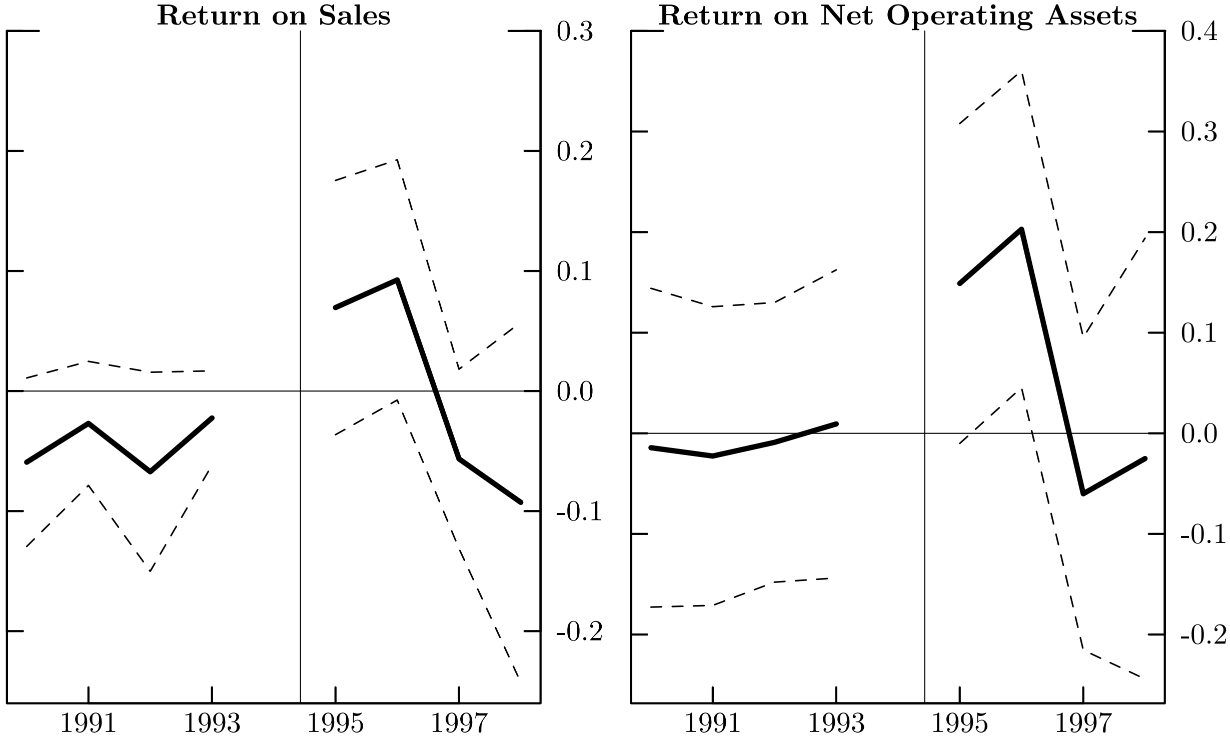
The figure above is a typical timeline of protection term of plant and utility patents. See Figures 7 and 8 in the appendix for additional term adjustments made for qualifying patents under the Hatch-Waxman Act.

Figure 1.5: Bottom vs. Top 25th Percentile Treatment Dynamics on Cash Flow and EBIT



Each point is the estimated β_τ from the following fixed effects model: $y_{it} = \alpha_i + \alpha_t + \sum_{\tau=1990}^{1993} \beta_\tau(\mathbb{1}_{i\in\text{Treatment}} \times \mathbb{1}_{t=\tau}) + \sum_{\tau=1995}^{1998} \beta_\tau(\mathbb{1}_{i\in\text{Treatment}} \times \mathbb{1}_{t=\tau}) + \gamma' C_{it} + \epsilon_{it}$, where α_i and α_t are time and firm fixed effects, repsectively, and C_{it} is a vector of control variables (share of patent portfolio expired in the previous period, the natural logarithm of portfolio size, the natural logarithm of book assets, Tobin's Q, book leverage, capital intensity, the natural logarithm of the number of employees, and the natural logarithm of firm age). The continuous treatment variable is defined for each firm as the citation weighted difference between the number of term-extended and counterfactual patents scaled by the number of patents owned that have not expired by Dec. 31, 1995 (also citation weighted). $\mathbb{1}_{i\in\text{Treatment}}$ is equal to 1 when the continuous treatment of firm i has a value above the 75th percentile of the sample. $\mathbb{1}_{i\in\text{Treatment}}$ is equal to 0 when the continuous treatment of firm i has a value below the 25th percentile of the sample. Firms that have continuous treatment values between the 25th and 75th percentiles are not used. Each point estimate can be interpreted relative to $\tau = 1994$. See Table 1.15 in the appendix for variable construction. Dashed bands represent 90% confidence intervals. Standard errors are clustered at the firm level.

Figure 1.6: Bottom vs. Top 25th Percentile Treatment Dynamics on ROS and RNOA



Each point is the estimated β_τ from the following fixed effects model: $y_{it} = \alpha_i + \alpha_t + \sum_{\tau=1990}^{1993} \beta_\tau(\mathbb{1}_{i\in\text{Treatment}} \times \mathbb{1}_{t=\tau}) + \sum_{\tau=1995}^{1998} \beta_\tau(\mathbb{1}_{i\in\text{Treatment}} \times \mathbb{1}_{t=\tau}) + \gamma' C_{it} + \epsilon_{it}$, where α_i and α_t are time and firm fixed effects, repsectively, and C_{it} is a vector of control variables (share of patent portfolio expired in the previous period, the natural logarithm of portfolio size, the natural logarithm of book assets, Tobin's Q, book leverage, capital intensity, the natural logarithm of the number of employees, and the natural logarithm of firm age). The continuous treatment variable is defined for each firm as the citation weighted difference between the number of term-extended and counterfactual patents scaled by the number of patents owned that have not expired by Dec. 31, 1995 (also citation weighted). $\mathbb{1}_{i\in\text{Treatment}}$ is equal to 1 when the continuous treatment of firm i has a value above the 75th percentile of the sample. $\mathbb{1}_{i\in\text{Treatment}}$ is equal to 0 when the continuous treatment of firm i has a value below the 25th percentile of the sample. Firms that have continuous treatment values between the 25th and 75th percentiles are not used. Each point estimate can be interpreted relative to $\tau = 1994$. See 1.15 in the appendix for variable construction. Dashed bands represent 90% confidence intervals. Standard errors are clustered at the firm level.

1.8 Tables

Table 1.1: Sample by Industry Split Between Top/Bottom 25th %-tile of Treatment Values

	Control ($\leq$25%ile)	Treatment ($\geq$75%ile)	Difference
Consumer Non-Durables	20	14	6
Consumer Durables	10	13	-3
Manufacturing	68	65	3
Energy	7	11	-4
Chemicals	7	14	-7
Computers, Software, and Electronic Equipment	38	37	1
Telecommunications	1	0	1
Utilities	4	3	1
Wholesale and Retail	10	13	-3
Healthcare, Medical Equipment, and Drugs	15	8	7
Finance	6	5	1
Other	19	22	-3
Number of Obs.	205	205	0

Sample above is a snapshot of firms in 1995. The continuous treatment variable is defined for each firm as the citation weighted difference between the number of term-extended and counterfactual patents scaled by the number of patents owned that have not expired by Dec. 31, 1995 (also citation weighted). A firm is in the "treatment" group when its continuous treatment has a value above the 75th percentile of the sample. A firm is in the "control" group when its continuous treatment has a value below the 25th percentile of the sample. Firms that have continuous treatment values between the 25th and 75th percentiles are not shown here.

Table 1.2: Descriptive Statistics of Firms (Full Sample)

Variable	N	Mean	Std. Dev.	25%ile	50%ile	75%ile
ROS	1044	0.08	0.10	0.04	0.08	0.12
GPM	1044	0.35	0.17	0.24	0.34	0.45
NPM	1044	0.03	0.11	0.01	0.04	0.07
RNOA	1044	0.14	0.59	0.08	0.15	0.24
Cash Flow	1044	0.08	0.11	0.05	0.09	0.13
EBIT	1044	0.08	0.10	0.04	0.09	0.13
R&D to Book Assets	931	0.05	0.05	0.01	0.03	0.07
Capital Expenditure to Book Assets	1027	0.06	0.04	0.03	0.05	0.07
Capital Intensity	1044	0.30	0.16	0.18	0.27	0.39
Tobin's Q	931	1.69	1.24	1.11	1.37	1.85
Employees	1016	22.64	55.31	1.02	4.11	18.05
Book Leverage	1044	0.25	0.27	0.10	0.21	0.33
Debt Issuance	998	0.08	0.24	0.00	0.02	0.07
ln(Equity Issuance)	1030	3.55	2.49	2.11	3.53	5.14
Cash Holdings	1044	0.10	0.12	0.02	0.06	0.15
ln(Book Assets)	1044	6.32	2.44	4.58	6.27	8.14
Age	1044	24.33	14.10	12.00	23.50	36.00
ln(Portfolio Size)	1040	4.44	2.03	3.00	4.31	5.75
Share Expiring	1010	0.07	0.15	0.00	0.02	0.09
Net Patent Transfer	1040	−0.01	0.22	0.00	0.00	0.00
Share of New Patent Classes	1044	0.21	0.35	0.00	0.00	0.00
Patents from Private Firms	1040	0.01	0.05	0.00	0.00	0.00
Patents from Public Firms	1040	0.01	0.05	0.00	0.00	0.00
Share of External Citations	1044	0.39	0.47	0.00	0.00	0.96
Value of Patents from Public Firms	1044	0.01	0.08	0.00	0.00	0.00

Pre-treatment period shown above covers years 1993 and 1994. Firms included in the sample have at least one patent expiring in 1995. The continuous treatment variable is defined for each firm as the citation weighted difference between the number of term-extended and counterfactual patents scaled by the number of patents owned that have not expired by Dec. 31, 1995 (also citation weighted).

Table 1.3: Descriptive Statistics of Executives Variables (Full Sample)

Variable	N	Mean	Std. Dev.	25%ile	50%ile	75%ile
ln(Total Compensation)	3683	6.81	0.86	6.18	6.74	7.37
ln(Salary)	3901	5.75	0.56	5.37	5.72	6.11
ln(Bonus)	3901	4.69	1.86	4.30	5.11	5.79
Options Granted to Unvested Stock	3901	1.07	4.46	0.20	0.44	0.76
Executive Age	2170	54.57	7.17	50.00	55.00	59.00
CEO	3901	0.17	0.37	0.00	0.00	0.00
Director	3901	0.40	0.49	0.00	0.00	1.00
Interlock	3901	0.03	0.16	0.00	0.00	0.00
Share Expiring	3557	0.08	0.14	0.00	0.05	0.10
ln(Portfolio Size)	3890	5.19	1.82	3.87	5.12	6.62
ln(Book Assets)	3895	7.67	1.66	6.46	7.59	8.76
Tobin's Q	3895	1.71	1.01	1.17	1.42	1.92
Book Leverage	3884	0.23	0.14	0.14	0.22	0.32
Capital Intensity	3895	0.33	0.18	0.19	0.29	0.43
Employees	3895	29.72	56.85	4.70	12.54	34.00
Firm Age	3901	32.85	12.47	25.00	36.00	43.00

Pre-treatment period shown above covers years 1993 and 1994. Firms of executives included in the sample have at least one patent expiring in 1995. The continuous treatment variable is defined for each firm as the citation weighted difference between the number of term-extended and counterfactual patents scaled by the number of patents owned that have not expired by Dec. 31, 1995 (also citation weighted).

Table 1.4: Predicting Profit Losses with Share of Patents Expiring (1992-2002)

	ROS	RNOA	GPM	NPM	Cash Flow	EBIT
	(1)	(2)	(3)	(4)	(5)	(6)
Expiring Share	−0.063***	−0.080*	−0.017	−0.064**	−0.052***	−0.053***
	(0.023)	(0.043)	(0.025)	(0.025)	(0.012)	(0.010)
ln(Portfolio Size)	−0.009	−0.018	−0.001	−0.035**	−0.043***	−0.044***
	(0.018)	(0.030)	(0.015)	(0.018)	(0.007)	(0.006)
ln(Book Assets)	−0.022	0.108	0.001	0.042	0.196***	0.166***
	(0.044)	(0.067)	(0.037)	(0.050)	(0.028)	(0.023)
Tobin's Q	0.009*	0.019**	0.003	0.012**	−0.005**	−0.006***
	(0.005)	(0.008)	(0.005)	(0.006)	(0.002)	(0.002)
Book Leverage	−0.126*	0.337*	−0.171***	−0.326***	−0.422***	−0.260***
	(0.076)	(0.174)	(0.064)	(0.073)	(0.056)	(0.048)
Capital Intensity	−0.158	−0.485**	−0.028	−0.187	−0.196**	−0.272***
	(0.023)	(0.043)	(0.025)	(0.025)	(0.012)	(0.010)
ln(Employees)	0.112**	−0.058	0.033	0.039	−0.093***	−0.063***
	(0.048)	(0.071)	(0.035)	(0.051)	(0.023)	(0.019)
ln(Age)	0.080*	0.132*	0.102**	0.081*	−0.033**	−0.027*
	(0.047)	(0.071)	(0.042)	(0.043)	(0.017)	(0.014)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	13914	11767	13990	13882	14207	14233
Adj. R^2	0.675	0.437	0.622	0.619	0.613	0.732

Significance levels 10% 5%, and 1% are denoted by *, **, ***, respectively. Standard errors in parentheses are clustered at the firm level. Sample starts from 1992 since data is only available for patents granted since 1975, which implies that the earliest expiry is in 1992. Patent maintenance fees were in force for applications filed on or after December 12, 1980.

Table 1.5: Firm-Level Differences Between Top/Bottom 25th Percentile of Treatment Values

	≤25%ile		**≥75%ile**			
Variable	Mean	Std. Dev.	Mean	Std. Dev.	Diff	Std. Error
ROS	0.07	0.17	0.06	0.15	0.01	0.01
GPM	0.31	0.14	0.30	0.17	0.01	0.01
NPM	0.01	0.19	0.01	0.18	0.00	0.01
RNOA	0.14	0.34	0.09	0.51	0.05	0.03
Cash Flow	0.06	0.17	0.06	0.14	0.00	0.01
EBIT	0.08	0.10	0.07	0.12	0.01*	0.01
R&D	0.04	0.05	0.04	0.05	−0.00	0.00
Capital Expenditure	0.05	0.05	0.05	0.04	−0.00	0.00
Capital Intensity	0.31	0.20	0.32	0.20	−0.01	0.04
Tobin's Q	1.55	0.95	1.44	1.67	0.11*	0.06
Employees	8.73	18.91	11.82	49.07	−3.09	2.72
Book Leverage	0.28	0.31	0.30	0.33	−0.02	0.02
Debt Issuance	0.10	0.56	0.10	0.27	0.00	0.03
ln(Equity Issuance)	2.92	2.28	2.66	2.40	0.26	0.17
Cash Holdings	0.09	0.11	0.09	0.13	0.00	0.01
ln(Book Assets)	5.80	2.21	5.63	2.43	0.17	0.16
Age	25.55	13.31	22.56	13.05	2.98***	0.93
ln(Portfolio Size)	3.27	1.40	2.93	1.58	0.34***	0.11
Share Expiring	0.10	0.21	0.09	0.20	0.01	0.01
Inventor Per Patent App.	1.85	1.25	1.76	1.05	0.09	0.11
Net Patent Transfer	−0.01	0.29	−0.42	6.92	0.41	0.35
Share of New Patent Classes	0.14	0.31	0.11	0.29	−0.03	0.02
Patents from Private Firms	0.01	0.07	0.01	0.07	0.00	0.01
Patents from Public Firms	0.01	0.05	0.01	0.07	0.00	0.00
Share of External Citations	0.24	0.42	0.23	0.41	−0.01	0.03
Value of Patents from Public Firms	0.00	0.03	0.00	0.02	−0.00	0.00

The continuous treatment variable is defined for each firm as the citation weighted difference between the number of term-extended and counterfactual patents scaled by the number of patents owned that have not expired by Dec. 31, 1995 (also citation weighted). The last two columns are derived from two sample t-Tests with unequal variances. 1%, 5% and 10% significance levels are denoted by***, ** and *, respectively.

Table 1.6: Top vs. Bottom 25th Percentile Treatment Dynamics on Profits from URAA Patent Term Extensions

	Cash Flow	EBIT	ROS	RNOA
	(1)	(2)	(3)	(4)
25/75th %-ile Treatment × $\mathbb{1}_{1990}$	0.009	−0.005	−0.043	−0.006
	(0.016)	(0.013)	(0.036)	(0.090)
25/75th %-ile Treatment × $\mathbb{1}_{1991}$	0.006	−0.007	−0.018	−0.019
	(0.015)	(0.014)	(0.030)	(0.085)
25/75th %-ile Treatment × $\mathbb{1}_{1992}$	0.012	−0.004	−0.058	−0.010
	(0.013)	(0.011)	(0.044)	(0.080)
25/75th %-ile Treatment × $\mathbb{1}_{1993}$	0.005	−0.005	−0.018	0.001
	(0.017)	(0.010)	(0.023)	(0.089)
25/75th %-ile Treatment × $\mathbb{1}_{1995}$	0.036**	0.018*	0.070	0.134
	(0.016)	(0.010)	(0.063)	(0.092)
25/75th %-ile Treatment × $\mathbb{1}_{1996}$	0.047**	0.023*	0.092	0.191**
	(0.020)	(0.014)	(0.057)	(0.091)
25/75th %-ile Treatment × $\mathbb{1}_{1997}$	0.012	0.022	−0.039	−0.029
	(0.022)	(0.015)	(0.038)	(0.089)
25/75th %-ile Treatment × $\mathbb{1}_{1998}$	0.019	0.006	−0.075	0.008
	(0.016)	(0.016)	(0.082)	(0.126)
Controls	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Obs.	1974	1979	1963	1658
Adj. R^2	0.339	0.572	0.473	0.259

Significance levels 10%, 5%, and 1% are denoted by *, **, ***, respectively. Standard errors in parentheses are clustered at the firm level. The continuous treatment variable is defined for each firm as the citation weighted difference between the number of term-extended and counterfactual patents scaled by the number of patents owned that have not expired by Dec. 31, 1995 (also citation weighted). Time interval of interest is 1993 through 1996 (i.e., 2 years prior and after the effective policy date).

Table 1.7: Treatment on Profits from URAA Patent Term Extensions

	Cash Flow	EBIT	ROS	RNOA
	(1)	(2)	(3)	(4)
Treatment × Post	0.099***	0.088***	0.050**	0.271***
	(0.036)	(0.032)	(0.025)	(0.080)
Share Expiring	−0.015	−0.019**	0.007	−0.010
	(0.013)	(0.009)	(0.031)	(0.051)
ln(Portfolio Size)	−0.003	−0.015	0.037	−0.002
	(0.013)	(0.012)	(0.050)	(0.048)
ln(Book Assets)	−0.025	−0.018	−0.071	−0.105
	(0.024)	(0.021)	(0.089)	(0.121)
Tobin's Q	0.002	0.003	0.003	0.002
	(0.003)	(0.004)	(0.006)	(0.015)
Book Leverage	−0.236***	−0.055***	−0.043	−0.035
	(0.062)	(0.020)	(0.066)	(0.031)
Capital Intensity	−0.189**	−0.170*	−0.178	−0.274
	(0.091)	(0.090)	(0.145)	(0.439)
ln(Employees)	0.013	0.043**	0.066	0.144
	(0.018)	(0.021)	(0.064)	(0.108)
ln(Age)	−0.021	−0.039***	0.024	−0.011
	(0.015)	(0.015)	(0.030)	(0.055)
Year FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Obs.	2173	2180	2165	1667
Adj. R^2	0.509	0.707	0.951	0.327

Significance levels 10%, 5%, and 1% are denoted by *, **, ***, respectively. Standard errors in parentheses are clustered at the firm level. The continuous treatment variable is defined for each firm as the citation weighted difference between the number of term-extended and counterfactual patents scaled by the number of patents owned that have not expired by Dec. 31, 1995 (also citation weighted). Time interval of interest is 1993 through 1996 (i.e., 2 years prior and after the effective policy date).

Table 1.8: Treatment on Investments and Capital Structure from URAA Patent Term Extensions

	R&D Expense	Capital Expenditure	Equity Issuance	Debt Issuance	Cash Holdings	Net Patent Transfer	ln(Patents Acquired)	𝟙(Patents Acquired)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Treatment × Post	−0.007	0.018***	0.035	−0.107**	0.020*	0.147**	0.392*	0.115*
	(0.005)	(0.007)	(0.067)	(0.051)	(0.011)	(0.074)	(0.229)	(0.065)
Share Expiring	0.003	−0.002	−0.009	−0.019	−0.009	−0.008	−0.030	0.024
	(0.004)	(0.005)	(0.026)	(0.018)	(0.008)	(0.079)	(0.215)	(0.054)
ln(Portfolio Size)	0.008**	−0.006*	0.007	−0.019	−0.010	−0.263***	−0.398*	−0.050
	(0.003)	(0.004)	(0.031)	(0.026)	(0.007)	(0.084)	(0.242)	(0.054)
ln(Book Assets)	−0.034***	0.015***	0.147***	0.090***	0.014	0.053	0.227	0.067
	(0.008)	(0.005)	(0.043)	(0.023)	(0.013)	(0.035)	(0.229)	(0.059)
Tobin's Q	−0.001**	0.000	0.013	−0.001	0.006*	0.003	0.085***	0.022***
	(0.001)	(0.000)	(0.009)	(0.007)	(0.003)	(0.003)	(0.021)	(0.007)
Book Leverage	0.018	−0.022**	−0.038	0.336***	−0.014*	−0.034	−0.201*	−0.050*
	(0.013)	(0.009)	(0.035)	(0.110)	(0.008)	(0.028)	(0.106)	(0.026)
Capital Intensity	0.019	0.241***	0.127	0.116	−0.196***	0.076	0.038	0.045
	(0.020)	(0.026)	(0.130)	(0.140)	(0.034)	(0.115)	(0.815)	(0.220)
ln(Employees)	0.017***	−0.007	0.046	−0.019	−0.016	−0.057	−0.326	−0.070
	(0.005)	(0.005)	(0.038)	(0.028)	(0.011)	(0.040)	(0.230)	(0.068)
ln(Age)	0.004	−0.006	0.199**	−0.103**	−0.018	0.029	0.951**	0.239**
	(0.006)	(0.007)	(0.096)	(0.043)	(0.021)	(0.049)	(0.388)	(0.095)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	2092	2054	2096	2004	2086	2064	2064	2064
Adj. R^2	0.887	0.716	0.995	0.653	0.735	0.043	0.578	0.486

Significance levels 10%, 5%, and 1% are denoted by *, **, ***, respectively. Standard errors in parentheses are clustered at the firm level. The continuous treatment variable is defined for each firm as the citation weighted difference between the number of term-extended and counterfactual patents scaled by the number of patents owned that have not expired by Dec. 31, 1995 (also citation weighted). Time interval of interest is 1993 through 1996 (i.e., 2 years prior and after the effective policy date).

Table 1.9: Treatment on Technology Acquisitions from URAA Patent Term Extensions

	Share of New Patent Classes	Patents from Private Firms	Patents from Public Firms	Share of External Citations	Value of Patents from Public Firms
	(1)	(2)	(3)	(4)	(5)
Treatment × Post	0.122**	0.017*	0.002	−0.165*	−0.003
	(0.053)	(0.010)	(0.010)	(0.100)	(0.014)
Share Expiring	0.004	−0.011	0.014	−0.033	0.021
	(0.041)	(0.008)	(0.021)	(0.055)	(0.020)
ln(Portfolio Size)	−0.071	−0.024*	−0.037*	0.035	0.038*
	(0.045)	(0.013)	(0.020)	(0.063)	(0.022)
ln(Book Assets)	0.036	0.002	−0.002	0.083	0.002
	(0.053)	(0.008)	(0.010)	(0.063)	(0.024)
Tobin's Q	0.004	0.000	−0.001	−0.002	0.001
	(0.005)	(0.001)	(0.001)	(0.007)	(0.005)
Book Leverage	−0.018	−0.002	−0.005	0.023	−0.002
	(0.021)	(0.004)	(0.005)	(0.022)	(0.009)
Capital Intensity	−0.047	0.011	−0.023	0.318	0.029
	(0.180)	(0.026)	(0.025)	(0.242)	(0.056)
ln(Employees)	−0.055	−0.004	−0.006	−0.048	0.068
	(0.056)	(0.007)	(0.007)	(0.065)	(0.049)
ln(Age)	0.121	0.003	0.007	0.001	0.005
	(0.077)	(0.007)	(0.012)	(0.102)	(0.060)
Year FE	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes
Obs.	2064	2064	2064	2064	2064
Adj. R^2	0.301	0.021	0.027	0.457	0.037

Significance levels 10%, 5%, and 1% are denoted by *, **, ***, respectively. Standard errors in parentheses are clustered at the firm level. The continuous treatment variable is defined for each firm as the citation weighted difference between the number of term-extended and counterfactual patents scaled by the number of patents owned that have not expired by Dec. 31, 1995 (also citation weighted). Time interval of interest is 1993 through 1996 (i.e., 2 years prior and after the effective policy date).

Table 1.10: Cash Flow Sensitivity of Investment and Capital Structure by Instrumental Variable Regressions

	Capital Expenditure		Debt Issuance		Net Patent Transfer		Share of New Patent Classes	
	Stage 1	Stage 2	Stage 1	Stage 2	Stage 1	Stage 2	Stage 1	Stage 2
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Treatment × Post	0.134***		0.131***		0.128***		0.128***	
	(0.049)		(0.048)		(0.041)		(0.041)	
Cash Flow		0.125**		−0.543*		0.901*		0.984*
(Instrumented)		(0.064)		(0.325)		(0.493)		(0.554)
Share Expiring	−0.002	0.000	−0.008	−0.003	−0.050**	0.062	−0.050**	0.027
	(0.013)	(0.005)	(0.013)	(0.014)	(0.020)	(0.051)	(0.020)	(0.046)
ln(Portfolio Size)	0.001	−0.006	−0.003	−0.003	−0.017	−0.105***	−0.017	−0.055
	(0.012)	(0.004)	(0.012)	(0.016)	(0.015)	(0.027)	(0.015)	(0.046)
ln(Book Assets)	−0.078**	0.022***	−0.080**	0.035	−0.028	0.042	−0.028	0.040
	(0.034)	(0.007)	(0.037)	(0.033)	(0.026)	(0.034)	(0.026)	(0.063)
Tobin's Q	0.001	0.000	0.024***	0.005	−0.003	0.009	−0.003	0.002
	(0.002)	(0.001)	(0.006)	(0.009)	(0.008)	(0.010)	(0.008)	(0.005)
Book Leverage	−0.233***	0.009	−0.174***	0.249***	−0.247***	0.199	−0.247***	0.256
	(0.066)	(0.020)	(0.065)	(0.077)	(0.031)	(0.129)	(0.031)	(0.156)
Capital Intensity	−0.477**	0.294***	−0.404*	−0.239	−0.138	0.281*	−0.138	0.232
	(0.202)	(0.037)	(0.224)	(0.162)	(0.147)	(0.170)	(0.147)	(0.277)
ln(Employees)	0.050**	−0.012*	0.047**	0.004	0.041	−0.082**	0.041	−0.075
	(0.022)	(0.006)	(0.022)	(0.021)	(0.031)	(0.034)	(0.031)	(0.066)
ln(Age)	−0.009	−0.003	−0.003	−0.065**	−0.006	−0.015	−0.006	0.156*
	(0.019)	(0.008)	(0.020)	(0.029)	(0.020)	(0.052)	(0.020)	(0.081)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	2062	2062	2000	2000	2045	2045	2045	2045
Cragg-Donald		27.758		27.787		21.786		21.786
Kleibergen-Paap rk		7.596		7.596		9.955		9.955

Significance levels 10%, 5%, and 1% are denoted by *, **, ***, respectively. Standard errors in parentheses are clustered at the firm level.

