Three essays on corporate finance

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THREE ESSAYS ON CORPORATE FINANCE

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NANYANG BUSINESS SCHOOL

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A thesis submitted to the Nanyang Technological University in partial fulfilment of the requirement for the degree of Doctor of Philosophy

2019

Statement of Originality

I hereby certify that the work embodied in this thesis is the result of original research, is free of plagiarised materials, and has not been submitted for a higher degree to any other University or Institution.

20/2/2019
Date

Lee Min Suk

Supervisor Declaration Statement

I have reviewed the content and presentation style of this thesis and declare it is free of plagiarism and of sufficient grammatical clarity to be examined. To the best of my knowledge, the research and writing are those of the candidate with amendments, changes and improvements as suggested by me as the Supervisor. I confirm that the investigations were conducted in accord with the ethics policies and integrity standards of Nanyang Technological University and that the research data are presented honestly and without prejudice.

20/2/2019 ....

Date Low Angie

Authorship Attribution Statement

This thesis contains material from one paper from papers accepted at conferences in which I am listed as an author.

Chapter 1 is accepted for the 13th Conference on Asia-Pacific Financial Markets in 2018.

The contributions of the co-authors are as follows:

- Associate Professor Low provided the directions for research, suggestions for the tests and analysis, and edited and revised the manuscript drafts.
- Professor Teoh provided expertise in the area of research where needed, made suggestions for further tests to be done, and edited and revised the manuscript drafts. Professor Teoh also helped acquire data for some additional tests.
- I designed the baseline tests with Associate Professor Low and performed all datawork and tests. I also analyzed the data and wrote the drafts of the manuscript.

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Lee Min Suk

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Summary

This thesis consists of three chapters, each looking to address different research question. The summary for each chapter is as follows.

First chapter:
A larger CEO network can reduce cost of equity by reducing information asymmetry between the firm and outsiders, and increase trust between the firm and other firms or stakeholders. Alternatively, a larger network can increase cost of equity because the higher CEO connectedness reduces the costs to the CEO of being fired, which encourages greater agency problems and higher risk decisions. We find a positive relation between CEO's connectedness and the firm's cost of equity, suggesting that the costs, on average, outweigh the benefits. The positive relation between CEO connections and cost of equity is attenuated for firms with high information asymmetry, consistent with the beneficial effects of improved information flow mitigating some of the adverse effects from agency costs and risk-taking. We use multiple ways to handle endogeneity and reverse causality problems, and our results are generally robust.

Second chapter:
We study how increases in employment protection through the passage of state laws affect strategic alliance formation and firm's choice of growth strategy. We show that, following the adoption of these laws, there is a significant increase in strategic alliance activities, especially among high growth firms. More importantly, there is a shift away from capital-intensive investments, such as internal capital expenditures and M&As towards the more flexible strategic alliance. We also find that firms that form strategic alliances following the adoption of the law have higher innovation output. Overall, our findings are consistent with employment protection making investments within the firm more irreversible and leading them to seek alternative growth strategies by moving investments outside their boundaries through strategic alliance formation.

Third chapter:
We study the effect of financial constraints on firms' decision on the choice of growth strategies. We show that financial constraints are positively associated with strategic alliance activities, and negatively associated with mergers and acquisitions. The finding is mixed for internal capital expenditures. We argue that the disciplinary role of financial constraints and the need for financing drive our results. We also present that financially constrained firms use strategic alliances as preferred growth strategy over internal investments and mergers and acquisitions.

CEO connectedness and the cost of equity capital

Abstract

A larger CEO network can reduce cost of equity by reducing information asymmetry between the firm and outsiders, and increase trust between the firm and other firms or stakeholders. Alternatively, a larger network can increase cost of equity because the higher CEO connectedness reduces the costs to the CEO of being fired, which encourages greater agency problems and higher risk decisions. We find a positive relation between CEO's connectedness and the firm's cost of equity, suggesting that the costs, on average, outweigh the benefits. The positive relation between CEO connections and cost of equity is attenuated for firms with high information asymmetry, consistent with the beneficial effects of improved information flow mitigating some of the adverse effects from agency costs and risk-taking. We use multiple ways to handle endogeneity and reverse causality problems, and our results are generally robust.

1. Introduction

The cost of equity capital is a measure that reflects investors' perceptions of risk and return from investing in the company's equity (Francis, LaFond, Olsson, and Schipper, 2004). It plays a critical role when a firm makes its financing and investment decisions and affects all aspects of firm decision-making. Past papers have mainly focused on how firm-level characteristics impact the cost of equity. In this paper, we propose that CEO-level characteristics, in particular CEO's connectedness, have important implications for a firm's cost of equity. There has been growing interest in the impact of social networks on capital markets.[1] The CEO of a Standard and Poor's 1,500 firm on average is connected to 135 executives and directors of other firms through his prior employment, education, and other social activities. We show that the size of a CEO's external social network outside the boundaries of the firm have a positive impact on the firm's cost of equity capital. Building on prior literature, we derive three non-mutually exclusive channels, namely information asymmetry, agency, and risk-taking, by which CEO connections can affect the cost of equity.