Table 1.11: Treatment on Capital Investments from URAA Patent Term Extensions by Kaplan-Zingales Index

	Least Constrained			Most Constrained
	(1)	(2)	(3)	(4)
Treatment × Post	0.008	0.003	0.022	0.034***
	(0.015)	(0.011)	(0.018)	(0.013)
Share Expiring	−0.005	−0.006	−0.009	0.010
	(0.011)	(0.005)	(0.006)	(0.009)
ln(Portfolio Size)	0.000	−0.017**	−0.010	0.000
	(0.005)	(0.007)	(0.009)	(0.005)
ln(Book Assets)	0.009	0.027***	0.017	0.010
	(0.007)	(0.009)	(0.014)	(0.011)
Tobin's Q	0.000	0.001	0.006**	−0.001*
	(0.001)	(0.002)	(0.003)	(0.000)
Book Leverage	−0.038**	−0.033*	0.003	0.001
	(0.015)	(0.019)	(0.036)	(0.016)
Capital Intensity	0.203***	0.335***	0.249***	0.169***
	(0.048)	(0.047)	(0.051)	(0.037)
ln(Employees)	−0.006	−0.016*	−0.011	−0.004
	(0.005)	(0.008)	(0.012)	(0.012)
ln(Age)	0.015*	−0.001	−0.032*	0.004
	(0.008)	(0.011)	(0.019)	(0.020)
Year FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Obs.	518	546	532	467
Adj. R^2	0.738	0.762	0.689	0.675

Significance levels 10%, 5%, and 1% are denoted by *, **, ***, respectively. Standard errors in parentheses are clustered at the firm level. The continuous treatment variable is defined for each firm as the citation weighted difference between the number of term-extended and counterfactual patents scaled by the number of patents owned that have not expired by Dec. 31, 1995 (also citation weighted). Time interval of interest is 1993 through 1996 (i.e., 2 years prior and after the effective policy date). The Kaplan-Zingales index of financial constraint, constructed by Lamont, Polk, and Saa-Requejo (2001), is defined as $KZ_{it} = -1.001909 \times \frac{CF_{it}}{K_{it-1}} + 0.2826389 \times Q_{it} + 3.139193 \times Leverage_{it} - 39.3678 \times \frac{Dividend_{it}}{K_{it-1}} - 1.314759 \times \frac{C_{it}}{K_{it-1}}$, where CF is cash flow; K is net plant, property, and equipement; Q is Tobin's Q; $Leverage$ is total long-term debt divided by the sum of long-term debt and stockholders' equity; $Dividend$ is total dividends; C is cash and short-term investments. Sample of firms is sorted into quartiles from the lowest (column 1) to highest (column 4) KZ index values in the pre-treatment year of 1994.

Table 1.12: Treatment on Capital Investments from URAA Patent Term Extensions by Size-Age Index

	Least Constrained			Most Constrained
	(1)	(2)	(3)	(4)
Treatment × Post	0.013	−0.011	0.016*	0.029***
	(0.016)	(0.016)	(0.009)	(0.007)
Share Expiring	0.002	0.007	−0.014**	0.007
	(0.004)	(0.010)	(0.006)	(0.006)
ln(Portfolio Size)	−0.007	−0.008	−0.006	−0.001
	(0.006)	(0.007)	(0.006)	(0.007)
ln(Book Assets)	0.002	0.023*	0.018	0.005
	(0.006)	(0.013)	(0.011)	(0.008)
Tobin's Q	−0.003	0.005	0.003*	0.000
	(0.003)	(0.004)	(0.002)	(0.000)
Book Leverage	−0.039***	0.003	−0.020	−0.018
	(0.013)	(0.026)	(0.016)	(0.016)
Capital Intensity	0.191***	0.248***	0.187***	0.224***
	(0.032)	(0.045)	(0.055)	(0.049)
ln(Employees)	−0.001	−0.024**	−0.015	0.009
	(0.008)	(0.011)	(0.010)	(0.008)
ln(Age)	−0.642	−0.229*	0.025*	−0.011
	(0.445)	(0.127)	(0.014)	(0.011)
Year FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Obs.	598	506	547	479
Adj. R^2	0.841	0.754	0.734	0.518

Significance levels 10% 5%, and 1% are denoted by *, **, ***, respectively. Standard errors in parentheses are clustered at the firm level. The continuous treatment variable is defined for each firm as the citation weighted difference between the number of term-extended and counterfactual patents scaled by the number of patents owned that have not expired by Dec. 31, 1995 (also citation weighted). Time interval of interest is 1993 through 1996 (i.e., 2 years prior and after the effective policy date). The Size-Age index of financial constraint, constructed by Hadlock and Pierce (2010), is defined as $SA_{it} = -0.737 \times \ln(\min\{AT_{it}, 4500\}) + 0.043 \times \ln(\min\{AT_{it}, 4500\})^2 - 0.04 \times \min\{Age_{it}, 37\}$, where AT is book assets and Age is firm age (i.e., number of reporting years in Compustat). Sample of firms is sorted into quartiles from the lowest (column 1) to highest (column 4) SA index values in the pre-treatment year of 1994.

Table 1.13: Treatment on Capital Investments from URAA Patent Term Extensions by Whited-Wu Index

	Least Constrained			Most Constrained
	(1)	(2)	(3)	(4)
Treatment × Post	0.013	−0.009	0.010	0.031***
	(0.016)	(0.027)	(0.006)	(0.009)
Share Expiring	0.002	−0.006	−0.013**	0.006
	(0.004)	(0.010)	(0.005)	(0.007)
ln(Portfolio Size)	−0.010	−0.022**	−0.001	−0.001
	(0.007)	(0.010)	(0.004)	(0.007)
ln(Book Assets)	−0.008	0.024**	0.028***	0.010
	(0.007)	(0.012)	(0.010)	(0.009)
Tobin's Q	−0.003	0.003	0.003	0.000
	(0.003)	(0.002)	(0.003)	(0.000)
Book Leverage	−0.028*	−0.029	−0.036**	0.000
	(0.015)	(0.031)	(0.016)	(0.016)
Capital Intensity	0.142***	0.257***	0.214***	0.204***
	(0.043)	(0.032)	(0.052)	(0.046)
ln(Employees)	−0.003	−0.008	−0.026***	0.005
	(0.008)	(0.009)	(0.009)	(0.008)
ln(Age)	0.026**	0.000	−0.010	−0.017
	(0.011)	(0.007)	(0.019)	(0.017)
Year FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Obs.	544	516	533	510
Adj. R^2	0.871	0.757	0.691	0.599

Significance levels 10% 5%, and 1% are denoted by *, **, ***, respectively. Standard errors in parentheses are clustered at the firm level. The continuous treatment variable is defined for each firm as the citation weighted difference between the number of term-extended and counterfactual patents scaled by the number of patents owned that have not expired by Dec. 31, 1995 (also citation weighted). Time interval of interest is 1993 through 1996 (i.e., 2 years prior and after the effective policy date). The Whited-Wu index of financial constraint, constructed by Whited and Wu (2006), is defined as $WW_{it} = -0.091 \times CF_{it} - 0.062 \times DIVPOS_{it} + 0.021 \times TLTD_{it} - 0.044 \times \ln(AT_{it}) + 0.102 \times ISG_{it} - 0.035 \times SG_{it}$, where CF is cash flow, $DIVPOS$ is an indicator for whether the firm pays dividends, $TLTD$ is total long-term debt divided by book assets, AT is book assets, ISG is the 3-digit SIC industry sales growth in which the firm belongs, and SG is the firm's sales growth. Sample of firms is sorted into quartiles from the lowest (column 1) to highest (column 4) WW index values in the pre-treatment year of 1994.

Table 1.14: Treatment on Executive Compensation from URAA Patent Term Extensions

	ln(Salary)	ln(Total Compensation)	ln(Options Award Value)	ln(Bonus)
	(1)	(2)	(3)	(4)
Treatment × Post	−0.077	0.056	0.446	0.398
	(0.064)	(0.121)	(0.800)	(0.380)
ln(Executive Age)	0.179**	−0.035	−2.517***	−0.853***
	(0.070)	(0.080)	(0.349)	(0.210)
CEO	0.080**	0.170***	0.545***	−0.095
	(0.034)	(0.036)	(0.178)	(0.099)
Director	0.110***	0.188***	0.376***	−0.120**
	(0.018)	(0.023)	(0.100)	(0.060)
Interlock	−0.051	−0.056	−0.337*	−0.244*
	(0.043)	(0.045)	(0.192)	(0.143)
Share Expiring	0.034	−0.011	0.046	0.365
	(0.025)	(0.055)	(0.313)	(0.230)
ln(Portfolio Size)	0.038	0.053	0.098	−0.046
	(0.041)	(0.074)	(0.346)	(0.246)
ln(Book Assets)	0.196***	0.263**	−0.175	−0.120
	(0.043)	(0.117)	(0.416)	(0.306)
Tobin's Q	0.005	0.116***	0.030	0.397***
	(0.008)	(0.043)	(0.142)	(0.114)
Book Leverage	−0.142	−0.404*	−2.127**	−2.098***
	(0.092)	(0.237)	(1.059)	(0.709)
Capital Intensity	0.111	−0.415	−4.013**	−3.281**
	(0.121)	(0.347)	(1.883)	(1.355)
ln(Employees)	−0.014	0.082	0.993**	0.371
	(0.035)	(0.122)	(0.506)	(0.323)
ln(Firm Age)	0.063	0.279	1.035	0.518
	(0.096)	(0.291)	(1.188)	(0.404)
Year FE	Yes	Yes	Yes	Yes
Excutive-Firm FE	Yes	Yes	Yes	Yes
Salary + Bonus Rank FE	Yes	Yes	Yes	Yes
Obs.	5166	4838	4838	5166
Adj. R^2	0.833	0.795	0.486	0.604

Significance levels 10% 5%, and 1% are denoted by *, **, ***, respectively. Standard errors in parentheses are clustered at the firm level. The continuous treatment variable is defined for each firm as the citation weighted difference between the number of term-extended and counterfactual patents scaled by the number of patents owned by that have not expired by Dec. 31, 1995 (also citation weighted). Time interval of interest is 1993 through 1996 (i.e., 2 years prior and after the effective policy date).

1.9 Appendix

1.9.1 Adjustments and Exceptions in Determining Patent Expiration Dates

1.9.1.1 Maintenance Fees

Any utility patent filed on or after December 12, 1980 is required to pay maintenance fees. Maintenance fees are due 3.5, 7.5, and 11.5 years after the grant date.[36] The purpose of maintenance fees is to encourage abandonment of noncommercial patents. If patent assignees fail to pay their fees on their patents, they forfeit their protection and the protected technology becomes publicly available for use with impunity.[37] USPTO has made maintenance fee data publicly available, and I have incorporated this information into my dataset, particularly in the construction of each firm's patent portfolio over time. Note that maintenance fees do not affect patents used in the construction of the treatment variable since the relevant expiring patents were granted in 1978 or earlier.

1.9.1.2 Drug Price Competition and Patent Term Restoration Act of 1984

The Drug Price Competition and Patent Term Restoration Act, also known as the Hatch-Waxman Act (35 U.S.C. §156), restores to a patent owner a term which was effectively lost due to pre-market approval requirements before a regulating agency (e.g., Food and Drug Administration or the U.S. Department of Agriculture). The total market exclusivity time of a drug or product (e.g., medical device, food additive, etc.) cannot exceed 14 years, regardless of how much time was lost to clinical testing and regulatory review (35 U.S.C. §156(c)(3)). Also, the total time of extension is limited to no more than 5 years (35 U.S.C. §156(g)(6)).

However, the actual extension depends on the patent's issue date. If both a drug patent issued and clinical testing for such drug began prior to the enactment of the Hatch-Waxman

[36] Plant and design patents are exempt.

[37] "Lapsed" patents are patents that expired due to failure to pay maintenance fees on time (grace period of six months).

Act on September 25, 1984, then the maximum available extension is two years. For patents issued after September 24, 1984, and for patents issued before this date but for which clinical trials had not yet begun, the maximum available extension is five years. The final expiration date of the patent can be no more than 14 years after the date of first FDA approval.

The rules governing the concurrent availability of a Hatch-Waxman extension and an adjustment under the URAA were outlined in Merck & Co. v. Kessler (Fed. Cir. 1996). The Federal Circuit held that patents may not have a full Hatch-Waxman extension renewed after a URAA adjustment has been made. The USPTO publishes the expiration dates of patents receiving a Hatch-Waxman Act extension. Using this, I determine whether a patent benefited from a URAA term extension. Figures 1.7, 1.8, and 1.9 in the appendix provide detailed timelines of how the Hatch-Watchman Act and URAA determine the expiration dates of drug-related patents.

[Insert Figures 1.7, 1.8, 1.9]

1.9.1.3 Terminally Disclaimed Patents

A patent is terminally disclaimed if its term has been shortened. A patentee elects to truncate a patent's term in order to avoid double patenting or extending the life of a patent with a newer but nearly identical patent, which is not allowed in the U.S. patent system. Terminal disclaimers help ensure that a patentee's technological monopoly is not improperly extended by filing multiple continuation applications that cover basically the same invention as the parent patent. To avoid complete rejection, one can disclaim the term of a patent that is tied to a reference patent.[38] This patent therefore expires on the same date as the reference patent.

If a patent to which a second patent is terminally disclaimed is granted a term adjustment pursuant to the URAA, then the second, terminally disclaimed patent gets the benefit of this new expiration date only if the disclaimer expressly references the "full statutory term"

[38] Both patents belong to the same owner/assignee/inventor.

of the first patent. If the disclaimer references a specific date, then the terminally disclaimed patent expires on that date, regardless of any URAA term extension of the first patent.

To identify terminally disclaimed patents, I use Google Patent Search to locate the phrases "terminal disclaimer" or "terminally disclaimed" in various sections of official patent documents. I make the proper adjustments to the patent expiration dates manually.

1.9.2 Construction of Financial Constraint Indexes

The Kaplan-Zingales Index (Lamont, Polk, and Saá-Requejo 2001) is defined as

$$\begin{aligned} KZ_{it} = & -1.001909 \times \frac{CF_{it}}{K_{it-1}} + 0.2826389 \times Q_{it} + 3.139193 \times Leverage_{it} - \\ & 39.3678 \times \frac{Dividend_{it}}{K_{it-1}} - 1.314759 \times \frac{C_{it}}{K_{it-1}} \end{aligned} \tag{1.7}$$

where CF is cash flow; K is net plant, property, and equipement; Q is Tobin's Q; $Leverage$ is total long-term debt divided by the sum of long-term debt and stockholders' equity; $Dividend$ is total dividends; C is cash and short-term investments.

The Size-Age Index (Hadlock and Pierce 2001) is defined as the following:

$$\begin{aligned} SA_{it} = & -0.737 \times \ln(\min\{AT_{it}, 4500\}) + 0.043 \times \ln(\min\{AT_{it}, 4500\})^2 - \\ & 0.04 \times \min\{Age_{it}, 37\} \end{aligned} \tag{1.8}$$

where AT is book assets and Age is firm age (i.e., number of reporting years in Compustat).

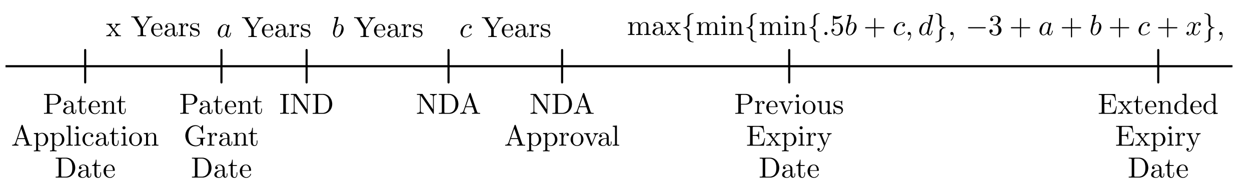
Lastly, the Whited-Wu Index (Whited and Wu 2006) is defined as the following:

$$WW_{it} = -0.091 \times CF_{it} - 0.062 \times DIVPOS_{it} + 0.021 \times TLTD_{it} - 0.044 \times \ln(AT_{it}) + 0.102 \times ISG_{it} - 0.035 \times SG_{it} \quad (1.9)$$

where CF is cash flow; $DIVPOS$ is an indicator for whether the firm pays dividends; $TLTD$ is total long-term debt divided by book assets; AT is book assets; ISG is the 3-digit SIC industry sales growth in which the firm belongs; and SG is the firm's sales growth.

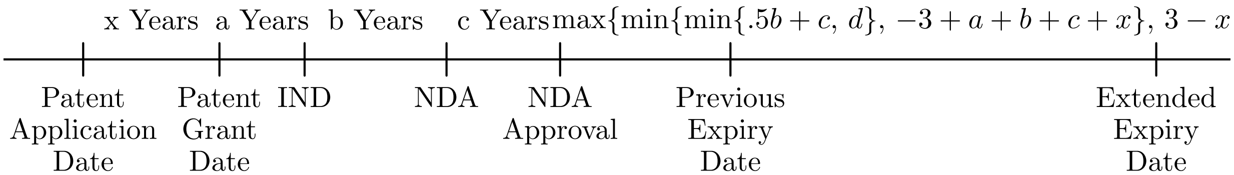
1.9.3 Figures

Figure 1.7: Hatch-Waxman Patent Term Extension (Before the Enactment of URAA)



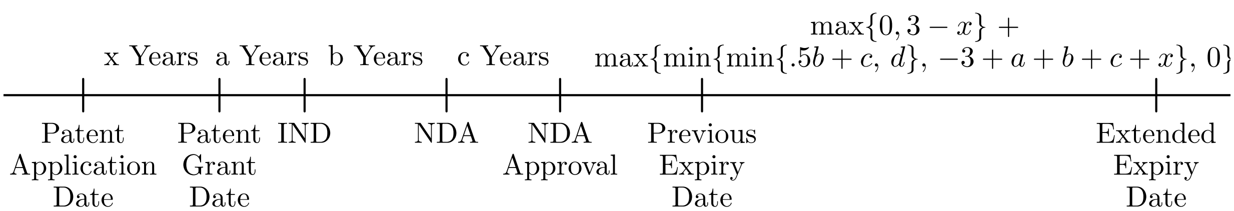
d equals to 2 if both the patent grant and testing date began before September 25, 1984. For patents issued after September 24, 1984 and for patents issued before this date but for which clinical trials had not yet begun, d equals 5. IND and NDA stand for Investigational New Drug and New Drug Application, respectively. See Merck & Co. v. Kessler (Fed. Cir. 1996). Final expiration date of the patent can be no more than 14 years after the date of first FDA approval (see U.S.C. §156 (c)(3)). The average duration of an NDA review by the Food and Drug Administration is 15 to 16 months (Mossinghoff 1999).

Figure 1.8: Combined URAA and Hatch-Waxman Patent Term Extensions (Patents in force on June 8, 1995 solely due to Hatch-Waxman Extension)



d equals to 2 if both the patent grant and testing date began before September 25, 1984. For patents issued after September 24, 1984 and for patents issued before this date but for which clinical trials had not yet begun, d equals 5. IND and NDA stand for Investigational New Drug and New Drug Application, respectively. See Merck & Co. v. Kessler (Fed. Cir. 1996). Final expiration date of the patent can be no more than 14 years after the date of first FDA approval (see U.S.C. §156 (c)(3)). The average duration of an NDA review by the Food and Drug Administration is 15 to 16 months (Mossinghoff 1999).

Figure 1.9: Combined URAA and Hatch-Waxman Patent Term Extensions (Patents in force on June 8, 1995 without using Hatch-Waxman Extension)



d equals to 2 if both the patent grant and testing date began before September 25, 1984. For patents issued after September 24, 1984 and for patents issued before this date but for which clinical trials had not yet begun, d equals 5. IND and NDA stand for Investigational New Drug and New Drug Application, respectively. See Merck & Co. v. Kessler (Fed. Cir. 1996). Final expiration date of the patent can be no more than 14 years after the date of first FDA approval (see U.S.C. §156 (c)(3)). The average duration of an NDA review by the Food and Drug Administration is 15 to 16 months (Mossinghoff 1999).

1.9.4 Tables

Table 1.15: Variable Definitions (Part 1)

Name	Formula/Description	Source
Return on Sales (ROS)	$\frac{\texttt{OIADP}_t}{\texttt{SALE}_t}$: OIADP is operating income after depreciation and SALE is net sales.	Compustat
Gross Profit Margin (GPM)	$\frac{\texttt{SALE}_t - \texttt{COGS}_t}{\texttt{SALE}_t}$: COGS is cost of goods sold.	Compustat
Net Profit Margin (NPM)	$\frac{\texttt{IB}_t}{\texttt{SALE}_t}$: IB is income before extraordinary items.	Compustat
Return on Net Operating Assets (RNOA)	$\frac{\texttt{OIADP}_t}{\texttt{CEQ}_t + \texttt{PSTK}_t + \texttt{DLTT}_t + \texttt{DLC}_t + \texttt{MIB}_t - \texttt{CHE}_t}$: CEQ is common equity; PSTK is preferred stock, DLTT is long-term debt, DLC is debt in current liabilities; MIB is minority interest; and CHE is cash and short-term investments.	Compustat
Cash Flow	$\frac{\texttt{IB}_t + \texttt{DP}_t}{\texttt{AT}_t}$: DP is depreciation and amortization and AT is total book assets.	Compustat
EBIT	$\frac{\texttt{EBIT}_t}{\texttt{AT}_t}$: EBIT is earnings before interest and taxes.	Compustat
R&D to Book Assets	$\frac{\texttt{XRD}_t}{\texttt{AT}_t}$	Compustat
Capital Expenditure to Book Assets	$\frac{\texttt{CAPX}_t}{\texttt{AT}_t}$: $\texttt{CAPX}_t$ is capital expenditure.	Compustat
Capital Intensity	$\frac{\texttt{PPENT}_t}{\texttt{AT}_t}$: PPENT is property, plant and equipment (net).	Compustat
Tobin's Q	$\frac{\texttt{AT}_t + \texttt{CSHO}_t \times \texttt{PRCC\_F}_t - (\texttt{SEQ}_t - \texttt{PSTKL}_t + \texttt{TXDITC}_t - \texttt{PRBA}_t)}{\texttt{AT}_t}$: CSHO is common shares outstanding; PRCC_F is fiscal year closing equity price; SEQ is stockholders' equity; PSTKL is preferred stock liquidating value; TXDITC is deferred taxes and investment tax credit; and PRBA is postretirement benefit asset.	Compustat
Employees	EMP: Number of employees.	Compustat
Book Leverage	$\frac{\texttt{DLTT}_t + \texttt{DLC}_t}{\texttt{AT}_t}$: DLTT is total long-term debt and DLC is debt in current liabilities.	Compustat
Debt Issuance	$\frac{\texttt{DLTIS}_t}{\texttt{AT}_t}$: DLTIS is long-term debt issuance.	Compustat
ln(Equity Issuance)	$\ln(\texttt{CSHO}_t \times \texttt{AJEX}_t)$: CSHO is common shares outstanding and AJEX is an adjustment factor for stock splits.	Compustat
Cash Holdings	$\frac{\texttt{CH}_t}{\texttt{AT}_t}$: CH is cash.	Compustat
ln(Book Assets)	$ln(\texttt{AT}_t)$: Natural logarithm of book assets.	Compustat
Age	Age of the firm or executive.	Compustat/Execucomp
CEO	Dummy variable for being the CEO.	Execucomp
Director	Dummy variable for being a director of the board.	Execucomp
Interlock	Dummy variable for being listed on a compensation committee.	Execucomp
ln(Bonus)	$\ln(\texttt{BONUS}_t + 1)$: Natural logarithm of bonuses.	Execucomp
ln(Options Award Value)	$\ln(\texttt{OPTION\_AWARDS\_BLK\_VALUE}_t + 1)$: Natural logarithm of value of options granted based on Black-Scholes formula.	Execucomp
ln(Salary)	$\ln(\texttt{SALARY}_t + 1)$: Natural logarithm of salary	Execucomp

Table 1.16: Variable Definitions (Part 2)

Name	Formula/Description	Source
ln(Portfolio Size)	Natural logarithm of total number of unexpired patents in portfolio (as of end of fiscal year).	USPTO
ln(Patents Acquired)	Natural logarithm of the number of citation-weighted patents externally acquired voluntarily reported to USPTO.	USPTO
$\mathbb{1}$(Patents Acquired)	Indicator variable for whether patents were acquired externally (ignoring grants and intra-firm assignments).	USPTO
Net Patent Transfer	The difference between the citation-weighted patents acquired and sold as a share of current citation-weighted patent portfolio size.	USPTO
Share Expiring	Share of patent portfolio that is expired in the previous year (not due to failure to pay maintenance fees).	USPTO
Share of New Patent Classes	Proportion of new patent class/subclasses relative to those class/subclasses already covered by a firm's patent portfolio.	USPTO
Patents from Private Firms	Number of patents acquired that originated from private firms scaled by a firm's patent portfolio size.	Kogan et al. (2016)
Patents from Public Firms	Number of patents acquired that originated from public firms scaled by a firm's patent portfolio size.	Kogan et al. (2016)
Share of External Citations	Proportion of citations made to patents outside a firm's patent portfolio relative to internal ones.	USPTO
Value of Patents from Public Firms	Estimated aggregate value of patents acquired scaled by book assets.	Kogan et al. (2016)

Table 1.17: Descriptive Statistics of Firms with Treatment Value below the 25th Percentile

Variable	N	Mean	Std. Dev.	25%ile	50%ile	75%ile
ROS	386	0.07	0.17	0.04	0.08	0.11
GPM	386	0.31	0.14	0.22	0.31	0.39
NPM	386	0.01	0.19	0.01	0.04	0.07
RNOA	324	0.14	0.34	0.07	0.14	0.23
Cash Flow	387	0.06	0.17	0.04	0.08	0.12
EBIT	389	0.08	0.10	0.04	0.08	0.13
R&D to Book Assets	266	0.04	0.05	0.01	0.02	0.05
Capital Expenditure to Book Assets	391	0.05	0.05	0.03	0.04	0.07
Capital Intensity	389	0.31	0.20	0.17	0.27	0.40
Tobin's Q	345	1.55	0.95	1.07	1.29	1.72
Employees	382	8.73	18.91	0.86	2.85	7.95
Book Leverage	390	0.28	0.31	0.09	0.23	0.36
Debt Issuance	379	0.10	0.56	0.00	0.01	0.08
ln(Equity Issuance)	386	2.92	2.28	2.07	3.01	4.25
Cash Holdings	391	0.09	0.11	0.01	0.05	0.13
ln(Book Assets)	391	5.80	2.21	4.52	5.77	7.22
Age	407	25.55	13.31	15.00	26.00	34.00
ln(Portfolio Size)	397	3.27	1.40	2.30	3.30	4.17
Share Expiring	390	0.10	0.21	0.00	0.00	0.11
Inventor Per Patent App.	254	1.85	1.25	1.00	1.66	2.00
Net Patent Transfer	397	−0.01	0.29	0.00	0.00	0.00
Share of New Patent Classes	407	0.14	0.31	0.00	0.00	0.00
Patents from Private Firms	397	0.01	0.07	0.00	0.00	0.00
Patents from Public Firms	397	0.01	0.04	0.00	0.00	0.00
Share of External Citations	407	0.24	0.42	0.00	0.00	0.00
Value of Patents from Public Firms	391	0.00	0.03	0.00	0.00	0.00

Pre-treatment period shown above covers years 1993 and 1994. The continuous treatment variable is defined for each firm as the citation weighted difference between the number of term-extended and counterfactual patents scaled by the number of patents owned that have not expired by Dec. 31, 1995 (also citation weighted). A firm is in the "treatment" group when its continuous treatment has a value above the 75th percentile of the sample. A firm is in the "control" group when its continuous treatment has a value below the 25th percentile of the sample. Firms that have continuous treatment values between the 25th and 75th percentiles are not shown here.

Table 1.18: Descriptive Statistics of Firms with Treatment Value above the 75th Percentile

Variable	N	Mean	Std. Dev.	25%ile	50%ile	75%ile
ROS	388	0.06	0.15	0.02	0.07	0.11
GPM	388	0.30	0.17	0.18	0.29	0.39
NPM	388	0.01	0.18	−0.01	0.04	0.07
RNOA	335	0.09	0.51	0.05	0.12	0.21
Cash Flow	388	0.06	0.14	0.03	0.08	0.12
EBIT	388	0.07	0.12	0.03	0.08	0.12
R&D to Book Assets	240	0.04	0.05	0.01	0.02	0.06
Capital Expenditure to Book Assets	382	0.05	0.04	0.02	0.04	0.07
Capital Intensity	388	0.32	0.20	0.17	0.27	0.44
Tobin's Q	328	1.44	0.67	1.06	1.30	1.63
Employees	373	11.82	49.07	0.65	2.02	9.00
Book Leverage	388	0.30	0.33	0.12	0.26	0.38
Debt Issuance	370	0.10	0.27	0.00	0.02	0.11
ln(Equity Issuance)	383	2.66	2.40	1.64	2.79	4.16
Cash Holdings	388	0.09	0.13	0.01	0.04	0.12
ln(Book Assets)	388	5.63	2.43	3.87	5.58	7.43
Age	397	22.56	13.05	12.00	22.00	33.00
ln(Portfolio Size)	389	2.93	1.58	1.79	2.64	3.97
Share Expiring	372	0.09	0.20	0.00	0.00	0.10
Inventor Per Patent App.	211	1.76	1.05	1.00	1.50	2.00
Net Patent Transfer	389	−0.42	6.92	0.00	0.00	0.00
Share of New Patent Classes	397	0.11	0.29	0.00	0.00	0.00
Patents from Private Firms	389	0.01	0.07	0.00	0.00	0.00
Patents from Public Firms	389	0.01	0.07	0.00	0.00	0.00
Share of External Citations	397	0.23	0.41	0.00	0.00	0.00
Value of Patents from Public Firms	388	0.00	0.02	0.00	0.00	0.00

Pre-treatment period shown above covers years 1993 and 1994. The continuous treatment variable is defined for each firm as the citation weighted difference between the number of term-extended and counterfactual patents scaled by the number of patents owned that have not expired by Dec. 31, 1995 (also citation weighted). A firm is in the "treatment" group when its continuous treatment has a value above the 75th percentile of the sample. A firm is in the "control" group when its continuous treatment has a value below the 25th percentile of the sample. Firms that have continuous treatment values between the 25th and 75th percentiles are not shown here.

Table 1.19: Placebo Treatment on Cash Flow, Investments, and Capital Sturcture Using June 7, 1994 as the Cutoff Date

	Cash Flow	R&D Expense	Capital Expenditure	Equity Issuance	Debt Issuance	Cash Holdings	Net Patent Transfer
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Treatment × Post	−0.020	−0.006	−0.005	0.033	0.019	0.000	0.005
	(0.019)	(0.011)	(0.006)	(0.036)	(0.014)	(0.009)	(0.053)
Share Expiring	0.007	0.007	−0.001	−0.009	−0.020	0.002	−0.050
	(0.012)	(0.007)	(0.005)	(0.019)	(0.015)	(0.008)	(0.073)
ln(Portfolio Size)	0.015	0.006	−0.006	0.007	−0.009	0.002	−0.270***
	(0.016)	(0.010)	(0.006)	(0.032)	(0.022)	(0.012)	(0.059)
ln(Book Assets)	−0.001	−0.044***	0.018**	0.195***	0.013	0.003	0.059
	(0.024)	(0.016)	(0.007)	(0.043)	(0.027)	(0.017)	(0.041)
Tobin's Q	−0.002	−0.003**	0.001*	0.008*	−0.001	0.005	0.005
	(0.003)	(0.002)	(0.001)	(0.004)	(0.011)	(0.004)	(0.004)
Book Leverage	−0.200***	0.007	−0.021**	−0.006	0.330***	−0.066***	−0.092
	(0.064)	(0.011)	(0.009)	(0.013)	(0.108)	(0.021)	(0.085)
Capital Intensity	−0.118*	0.115**	0.259***	0.173	0.101	−0.288***	0.005
	(0.070)	(0.053)	(0.032)	(0.140)	(0.100)	(0.049)	(0.132)
ln(Employees)	−0.012	0.018*	−0.009	0.000	0.017	−0.011	0.035
	(0.021)	(0.010)	(0.007)	(0.001)	(0.022)	(0.015)	(0.060)
ln(Age)	0.005	0.023	−0.010	0.202**	−0.092*	0.001	0.007
	(0.027)	(0.020)	(0.008)	(0.097)	(0.049)	(0.023)	(0.061)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	2097	2017	2040	2101	2033	2095	1997
Adj. R^2	0.611	0.886	0.703	0.992	0.553	0.699	0.074

Significance levels 10%, 5%, and 1% are denoted by *, **, ***, respectively. Standard errors in parentheses are clustered at the firm level. The *placebo* continuous treatment variable is defined for each firm as the citation weighted difference between the number of pseudo-term-extended and pseudo-counterfactual patents scaled by the number of patents owned that have not expired by Dec. 31, 1994 (also citation weighted). Time interval of interest is 1992 through 1995 (i.e., 2 years prior and after the pseudo-effective policy date of June 7, 1994).

Table 1.20: Non-Citation-Weighted Treatment on Cash Flow, Investments, and Capital Sturcture from URAA Patent Term Extensions

	Cash Flow	R&D Expense	Capital Expenditure	Equity Issuance	Debt Issuance	Cash Holdings	Net Patent Transfer
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Treatment × Post	0.133***	−0.010	0.026***	0.041	−0.115**	0.021	0.203**
	(0.050)	(0.007)	(0.006)	(0.063)	(0.057)	(0.016)	(0.088)
Share Expiring	−0.011	0.003	−0.001	−0.018	−0.047**	−0.008	−0.007
	(0.014)	(0.004)	(0.004)	(0.023)	(0.020)	(0.008)	(0.078)
ln(Portfolio Size)	−0.005	0.008**	−0.007*	−0.021	−0.021	−0.010	−0.265***
	(0.013)	(0.004)	(0.004)	(0.026)	(0.025)	(0.007)	(0.083)
ln(Book Assets)	−0.025	−0.034***	0.015***	0.182***	0.082***	0.014	0.054
	(0.024)	(0.008)	(0.005)	(0.033)	(0.020)	(0.013)	(0.035)
Tobin's Q	0.002	−0.001**	0.000	0.013	0.003	0.006*	0.003
	(0.003)	(0.000)	(0.000)	(0.010)	(0.008)	(0.003)	(0.003)
Book Leverage	−0.239***	0.018	−0.022**	−0.037	0.409***	−0.014*	−0.034
	(0.060)	(0.013)	(0.009)	(0.036)	(0.127)	(0.008)	(0.028)
Capital Intensity	−0.189**	0.019	0.240***	0.188	0.230*	−0.194***	0.081
	(0.092)	(0.020)	(0.026)	(0.133)	(0.138)	(0.034)	(0.114)
ln(Employees)	0.015	0.017***	−0.006	0.000	−0.028	−0.015	−0.057
	(0.018)	(0.005)	(0.005)	(0.001)	(0.025)	(0.011)	(0.040)
ln(Age)	−0.023	0.004	−0.006	0.205**	−0.084**	−0.019	0.027
	(0.015)	(0.006)	(0.007)	(0.097)	(0.040)	(0.021)	(0.049)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	2173	2092	2054	2096	2004	2086	2064
Adj. R^2	0.512	0.887	0.717	0.995	0.653	0.735	0.045

Significance levels 10%, 5%, and 1% are denoted by *, **, ***, respectively. Standard errors in parentheses are clustered at the firm level. The continuous treatment variable is defined for each firm as the difference between the number of term-extended and counterfactual patents scaled by the number of patents owned that have not expired by Dec. 31, 1995. Time interval of interest is 1993 through 1996 (i.e., 2 years prior and after the effective policy date).

CHAPTER 2

Director Networks, Turnover, and Governance: Evidence from Corporate Bankruptcies

The growth and success of a firm depends on its ability to adapt to its environment. This may require knowledge beyond its ken. Directors, therefore, are often brought in to guide corporate strategy by advising in areas such as research and development, production, restructuring, regulations and law and mergers, acquisitions, and divestitures. However, companies, according to surveys, rely mainly on board and management contacts to recruit directors, suggesting that information on out-of-network directors is scarce or untrustworthy and may require third-party verification.[1] This paper seeks to establish the level of reliance on social networks in the market for directorships.

To identify this network dependency, I use corporate bankruptcies as events that potentially deactivate network channels between directors that are *directly* associated with bankrupt firms from either past or current employment or board appointments ("Event Directors") and directors that are only *indirectly* associated with bankrupt firms through professional connections ("Treatment Directors"). The latter group of "Treatment Directors", therefore, should be immune to any firm-level effects arising from corporate bankruptcies as they have no work histories with any of these firms that have filed for bankruptcy. Using directors that share the same boards as Treatment Directors who have no work histories with directors *directly* associated with bankrupt firms as the control sample ("Control Directors"), I am able to estimate the causal effects of losing social connections while accounting for any confounding firm level factors.

[1]See Figure 2.2.

Under a difference-in-differences framework, I find that being connected to Event Directors (or equivalently losing connections with Event Directors) at the time of bankruptcy filings reduces the probability of finding additional directorships within a 1-year period by 11 percent and decreases the net directorships acquired by 0.13 board positions for the average Treatment Director. While Event Directors dropped board positions leading up to and after the year of bankruptcy filings, Treatment Directors did not experience any significant changes in the probability of dropping directorships. This quasi-natural experimental setup captures the effects caused by a suspension of network ties while mitigating any effects arising from corporate bankruptcies.

Contrary to the decline in compensation measures for Event Directors, Treatment Directors experience no changes in compensation at or before the bankruptcy filing year. Even with the loss of connections and being immobilized, Treatment Directors seem to be able to maintain their levels of total compensation over time by remaining on their current boards. This could also imply that any stigma associated with having worked with someone involved with bankruptcies has negligible effects on director turnover and compensation.

Additionally, I find that this reduction in director turnover or mobility is stronger for directors with board positions at firms with weak shareholder rights, as measured by the G-Index defined in Gompers, Ishii, and Metrick (2003) at the time of bankruptcy filing. This suggests that directors at firms with poor corporate governance may be less transparent and are able to have more discretion in choosing their board members without much interference or oversight from shareholders.

Lastly, in order to estimate the average treatment effects on firm-level outcome variables, I construct a continuous treatment measure of director network shocks for each firm. Specifically, for each non-bankrupt firm, I compute the proportion of Treatment Directors occupying its board (among Treatment and Control Directors only) for the years in which firms associated with Event Directors file for bankruptcy. Note that by this construction, there may be firms with boards that consists of only Control or Treatment Directors, as these directors most likely hold multiple directorships at one time. Although I do not find any noticeable effects on firm value or profitability, measures of aggregated director turnover mirror the director level findings. I find that a one standard deviation increase of 36 percentage points in the average share of the board of directors having professional ties to Event Directors leads to a removal of 0.2 directors and a reduction in the probability of adding a director by 4 percent. The probability of dropping directors also interestingly increases by 3 percent, suggesting that perhaps some directors were unable to renew their positions due to a loss of network connections.

This paper contributes to the current director network literature in two ways. Firstly, this paper exploits a quasi-natural experiment that can be generalized to use any event that could arguably suspend some connections in the director network to study the impact of business connections on director level outcomes. Bankruptcies are used as the corporate event that destabilizes the director network in this paper. Treatment Directors are those who are connected to directors who have a history with bankrupt firms at the time of their bankruptcy filings. The control group is made up of directors who share the same board as the Treatment Directors at the time of bankruptcy filings but lack any connections with directors who have a history with bankrupt firms. This way, any treatment effects attributable to firm heterogeneity between Treatment and Control Directors are mitigated. Secondly, through this experimental setup, plausible causal evidence suggesting that severed connections to a set of directors hinder director mobility can be derived. It can therefore be established that a loss of connections reduces a director's ability to acquire additional board appointments.

My paper is organized as follows. Section 1 summarizes the related literature on social networks. Section 2 discusses the role of social networks in the market for directorships. Section 3 describes my dataset and the construction of relevant variables. Section 4 discusses my identification strategy. Section 5 documents my results. Section 6 concludes.

2.1 Literature Review

The network literature in corporate finance focuses on two possible roles of social networks. First, social networks can function as a kind of human capital with externalities. Directors with the most skill and talent often have the largest number of connections or contacts. These individuals create positive externalities that spill over to other directors through the exchange of ideas, for example (Murphy, Shleifer, and Vishny 1992). Social networks can therefore be viewed as an aggregation of human capital among directors, which can facilitate firm productivity as shown in Acemoglu and Angrist (2000). Moreover, information exchange generates trust, which reduces information uncertainty about the quality and skill relevance of directors. This network of trust therefore can also reduce search costs for the firm and possibly allow firms to acquire preferential treatment (e.g. better access to external finance, etc.). The human capital perspective posits that director networks not only provides meaningful information on directors to the firm, but also relays firm information throughout the director network.

There is extensive empirical evidence of the benefits of social networks in the finance literature. Engelberg, Gao, and Parsons (2013a), for example, find that loans made between connected parties lead to improved firm performance. Hochberg, Ljungqvist, and Lu (2007) show that network centrality among venture capitalists lead to privileged access to better deals. Cohen, Nelson, and Walsh (2000) find that shared educational background among mutual fund managers and corporate board members lead to the exchange of insider information that translates to better firm performance. Cai and Sevilir (2012) find that acquirer firms in M&A deals obtain significantly higher announcement returns (i.e., lower takeover premiums and/or value creation) when acquirer and target firms share a director (or have interlocking directorates) or have directors from each firm share a board.

On the other hand, social networks can also be a source of agency costs. Boards may have incentives to appoint directors in such a way that is suboptimal for the firm. That is, while cronyism may play a role, within the moral hazard framework of Holmström (1979), Holmström (1982), and Fudenberg and Tirole (1986), it is possible for board members to nominate those who have the capability of obtaining directorships for them in the future. That is, board members may rely on their social networks, specifically connections with directors who also have appointments at other boards, for future directorships. Social networks therefore mitigate director career concerns. In doing so, directors are using social networks to misappropriate firm resources for personal benefits.

There are also several papers that document empirical evidence of agency costs manifested from social networks. Kramarz and Thesmar (2013) and Nguyen (2012) show that being apart of the École network is highly predictive of whether one receives an executive position in French companies. Here, practicing favoritism and having a strong personal preference for a specific pedigree may not align with the interest of the firm. Related to firm performance, Fracassi and Tate (2012) find evidence that CEO-director ties weaken the effectiveness of board monitoring and reduce firm value. Similarly, Duchin and Sosyura (2013) find that managerial connections relate negatively with investment efficiency and firm value in firms with weak governance. Renneboog and Zhao (2011), Hallock (1997), Fich and White (2003), and Engelberg, Gao, and Parsons (2013b), find that executives' network centrality is positively associated with their compensation.[2] Likewise, Brown and Petersen (2011) and Guedj and Barnea (2009) show that CEO compensation increases with director interconnectedness.

This paper contributes to both strands of the literature since the focus is on the directorship market and its dependence on network ties. Specifically, the effects of network dependency on firm level outcomes are analyzed through a quasi-natural experiment by comparing firms with high concentrations to firms with low concentrations of board members who have lost connections resulting from corporate bankruptcies. This is an ideal setting to observe whether director networks serve as a conduit to share information and enhance firm value or as a system for rent extraction.

2.2 Market for Directorships

The notion that workers rely on their personal networks in their search for employment is a heavily researched topic in both labor economics and sociology. Granovetter (1973), who

[2]However, it can be argued that the size of executives' compensation should be commensurate with the size of their social networks, as the firm expects them to exploit their contacts to enhance firm value. Alternatively, their social networks could also be a signal of manager quality.

made early headway in the social network field, demonstrate, in his field work, the importance of weak ties or indirect connections in various labor markets during job searches. We should expect this social norm in recruitment practices to appear in the market for directorships as well.

As discussed in the introduction, there are two general theories that can describe the function of social networks in the market for directorships. The human capital theory interprets social networks as an input in board productivity (Acemoglu and Angrist 2000). Because social networks facilitate information sharing, firms may benefit more from directors who are more central than others. Assuming that a director's marginal productivity is a function of the entire director network (i.e., aggregate human capital) and his personal connections, any external negative shock to his personal connections can damage his performance. Moreover, if we believe that his marginal productivity is linked with bonus levels and future directorships, a negative shock should inhibit his mobility and possibly his compensation levels as well.

The agency cost theory interprets social networks as a hidden mechanism that shareholders (i.e., the principal) may not necessarily observe from the board (i.e., the agent). Under the moral hazard framework, the shareholders of a company entrust the board to optimally nominate directors to serve in the company's best interest. However, we do not observe the board's effort levels in their search for the most capable director or in guiding management. Because these actions are hidden from shareholders, boards can hire directors with the possible agreement to receive kickbacks in return for nominations. The nominated director could have a role in determining board and management compensation in the future (e.g., serving on the governance or nomination committee). This mirrors the model presented in Holmström (1979). The existence of incentive compatibility constraints and limited liability will allow the agent to obtain rent.

Therefore, if there is a negative shock to a director's social network, both the human capital theory and the agency cost theory predicts a possible decrease in compensation and mobility levels. Within the human capital theory framework, a negative shock to social networks affects essentially every director in the network and therefore could translate to director productivity shocks. Dampening of information exchange may slow down director recruitment and also performance-based compensation for a period of time. The agency cost theory, on the other hand, suggests two things from a negative shock to director networks. First, the incentive compatibility constraint may be relaxed as a result, which limits the rent that directors are able to take. We could observe a decline in compensation from this. Second, because directors rely on personal contacts to acquire future board appointments, whether due to social norms or incentives to receive private benefits through kickbacks, a negative shock to director networks will translate to poor career prospects.

[Insert Figure 2.1]

Figure 2.1 lists the sources that boards use to recruit new board members taken from PricewaterhouseCoopers' 2010 and 2012 Annual Corporate Directors Surveys. Among roughly 1,000 directors for each year, over 80 percent admit to using personal contacts and almost 60 percent admit to using management contacts. While roughly 60 percent use search firms as well, it is clear that personal contacts from both management and the board play a large role in the selection of directors. That is, we anticipate that there is a positive relationship between the number of business connections and the number of directorships that a director holds. Similarly, there should also be a positive correlation between connections and compensation. Within my dataset, the correlation between the number of directorships held and degree centrality (i.e., the number of direct connections to individual executives) is around 40 percent in the two years prior to the event year (i.e., bankruptcy filings) in my sample. Similarly, the correlation coefficient between the natural logarithm of total compensation and degree centrality is around 20 percent.

The decision to make or remove connections in most cases is endogenous. Directors may sit on boards to make direct connections with specific individuals strategically. Boards may also seek out a specific director to complement its team. Self-selection is an issue as a result when dealing with the creation or removal of a connection. In fact, it is difficult to determine whether a particular connection is lost (other than from those arising from deaths). However, by studying directors who are only indirectly related to corporate bankruptcies, which I interpret as sources of social network breakdown, I am able to make plausibly unbiased claims about the impact and importance of business connections. While it is likely for directors to eschew firms that are prone to bankruptcy, it is hard to claim that directors purposely avoid other directors who have associations with firms that are prone to bankruptcy.

2.3 Data

2.3.1 Data Sources

I construct both a director-year and firm-year level datasets from four sources: BoardEx of Management Diagnostics Ltd., Compustat and Execucomp of Standard & Poor's, and UCLA-LoPucki Bankruptcy Research Database (BRD). BoardEx tracks the employment history of over 500,000 directors and senior managers globally, which serves as the core of my datasets. Given the sparse employment data prior to 1990, I restrict my experiment to only include bankruptcy filing years between 2000 and 2009. Table 2.2 summarizes the variables derived from BoardEx. The sample averages of my variables are similar to those of Engelberg et al. (2013).

[Insert Table 2.2]

Using BoardEx as the base of my dataset, I match director and executive bonus, salary, and total compensation from Execucomp. I obtain bankruptcy data from BRD, which contains information on approximately 1,000 large public company bankruptcies. These firms have reported assets worth $100 million or more measured in 1980 dollars and have filed 10-Ks with the Securities and Exchange Commission. The bankruptcy filing dates are used to identify Treatment and Control Directors. Lastly, when possible, the company on which a director serves is also mapped into Compustat in order to pull annual company accounting fundamentals.

Because BoardEx uses a different identification system than Compustat (i.e., GVKEY for firm identification) and Execucomp (i.e., EXECID for executive identification), I resort to fuzzy string matching algorithms in order to combine these three databases. I decide to use the trigram method to first map BoardEx firm identification numbers (COMPID) to Compustat identification numbers (GVKEY).[3] This allows me to identify bankrupt firms in BoardEx (BRD identifies firms by GVKEY). To map BoardEx's director identification numbers (DIRECTID) to Execucomp's identification numbers (EXECID), I first match on gender, generational title (e.g., Jr., Sr., etc.), surname, and company name. I again use the trigram method to make the final full name match. All final matches are manually inspected. My matching procedure yields 8,431 unique company matches and 15,153 unique manager and director matches.[4] Among the bankrupt firms listed in BRD, I identify 523 of them in BoardEx.

2.3.2 Constructing Network Variables

2.3.2.1 Edges

I construct a set of "edges" or an "edgelist" for each year in which BoardEx has at least two executives working at a company. An edge is defined as an unordered set of two directors:

$$\{x, y\} \text{ such that } x, y \in f_t \tag{2.1}$$

where x and y are elements or "vertices" representing executives and f_t is the set of all executives employed at a particular firm at a given time t. An edge is assumed to be formed when two executives share the same firm at a particular time period. An edgelist at time t across all firms is thus defined as:

$$E_t = \bigcup_{f_t \in \mathbb{F}_t} \{\{x, y\} | x, y \in f_t\} \tag{2.2}$$

[3] Trigram phrase matching identifies phrases that have a high probability of being similar. Each phrase is represented by a set of character trigrams that are extracted from the phrase. The similarity of two phrases is then computed using the vector cosine similarity measure. This method is especially good at catching misspellings.

[4] The number of unique company matches is very close to the number of 8,428 achieved by Engelberg et al. (2012).

where $\mathbb{F}_t$ is the universe of firms at time t. An aggregate edgelist is defined as the union of edgelists since the beginning of time:

$$L_t = \bigcup_{s=-\infty}^{t} E_s \tag{2.3}$$

Since the vertices are people in my definition above, I expect some to die over time. Some executive deaths are reported in Execucomp. However, I do not assume that the death data is exhaustive. To address the issue of missing death data, I modify the definitions above to account for directors permanently exiting the business universe either by dying or by reaching the age of 90:

$$\begin{aligned} W_t &= \{z | z \in Z \text{ is dead or is 90 years old at time } t\} \\ A_t &= \{\{x, y\} | \{x, y\} \cap W_t = \varnothing \text{ and } \exists s \leq t \text{ such that } \{x, y\} \in E_s\} \subseteq L_t \end{aligned} \tag{2.4}$$

where Z is the universe set of executives or vertices. A_t is the modified aggregate edgelist.[5]

2.3.2.2 Degree Centrality

Degree centrality is defined as the number of "ties" that a vertex has:

$$\begin{aligned} D_t(z) &= \sum_{B \in E_t} \mathbb{1}_B(z) \\ \Delta_t(z) &= \sum_{B \in A_t} \mathbb{1}_B(z) \end{aligned} \tag{2.5}$$

$D_t(z)$ counts the number of coworkers that executive z has at a company given a specific year t. Likewise, $\Delta_t(z)$ counts the number of people who have shared the same firm with executive z at any point in time up to time t. Intuitively, $D_t(z)$ measures how central executive z is in

[5]My results are not sensitive to changes in the terminal age cutoff (e.g., varying it from 80 to 90 years).

the business world at a specific point in time. A more central executive could produce more network instability, for example, if he or she were to temporarily become inactive as a result of bankruptcy. Similar to $D_t(\cdot)$, $\Delta_t(\cdot)$ for an executive also measures centrality accounting for employment history and high mobility. $\Delta_t(\cdot)$ could proxy for industry experience or industry demand, which results in high mobility or serving on several boards.

2.4 Empirical Specification

2.4.1 Staggered Difference-in-Differences

The goal of this quasi-natural experiment is to isolate the effects on director mobility and compensation that is solely attributed to the association with Event Directors. As seen in Table 2.1, there is at least one bankruptcy filing for every given year between 2000 and 2009. For each year, I identify directors who do not serve on any company that has filed for bankruptcy and directors who serve or have served on at least one of the boards of bankrupt firms. This latter group I call the "event group" because of their direct association with the event (i.e., the bankruptcy filing). Using the former group, I construct a treatment group that includes directors outside of the event group who share or have shared company boards with directors in the event group at non-bankrupt filing firms. The control group is therefore those directors that share at least one board with Treatment Directors, but lack a current or past connection with Event Directors. This implies that a Control Director either left a particular board before an event director joined or shared a board with Treatment Directors that has no history of Event Directors. We can define these groups using basic set notation.

[Insert Table 2.1]

Let time $t = 0$ denote the time of bankruptcy filing. Without loss of generality, let x, y, and z represent three distinct directors. Let f_t^N represent a set of directors at time t for firm N that has never filed for bankruptcy and $f_{s,t}^B$ denote a set of directors at time s for firm B that filed for bankruptcy at time t. Assume x has a board appointment at f_0^N (i.e., at time horizon t equal to zero) and has or has had board appointments at $f_{s,0}^B$ at some time $s \leq 0$.

By definition, x is an Event Director. If y is a director at f_0^N but is or was not a director at $f_{s,0}^B$ or any other bankruptcy filing firm at time zero for all time $s \leq 0$, he or she is then a Treatment Director. In other words, y is a Treatment Director if and only if:

$$\begin{aligned} y \notin f_{s,0}^B, &\text{ for all } f_{s,0}^B \text{ and for all } s \leq 0 \\ \{x, y\} \in A_0 & \end{aligned} \tag{2.6}$$

where A_0 is the aggregate edgelist up to time 0. Moreover, z is a control group director if and only if

$$\begin{aligned} \{x, z\} \notin A_0 &\text{ for all } x \\ \{y, z\} \in A_0 &\text{ for some } y \end{aligned} \tag{2.7}$$

The Event, Treatment, and Control Director sets can then be formally defined as following:

$$\begin{aligned} \text{Event: } & V \equiv \{x | x \in f_0^N \cap f_{s,0}^B \text{ for some } f_0^N,\, f_{s,0}^B, \text{ and } s \leq 0\} \\ \text{Treatment: } & T \equiv \{y | y \notin V,\, \{x, y\} \in A_0 \text{ for some } x \in V\} \\ \text{Control: } & C \equiv \{z | \{x, z\} \notin A_0 \text{ for all } x \in V \text{ and } \{y, z\} \in A_0 \text{ for some } y \in T\} \end{aligned} \tag{2.8}$$

The null hypothesis is that Treatment Directors are immune to any negative network effects resulting from being associated with Event Directors. To test this hypothesis, I estimate the following multi-period difference-in-differences model:

$$y_{it} = \alpha_i + \alpha_t + \tau(\mathbb{1}_{i \in T} \times Post) + \gamma' C_{it} + \epsilon_{it} \tag{2.9}$$

where y_{it} is the outcome variable, α_i and α_t are firm and year fixed effects, respectively, $\mathbb{1}_{i \in T}$ is an indicator for whether a director is in the treatment group or control group (i.e.,

$\mathbb{1}_{i \in T} = 1$ or $\mathbb{1}_{i \in T} = 0$, respectively), $Post$ is an indicator for the post treatment period, C_{it} is a vector of covariates listed in Table 2.11, and ϵ_{it} is an error term. The coefficient τ measures the treatment of having an association with directors from the event group. Under the null hypothesis, we expect $\tau = 0$. However, if having a connection with an Event Director has a negative impact on y_{it}, we should find that $\tau < 0$. At the director level, the key outcome variables of interest are those concerning director turnover or mobility and compensation. Specifically, in terms of director turnover, the outcome variables I consider are directorships added minus dropped over a year, an dummy variable for whether a directorship was added over a year, and a dummy variable for whether a directorship was dropped over a year for each director. For director compensation, I consider the natural logarithm of total compensation, salary, bonus, and number of options awarded for each director.

[Insert Table 2.11]

Equation 2.9 is estimated with error clustering at the Event Director level.[6] Under this difference-in-differences specification, time trends across groups are captured by year fixed effects. Additionally, time-constant unobserved heterogeneity are canceled out by the included firm fixed effects.

However, in order to credibly make causal claims, the changes in outcome variables between treatment and control groups need to remain constant in the absence of the treatment. This assumption can be visually inspected by plotting past outcome values to ensure that the trends are stable and relatively parallel. Figures 2.2 and 2.5 plot the mean measures of director turnover and compensation, respectively, with 95 percent confidence intervals for Event, Control and Treatment Directors.[7] In all panels in both figures, the pre-treatment trends in turnover and compensation measures between the average Control and Treatment Director are roughly parallel.

[6]It is possible that a director may receive treatment from more than one Event Director or bankruptcy filing firm. In those cases I randomly choose an Event Director as the source of the network shock.

[7]Confidence intervals are constructed based on the assumption that the error distribution is approximately normal.

The exogeneity of $\mathbb{1}_{i \in T}$ requires directors to be unable to select themselves into or out of the treatment or control groups. There are two scenarios in which a director can self-select themselves into the control group. First, a director can avoid an Event Director by leaving boards of non-bankruptcy filing firms prior to the joining of an Event Director. Second, a director can sit on a different board that has no historical link with any Event Director. In both cases, the director intentionally avoids an Event Director, with the latter scenario being the stronger case of Event Director aversion, as the director abstains from a firm even if Event Directors no longer occupy any board seats. This behavior of Event Director aversion is difficult to rationalize. While it is possible that social stigma could motivate one to avoid others, it seems unlikely for a director to avoid another before the actual occurrence of bankruptcy, the reputation damaging event.

Are there incentives to self-select into the treatment group? A director may want to make connections with an Event Director to access a larger social network. Indeed, Event Directors do have higher degree and aggregate degree centralities as noted in Table 2.2. However, it seems unlikely that a director has any incentive to seek out Event Directors when a corporate bankruptcy is imminent. As a robustness check, I excluded Treatment Directors whose connection with Event directors only existed at most two years prior to the year of bankruptcy filing and found no material difference in estimated results.

2.4.2 Director Heterogeneity across Control and Treatment Groups

In order to estimate the average treatment effect of losing connections with Event Directors, Control Directors ideally should be equally as likely as Treatment Directors to receive the treatment (i.e., satisfying the overlap assumption). This, however, is unlikely given that Treatment Directors on average have a wider professional network than Control Directors within our sample. As shown in Table 2.2, the degree and aggregate degree centralities of the average Treatment Director is much higher than the average Control Director. Treatment Directors have on average 19 more current connections and 35 more lifetime connections two years before the event or bankruptcy filing year. This naturally implies that Treatment

Directors are therefore much more likely to receive treatment, unfortunately.

[Insert Table 2.2]

Treatment Directors additionally differ from Control Directors in several other dimensions. They are 3.4 percent more likely to be CEOs and 3.5 percent more likely to hold at least one independent directorships. They also hold on average 1 more directorship and sit on larger boards than Control Directors. Not surprisingly, Treatment Directors are less likely to sit on boards with directors that sit on multiple boards most likely because they are the "multiple director" themselves. Nonetheless, assuming exogeneity of $\mathbb{1}_{i \in T}$, estimation of the average treatment effect of the treated is still feasible, which is what is essentially estimated throughout this paper.

2.5 Results

To test the consequences of being connected to directors directly affected by a bankruptcy (or temporarily losing nodes in a professional network), I compare measures of director mobility and compensation before and after each bankruptcy filing for directors with a "broken" connection and for those without.

The measures of director mobility used are net directorships added minus dropped and the probability of adding a directorship over a one-year period. These measures are similar to Kaplan and Reishus (1990), but my treatment effects are estimated using a 4-year window around the event (i.e., bankruptcy filing). For compensation, I look at director bonuses, salaries, total compensation, and option grants.

2.5.1 Director Turnover

As documented in the literature, there is a positive relationship between firm performance and director mobility. Fama and Jensen (1983) and Vafeas (1999) view that director mobility is strongly linked with firm performance in a reputational sense. Several papers provide empirical support to this idea. Gilson (1990) finds that directors of bankrupt firms or firms undergoing debt restructuring hold 35 percent fewer board seats three years after resigning. Brickley, Linck, and Coles (1999) show that the likelihood of a retired CEO serving on any board as a director is strongly related to firm performance under his or her tenure. Assuming dividend reductions and being targeted for takeovers is related to firm performance, Kaplan and Reishus (1990) and Shivdasani (1993) also provide evidence for the reputation story. Controlling for industry and asset size, Kaplan and Reishus (1990) observe that only 10 percent of top managers from dividend-reduction companies obtain additional directorships within three years of the dividend cut compared to 22.6 percent of top mangers from comparable firms. Similarly, also controlling for industry and asset size, Shivdasani (1993) discovers that directors of firms targeted for hostile takeover hold fewer outside board positions than other directors at comparable non-targeted firms. These results are consistent with the notion established by Fama (1980), who argues that additional directorships serve as incentive for directors to be diligent monitors. In other words, the present literature tell us that the external labor market punishes directors for poor performance that can be attributable to them.

However, Treatment and Control Directors in this paper do not necessarily come from firms that are performing poorly. The firms used to construct the treatment and control groups have avoided bankruptcy. Here, I essentially control for the possible confounding effects on mobility originating from firm performance. I am therefore able study the isolated network impact on director mobility. Directors in my sample have never served on bankrupt firms; the only link Treatment Directors have with bankrupt firms is through their network connection with directors that have a work history with bankruptcy filing firms.

[Insert Figure 2.2]

In the top left panel of Figure 2.2, there is a sharp discontinuity in the number at which Treatment Directors add and drop directorships over a one-year period around bankruptcy filings. Prior to the bankruptcy filing events, both Treatment and Control Directors were adding more than they are dropping directorships on average. After the bankruptcy filing event, Treatment Directors became immobile on average. The Control Directors, who also experienced a slight slow-down in mobility, added as many as they dropped on average after the bankruptcy event.

Normalizing directorship additions to a single unit, we observe a similar discontinuity in the probability of adding directorships in the top right panel of Figure 2.2. Visually, these panels support the hypothesis that directors do indeed rely on business connections to find directorships. When a director suddenly loses connections as a result of firms declaring bankruptcy, his or her ability to find additional directorships is hampered. Since the average number of directorships is relatively stable for Treatment Directors (see bottom right panel of Figure 2.2), this implies that some Treatment Directors may be forced to stay longer on certain boards than desired.

The probability of dropping directorships, on the other hand, seems to be fairly stable for the Treatment Directors, which again suggests that these directors are not switching boards. What is reassuring is that the probability of dropping directorships reaches a peak for Event Directors at the time of bankruptcy filing, as shown in the bottom left panel of Figure 2.2. This gives some credibility to the argument that corporate bankruptcies themselves do have an adverse effect on director turnover.

[Insert Table 2.5]

The estimated treatment effects on director turnover over a 4-year window around the bankruptcy filing year is documented in Table 2.5. Columns 1, 3, and 5 of Table 2.5 utilizes the full sample of directors from BoardEx. Columns 2, 4, and 6 consider only directors for which firm performance measures are available (i.e., from Compustat). For a given director turnover measure, the estimated treatment effects are similar regardless of the specification. I find that a loss of connections with Event Directors decreases net directorships acquired by 0.13 to 0.15 board seats and decreases the probability of adding directorships by 11 to 13 percent (significant at the 1% level). The probability of dropping directorships also declines, but the magnitude is small and not statistically significant.

2.5.2 Director Compensation

The mechanism through which director networks influence director compensation is less clear. There are two prevailing theories on how director networks can relate to compensation. One theory interprets director networks as social capital from which directors, through preferential treatment (e.g., trust, familiarity, exclusivity, etc.), acquire superior information to improve firm performance. This inherently assumes that compensation is linked with firm performance. Therefore losing this valuable social capital could reduce firm performance and subsequently reduce the part of director compensation that is performance based.

However, trust and familiarity among directors may also be a hindrance to firms. The other theory claims that directors may collude to extract rents from the firms on which they sit as board members. This excess pay could be suboptimal in a contract that seeks to maximize shareholder value. In other words, a loss in network connections could also reduce a director's compensation levels if the contacts lost are with other directors who play a role in determining his or her compensation. It is important to note that the committees on which these directors serve are not observed due to limitations of the dataset. Whether or not Event Directors, who are connected to Treatment Directors, are assigned the task of determining Treatment Director compensation packages is unknown. If Event Directors were to lose that ability because their attention is being diverted towards restructuring bankrupt firms or they exit completely from the directorship market all together, then there can be some discontinuity of bonuses and total compensation of Treatment Directors from a director network shock.

[Insert Figure 2.5]

Figure 2.5 shows that director compensation (i.e., as measured by total compensation, salaries, bonuses, and option grants) experiences no apparent changes resulting from a loss of connections with Event Directors. This suggests that Treatment Directors are still able to maintain their original level of compensation despite being unable to find new directorships. Event Directors, conversely, experience volatile swings in their compensation, with the nadir of total compensation occurring in the year of bankruptcy filing. From the plots in Figure 2.5, director compensation does not seem to have a strong link with director network ties.[8]

[Insert Table 2.9]

The estimation results of Equation 2.9 on director compensation measures are noted in Table 2.9. I find no statistically significant treatment effects on total compensation, salary, bonus, or number of options awarded arising from a loss of connections to Event Directors.

2.5.3 Director Turnover at the Firm Level

To estimate the treatment effects of aggregate connection losses at the firm level, I construct the following continuous treatment variable for each firm j:

$$S_j \equiv \frac{|T_j|}{|T_j| + |C_j|} \tag{2.10}$$

where T_j and C_j are defined in Equation 2.8, but now split by firm. Equation 2.10 measures the intensity of the director network shock aggregated at the firm level. Moreover, because $|T_j|$ is scaled by each firm's board size (i.e., assuming $|T_j| + |C_j| > 0$), S_j is comparable across firms. I estimate the following difference-in-differences model using S_j over a 4-year window around the bankruptcy filing year to calculate the firm level treatment effects:

$$y_{jt} = \alpha_j + \alpha_t + \tau(S_j \times Post) + \gamma' C_{jt} + \epsilon_{jt} \tag{2.11}$$

where α_j and α_t are firm and year fixed effects, respectively, C_{jt} is a vector of time-varying firm characteristics (i.e., board size, Tobin's Q, book leverage, book assets, ROA, ROE, RNOA, ROS, and firm age), and ϵ_{jt} is the error term.

In order to inspect the assumption that firms with different treatment intensities have the same pre-treatment trends, I compare a subset of firms that have treatment values S_i

[8] Aggregate director meeting and retainer fees also experience no apparent impact.

above the 75th percentile (high treatment firms) in my sample to another subset of firms that have treatment values below the 25th percentile (low treatment firms). I plot the average turnover measures for each subset of firms in Figure 2.6. Differences in firm characteristics in the pre-treatment period between high and low treatment firms are listed Table 2.3.

[Insert Table 2.3]

Interestingly, there is a lot of firm heterogeneity between high and low treatment firms. Within 2 years prior to the event year, high treatment firms are younger (by about a year) and perform worse than low treatment firms on average, as measured by ROA, ROE, ROS, and Tobin's Q (although the latter 2 measures are statistically insignificant). This is not particularly surprising if we believe that high dependence on network connections leads to poor firm performance. Additionally board size is smaller by about 0.7 directors for high treatment firms.

[Insert Figure 2.6]

In general, the treatment effects at the firm level mirrors the binary treatment at the director level. There is a sharp negative discontinuity in both the average net directors added minus dropped and the probability of adding directors, as displayed in the top two plots in Figure 2.6. The probability of dropping, on the other hand, increases slightly in the surrounding years around the time of bankruptcy filing for the high treatment value firms. It is possible that Treatment Directors, in aggregate, lose some positions that were gained mostly through networking and are therefore difficult to maintain. Alternatively, the attention of Treatment Directors could be diverted to assisting Event Directors. Board size seem relatively constant for high treatment firms, suggesting that directors in aggregate are essentially immobilized by the loss of connections with Event Directors.

[Insert Table 2.10]

These discontinuities are reflected in the estimation of Equation 2.11 over a 6-year window around the bankruptcy filing year. I find that a one standard deviation increase of 36 percentage points in the share of directors on the board of an average firm that lost connections with Event Directors reduces net directors recruited by 0.2, reduces the probability of adding directors by 4 percent, but increases the probability of dropping directors by 3 percent. The magnitudes are all statistically significant at the 1 percent level.

2.5.4 Director Networks and Firm Value

Despite the heterogeneity in firm characteristics, the average firm performance measures seem to move together for high and low treatment firms. Furthermore, there is no distinct discontinuity in the post-treatment period. This can interpreted that the loss of network connections to Event Directors in aggregate has no material impact on or relevance to the value of the firm. ROA and ROS, for example, essentially move together between high and low treatment firms. High treatment firms interestingly are much more leveraged than low treatment firms. However, the aggregate loss of director connections did not produce any noticeable changes in leverage levels. Tobin's Q, on the other hand, seems to gradually increase in the post-treatment period for the high treatment firms. This is suggestive evidence that network ties may be a source of agency costs for the firm. Unfortunately, the pre-treatment trends is fairly volatile for the high treatment firms. This makes it difficult to justify being able to estimate treatment effects from Equation 2.11. The regression results are omitted here for brevity.

[Insert Figure 2.7]

2.6 Extensions and Robustness Checks

2.6.1 Director Mobility and Degree Centrality

Due to the nature of the design of this quasi-natural experiment, directors that have a larger professional network, which is measured here by degree centrality, are mechanically more likely to be selected for treatment. Since the degree centrality of a director is endogenous, the impact of the treatment could therefore vary depending on how central or connected a director is at the time of bankruptcy filing. This hypothesis can be tested by splitting the Treatment and Control Directors into subgroups that are sorted by the size of their degree centralities and then estimating the baseline difference-in-differences model specified in Equation 2.9 for each subgroup with the probability of adding a directorship as the dependent variable. Table 2.7 and 2.8 documents the estimation results based on sorting Treatment and Control directors into quintiles by degree centrality and aggregate degree centrality, respectively.

[Insert Table 2.7]

In Table 2.7, the point estimates of the treatment effect on the probability of adding directorships for each subgroup not surprisingly are all negative. However, the treatment effect for the lowest two quintiles (i.e., Columns 1 and 2) are not statistically significant. The treatment effect becomes statistically significant at the 5 percent level starting in Column 3. In both Columns 3 and 4, a network connection loss to Event Directors decreases the probability of adding directorships by roughly 4 percent. For directors with the highest degree centralities in Column 5, a network connection loss to Event Directors decreases the probability of adding directorships by 20 percent. This is statistically significant at the 1 percent level. These results suggest that the effects of a network shock is in fact more severe for directors who are currently holding more directorships.

[Insert Table 2.8]

Sorting firms by aggregate degree centralities in Table 2.8, on the other hand, is not as interesting, as the treatment effect is statistically significant at the 1 percent level for the top 4 quintiles (Columns 2, 3, 4, and 5). The treatment for the directors with the lowest aggregate degree centralities is not statistically significant. However, the treatment magnitude does increase roughly monotonically with aggregate degree centrality. The most central directors experience an 18 percent decline in the probability of adding directors (Column 5) compared to a 3 percent decline for the least central directors (Column 1).

2.6.2 Director Turnover and Corporate Governance

Do firms with poor corporate governance have a stronger dependence on professional networks in the recruitment of their directors? Firms with weaker shareholder rights can limit shareholder interference in the nomination and appointment of directors onto their boards. For example, these limitations can take the form of classified (staggered) boards or the lack of cumulative voting. For firms with classified boards, directors are placed into different classes and serve overlapping terms to prevent outsiders from immediately gaining control of the board. Cumulative voting allows each shareholder to allocate his or her total votes in any manner desired for director elections, where the total number of votes is the product of the number of shares owned and the number of directors to be elected. This arrangement allows shareholders to concentrate their votes. Firms with weaker shareholder rights can rely more on personal networks to fill board vacancies than firms with stronger shareholder rights, as firms with weaker shareholder rights have inherently more discretion in their choice of candidates. Director turnover or mobility therefore potentially could be disrupted for firms with weaker shareholder rights when their directors lose access to their personal connections.

In order to test the hypothesis that firms with weaker shareholder rights rely more on director networks to recruit directors, I first compute the average G-Index of the firms in which each director has a board seat in the year of bankruptcy filing.[9] G-Index or the governance index is a measure of shareholder rights. A higher index indicates fewer shareholder rights. Then, I split my sample of directors as either those that sit on firms with an average G-Index score above the sample median of 9 (high G-Index group) and those with G-Index scores below it (low G-Index group). Finally, within each sample partition, I estimate the baseline difference-in-differences model as specified in Equation 2.9. If high G-Index directors are more susceptible to a network shock, then the treatment effect ideally should only be statistically significant for high G-Index directors and not for low G-Index directors. Figures 2.3 and 2.4 show the mean director mobility measures over time for high G-Index and low G-Index directors, respectively. Table 2.6 documents the estimation of the

[9] See Gompers, Ishii, and Metrick (2003) for details of variable construction.

average treatment effect for both high and low G-Index directors.

[Insert Figures 2.3 and 2.4]

Comparing Figure 2.3 with Figure 2.4, the discontinuity in directorships added minus dropped and the probability of adding a directorship (top two panels of Figures 2.3 and 2.4) is apparent for high G-Index directors but essentially nonexistent for low G-Index directors. The probability of dropping a directorship and the average number of directorships held is flat over time for both high and low G-Index directors (bottom panels of Figures 2.3 and 2.4). Visually, this is fairly strong evidence that directors that sit on average boards of firms with poor governance are more reliant on personal connections to acquire additional directorships. The G-Index, of course, is endogenous to the firm as it could just reflect an unobservable industry factor or board and shareholder preferences (e.g., industry practices, preference for directors with larger professional networks, etc.). I remain agnostic here about whether having more or less shareholder rights is beneficial to the firm. The purpose of this exercise is to highlight the fact that firms with ostensibly weaker shareholder rights can explain some of the reliance on director networks in the directorship recruitment market.

[Insert Table 2.4]

However, it is worth noting that directors with high degree and aggregate degree centralities seem to be attracted to firms with high G-Index values within both Treatment and Control Director groups. Table 2.4 shows mean differences in several director characteristics between those that have board positions at high and low G-Index firms in each experimental group. I also find that high G-Index firms have larger boards. In general, we cannot distinguish between whether shareholders are selecting highly central directors by creating a weak shareholder rights environment for them to utilize their networks or highly central directors are extracting rent by intentionally removing shareholder rights.

[Insert Table 2.6]

Table 2.6 documents the estimation results for high and low G-Index firms. Columns 1, 4, and 7 estimates the treatment effects on net directorships added, probability of adding a directorship, and probability dropping a directorship, respectively, for directors who have board positions at high G-Index firms. Columns 2, 5, and 8 estimate the treatment effects for the same set of variables for directors that have directorships at low G-Index firms. I find that the treatment effect is not statistically significant in general for directors having board positions at low G-Index firms (i.e., strong shareholder rights). Directors with board positions at high G-Index firms, conversely, experience a 12 percent drop in the probability of finding an additional directorship in a 1-year period given a loss of connections to Event Directors. As shown in Columns 3, 6, and 9 of Table 2.6, I find no statistically significant joint effects between the treatment and being a board member at a high G-Index firm.

2.7 Conclusion

Information is often difficult to verify. For instance, references and letters of recommendations from those with established credibility (i.e., those who are in the network) are usually mandatory with any job application as a way to attribute credibility to someone who is not in the network. These practices are low cost methods of overcoming information uncertainty. That is, reducing the universe of possible job candidates to just those with direct or indirect ties speeds up the hiring process dramatically. However, this may not always yield optimal outcomes; a capable director can be overlooked because nobody in the network can vouch for his or her qualifications.

The market for directorships, as this paper has shown, is a prime example where who you know is more credible and trustworthy than those who you do not know, despite having information about them given to you. My results show that director recruitment depends heavily on personal contacts from company board and management. Using the experimental setup outlined in previous sections, I show that director mobility is significantly impeded when certain connections are temporarily suspended by corporate bankruptcies. Moreover, I show that the directorship market dependency on network ties is stronger for firms with weaker shareholder rights. Also, directors that have higher degree centralities than other directors experience a stronger decline in their ability to acquire additional directorships.

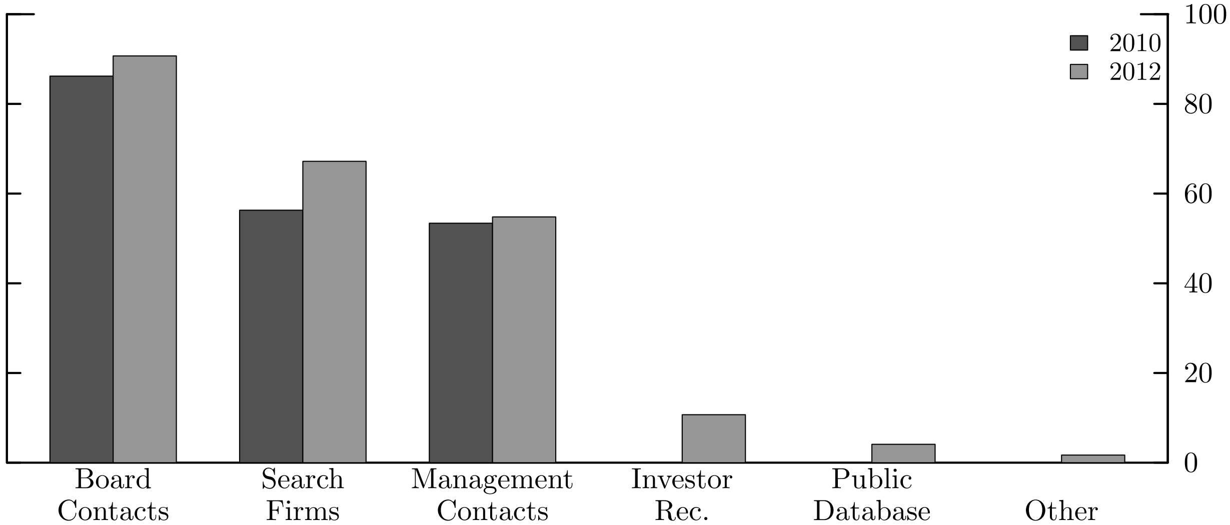
This paper provides a methodology that can be easily extended to other corporate events that is strongly related to executive networks. The methodology outlined in this paper allows one to make causal arguments on the treatment effect resulting from connection losses, assuming the corporate event is convincingly related to breakdowns in executives' social networks.

The findings of this paper should also bring to light what it really means to be an "independent" director or board independence in general. An independent director's ability to add directorships measures his or her external demand for his or her board service. However, all else equal, independence may be compromised if the director relies on his or her personal connections to acquire additional directorships. System-wide reliance of such a practice inherently generates quid pro quo relationships, which prevents directors to be truly disinterested.

Director and board independence is a social network issue underpinned in several fields including law, pscyhology, and economics. In the case of *re Oracle Corp. Derivative Litigation, 824 A.2nd* (Del. Ch. 2003), the court found that non-economic ties need to be considered in determining the independence of a board committee. Pscyhology provide us with several cognitive biases that prevent people to be objective. For example, people are often susceptible to confirmation bias (Nickerson 1998) and in-group favoritism (Taylor and Doria 1981). While this paper contributes to the literature by exploring the impact of social networks on director mobility, further research may explore the relationship between executive-level and firm-level networks. The evolution of these networks over time needs further examination as well.

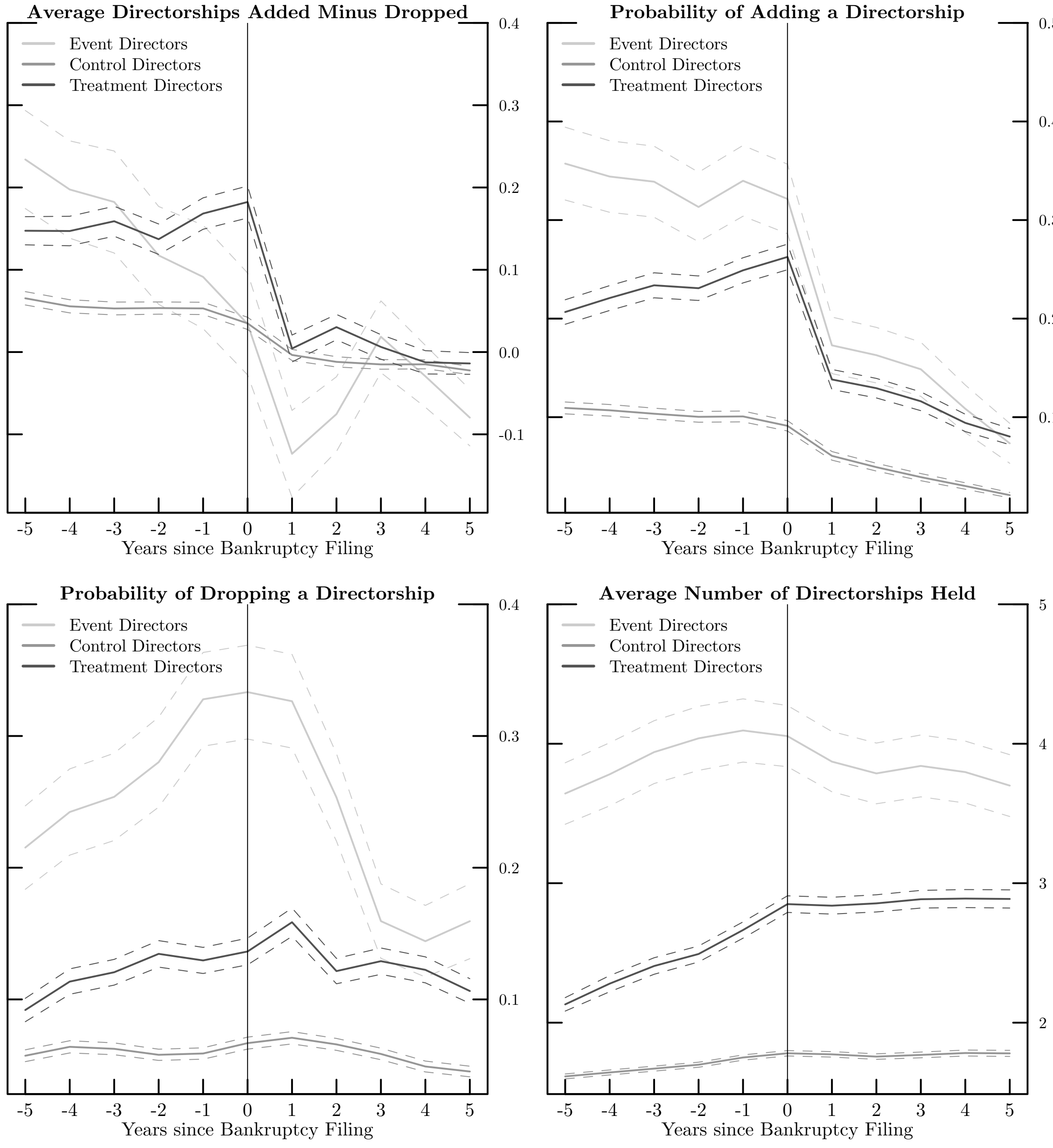
2.8 Figures

Figure 2.1: Industry Surveys of Sources used to Recruit New Board Members



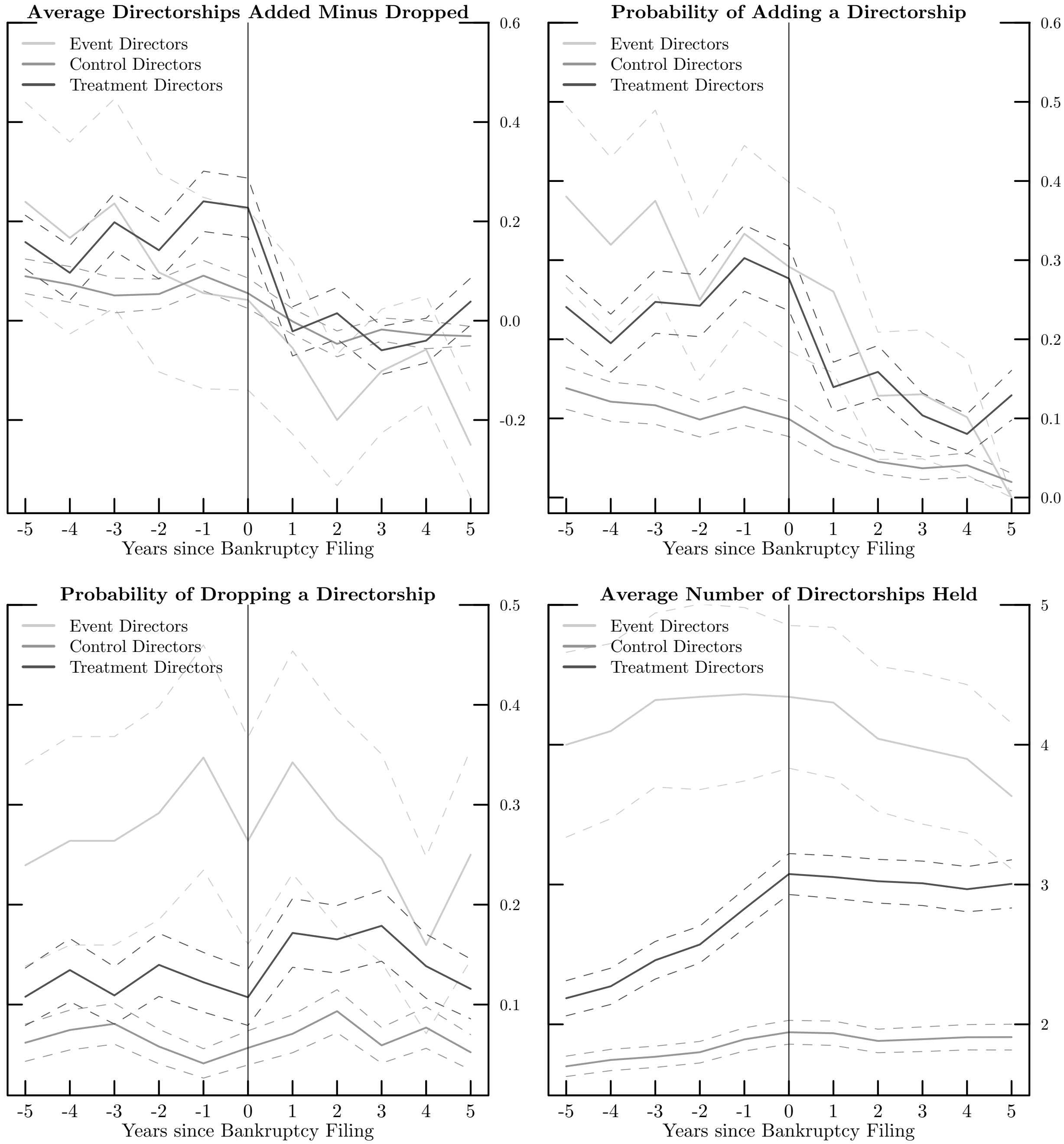
Surveys are from PricewaterhouseCoopers' 2010 and 2012 Annual Corporate Directors Surveys. The sample size of the 2010 and 2012 surveys are 1110 and 860, respectively.

Figure 2.2: Average Director Turnover Measures



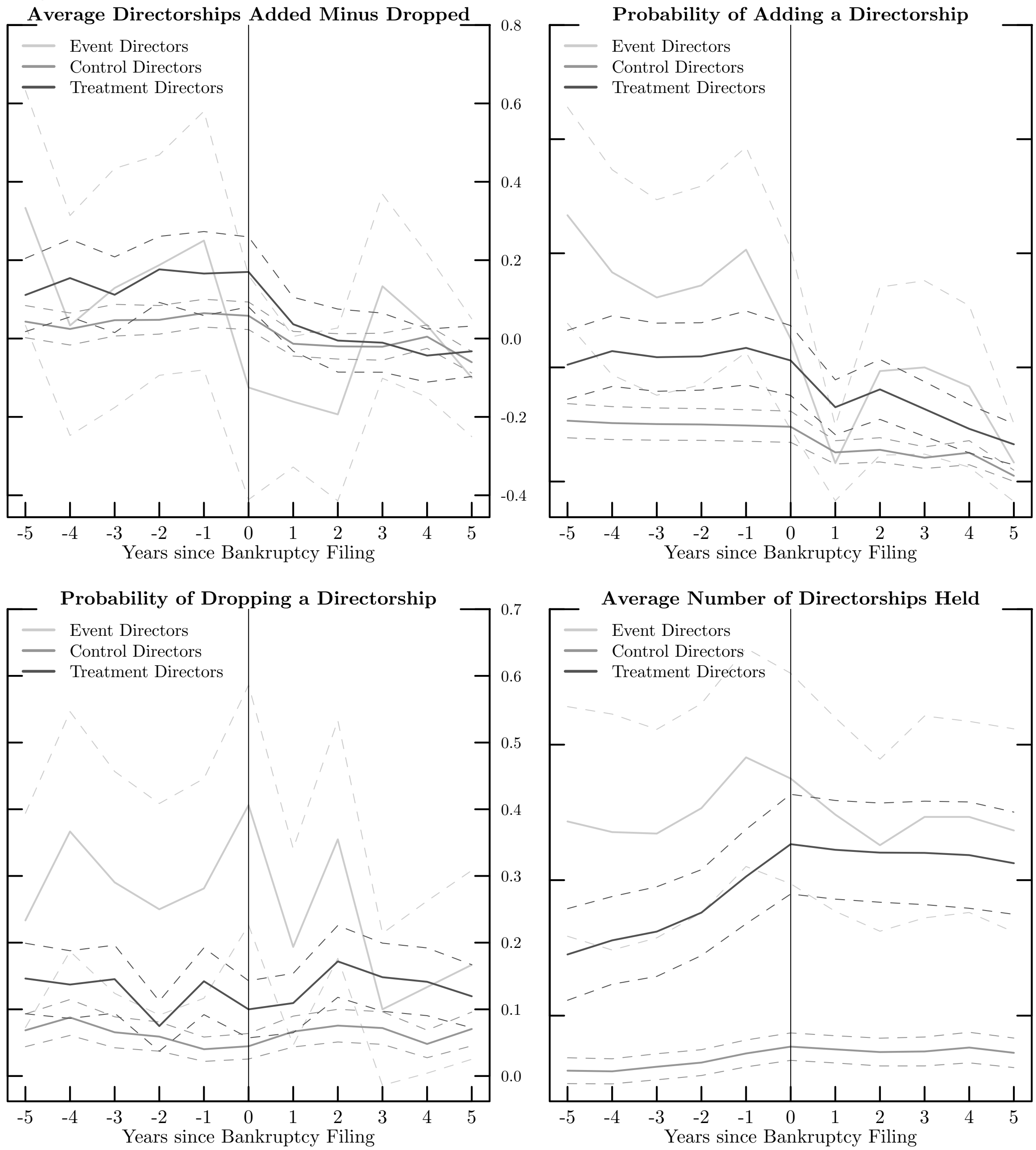
Only executives holding directorships at year zero are used to generate these plots. Event Directors are directors that hold or have held a board position for at least one firm that has filed for bankruptcy at year zero. Treatment Directors are directors that hold board appointments with Event Directors at year zero. Control Directors are directors that share a board with the Treatment Directors at year zero, but have no work histories with Event Directors. Both Treatment and Control Directors have never served on a board of a firm that has filed for bankruptcy. Each solid line in each plot represents the mean of a director turnover measure for an experimental group. The dashed lines are 95 percent confidence intervals assuming the error distribution is approximately normal with unknown variance. Bankruptcy filing years are restricted to years between 2000 and 2009.

Figure 2.3: Director Turnover of those with Board Positions on Firms with High G-Index



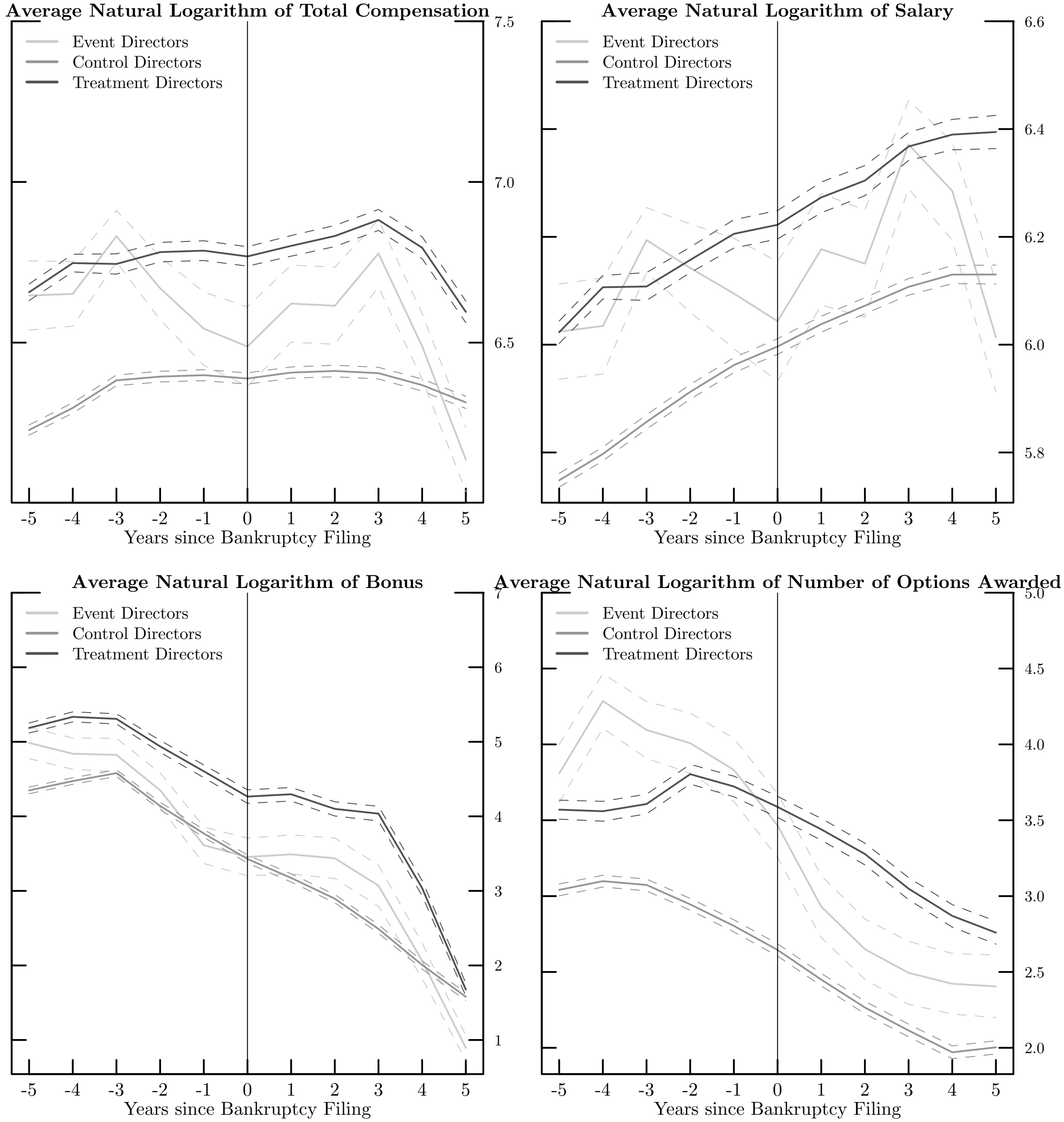
Only executives holding directorships at firms with average G-Index greater than or equal to 9 (median) at year zero are used to generate these plots (see Gompers, Ishii, and Metrick 2003). Event Directors are directors that hold or have held a board position for at least one firm that has filed for bankruptcy at year zero. Treatment Directors are directors that hold board appointments with Event Directors at year zero. Control Directors are directors that share a board with the Treatment Directors at year zero, but have no work histories with Event Directors. Both Treatment and Control Directors have never served on a board of a firm that has filed for bankruptcy. Each solid line in each plot represents the mean of a director turnover measure for an experimental group. The dashed lines are 95 percent confidence intervals assuming the error distribution is approximately normal with unknown variance. Bankruptcy filing years are restricted to years between 2000 and 2009.

Figure 2.4: Director Turnover of those with Board Positions on Firms with Low G-Index



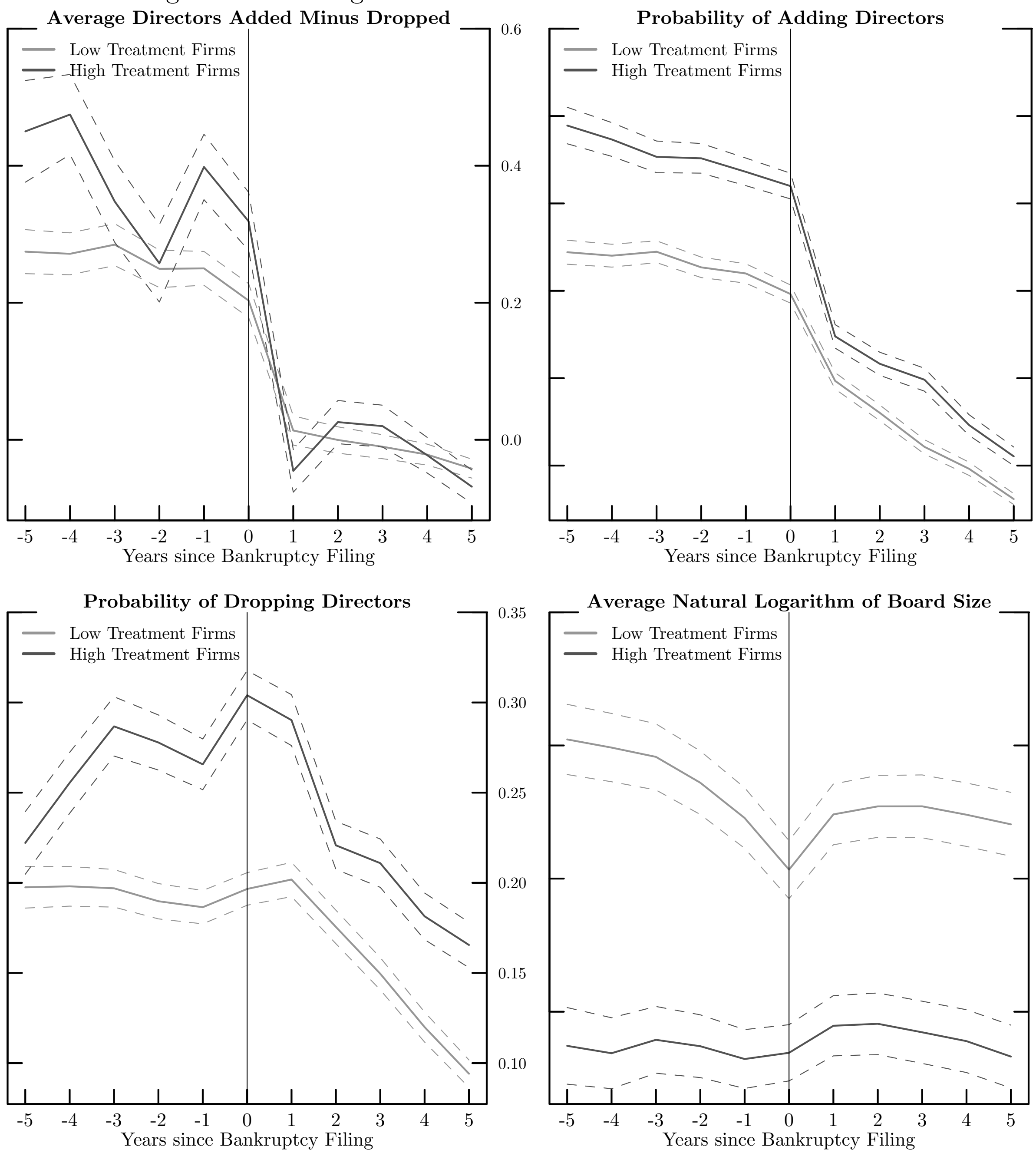
Only executives holding directorships at firms with average G-Index below 9 (median) at year zero are used to generate these plots (see Gompers, Ishii, and Metrick 2003). Event Directors are directors that hold or have held a board position for at least one firm that has filed for bankruptcy at year zero. Treatment Directors are directors that hold board appointments with Event Directors at year zero. Control Directors are directors that share a board with the Treatment Directors at year zero, but have no work histories with Event Directors. Both Treatment and Control Directors have never served on a board of a firm that has filed for bankruptcy. Each solid line in each plot represents the mean of a director turnover measure for an experimental group. The dashed lines are 95 percent confidence intervals assuming the error distribution is approximately normal with unknown variance. Bankruptcy filing years are restricted to years between 2000 and 2009.

Figure 2.5: Director Compensation



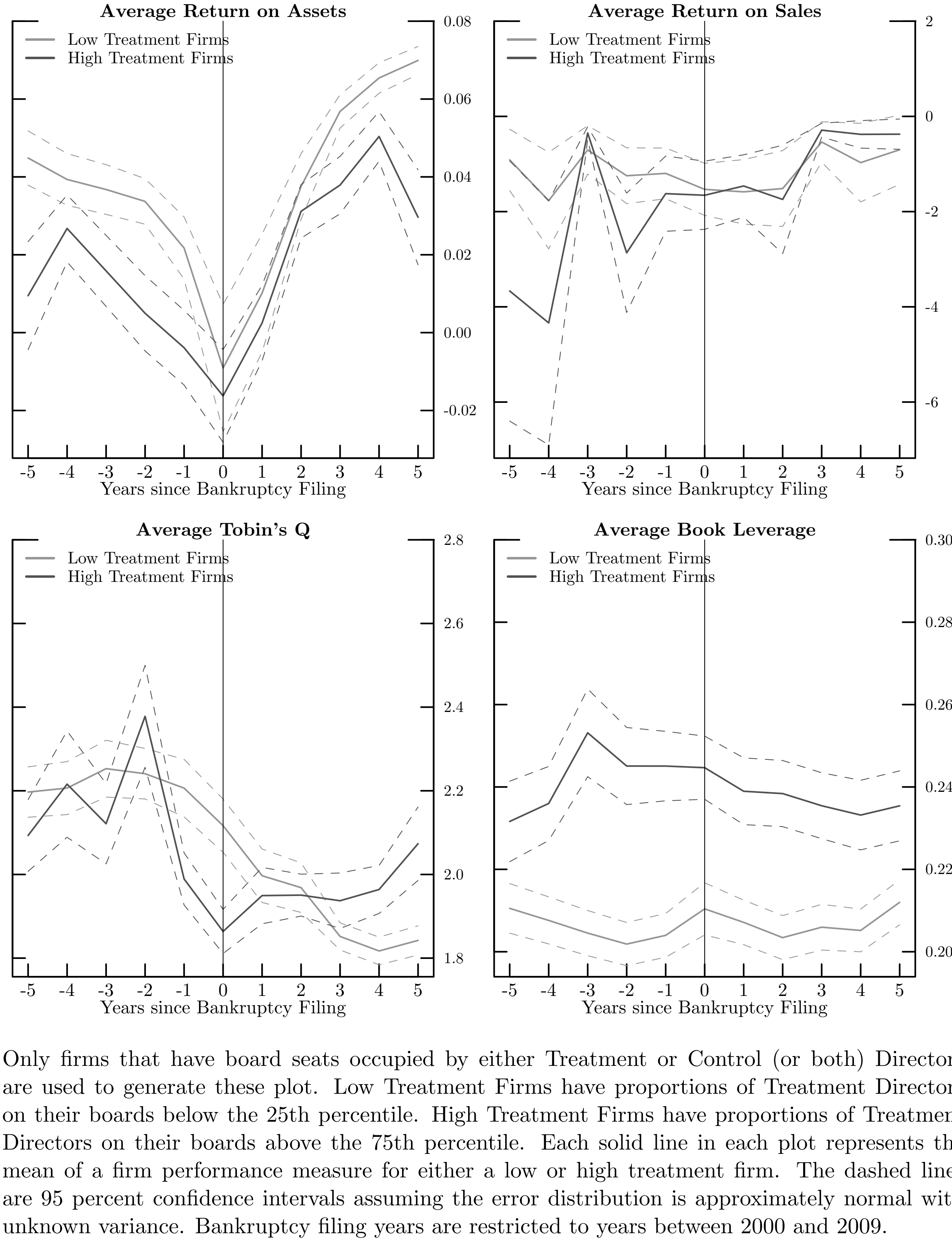
Only executives holding directorships at year zero are used to generate these plots. Event Directors are directors that hold or have held a board position for at least one firm that has filed for bankruptcy at year zero. Treatment Directors are directors that hold board appointments with Event Directors at year zero. Control Directors are directors that share a board with the Treatment Directors at year zero, but have no work histories with Event Directors. Both Treatment and Control Directors have never served on a board of a firm that has filed for bankruptcy. Each solid line in each plot represents the mean of a director compensation measure for an experimental group. The dashed lines are 95 percent confidence intervals assuming the error distribution is approximately normal with unknown variance. Bankruptcy filing years are restricted to years between 2000 and 2009.

Figure 2.6: Average Director Turnover Measures at the Firm Level



Only firms that have board seats occupied by either Treatment or Control (or both) Directors are used to generate these plot. Low Treatment Firms have proportions of Treatment Directors on their boards below the 25th percentile. High Treatment Firms have proportions of Treatment Directors on their boards above the 75th percentile. Each solid line in each plot represents the mean of an aggregated director turnover measure for either a low or high treatment firm. The dashed lines are 95 percent confidence intervals assuming the error distribution is approximately normal with unknown variance. Bankruptcy filing years are restricted to years between 2000 and 2009.

Figure 2.7: Average Firm Performance Measures



Only firms that have board seats occupied by either Treatment or Control (or both) Directors are used to generate these plot. Low Treatment Firms have proportions of Treatment Directors on their boards below the 25th percentile. High Treatment Firms have proportions of Treatment Directors on their boards above the 75th percentile. Each solid line in each plot represents the mean of a firm performance measure for either a low or high treatment firm. The dashed lines are 95 percent confidence intervals assuming the error distribution is approximately normal with unknown variance. Bankruptcy filing years are restricted to years between 2000 and 2009.

2.9 Tables

Table 2.1: Experimental Group Sample Sizes by Bankruptcy Filing Year

Filing Year	Control	Treament	Event	Total
1986	12	6	1	19
1987	21	38	6	65
1991	49	55	7	111
1992	199	169	19	387
1993	4	6	1	11
1994	120	71	6	197
1995	262	180	10	452
1996	129	65	9	203
1997	217	116	10	343
1998	478	170	18	666
1999	361	261	32	654
2000	1321	1098	94	2513
2001	1668	1467	161	3296
2002	1547	916	125	2588
2003	1404	368	74	1846
2004	1133	262	42	1437
2005	1390	326	66	1782
2006	1443	344	57	1844
2007	1230	184	19	1433
2008	1764	556	133	2453
2009	2184	1097	358	3639
2010	809	115	48	972
2011	1199	77	30	1306
Total	18944	7947	1326	28217

Only executives holding directorships at year zero are used to generate these plots. Event Directors are directors that hold or have held a board position for at least one firm that has filed for bankruptcy at year zero. Treatment Directors are directors that hold board appointments with Event Directors at year zero. Control Directors are directors that share a board with the Treatment Directors at year zero, but have no work histories with Event Directors. Both Treatment and Control Directors have never served on a board of a firm that has filed for bankruptcy. Bankruptcy filing years are restricted to years between 2000 and 2009.

Table 2.2: Director-Level Differences in Characteristics

	Control		Treatment		Event			
Variable	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Treatment–Control	Std. Error
CEO	0.286	0.452	0.319	0.466	0.362	0.481	0.034***	0.006
Age	59.118	9.794	57.068	9.12	59.18	9.342	−2.05***	0.116
Independent	0.647	0.478	0.682	0.466	0.766	0.424	0.035***	0.006
Ties to a Multiple Director	0.720	0.449	0.634	0.482	0.479	0.500	−0.087***	0.006
Number of Directorships	1.762	1.041	2.701	1.999	4.074	2.948	0.939***	0.018
Average Board Size	6.845	3.682	7.589	3.94	6.621	3.319	0.744***	0.0485
Degree Centrality ($D_t(\cdot)$)	14.734	7.348	33.964	41.447	48.477	65.158	19.231***	0.444
Aggregate Degree Centrality ($\Delta_t(\cdot)$)	34.399	41.286	69.502	72.565	119.695	121.453	35.103***	0.818

Only executives holding directorships at year zero are shown here. Pre-treatment period shown above covers the bankruptcy filing year and the year before. Event Directors are directors that hold or have held a board position for at least one firm that has filed for bankruptcy at year zero. Treatment Directors are directors that hold board appointments with Event Directors at year zero. Control Directors are directors that share a board with the Treatment Directors at year zero, but have no work histories with Event Directors. Both Treatment and Control Directors have never served on a board of a firm that has filed for bankruptcy. Bankruptcy filing years are restricted to years between 2000 and 2009.

Table 2.3: Firm-Level Differences in Characteristics Between High Treatment and Low Treatment Firms

	≤25%ile (Low)		≥75%ile (High)			
Variable	Mean	Std. Dev.	Mean	Std. Dev.	High–Low	Std. Error
Board Size	2.897	2.249	2.185	1.432	−0.712***	0.052
Tobin's Q	2.223	2.675	2.171	2.838	−0.052	0.084
Book Leverage	0.192	0.214	0.225	0.234	0.032***	0.007
ln(Book Assets)	6.359	1.920	6.539	2.249	−0.180***	0.065
ROA	0.030	0.283	−0.004	0.297	−0.033***	0.009
ROE	0.103	2.250	−0.019	1.647	−0.122**	0.056
RNOA	−0.212	23.555	−0.095	8.875	0.117	0.479
ROS	−0.801	14.626	−1.070	19.111	−0.268	0.542
Firm Age	15.803	12.570	14.541	12.791	−1.262***	0.385

Only executives holding directorships at year zero are shown here. Pre-treatment period shown above covers the bankruptcy filing year and the year before. Event Directors are directors that hold or have held a board position for at least one firm that has filed for bankruptcy at year zero. Treatment Directors are directors that hold board appointments with Event Directors at year zero. Control Directors are directors that share a board with the Treatment Directors at year zero, but have no work histories with Event Directors. Both Treatment and Control Directors have never served on a board of a firm that has filed for bankruptcy. Bankruptcy filing years are restricted to years between 2000 and 2009.

Table 2.4: Director-Level Differences in Characteristics Between High and Low G-Index Firms

Treatment Directors						
	G-Index $\geq$ Median		G-Index $<$ Median			
Variable	Mean	Std. Dev.	Mean	Std. Dev.	High–Low	Std. Error
CEO	0.370	0.483	0.293	0.455	0.076***	0.028
Age	57.624	8.345	56.976	9.621	0.648	0.563
Independent	0.565	0.495	0.633	0.482	−0.072***	0.008
Ties to a Multiple Director	0.720	0.449	0.634	0.482	0.068**	0.029
Number of Directorships	2.950	1.574	3.146	2.511	−0.195	0.138
Average Board Size	8.761	3.628	6.962	3.133	1.798***	0.199
Degree Centrality ($D_t(\cdot)$)	43.648	47.776	35.764	44.184	7.883***	2.749
Aggregate Degree Centrality ($\Delta_t(\cdot)$)	88.748	83.965	67.481	70.956	21.267***	4.554
Average ROA	0.081	0.084	0.059	0.085	0.022***	0.005
Average Market to Book Ratio	2.169	1.843	2.083	1.367	0.086	0.093
Control Directors						
	G-Index $\geq$ Median		G-Index $<$ Median			
Variable	Mean	Std. Dev.	Mean	Std. Dev.	High–Low	Std. Error
CEO	0.300	0.458	0.308	0.462	−0.007	0.019
Age	59.616	9.104	59.497	9.609	0.118	0.402
Independent	0.723	0.447	0.645	0.478	0.078***	0.019
Ties to a Multiple Director	0.762	0.425	0.797	0.402	−0.034*	0.017
Number of Directorships	1.917	1.135	1.746	1.079	0.171***	0.047
Average Board Size	7.781	3.501	6.411	2.716	1.370***	0.130
Degree Centrality ($D_t(\cdot)$)	18.624	7.295	15.878	7.149	2.745***	0.307
Aggregate Degree Centrality ($\Delta_t(\cdot)$)	39.224	42.780	36.414	44.368	2.810	1.867
Average ROA	0.065	0.089	0.080	0.131	−0.014***	0.005
Average Market to Book Ratio	1.999	1.402	2.770	2.151	−0.771***	0.081

Only executives holding directorships at year zero are shown here. Pre-treatment period shown above covers the bankruptcy filing year and the year before. Event Directors are directors that hold or have held a board position for at least one firm that has filed for bankruptcy at year zero. Treatment Directors are directors that hold board appointments with Event Directors at year zero. Control Directors are directors that share a board with the Treatment Directors at year zero, but have no work histories with Event Directors. Both Treatment and Control Directors have never served on a board of a firm that has filed for bankruptcy. Bankruptcy filing years are restricted to years between 2000 and 2009.

Table 2.5: Director Turnover Around Bankruptcy Filing

	Directorships Added Minus Dropped		Probability of Adding		Probability of Dropping	
	(1)	(2)	(3)	(4)	(5)	(6)
Treatment × Post-Bankruptcy	−0.132***	−0.155***	−0.113***	−0.132***	−0.013	−0.020*
	(0.013)	(0.018)	(0.008)	(0.011)	(0.009)	(0.012)
CEO	0.014	0.002	−0.014	−0.019	−0.032***	−0.030**
	(0.017)	(0.030)	(0.012)	(0.017)	(0.009)	(0.014)
ln(Age)	−3.844***	−4.578***	−2.347***	−3.019***	0.958***	0.879***
	(0.308)	(0.479)	(0.194)	(0.277)	(0.168)	(0.256)
Independent	0.017	0.062*	0.027	0.083***	−0.010	0.007
	(0.020)	(0.032)	(0.017)	(0.023)	(0.015)	(0.020)
Ties to a Multiple Director	−0.005	−0.013	−0.003	−0.021**	0.020***	0.009
	(0.009)	(0.013)	(0.008)	(0.010)	(0.005)	(0.007)
Number of Directorships	0.402***	0.457***	0.210***	0.233***	−0.114***	−0.130***
	(0.017)	(0.016)	(0.009)	(0.009)	(0.008)	(0.008)
Average Board Size	−0.005*	0.001	−0.002	0.003	0.001	0.001
	(0.003)	(0.004)	(0.002)	(0.002)	(0.002)	(0.003)
Degree Centrality	0.008***	0.008***	0.000	0.001	−0.008***	−0.007***
	(0.002)	(0.002)	(0.000)	(0.001)	(0.002)	(0.002)
Aggregate Degree Centrality	−0.008***	−0.009***	0.000	−0.001	0.008***	0.008***
	(0.002)	(0.002)	(0.000)	(0.001)	(0.002)	(0.002)
Average ROA		0.052		−0.008		−0.081**
		(0.059)		(0.034)		(0.033)
Average Market to Book Ratio		0.012***		0.008***		−0.001
		(0.003)		(0.002)		(0.001)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Director FE	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	63588	31882	63588	31882	63588	31882
Adj. R^2	0.274	0.310	0.308	0.344	0.204	0.226

Significance levels 10%, 5%, and 1% are denoted by *, **, ***, respectively. Standard errors in parentheses are clustered at the event director level. Only executives holding directorships at year zero are shown here. Bankruptcy filing years are restricted to years between 2000 and 2009. Event study window covers 2 years before and 2 years after the bankruptcy filing year.

Table 2.6: Corporate Governance and Director Turnover Around Bankruptcy Filing

	Directorships Added Minus Dropped			Probability of Adding			Probability of Dropping		
	G-Index ≥ Median (1)	G-Index < Median (2)	Full Sample (3)	G-Index ≥ Median (4)	G-Index < Median (5)	Full Sample (6)	G-Index ≥ Median (7)	G-Index < Median (8)	Full Sample (9)
Treatment × Post-Bankruptcy	−0.183*** (0.032)	−0.082 (0.051)	−0.135** (0.057)	−0.121*** (0.026)	−0.080* (0.039)	−0.086** (0.033)	0.014 (0.024)	−0.051 (0.036)	−0.011 (0.029)
Post-Bankruptcy × (G-Index ≥ Median)			−0.038** (0.016)			−0.026*** (0.008)			0.004 (0.011)
Treatment × Post-Bankruptcy × (G-Index ≥ Median)			−0.011 (0.067)			−0.017 (0.046)			0.013 (0.041)
Director Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Director FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	4535	2475	7010	4535	2475	7010	4535	2475	7010
Adj. R^2	0.302	0.305	0.300	0.298	0.316	0.303	0.192	0.213	0.195

Significance levels 10%, 5%, and 1% are denoted by *, **, ***, respectively. Standard errors in parentheses are clustered at the event director level. Only executives holding directorships at year zero are shown here. Event Directors are directors that hold or have held a board position for at least one firm that has filed for bankruptcy at year zero. Treatment Directors are directors that hold board appointments with Event Directors at year zero. Control Directors are directors that share a board with the Treatment Directors at year zero, but have no work histories with Event Directors. Both Treatment and Control Directors have never served on a board of a firm that has filed for bankruptcy. Bankruptcy filing years are restricted to years between 2000 and 2009. Event study window covers 2 years before and 2 years after the bankruptcy filing year. Median G-Index value is 9.

Table 2.7: Director Turnover Around Bankruptcy Filing by Degree Centrality

	Least Central				Most Central
	(1)	(2)	(3)	(4)	(5)
Treatment × Post-Bankruptcy	−0.040	−0.027	−0.045**	−0.044**	−0.208***
	(0.037)	(0.018)	(0.021)	(0.017)	(0.022)
CEO	0.050	−0.037	−0.018	−0.076**	0.000
	(0.032)	(0.026)	(0.036)	(0.038)	(0.036)
ln(Age)	−0.718	−2.002***	−2.707***	−4.163***	−12.516***
	(0.658)	(0.342)	(0.504)	(0.967)	(1.714)
Independent	0.075	−0.003	0.109**	0.075*	0.155***
	(0.055)	(0.029)	(0.043)	(0.045)	(0.052)
Ties to a Multiple Director	−0.068**	0.011	0.008	−0.035*	0.012
	(0.028)	(0.023)	(0.023)	(0.018)	(0.023)
Number of Directorships	0.263***	0.286***	0.265***	0.268***	0.242***
	(0.024)	(0.018)	(0.020)	(0.015)	(0.015)
Average Board Size	0.005	0.005*	0.005	−0.001	0.005
	(0.006)	(0.003)	(0.004)	(0.004)	(0.005)
Average ROA	−0.196***	−0.123**	0.060	0.125*	−0.001
	(0.069)	(0.061)	(0.066)	(0.073)	(0.183)
Average Market to Book Ratio	0.013***	0.009***	0.002	0.005	0.011
	(0.003)	(0.003)	(0.005)	(0.003)	(0.007)
Year FE	Yes	Yes	Yes	Yes	Yes
Director FE	Yes	Yes	Yes	Yes	Yes
Obs.	5149	7816	6325	7262	5275
Adj. R^2	0.425	0.338	0.313	0.304	0.272

Significance levels 10%, 5%, and 1% are denoted by *, **, ***, respectively. Standard errors in parentheses are clustered at the event director level. Only executives holding directorships at year zero are shown here. Event Directors are directors that hold or have held a board position for at least one firm that has filed for bankruptcy at year zero. Treatment Directors are directors that hold board appointments with Event Directors at year zero. Control Directors are directors that share a board with the Treatment Directors at year zero, but have no work histories with Event Directors. Both Treatment and Control Directors have never served on a board of a firm that has filed for bankruptcy. Bankruptcy filing years are restricted to years between 2000 and 2009. Event study window covers 2 years before and 2 years after the bankruptcy filing year. Degree centrality counts the number of director associations or the number of shared directorships at boards on which a director is currently a member.

Table 2.8: Director Turnover Around Bankruptcy Filing by Aggregate Degree Centrality

	Least Central				Most Central
	(1)	(2)	(3)	(4)	(5)
Treatment × Post-Bankruptcy	−0.028	−0.079***	−0.073***	−0.134***	−0.183***
	(0.023)	(0.020)	(0.018)	(0.019)	(0.022)
CEO	−0.008	−0.015	0.016	−0.064	−0.037
	(0.023)	(0.033)	(0.035)	(0.039)	(0.039)
ln(Age)	−1.299***	−3.336***	−3.677***	−5.250***	−6.237***
	(0.443)	(0.642)	(0.544)	(0.860)	(1.568)
Independent	0.089**	0.084***	0.084*	0.046	0.062
	(0.036)	(0.032)	(0.043)	(0.039)	(0.052)
Ties to a Multiple Director	−0.058**	−0.006	−0.006	−0.001	−0.027
	(0.024)	(0.021)	(0.017)	(0.020)	(0.031)
Number of Directorships	0.266***	0.281***	0.236***	0.265***	0.233***
	(0.025)	(0.016)	(0.016)	(0.013)	(0.016)
Average Board Size	0.005	0.003	0.000	0.003	−0.002
	(0.003)	(0.003)	(0.005)	(0.006)	(0.006)
Average ROA	−0.175***	−0.038	−0.015	0.268***	−0.126
	(0.058)	(0.059)	(0.067)	(0.090)	(0.110)
Average Market to Book Ratio	0.012***	−0.001	0.006	0.012***	0.006
	(0.002)	(0.004)	(0.004)	(0.005)	(0.004)
Year FE	Yes	Yes	Yes	Yes	Yes
Director FE	Yes	Yes	Yes	Yes	Yes
Obs.	7760	7101	6787	6060	4162
Adj. R^2	0.393	0.327	0.309	0.310	0.344

Significance levels 10%, 5%, and 1% are denoted by *, **, ***, respectively. Standard errors in parentheses are clustered at the event director level. Only executives holding directorships at year zero are shown here. Event Directors are directors that hold or have held a board position for at least one firm that has filed for bankruptcy at year zero. Treatment Directors are directors that hold board appointments with Event Directors at year zero. Control Directors are directors that share a board with the Treatment Directors at year zero, but have no work histories with Event Directors. Both Treatment and Control Directors have never served on a board of a firm that has filed for bankruptcy. Bankruptcy filing years are restricted to years between 2000 and 2009. Event study window covers 2 years before and 2 years after the bankruptcy filing year. Aggregate degree centrality is defined as the num of a director's past and current professional connections.

Table 2.9: Director Compensation Around Bankruptcy Filing

	ln(Total Compensation)	ln(Salary)	ln(Bonus)	ln(Number of Options Awarded)
	(1)	(2)	(3)	(4)
Treatment × Post-Bankruptcy	0.025	0.027	−0.072	0.007
	(0.037)	(0.027)	(0.135)	(0.088)
CEO	0.254***	0.221***	0.250	0.314*
	(0.068)	(0.059)	(0.229)	(0.178)
ln(Age)	0.906	1.924	0.037	7.076
	(2.415)	(2.423)	(9.151)	(6.574)
Independent	0.040	0.077**	−0.174	−0.372**
	(0.059)	(0.037)	(0.233)	(0.172)
Ties to a Multiple Director	−0.053**	−0.027	−0.319***	0.045
	(0.026)	(0.021)	(0.108)	(0.071)
Number of Directorships	0.045	0.020	0.282***	0.100
	(0.040)	(0.026)	(0.096)	(0.087)
Average Board Size	0.018	0.013	0.016	−0.041
	(0.013)	(0.009)	(0.040)	(0.033)
Degree Centrality	−0.006	−0.012**	−0.007	0.003
	(0.008)	(0.006)	(0.016)	(0.012)
Aggregate Degree Centrality	−0.001	0.004	−0.005	−0.002
	(0.005)	(0.004)	(0.013)	(0.011)
Average ROA	0.245*	0.028	1.206	0.245
	(0.136)	(0.094)	(0.800)	(0.527)
Average Market to Book Ratio	0.008	0.008	−0.032	−0.048
	(0.006)	(0.005)	(0.026)	(0.030)
Year FE	Yes	Yes	Yes	Yes
Director FE	Yes	Yes	Yes	Yes
Obs.	6102	6102	6102	6079
Adj. R^2	0.791	0.838	0.611	0.567

Significance levels 10%, 5%, and 1% are denoted by *, **, ***, respectively. Standard errors in parentheses are clustered at the event director level. Only executives holding directorships at year zero are shown here. Event Directors are directors that hold or have held a board position for at least one firm that has filed for bankruptcy at year zero. Treatment Directors are directors that hold board appointments with Event Directors at year zero. Control Directors are directors that share a board with the Treatment Directors at year zero, but have no work histories with Event Directors. Both Treatment and Control Directors have never served on a board of a firm that has filed for bankruptcy. Bankruptcy filing years are restricted to years between 2000 and 2009. Event study window covers 2 years before and 2 years after the bankruptcy filing year.

Table 2.10: Firm-Level Director Turnover Around Bankruptcy Filing

	Directorships Added Minus Dropped	Probability of Adding	Probability of Dropping
	(1)	(2)	(3)
% Treatment × Post-Bankruptcy	−0.509***	−0.116***	0.075***
	(0.069)	(0.026)	(0.025)
ln(Board Size)	0.277***	0.361***	0.341***
	(0.062)	(0.030)	(0.029)
Tobin's Q	0.001	−0.003	−0.008*
	(0.014)	(0.006)	(0.005)
Book Leverage	0.013	−0.040	−0.079
	(0.189)	(0.078)	(0.054)
ln(Book Assets)	0.048	0.030*	0.000
	(0.044)	(0.018)	(0.020)
ROA	0.019	0.021	0.001
	(0.024)	(0.014)	(0.012)
ROE	0.001	0.000	−0.001
	(0.002)	(0.001)	(0.001)
RNOA	0.000***	0.000***	0.000
	(0.000)	(0.000)	(0.000)
ROS	0.000	0.000	0.000
	(0.001)	(0.000)	(0.000)
ln(Firm Age)	−0.699***	−0.295***	−0.004
	(0.139)	(0.058)	(0.051)
Year FE	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Obs.	10261	10261	10261
Adj. R^2	0.093	0.249	0.184

Significance levels 10%, 5%, and 1% are denoted by *, **, ***, respectively. Standard errors in parentheses are clustered at the event director level. Only firms that have board seats occupied by either Treatment or Control (or both) Directors are used. Low Treatment Firms have proportions of Treatment Directors on their boards below the 25th percentile. High Treatment Firms have proportions of Treatment Directors on their boards above the 75th percentile. Bankruptcy filing years are restricted to years between 2000 and 2009.

Table 2.11: Description of Control Variables

Variable Name	Description
Treatment	Binary variable indicating whether a director belongs in the treatment group: Event Directors are directors that held or have held a board position at at least one firm that has filed for bankruptcy at year zero. Treatment Directors are directors that had held board appointments with Event Directors at year zero. Control Directors are directors that share a board with the Treatment Directors, but have no work history with Event Directors. Both Treatment and Control Directors never served on a board of a firm that has filed for bankruptcy.
Post-Bankruptcy	Binary variable indicating post-treatment time period
CEO	Binary variable indicating whether a director is also the CEO of the company
Age	Age of the director
Independent	Indicator for whether a director is designated as being independent
Ties to a Multiple Director	Indicator for having connections with at least one director who sits on more than 1 board
Number of Directorships	Number of boards of which a director is currently a member
Average Board Size	The average size of the board on which a director sits
Degree Centrality ($D_t(\cdot)$)	Degree centrality counts the number of director associations or the number of shared directorships at boards on which a director is currently a member
Aggregate Degree Centrality ($\Delta_t(\cdot)$)	Professional component of the "Rolodex" variable from Engelberg, Gao, and Parsons (2013b): This is the sum of a director's current and past professional connections.
Average ROA	Average return on assets of firms on which director is serving as a board member
Average Market to Book Ratio	Average market to book ratio of firms on which director is serving as a board member

CHAPTER 3

Family Feud: Proxy Vote Disagreements between Passive and Active Funds

Recent empirical studies in the mutual fund literature find that changes in the share of passive mutual fund ownership of a given firm can lead to changes in its corporate governance practices. The argument for positive changes in corporate governance in response to increases in ownership share of passive funds relies on the fact that passive funds lack an exit option. Since passive funds emulate the portfolio holdings of stock indexes, they are unable to liquidate their stakes in poor performing firms. However, does this necessarily imply that passive funds vote differently than active ones in their proxy voting ballots? It can be argued that compared to active funds, index funds have less resources to monitor (e.g., lower fees, more diversified holdings, etc.) and therefore, on average, may not behave differently than active funds. Additionally, funds within a given fund family are likely to share similar information. This paper seeks to understand whether passive funds vote differently than active ones with respect to corporate governance related agenda items on proxy ballots.

Whether more passive fund owners leads to better or worse firm governance is still an open question empirically. In this paper, we explore the proxy voting channel for mutual funds to influence corporate governance practices for firms in which they have holdings. Based on the recorded votes of mutual funds from various governance related agenda ballot items from 2003 to 2015, we find that passively managed mutual funds on average tend to disagree with management recommendations compared to their actively managed counterparts. However, voter efficacy of passive funds are not equal across agenda item categories. We find that passive funds are more successful than active funds at achieving their desired outcome on shareholder rights related agenda items. Conversely, passive funds are less likely than active funds to get their way on executive compensation agenda items. On average, we find that passive funds are exercising their "voice" through the voting channel.

Section 1 reviews the related literature on mutual fund families and the relationship between passive institutional investors and corporate governance. Section 2 summarizes our empirical strategy and the datasets used to answer our research questions. Section 3 documents our results. Section 4 concludes.

3.1 Literature Review

3.1.1 Passive Institutional Investors and Corporate Governance

Passive institutional investors are becoming an increasingly large component of shareholders in the U.S. stock market through the popularization of indexation. Because indexation prevents passive funds from divesting poor performing stocks in their portfolios, some recent papers have argued that the lack of an exit option disciplines passive funds to improve the returns of their firm holdings through the "voice" channel. However, the empirical findings are mixed. Appel, Gormley, and Keim (2016) show that increases in index fund ownership of a firm can lead to improvements of its corporate governance. Using Russell index reconstitutions as a source of exogenous variation in the percentage share of passive mutual fund ownership, they demonstrate that more passive ownership leads to the removals of poison pills, establishment of equal voting rights, and increases in board independence. Similarly, Mullins (2014) find that firms added to the Russell 1000 (from the Russell 2000) substantially increase the performance sensitivity of their CEOs' pay and the likelihood of CEO turnover within two years. These firms also exhibit greater resistance to management proposals at shareholder meetings, lower rates of failure of shareholder proposals, and have materially lower capital expenditures and fewer cash and diversifying acquisitions. Using the similar identification strategies as above, Crane, Michenaud, and Weston (2016) find that higher institutional ownership causes firms to pay more dividends and Boone and White (2015) find that higher institutional ownership leads to greater levels of transparency from management.[1]

In contrast, Schmidt and Fahlenbrach (2017) provide evidence that the power of CEOs increases in firms with more passive owners, as measured by CEO title accumulations. Additionally, shareholders react more negatively to the accumulation of titles and the appointment of new directors in firms with more passive owners. Lastly, Schmidt and Fahlenbrach (2017) also finds that firms engage in more value-destroying mergers and acquisitions (M&A) after increases in passive ownership.

These contradictory findings potentially stem from the fact that we are unable to disentangle effects that are driven by simply having more institutional investors from the fund strategy of being passive or indexers. Moreover, the existing literature is silent on the exact mechanism in which passive institutional investors can generate corporate governance changes. This paper attempts to reconcile these competing results by analyzing mutual fund proxy voting behavior between passive and active mutual funds.

3.1.2 Agency Issues in Mutual Fund Proxy Voting

The literature in mutual fund proxy voting finds that mutual fund votes can be subject to manipulation. This manipulation can lead to voting outcomes that do not coincide with shareholder interests. Several papers such as Ashraf, Jayaraman, and Ryan (2012), Davis and Kim (2007), and Ng, Wang, and Zaiats (2009) show that fund votes can be influenced by existing business ties. Ashraf, Jayaraman, and Ryan (2012) find that fund families often support management when they have pension ties to firms in which they are also stakeholders. Similarly, Davis and Kim (2007) and Ng, Wang, and Zaiats (2009) uncover a positive relationship between business ties and the propensity to vote with management. Others such as Iliev and Lowry (2015) and Matvos and Ostrovsky (2013) suggest that mutual fund votes can be determined by recommendations of proxy advisory firms (e.g., ISS) or by other mutual funds (e.g., herding or peer effects), respectively. In this paper, we explore the

[1] While theses studies focus mainly on the effect of passive investors on corporate governance issues, some recent studies look into how passive investors affect firm operation decisions and product market competition. See He and Huang (2014), Azar, Schmalz, and Tecu (2015), and Azar, Raina, and Schmalz (2016).

possibility that passive mutual funds are less susceptible to agency issues, and therefore vote differently than their active counterparts.

3.1.3 Competition within Mutual Fund Families

This paper lastly relates to the literature of fund competition within fund families. Several papers provide evidence of coordination failure among funds in a fund family. Kempf and Ruenzi (2008), for example, show that fund managers compete with other fund managers of their own company for the best rank in the fund family. Likewise, Gaspar, Massa, and Matos (2006) find that fund management companies have incentives to cross-subsidize the performance of "high value funds" (i.e., high fees or high past performers) at the expense of low value funds. This result is also supported by similar findings of Nanda, Wang, and Zheng (2004). Nanda, Wang, and Zheng (2004) show that exceptional fund performance leads to greater cash inflow to other funds in its family. These papers suggest that fund families should not be viewed as coordinated entities. Our paper finds potential coordination failures with respect to mutual fund proxy voting.

3.2 Data and Empirical Strategy

The core of our dataset is derived from SEC N-PX forms that are completed by registered management investment companies. These forms report the proxy voting records of registered management investment companies for each 12-month period. The SEC makes this information available to the public.

In order to account for mutual fund-specific characteristics (i.e., size, style, holdings, etc.), we merge the N-PX dataset with both CRSP-Compustat and Thomson Reuters S12 mutual fund holdings data. We do this manually in the same approach as Iliev and Lowry (2015) and Matvos and Ostrovsky (2013) by first matching on fund family name and then by fund name.

We split our constructed dataset into 9 categories derived from classifications created by ISS themselves. The 9 categories broadly cover agenda items related to corporate governance (executive compensation, shareholder rights, social issues, and board issues) and corporate financing/regulation (auditing, capital, restructuring, dividend payouts, and routine). We focus on corporate governance related agenda items since we are interested in how disagreements within mutual fund families can impact vote dispersion within mutual fund families.

3.2.1 Outcome Variables of Interest

The primary outcome variables of interest are disagreement measures between passive and active mutual funds. We study these measures via panel regression. At the proxy ballot agenda item level, we look at whether passive mutual funds are more likely to disagree with management and also whether they vote in the same direction as the realized vote outcome (ex post).[2] Standard errors in the panel regression specification are clustered at the fund and firm levels. We also include fund family-year, firm-year, and ISS agenda type-year fixed effects in our baseline model.

3.2.2 Measuring Pivotal Votes

Do passive mutual funds behave more like activist shareholders when their votes are pivotal? As a first step, we use a naive ex-post measure of pivotal votes defined as the following:

$$\text{abs(Vote Distance)} = \left|\text{\% Voted For an Agenda Item} - \text{Vote Passing Threshold}\right| \tag{3.1}$$

abs(Vote Distance) is large when an agenda item passes or fails to pass by a wide margin.

[2]We identify passive mutual funds using the same methodologies used by Appel, Gormley, and Keim (2016). Specifically, we categorize funds as passive funds if their names contain at least one of the following strings: Index, Idx, Indx, Ind_ (where _ indicates a space), Russell, S & P, S and P, S&P, SandP, SP, DOW, Dow, DJ, MSCI, Bloomberg, KBW, NASDAQ, NYSE, STOXX, FTSE, Wilshire, Morningstar, 100, 400, 500, 600, 900, 1000, 1500, 2000, and 5000. We also use the classification variable provided by CRSP to identify passive mutual funds.

This scenario suggests ex-ante that the marginal vote does not matter.[3] Conversely, an agenda item that nearly passes or fails to pass would have a small abs(Vote Distance). This scenario suggests that the marginal vote could potentially sway the vote outcome. To see if passive mutual funds have more activist tendencies when their vote are more pivotal, we interact the binary variable of being a passive mutual fund with this measure of how pivotal a vote is for each agenda item. Shareholder activism would be less meaningful if mutual funds disagree with management (and each other) when their votes do not matter. Figures 3.1, 3.2, 3.3, and 3.4 are histograms of the vote distance (without taking absolute value) for agenda items related to executive compensation, shareholder rights, social issues, and board issues, respectively.

[Insert Figures 3.1, 3.2, 3.3, and 3.4]

Something to take notice from these histograms is that the distributions of vote distance for executive compensation and board issues are highly asymmetric. This asymmetric pattern could arise from management pressures to collect sufficient votes to pass agenda items related to their own pay or position. On the other hand, the vote distance distribution for shareholder rights are far less skewed and have most of its mass around the cutoff or passing vote threshold. This suggests that these shareholder rights related agenda items may be less susceptible to vote manipulation or persuasion from management. Lastly, social issues related agenda items (e.g., climate change, energy efficiency, etc.) do not seem to be of a major concern by shareholders in general, as they often fail to pass.

3.2.3 Mutual Fund Type and Vote Dispersion

To measure mutual fund type dispersion (i.e., mutual funds being passive or active), we calculate the (unbiased) sample variance of being a passive mutual fund for each unique agenda item within a fund family. Note that since the variables in which we are calculating the variance are binary, the sample variance takes the following form:

[3] The main reason why this measure could be problematic is that votes could be manipulated. In other words, votes are rarely pivotal. Whether mutual fund votes are ever pivotal requires further study.

$$\frac{a}{n-1} - \frac{a^2}{n(n-1)} \tag{3.2}$$

where a is the number of passive mutual funds or "for" votes. The variance is maximized when $a = \frac{n}{2}$, which is intuitive since we are dealing with binary variables. For a given agenda item, a fund family is most dispersed when precisely half of its funds are passive.[4] Likewise, a vote is most dispersed when precisely half the votes are "for" and the other half are "against". Therefore, we measure vote dispersion for each unique agenda item within a fund family the same way. Table 3.1 documents our mutual fund type and vote dispersion measures across several quantiles for agenda items in which there are at least two funds casting a vote in the same fund family.

For each agenda item (for a particular company), there is an average of about 3 to 4 funds that cast a vote from the same fund family. However, these 3 to 4 funds tend to be either all passive or all active, as shown in the second row of Table 3.1. Mixtures of passive and active funds of the same fund family per agenda item are rare, but they interestingly correlate with the number of funds per agenda item and also vote dispersion across several corporate governance related agenda item categories. The main takeaway from Table 3.1 is that as the number of cross-holdings increases within fund family, dispersion in passive/active funds and agenda item votes increases as well.

3.3 Results

3.3.1 Proxy Vote Dispersion within Fund Family

To test the hypothesis that mutual fund type dispersion (passive vs. active) within fund family is positively related to vote dispersion, we aggregate at the agenda item level and calculate the standard deviations of indicators for passive or active funds and for proxy

[4]Note that the maximum value of the sample variance is a function of the sample size. The maximum variance is equal to $\frac{n}{4(n-1)}$. To account for the size effect in our regressions, we include the number of unique funds within a fund family casting votes for a specific agenda item as a control variable.

votes ("for" or "against"). Then, we regress our measure of mutual fund type dispersion on vote dispersion across several agenda item categories while controlling for the number of funds within the same fund family voting on a particular agenda item. Tables 3.2 and 3.3 documents our regression results.

[Insert Tables 3.2 and 3.3]

Table 3.2 shows the regression results of agenda items related to executive compensation (column 1), shareholder rights (column 2), social issues (column 3), and board issues (column 4). Although the coefficients are a bit difficult to interpret, the results suggest that passive funds potentially vote differently than active funds. Intuitively, as fund families move towards having precisely 50 percent passive funds, proxy votes also move towards having precisely 50 percent vote in a single direction. The magnitudes are small but statistically significant at the 1 percent level across these governance related agenda items. For more corporate financing related agenda items shown in Table 3.3, the relationship still somewhat holds, but less consistently. Table 3.3 reveals that for certain agenda items such as auditing (column 1) and restructuring (column 3) there is likely very little disagreement on what should be done at the fund family level.

3.3.2 Disagreements with Management Recommendations

Our baseline specification is a panel regression model estimated at the fund-agenda-item-year level. The main task here is to test whether passive mutual funds vote differently than active mutual funds within the same fund family. Firstly, we want to know how passive mutual funds vote with respect to management recommendations compared to active mutual funds. Tables 3.4, 3.6, 3.8, and 3.10 show the results of our estimated baseline model with a binary dependent variable equalling to 1 if management and fund agree on how to vote on a particular agenda item. For each of these tables, column 1 shows the estimated coefficient of just the indicator variable for whether a fund is passive or active, column 2 adds the absolute vote distance measure, column 3 includes the interaction of the passive indicator variable with the absolute vote distance measure and fund fixed effects, and column 4 adds fund control variables derived from CRSP. Each of these specifications include fund-family-year, firm-year, and ISS-agenda-type-year fixed effects.

[Insert Tables 3.4, 3.6, 3.8, and 3.10]

Across Tables 3.4, 3.6, 3.8, and 3.10, the estimated coefficient on the passive mutual fund indicator variable consistently appears negative and is statistically significant at the 1 percent level for executive compensation and shareholder rights related agenda items. On average, being passive is associated with an increase (decrease) of 1 percentage point in the likelihood of disagreeing (agreeing) with management recommendations on executive compensation related agenda items. Similarly, we observe an increase of 4 percentage points in the likelihood of disagreeing with management recommendations on shareholder rights related agenda items in response to being a passive mutual fund. Although the point estimates of being a passive mutual fund is negative for agenda items related to social and board issues, they are not statistically significant. This suggests that there is less disagreement between passive and active mutual funds on these agenda items.

The coefficient on the absolute vote distance measure is positive throughout Tables 3.4, 3.6, 3.8, and 3.10. As the marginal vote becomes less pivotal, the likelihood of deviating from management recommendations is lower. In fact the absolute vote distance measure is statistically and economically significant for executive compensation, shareholder rights, and social issues related agenda items. When we interact the passive mutual fund indicator with the absolute vote distance measure, we find that for higher levels of absolute vote distance, passive funds are more likely than active funds to disagree with management on executive compensation and shareholder rights related agenda items. We find similar results for shareholder rights related agenda items. Assuming our measure of vote distance is an accurate measure of how pivotal the marginal vote is ex-ante, these results suggest that passive mutual funds are more "active" in the sense that they vote contrary to the majority when their votes matter less.

Note that our absolute vote distance measure has little predictability on board related agenda items. This may be due to the fact that there is very little disagreement on how to vote for board related agenda items. There is also the possibility that mutual funds in general believe that management have more control over the outcomes of director elections (i.e., single unopposed director candidate, etc.) and therefore just yield their votes to them. Mutual fund voting patterns in director elections require further study.

3.3.3 Agreement with Vote Outcome

We use the same specification as explained in the previous section to see if passive mutual funds are more likely to vote the same way as the realized outcome of each agenda item. Tables 3.5, 3.7, 3.9, and 3.11 document the regression results on agenda items related to executive compensation, shareholder rights, social issues, and board issues, respectively. The dependent variable is equal to 1 if a fund achieves its desired voting outcome.

[Insert Tables 3.5, 3.7, 3.9, and 3.11]

In general, we find that voter efficacy of passive funds is not equal across all agenda item categories. Being passive is associated with being more successful than active funds at voting with the realized agenda item vote outcome related to shareholder rights: all else equal, being passive leads to an increase in likelihood of voting with the winning majority by 1 percentage point. Additionally, at higher levels of absolute vote distance, being passive is associated with agreeing more with the winning majority. These point estimates are statistically significant at the 1 percent level.

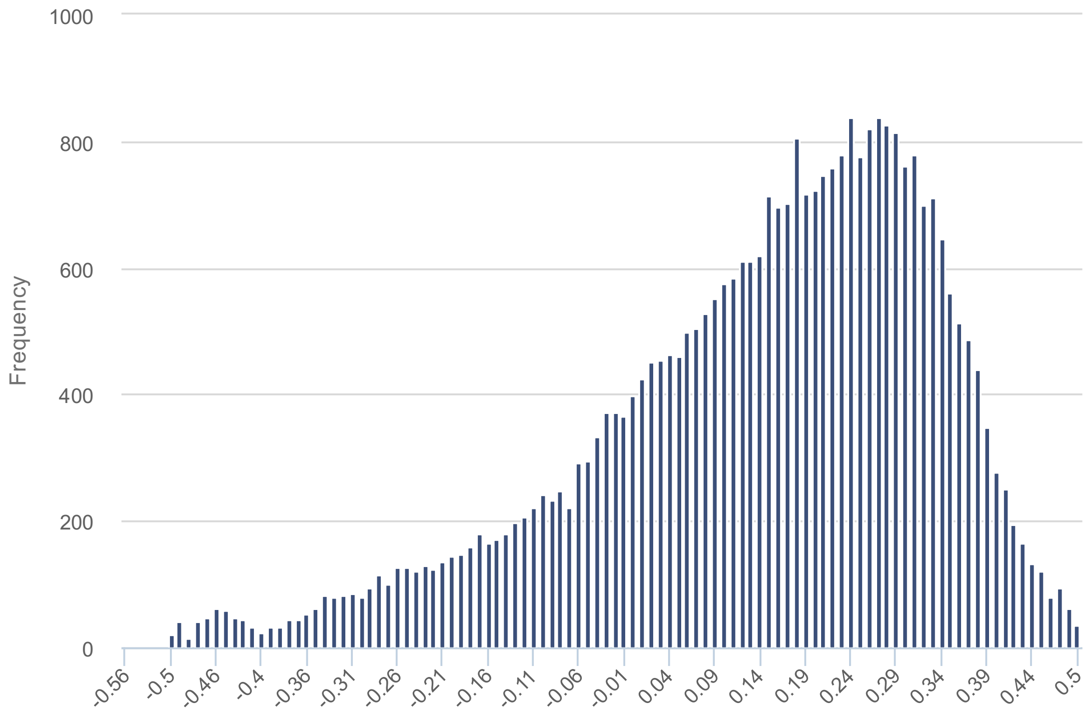
On the other hand, for executive compensation and social issues related agenda items, being a passive mutual fund leads to a decrease in probability of voting with the winning majority. Being passive is associated with a decrease in the probability of voting the same direction as the realized outcome of executive compensation related agenda items by about 1.3 percentage points. In fact, the larger the vote distance, the more likely passive mutual funds will not get their desired vote outcome for a particular compensation related agenda item. These point estimates are statistically significant at the 1 percent level. Although the point estimates for social issues related agenda items are not statistically significant, the fact that they are negative suggests that on average passive funds often go in the opposite direction of the majority.

3.4 Conclusion

In contrast to other papers that study the outcomes of monitoring by passive mutual funds, we focus our study on the actual monitoring behavior itself. We find significant differences in the way passive mutual funds vote compared to active mutual funds within fund family. Passiveness is correlated with more deviations from management recommendations. However, the vote efficacy of passive mutual funds are not equal across agenda item categories. Passive funds are more successful than active funds at voting with the winning majority for shareholder rights agenda items. Conversely, passive funds are less likely than active funds to get their way for executive compensation agenda items. On the surface, it appears that passive mutual funds are more active than active funds when it comes to proxy voting.

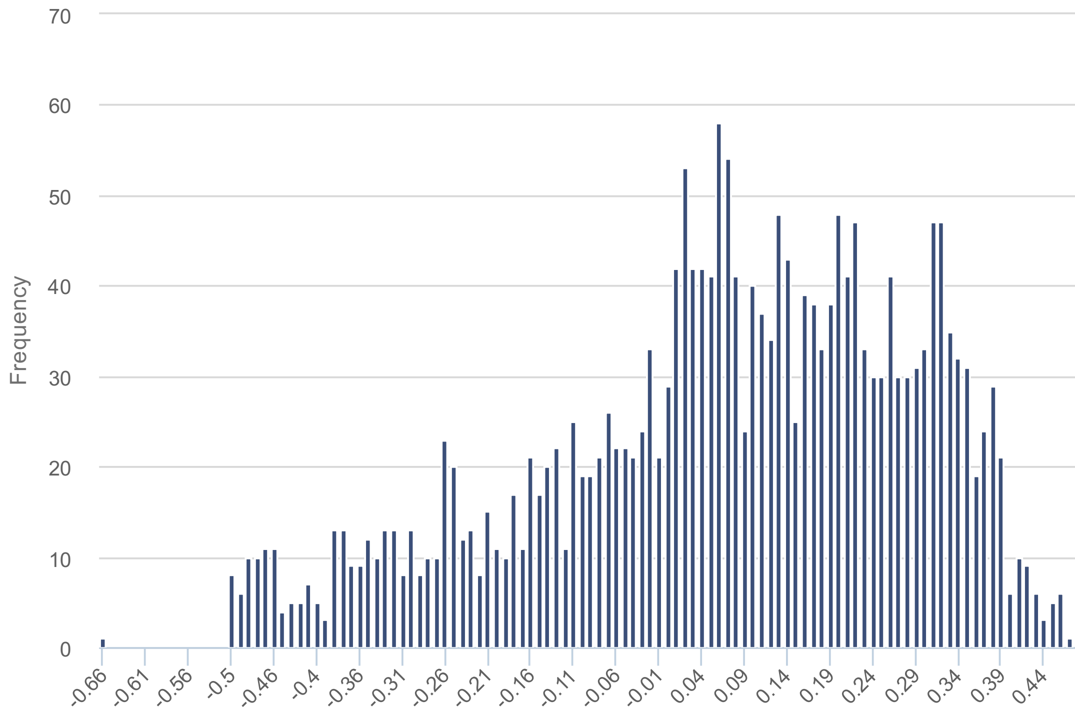
3.5 Figures

Figure 3.1: Vote Distance on Agenda Items related to Executive Compensation



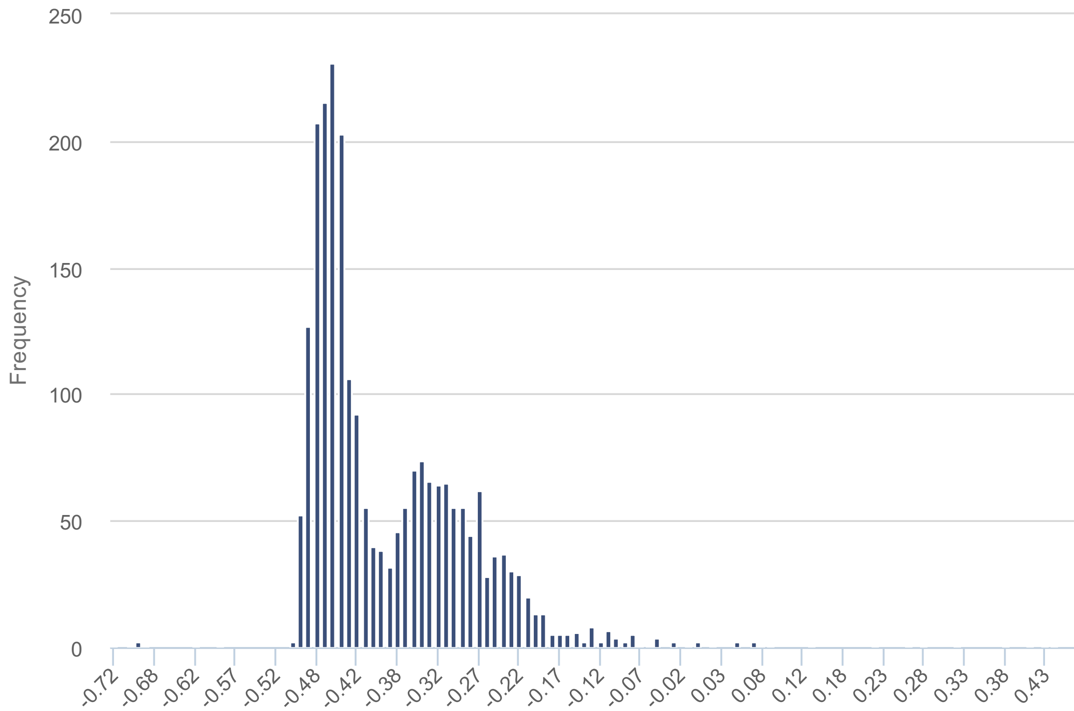
The x-axis is the vote distance defined as the difference between the percentage of "for" votes and the passing threshold. Frequency plot above includes agenda items from 2003 to 2015.

Figure 3.2: Vote Distance on Agenda Items related to Shareholder Rights



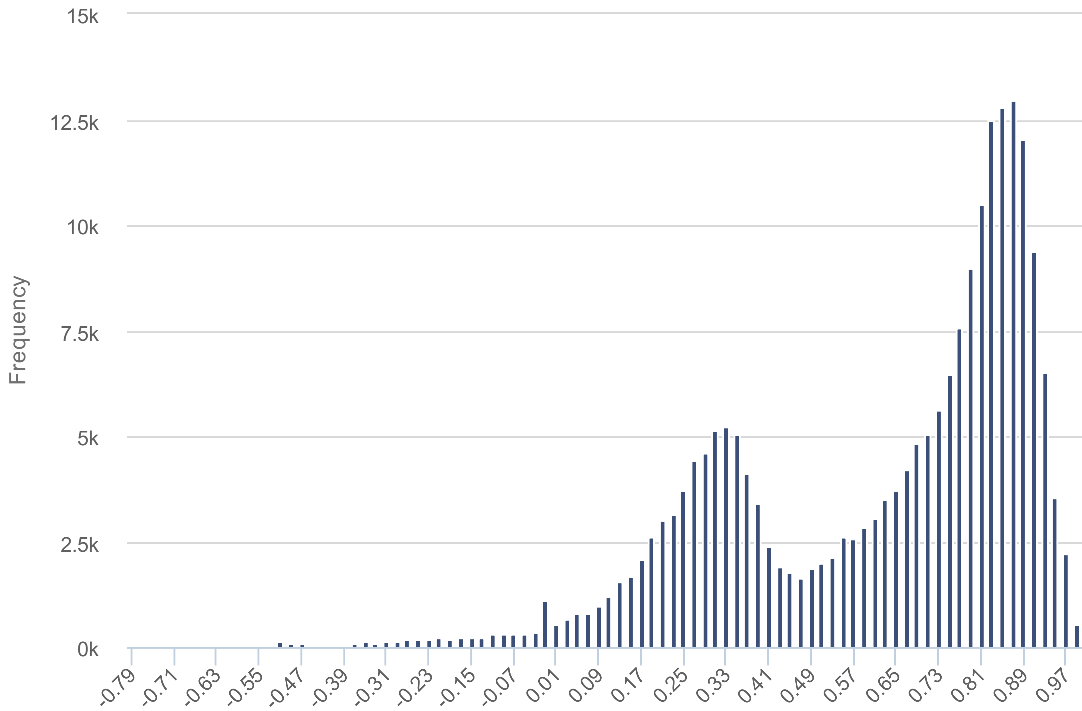
The x-axis is the vote distance defined as the difference between the percentage of "for" votes and the passing threshold. Frequency plot above includes agenda items from 2003 to 2015.

Figure 3.3: Vote Distance on Agenda Items related to Social Issues



The x-axis is the vote distance defined as the difference between the percentage of "for" votes and the passing threshold. Frequency plot above includes agenda items from 2003 to 2015.

Figure 3.4: Vote Distance on Agenda Items related to Board Issues



The x-axis is the vote distance defined as the difference between the percentage of "for" votes and the passing threshold. Frequency plot above includes agenda items from 2003 to 2015.

3.6 Tables

Table 3.1: Mutual Fund Type (Passive/Active) and Vote Dispersion Quantiles over Unique Agenda Items

	25%	50%	75%	80%	90%	95%	96%	97%	98%	99%
Funds per Agenda Item	2	3	6	6	9	13	14	16	18	23
Var(Passive/Active)	0.00	0.00	0.25	0.27	0.33	0.50	0.50	0.50	0.50	0.50
Var(Compensation)	0.00	0.00	0.00	0.00	0.00	0.20	0.25	0.30	0.33	0.50
Var(Shareholder Rights)	0.00	0.00	0.00	0.00	0.00	0.28	0.26	0.30	0.33	0.50
Var(Social Issues)	0.00	0.00	0.00	0.00	0.10	0.26	0.29	0.33	0.33	0.50
Var(Board Issues)	0.00	0.00	0.00	0.00	0.00	0.00	0.13	0.24	0.30	0.33

The data above only includes agenda items in which there is at least two funds casting a vote. The sample variance is biased adjusted (i.e., $n - 1$ denominator).

Table 3.2: Fund Family Dispersion and its Impact on Proxy Vote Dispersion related to Corporate Governance

	Executive Compensation	Shareholder Rights	Social Issues	Board Issues
	(1)	(2)	(3)	(4)
StdDev($\mathbb{1}$(Passive))	0.026***	0.032***	0.054***	0.018***
	(0.007)	(0.012)	(0.012)	(0.006)
log(Funds per Agenda Item + 1)	0.015***	0.014***	0.017***	0.011***
	(0.003)	(0.003)	(0.004)	(0.002)
ISS Agenda Type × Year FE	Yes	Yes	Yes	Yes
Fund Family × Year FE	Yes	Yes	Yes	Yes
Firm × Year FE	Yes	Yes	Yes	Yes
Obs.	1,401,717	167,360	186,557	9,034,701
Adj. R^2	0.205	0.211	0.285	0.179

Significance levels 10%, 5%, and 1% are denoted by *, **, and ***, respectively. Standard errors in parentheses are clustered at the fund level. Mutual fund proxy voting data begins in 2003 and ends in 2015. The dependent variable is the standard deviation of mutual fund votes (i.e., for or against/abstain) for each agenda item.

Table 3.3: Fund Family Dispersion and its Impact on Proxy Vote Dispersion related to Corporate Financing

	Audit	Capital	Restructure	Dividend	Routine
	(1)	(2)	(3)	(4)	(5)
StdDev($\mathbb{1}$(Passive))	0.007	0.030***	0.030	0.011*	0.024***
	(0.005)	(0.011)	(0.021)	(0.006)	(0.008)
log(Funds per Agenda Item + 1)	0.011***	0.011***	0.013	0.005**	0.016***
	(0.004)	(0.002)	(0.012)	(0.002)	(0.003)
ISS Agenda Type × Year FE	Yes	Yes	Yes	Yes	Yes
Fund Family × Year FE	Yes	Yes	Yes	Yes	Yes
Firm × Year FE	Yes	Yes	Yes	Yes	Yes
Obs.	1,792,946	576,512	219,861	96,877	421,713
Adj. R^2	0.158	0.177	0.143	0.097	0.159

Significance levels 10%, 5%, and 1% are denoted by *, **, and ***, respectively. Standard errors in parentheses are clustered at the fund level. Mutual fund proxy voting data begins in 2003 and ends in 2015. The dependent variable is the standard deviation of mutual fund votes (i.e., for or against/abstain) for each agenda item.

Table 3.4: Disagreement with Management Recommendations on Agenda Items related to Executive Compensation

	(1)	(2)	(3)	(4)
$\mathbb{1}$(Passive)	-0.011^{***}	-0.014^{***}		
	(0.003)	(0.004)		
abs(Vote Distance)		1.048	1.083^{*}	0.192^{***}
		(0.066)	(0.064)	(0.068)
$\mathbb{1}$(Passive) × abs(Vote Distance)			-0.086^{***}	-0.071^{***}
			(0.020)	(0.023)
Fund Age				-0.005^{***}
				(0.001)
Turnover Ratio				0.000
				(0.000)
log(TNA)				0.003^{***}
				(0.001)
Expense Ratio				−0.000
				(0.000)
% Flow				0.000^{***}
				(0.000)
log(Voting Shares)				0.114
				(0.099)
Fund FE	No	No	Yes	Yes
CRSP Fund Style FE	No	No	No	Yes
Fund Family × Year FE	Yes	Yes	Yes	Yes
Firm × Year FE	Yes	Yes	Yes	Yes
ISS Agenda Type × Year FE	Yes	Yes	Yes	Yes
Obs.	8,313,214	6,387,265	6,387,265	3,069,435
Adj. R^2	0.383	0.371	0.397	0.392

Significance levels 10%, 5%, and 1% are denoted by *, **, ***, respectively. Standard errors in parentheses are clustered at the fund and firm levels. Mutual fund proxy voting data begins in 2003 and ends in 2015. The dependent variable is equal to 1 if management and fund agree on how to vote on a particular agenda item on a proxy statement. Otherwise, the dependent variable is equal to equal to 0.

Table 3.5: Agreement with Vote Outcomes related to Executive Compensation

	(1)	(2)	(3)	(4)
$\mathbb{1}$(Passive)	-0.013^{***}	-0.013^{***}		
	(0.003)	(0.003)		
abs(Vote Distance)		1.094^{***}	1.123^{***}	1.126^{***}
		(0.064)	(0.062)	(0.066)
$\mathbb{1}$(Passive) × abs(Vote Distance)			-0.072^{***}	-0.055^{**}
			(0.018)	(0.022)
Fund Age				-0.004^{***}
				(0.001)
Turnover Ratio				0.000
				(0.000)
log(TNA)				0.003^{**}
				(0.001)
Expense Ratio				−0.000
				(0.000)
% Flow				0.000^{***}
				(0.000)
log(Voting Shares)				0.092
				(0.117)
Fund FE	No	No	Yes	Yes
CRSP Fund Style FE	No	No	No	Yes
Fund Family × Year FE	Yes	Yes	Yes	Yes
Firm × Year FE	Yes	Yes	Yes	Yes
ISS Agenda Type × Year FE	Yes	Yes	Yes	Yes
Obs.	6,387,225	6,364,244	6,364,244	3,061,180
Adj. R^2	0.329	0.344	0.368	0.364

Significance levels 10%, 5%, and 1% are denoted by *, **, ***, respectively. Standard errors in parentheses are clustered at the fund and firm levels. Mutual fund proxy voting data begins in 2003 and ends in 2015. The dependent variable is equal to 1 if fund achieves desired voting outcome. Otherwise, the dependent variable is equal to equal to 0.

Table 3.6: Disagreement with Management Recommendations on Agenda Items related to Shareholder Rights

	(1)	(2)	(3)	(4)
$\mathbb{1}$(Passive)	-0.041^{***}	-0.039^{***}		
	(0.009)	(0.008)		
abs(Vote Distance)		0.142	0.197^{*}	0.199^{*}
		(0.106)	(0.108)	(0.107)
$\mathbb{1}$(Passive) × abs(Vote Distance)			-0.126^{***}	-0.160^{***}
			(0.024)	(0.034)
Fund Age				−0.002
				(0.003)
Turnover Ratio				0.000
				(0.000)
log(TNA)				−0.003
				(0.002)
Expense Ratio				-0.001^{***}
				(0.000)
% Flow				−0.001
				(0.009)
log(Voting Shares)				−0.016
				(0.026)
Fund FE	No	No	Yes	Yes
CRSP Fund Style FE	No	No	No	Yes
Fund Family × Year FE	Yes	Yes	Yes	Yes
Firm × Year FE	Yes	Yes	Yes	Yes
ISS Agenda Type × Year FE	Yes	Yes	Yes	Yes
Obs.	1,028,215	738,700	738,700	337,918
Adj. R^2	0.572	0.593	0.622	0.606

Significance levels 10%, 5%, and 1% are denoted by *, **, ***, respectively. Standard errors in parentheses are clustered at the fund and firm levels. Mutual fund proxy voting data begins in 2003 and ends in 2015. The dependent variable is equal to 1 if management and fund agree on how to vote on a particular agenda item on a proxy statement. Otherwise, the dependent variable is equal to equal to 0.

Table 3.7: Agreement with Vote Outcomes related to Shareholder Rights

	(1)	(2)	(3)	(4)
$\mathbb{1}$(Passive)	0.01***	0.009***		
	(0.003)	(0.003)		
abs(Vote Distance)		0.753***	0.707***	0.743***
		(0.223)	(0.227)	(0.244)
$\mathbb{1}$(Passive) × abs(Vote Distance)			0.108***	0.095***
			(0.027)	(0.037)
Fund Age				−0.010
				(0.009)
Turnover Ratio				0.000*
				(0.000)
log(TNA)				−0.010**
				(0.004)
Expense Ratio				−0.000
				(0.000)
% Flow				−0.013
				(0.013)
log(Voting Shares)				−0.118
				(0.074)
Fund FE	No	No	Yes	Yes
CRSP Fund Style FE	No	No	No	Yes
Fund Family × Year FE	Yes	Yes	Yes	Yes
Firm × Year FE	Yes	Yes	Yes	Yes
ISS Agenda Type × Year FE	Yes	Yes	Yes	Yes
Obs.	705,540	690,928	690,928	318,331
Adj. R^2	0.595	0.598	0.602	0.585

Significance levels 10%, 5%, and 1% are denoted by *, **, ***, respectively. Standard errors in parentheses are clustered at the fund and firm levels. Mutual fund proxy voting data begins in 2003 and ends in 2015. The dependent variable is equal to 1 if fund achieves desired voting outcome. Otherwise, the dependent variable is equal to equal to 0.

Table 3.8: Disagreement with Management Recommendations on Agenda Items related to Social Issues

	(1)	(2)	(3)	(4)
$\mathbb{1}$(Passive)	-0.015^{***}	-0.009		
	(0.005)	(0.005)		
abs(Vote Distance)		1.705^{***}	1.731^{***}	1.575^{***}
		(0.171)	(0.170)	(0.199)
$\mathbb{1}$(Passive) × abs(Vote Distance)			-0.098	0.094
			(0.068)	(0.094)
Fund Age				0.002^{***}
				(0.001)
Turnover Ratio				-0.000^{*}
				(0.000)
log(TNA)				0.001
				(0.002)
Expense Ratio				-0.000
				(0.000)
% Flow				-0.007
				(0.009)
Fund FE	No	No	Yes	Yes
CRSP Fund Style FE	No	No	No	Yes
Fund Family × Year FE	Yes	Yes	Yes	Yes
Firm × Year FE	Yes	Yes	Yes	Yes
ISS Agenda Type × Year FE	Yes	Yes	Yes	Yes
Obs.	1,329,085	1,133,831	1,133,831	487,599
Adj. R^2	0.395	0.430	0.499	0.499

Significance levels 10%, 5%, and 1% are denoted by *, **, ***, respectively. Standard errors in parentheses are clustered at the fund and firm levels. Mutual fund proxy voting data begins in 2003 and ends in 2015. The dependent variable is equal to 1 if management and fund agree on how to vote on a particular agenda item on a proxy statement. Otherwise, the dependent variable is equal to equal to 0.

Table 3.9: Agreement with Vote Outcomes related to Social Issues

	(1)	(2)	(3)	(4)
𝟙(Passive)	-0.009^{*}	-0.009^{*}		
	(0.005)	(0.005)		
abs(Vote Distance)		1.727^{***}	1.745^{***}	1.660^{***}
		(0.169)	(0.170)	(0.176)
𝟙(Passive) × abs(Vote Distance)			-0.069	0.068
			(0.027)	(0.037)
Fund Age				0.001^{***}
				(0.000)
Turnover Ratio				-0.000^{*}
				(0.000)
log(TNA)				0.001
				(0.002)
Expense Ratio				-0.000
				(0.000)
% Flow				-0.009
				(0.009)
Fund FE	No	No	Yes	Yes
CRSP Fund Style FE	No	No	No	Yes
Fund Family × Year FE	Yes	Yes	Yes	Yes
Firm × Year FE	Yes	Yes	Yes	Yes
ISS Agenda Type × Year FE	Yes	Yes	Yes	Yes
Obs.	705,540	690,928	690,928	318,331
Adj. R^2	0.595	0.598	0.602	0.585

Significance levels 10%, 5%, and 1% are denoted by *, **, ***, respectively. Standard errors in parentheses are clustered at the fund and firm levels. Mutual fund proxy voting data begins in 2003 and ends in 2015. The dependent variable is equal to 1 if fund achieves desired voting outcome. Otherwise, the dependent variable is equal to equal to 0.

Table 3.10: Disagreement with Management Recommendations on Agenda Items related to Board Issues

	(1)	(2)	(3)	(4)
$\mathbb{1}$(Passive)	0.001	−0.003*		
	(0.002)	(0.002)		
abs(Vote Distance)		0.001	0.001	0.002
		(0.001)	(0.001)	(0.001)
$\mathbb{1}$(Passive) × abs(Vote Distance)			−0.001	−0.001
			(0.001)	(0.001)
Fund Age				0.003
				(0.003)
Turnover Ratio				0.000**
				(0.000)
log(TNA)				−0.000
				(0.001)
Expense Ratio				0.000
				(0.000)
% Flow				0.000
				(0.000)
log(Voting Shares)				−0.016
				(0.048)
Fund FE	No	No	Yes	Yes
CRSP Fund Style FE	No	No	No	Yes
Fund Family × Year FE	Yes	Yes	Yes	Yes
Firm × Year FE	Yes	Yes	Yes	Yes
ISS Agenda Type × Year FE	Yes	Yes	Yes	Yes
Obs.	53,660,127	40,544,151	40,544,151	18,884,394
Adj. R^2	0.301	0.301	0.322	0.322

Significance levels 10%, 5%, and 1% are denoted by *, **, ***, respectively. Standard errors in parentheses are clustered at the fund and firm levels. Mutual fund proxy voting data begins in 2003 and ends in 2015. The dependent variable is equal to 1 if management and fund agree on how to vote on a particular agenda item on a proxy statement. Otherwise, the dependent variable is equal to equal to 0.

Table 3.11: Agreement with Vote Outcomes related to Board Issues

	(1)	(2)	(3)	(4)
𝟙(Passive)	−0.003	−0.003		
	(0.002)	(0.002)		
abs(Vote Distance)		0.001	0.001	0.002
		(0.001)	(0.001)	(0.001)
𝟙(Passive) × abs(Vote Distance)			−0.001	−0.001
			(0.001)	(0.001)
Fund Age				0.003
				(0.002)
Turnover Ratio				0.000**
				(0.000)
log(TNA)				−0.001
				(0.001)
Expense Ratio				0.000
				(0.000)
% Flow				0.000
				(0.000)
log(Voting Shares)				0.014
				(0.045)
Fund FE	No	No	Yes	Yes
CRSP Fund Style FE	No	No	No	Yes
Fund Family × Year FE	Yes	Yes	Yes	Yes
Firm × Year FE	Yes	Yes	Yes	Yes
ISS Agenda Type × Year FE	Yes	Yes	Yes	Yes
Obs.	40,385,757	40,210,003	40,210,003	18,741,042
Adj. R^2	0.266	0.263	0.285	0.284

Significance levels 10%, 5%, and 1% are denoted by *, **, ***, respectively. Standard errors in parentheses are clustered at the fund and firm levels. Mutual fund proxy voting data begins in 2003 and ends in 2015. The dependent variable is equal to 1 if fund achieves desired voting outcome. Otherwise, the dependent variable is equal to equal to 0.

CHAPTER 4

Bibliography

Abrams, David S. 2009. "Did TRIPS Spur Innovation? An Empirical Analysis of Patent Duration and Incentives to Innovate". *University of Pennsylvania Law Review* 157 (6): 1613–1647.

Abrams, David S., Ufuk Akcigit, and Jillian Popadak. 2013. "Patent Value and Citations: Creative Destruction or Strategic Disruption?" PIER Working Paper 13-065.

Acemoglu, Daron, and Joshua Angrist. 2000. "How Large are Human-Capital Externalities? Evidence from Compulsory-Schooling Laws". *NBER Macroeconomics Annual* 15:9–74.

Aghion, Philippe, John Van Reenen, and Luigi Zingales. 2009. "Innovation and Institutional Ownership". NBER Working Paper No. 14769.

Almeida, Heitor, and Murillo Campello. 2001. "Financial Constraints and Investment-Cash Flow Sensitivities: New Research Directions". Available at SSRN: http://ssrn.com/ abstract=298027.

Appel, Ian R, Todd A Gormley, and Donald B Keim. 2016. "Passive investors, not passive owners". *Journal of Financial Economics* 121 (1): 111–141.

Arellano, Manuel. 1987. "Computing Robust Standard Errors for Within-Group Estimators". *Oxford Bulletin of Economics and Statistics* 49 (4): 431–434.

Ashraf, Rasha, Narayanan Jayaraman, and Harley E. Ryan. 2012. "Do pension-related business ties influence mutual fund proxy voting? Evidence from shareholder proposals on executive compensation". *Journal of Financial and Quantitative Analysis* 47 (3): 567–588.

Autor, David H. 2003. "Outsourcing at Will: The Contribution of Unjust Dismissal Doctrine to the Growth of Employment Outsourcing". *Journal of Labor Economics* 21 (1): 1–42.

Azar, José, Sahil Raina, and Martin C Schmalz. 2016. "Ultimate Ownership and Bank Competition". *Available at SSRN 2710252*.

Azar, José, Martin C Schmalz, and Isabel Tecu. 2015. "Anti-competitive effects of common ownership". *Ross School of Business Paper*, no. 1235.

Bates, Thomas W., Kathleen M. Kahle, and René M. Stulz. 2009. "Why Do U.S. Firms Hold so Much More Cash than They Used To?" *The Journal of Finance* 64 (5): 1985–2021.

Bena, Jan, and Kai Li. 2014. "Corporate Innovations and Mergers and Acquisitions". *The Journal of Finance* 69 (5): 1923–1960.

Bernstein, Shai. 2015. "Does Going Public Affect Innovation?" *The Journal of Finance* 70 (4): 1365–1403.

Bertrand, Marianne, and Sendhil Mullainathan. 2001. "Are CEOs Rewarded for Luck? The Ones without Principals Are". *The Quarterly Journal of Economics* 116 (3): 901–932.

Blanchard, Olivier Jean, Florencio Lopez de Silanes, and Andrei Shleifer. 1994. "What do Firms do with Cash Windfalls?" *Journal of Financial Economics* 36 (3): 337–360.

Bond, Stephen, Dietmar Harhoff, and John Van Reenen. 2005. "Investment, R&D and Financial Constraints in Britain and Germany". *Annales d'Économie et de Statistique* 79 (80): 433–460.

Boone, Audra L., and Joshua T. White. 2015. "The effect of institutional ownership on firm transparency and information production". *Journal of Financial Economics* 117 (3): 508–533.

Bound, John, David A. Jaeger, and Regina M. Baker. 1995. "Problems with Instrumental Variables Estimation When the Correlation Between the Instruments and the Endogeneous Explanatory Variable is Weak". *Journal of the American Statistical Association* 90 (430): 443–450.

Branch, Ben. 1974. "Research and Development Activity and Profitability: A Distributed Lag Analysis". *Journal of Political Economy* 82 (5): 999–1011.

Brickley, James A., James S. Linck, and Jeffrey L. Coles. 1999. "What Happens to CEOs after they Retire? New Evidence on Career Concerns, HOrizon Problems, and CEO Incentives". *Journal of Financial Economics* 52 (3): 341–377.

Brown, James R., Gustav Martinsson, and Bruce C. Petersen. 2012. "Do financing constraints matter for R&D?" *European Economic Review* 56 (8): 1512–1529.

Brown, James R., and Bruce C. Petersen. 2011. "Cash Holdings and R&D Smoothing". *Journal of Corporate Finance* 17 (3): 694–709.

Cai, Ye, and Merih Sevilir. 2012. "Board Connections and M&A Transactions". *Journal of Financial Economics* 103 (2): 327–349.

Calomiris, Charles W., and Robert G. Hubbard. 1995. "Internal Finance and Investment: Evidence from the Undistributed Profits Tax of 1936-37". *The Journal of Business* 68 (4): 443–482.

Carvalho, Nuno Pires de. 2005. *The TRIPS Regime of Patent Rights*. Frederick, MD: Aspen Publishers.

Cohen, Wesley M., Richard R. Nelson, and John P. Walsh. 2000. "Protecting Their Intellectual Assets: Appropriability Conditions and Why U.S. Manufacturing Firms Patent (or Not)". NBER Working Paper No. 7552.

Cragg, John G., and Stephen G. Donald. 1993. "Testing Identifiability and Specification in Instrumental Variable Models". *Econometric Theory* 9 (2): 222–240.

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*:hhw012.

Dass, Nishant, Vikram K. Nanda, and Steven Chong Xiao. 2015. "Intellectual Property Protection and Financial Markets: Patenting vs. Secrecy". Available at SSRN: http://ssrn.com/abstract=2517838.

Davis, Gerald F., and E. Han Kim. 2007. "Business ties and proxy voting by mutual funds". *Journal of Financial Economics* 85 (2): 552–570.

Duchin, Ran, and Benis Sosyura. 2013. "Divisional Managers and Internal Capital Markets". *The Journal of Finance* 68 (2): 387–429.

Engelberg, Joseph, Pengjie Gao, and Christopher A. Parsons. 2013a. "Friends with Money". *Journal of Financial Economics* 103 (1): 169–188.

— . 2013b. "The Price of a CEO's Rolodex". *Review of Financial Studies* 26 (1): 79–114.

Fama, Eugene F. 1980. "Agency Problems and the Theory of the Firm". *The Journal of Political Economy* 88 (2): 288–307.

Fama, Eugene F., and Michael C. Jensen. 1983. "Separation of Ownership and Control". *Journal of Law and Economics* 26 (2): 301–325.

Fang, Vivian W., Xuan Tian, and Sheri Tice. 2014. "Does Stock Liquidity Enhance or Impede Firm Innovation?" *The Journal of Finance* 69 (5): 1923–1960.

Farre-Mensa, Joan, and Alexander Ljungqvist. 2016. "Do Measures of Financial Constraints Measure Financial Constraints?" *The Review of Financial Studies* 29 (2): 271–308.

Fazzari, Steven M., R. Glenn Hubbard, and Bruce C. Petersen. 1988. "Financing Constraints and Corporate Investment". *Brookings Papers on Economic Activity* 1:141–206.

Fich, Eliezer, and Lawrence J. White. 2003. "CEO Compensation and Turnover: The Effects of Mutually Interlocked Boards". *Wake Forest Law Review* 38 (2): 935–960.

Fracassi, Cesare, and Geoffrey Tate. 2012. "External Networking and Internal Firm Governance". *The Journal of Finance* 67 (1): 153–194.

Fudenberg, Drew, and Jean Tirole. 1986. "A Signal-Jamming Theory of Predation". *The RAND Journal of Economics* 17 (3): 366–376.

Galasso, Alberto, and Timothy S. Simcoe. 2011. "CEO Overconfidence and Innovation". *Management Science* 57 (8): 1469–1484.

Garvey, Gerald T., and Todd T. Milbourn. 2006. "Asymmetric Benchmarking in Compensation: Executives are Rewarded for Good Luck but not Penalized for Bad". *Journal of Financial Economics* 82 (1): 197–225.

Gaspar, José-Miguel, Massimo Massa, and Pedro Matos. 2006. "Favoritism in Mutual Fund Families? Evidence on Strategic Cross-Fund Subsidization". *The Journal of Finance* 61 (1): 73–104.

Gilson, Stuart C. 1990. "Bankruptcy, Boards, Banks, and Blockers: Evidence on Changes in Corporate Ownership and Control when Firms Default". *Journal of Financial Economics* 27 (2): 355–387.

Gompers, Paul A., Joy L. Ishii, and Andrew Metrick. 2003. "Corporate Governance and Equity Prices". *The Quarterly Journal of Economics* 118 (1): 107–155.

Grabowski, Henry G. 1968. "The Determinants of Industrial Research and Development: A Study of the Chemical, Drug, and Petroleum Industries". *Journal of Political Economy* 76 (2): 292–306.

Granovetter, Mark S. 1973. "The Strength of Weak Ties". *American Journal of Sociology* 78 (6): 1360–1380.

Guedj, Ilan, and Amir Barnea. 2009. "Director Networks". *EFA 2007 Ljubljana Meetings Paper*.

Hadlock, Charles J., and Joshua R. Pierce. 2001. "New Evidence on Measuring Financial Constraints: Moving Beyond the KZ Index". *The RAND Journal of Economics* 32 (1): 101–128.

Hall, Bronwyn H., Adam B. Jaffe, and Manuel Trajtenberg. 2005. "Market Value and Patent Citations". *The RAND Journal of Economics* 36 (1): 16–38.

— . 2001. "The NBER Patent Citation Data File: Lessons, Insights and Methodological Tools". NBER Working Paper No. 8498.

Hall, Bronwyn H., and Josh Lerner. 2010. "The Financing of R&D and Innovation". *Handbook of the Economics of Innovation* 1:609–639.

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". *The RAND Journal of Economics* 32 (1): 101–128.

Hallock, Kevin F. 1997. "Reciprocally Interlocking Boards of Directors and Executive Compensation". *Journal of Financial and Quantitative Analysis* 32 (3): 331–344.

Hao, Kenneth Y., and Adam B. Jaffe. 1993. "Effect Of Liquidity On Firms' R&D Spending". *Economics of Innovation and New Technology* 2 (4): 275–282.

Harhoff, Dietmar. 1998. "Are There Financing Constraints for R&D and Investment in German Manufacturing Firms?" *Annales d'Économie et de Statistique* 49 (50): 421–456.

Harhoff, Dietmar, et al. 1999. "Citation Frequency and the Value of Patented Inventions". *The Review of Economics and Statistics* 81 (3): 511–515.

He, Jie, and Jiekun Huang. 2014. "Product market competition in a world of cross ownership: evidence from institutional blockholdings". *Available at SSRN 2380426*.

Himmelberg, Charles P., and Bruce C. Petersen. 1994. "R&D and Internal Finance: A Panel Study of Small Firms in High-Tech Industries". *The Review of Economics and Statistics* 76 (1): 38–51.

Hirshleifer, David, Angie Low, and Siew Hong Teoh. 2012. "Are Overconfident CEOs Better Innovators?" *The Journal of Finance* 67 (4): 1457–1498.

Hochberg, Yael V., Alexander Ljungqvist, and Yang Lu. 2007. "Whom you Know Matters: Venture Capital Networks and Investment Performance". *The Journal of Finance* 62 (1): 251–301.

Holmström, Bengt. 1979. "Moral Hazard and Observability". *The Bell Journal of Economics* 10 (1): 74–91.

— . 1982. "Moral Hazard in Teams". *The Bell Journal of Economics* 13 (2): 324–340.

Iliev, Peter, and Michelle Lowry. 2015. "Are Mutual Funds Active Voters?" *Review of Financial Studies* 28 (2): 446–485.

Kaplan, Steven N., and David Reishus. 1990. "Outside Directorships and Corporate Performance". *Journal of Financial Economics* 27 (2): 389–410.

Kempf, Alexander, and Stefan Ruenzi. 2008. "Tournaments in mutual-fund families". *Review of Financial Studies* 21 (2): 1013–1036.

Kleibergen, Frank, and Richard Paap. 2006. "Generalized Reduced Rank Tests using the Singular Value Decomposition". *Journal of Econometrics* 133 (1): 97–126.

Kogan, Leonid, et al. 2016. "Technological Innovation, Resource Allocation and Growth". *NBER Working Paper No. 17769.*

Kramarz, Francis, and David Thesmar. 2013. "Social Networks in the Boardroom". *Journal of the European Economic Association* 11 (4): 780–807.

Lamont, Owen. 1997. "Cash Flow and Investment: Evidence from Internal Capital Markets". *The Journal of Finance* 52 (1): 83–109.

Lamont, Owen, Christopher Polk, and Jesús Saá-Requejo. 2001. "New Evidence on Measuring Financial Constraints: Moving Beyond the KZ Index". *The RAND Journal of Economics* 32 (1): 101–128.

Lanjouw, Jean O., and Mark Schankerman. 2001. “Characteristics of patent Litigation: A Window on Competition”. *The RAND Journal of Economics* 32 (1): 129–151.

Lemus, Jorge, and Guillermo Marshall. 2016. “When the Clock Starts Ticking: Measuring Strategic Responses to TRIPS’s Patent Term Change”. Available at: https://sites.google.com/site/jorgelemuswebsite/TRIPS_Clock.pdf.

Lerner, Josh. 1995. “Patenting in the Shadow of Competitors”. *The Journal of Law and Economics* 38 (2): 463–495.

Levin, Richard C., et al. 1987. “Appropriating the Returns from Industrial Research and Development”. *Brookings Papers on Economic Activity* 1987 (3): 783–831.

Lia, Guan-Cheng, et al. 2014. “Disambiguation and Co-authorship Networks of the US Patent Inventor Database (1975–2010)”. *Research Policy* 43 (6): 941–955.

Lyandres, Evgeny, and Berardino Palazzo. 2015. “Cash Holdings, Competition, and Innovation”. Available at SSRN: http://ssrn.com/ abstract=2017222.

Malmendier, Ulrike, and Geoffrey Tate. 2005a. “CEO Overconfidence and Corporate Investment”. *The Journal of Finance* 60 (6): 2661–2700.

— . 2005b. “Does Overconfidence Affect Corporate Investment? CEO Overconfidence Measures Revisited”. *European Financial Management* 2 (5): 649–659.

— . 2008. “Who makes Acquisitions? CEO Overconfidence and the Market’s Reaction”. *Journal of Financial Economics* 89 (1): 20–43.

Mann, William. 2015. “Creditor Rights and Innovation: Evidence from Patent Collateral”. Available at SSRN: http://ssrn.com/ abstract=2356015.

Mansfield, Edwin. 1986. “Patents and Innovation: An Empirical Study”. *Management Science* 32 (2): 173–181.

Mansfield, Edwin, John Rapoport, and Jerome Schnee. 1972. *Research and Innovation in the Modern Corporation.* New York, NY: WW Norton & Company.

Mansfield, Edwin, Mark Schwartz, and Samuel Wagner. 1981. “Imitation Costs and Patents: An Empirical Study”. *The Economic Journal* 91 (364): 907–918.

Marco, Alan C., et al. 2015. “The USPTO Patent Assignment Dataset: Descriptions and Analysis”. USPTO Working Paper No. 2015-2.

Matvos, Gregor, and Michael Ostrovsky. 2013. "Heterogeneity and peer effects in mutual fund proxy voting". *Journal of Financial Economics* 98 (1): 90–112.

Meyer, Bruce D., W. Kip Viscusi, and David L. Durbin. 1995. "Workers' Compensation and Injury Duration: Evidence from a Natural Experiment". *The American Economic Review* 85 (3): 322–340.

Meyers, Stewart C., and Nicholas S. Majluf. 1984. "Corporate Financing and Investment Decisions when Firms have Information that Investors do not have". *Journal of Financial Economics* 12 (2): 187–221.

Modigliani, Franco, and Merton H. Miller. 1958. "The Cost of Capital, Corporation Finance and the Theory of Investment". *The American Economic Review* 48 (3): 261–297.

Mossinghoff, Gerald J. 1999. "Overview of the Hatch-Waxman Act and its Impact on the Drug Development Process". *Food & Drug Law Journal* 54 (2): 187–194.

Mueller, Dennis C. 1967. "The Firm Decision Process: An Econometric Investigation". *The Quarterly Journal of Economics* 81 (1): 58–87.

Mullins, W. 2014. "The governance impact of indexing: evidence from regression discontinuity". *Work. Pap., Smith Sch. Bus., Univ. Md.*

Munari, Federico, and Raffaele Oriani. 2011. *The Economic Valuation of Patents: Methods and Applications*. Northampton, MA: Edward Elgar Publishing.

Murphy, Kevin M., Andrei Shleifer, and Robert W. Vishny. 1992. "The Transition to a Market Economy: Pitfalls of Partial Reform". *The Quarterly Journal of Economics* 107 (3): 889–906.

Myers, Stewart C. 1977. "Determinants of Corporate Borrowing". *Journal of Financial Economics* 5 (1): 147–175.

Nanda, Vikram, Z. Jay Wang, and Lu Zheng. 2004. "Family Values and the Star Phenomenon: Strategies of Mutual Fund Families". *The Review of Financial Studies* 17 (3): 667–698.

Ng, Lilian, Qinghai Wang, and Nataliya Zaiats. 2009. "Firm performance and mutual fund voting". *Journal of Banking and Finance* 33 (12): 2207–2217.

Nguyen, Bang D. 2012. "Does the Rolodex Matter? Corporate Elite's Small World and the Effectivesness of Boards of Directors". *Management Science* 58 (2): 236–252.

Nickerson, Raymond S. 1998. "Confirmation BIas: A Ubiquitous Phenomenon in Many Guises". *Review of General Psychology* 2 (2): 175–220.

Pakes, Ariel, and Shmuel Nitzan. 1983. "Optimum Contracts for Research Personnel, Research Employment, and the Establishment of 'Rival' Enterprises". *Journal of Labor Economics* 1 (4): 345–365.

Ravenscraft, David, and Frederic M. Scherer. 1982. "The Lag Structure of Returns to Research and Development". *Applied Economics* 14 (6): 603–620.

Renneboog, Luc, and Yang Zhao. 2011. "Us Knows Us in the UK: On Director Networks and CEO Compensation". *Journal of Corporate Finance* 17 (4): 1132–1157.

Scherer, Frederic M. 1965. "Firm Size, Market Structure, Opportunity, and the Output of Patented Inventions". *The American Economic Review* 55 (5): 1097–1125.

Schmidt, Cornelius, and Rudiger Fahlenbrach. 2017. "Do exogenous changes in passive institutional ownership affect corporate governance and firm value?" *Journal of Financial Economics* 22 (1): 1–22.

Shivdasani, Anil. 1993. "Board Composition, Ownership Structure, and Hostile Takeovers". *Journal of Accounting and Economics* 16 (1): 167–198.

Stiglitz, Joseph E., and Andrew Weiss. 1981. "Credit Rationing in Markets with Imperfect Information". *The American Economic Review* 71 (3): 393–410.

Sukhatme, Neel U., and Judd N. L. Cramer. 2015. "How Much Do Patent Applicants Care About Patent Term? Cross-Industry Differences in Term Sensitivity". Available at SSRN: http://ssrn.com/ abstract=2293245.

Taylor, Donald M., and Janet R. Doria. 1981. "Self-Serving and Group-Serving Bias in Attribution". *The Journal of Social Psychology* 113 (2): 167–198.

Tirole, Jean. 2006. *The Theory of Corporate Finance*. Princeton, NJ: Princeton University Press.

Vafeas, Nikos. 1999. "Board Meeting Frequency and Firms Performance". *Journal Financial Economics* 53 (1): 113–142.

Weiss, Pia. 2010. *Patent Policy: Legal-Economic Effects in a National and International Framework*. New York, NY: Routledge.

White, Halbert. 2014. *Asymptotic Theory*. Orlando, FL: Academic Press.

Whited, Toni M., and Guojun Wu. 2006. "Financial Constraints Risk". *The Review of Financial Studies* 19 (2): 531–559.