Cohen, Frazzini, and Malloy (2008, 2010) suggest that social network ties between the CEO and the investment community serve as conduits for information flow and resource exchange. The greater information flow reduces information asymmetry between the firm and outside investors and can affect the cost of equity in various ways. The lower information asymmetry reduces monitoring costs by outsiders, which reduces the firm's cost of equity. Papers focusing on managerial ties specifically to financiers generally find support for this information asymmetry channel. For example, Engelberg, Gao, and Parsons (2012) find that direct social ties between

[1] Anecdotally, as pointed out by Bhandari (2017) a Morningstar report on Berkshire Hathaway question whether the successor of Warren Buffer can replace "the significant advantages that have come with having an investor of Buffett's caliber, with the knowledge and connections he has acquired over the years running the show." – Morningstar, 21 September 2015, Page 6.

borrowers and the banks reduce the borrowing rate in U.S. firms. Ferris, Javakhadze, and Rajkovic (2017b) document that firm connections to financiers, defined as investment companies, private equity, specialty and other finance companies or banks, lower the cost of equity capital for a sample of international firms, especially in underdeveloped financial markets. Fogel, Jandik, and McCumber (2018) examine the connectedness of the Chief Financial Officer (CFO) and find that it leads to a reduction in bank loan spreads consistent with networks helping to mitigate information asymmetries between firms and the lending community. Furthermore, social connections foster trust between transacting parties; CEOs with better connections can tap onto their vast networks to build long-lasting, stable relationships with firm stakeholders such as customers and suppliers, which leads to more stable operations and promotes more accurate information transfer within the network and hence lower cost of equity (Larcker, So, and Wang, 2013). Finally, Bhandari (2017) find that well-connected firms have a higher quality information environment due to better information transfer. These benefits from lowering information asymmetry via increased information flow or increased trust with important stakeholders lower the firm's cost of equity.[2]

A large number of previous research studies suggests how more CEO connections can exacerbate managerial agency problems and in turn affect the cost of equity. Fracassi and Tate (2012) and Hwang and Kim (2009) find evidence that CEO personal connections to his own board of directors undermine the effectiveness of director monitoring and corporate governance. Furthermore, network theory points to well-connected individuals having greater access to more

[2] One can argue that social connections may lead to increased information asymmetry among investors as the information transfer takes place between the CEO and a select few individuals within his network. In this case, the cost of equity may increase instead (Easley and O'hara, 2004). For example, Cai, Walkling, and Yang (2016) find that direct social ties between CEOs and investment firms increase the likelihood of informed trading. However, the likelihood of informed trading depends more on the type of individuals the CEO is connected to rather than the size of his connections. In a later test, we also examine the impact of CEO's connections to the investment firms.

information and resources and therefore such individuals have more influence in dictating outcomes. Thus, a well-connected CEO may use his social status to influence corporate policies and dictate board decisions (Fogel *et al.*, 2018). For example, well-connected CEOs may use his network contacts to help advance the careers of directors sitting on his board (Fahlenbrach, Kim, and Low, 2018). Furthermore, well-connected CEOs face less discipline from the threat of firing as they can often fall back on their social network to find another job (see e.g., Liu, 2014). Consistent with better-connected CEOs increasing agency problems, El-Khatib, Fogel, and Jandik (2015) document that merger and acquisition deals initiated by highly-connected CEOs carry greater value loss to both the acquirer and the combined entity than deals initiated by less-connected CEOs. Furthermore, Kirchmaier and Stathopoulos (2008) find that CEOs with large social network have worse firm performance.

Firms with higher agency problems need not necessarily experience a higher cost of equity. Cost of equity can increase because outside investors of firms with larger agency problems need to be compensated ex ante for the increased cost of monitoring or to price-protect from potential rent-seeking by the CEO (e.g., Ashbaugh-Skaife, Collins, and LaFond, 2004). However, Bertrand and Mullainathan (2003) find evidence that CEOs prefer the “quiet life” so they actually may be less inclined to shift to higher risk projects when they are not as intensively monitored. Their preference for lower risk may result in lower cost of equity capital instead.

There are also other arguments for how the size of a CEO’s personal connections can affect risk-taking and so affect the cost of equity. Personal contacts are very important in the job search process (Granovetter, 1974), and Mazerolle and Singh (2004) and Cingano and Rosolia (2012) show that re-employment outcomes following job displacements greatly improve as an individual’s social network size increases. Liu (2014) documents that CEO connectedness improves outside options, which can encourage departures for other full-time positions. As risk-taking entails a greater chance of failure for the CEO, a bigger social network can provide implicit labor market insurance. Furthermore, better-connected CEOs can access relevant network information (Hong, Lee, Matsunaga, and Oh, 2018) to better identify and execute valuable risky investment opportunities. This reduces the ex-ante risk of failure and encourages risk-taking by the CEO. Consistent with networks alleviating risk aversion and providing access to relevant investment-related information, Faleye, Kovacs, and Venkateswaran (2014) and Ferris, Javakhadze, and Rajkovic (2017a) find that CEO connections facilitate risky corporate investments.

The three channels via information asymmetry, agency, and risk-taking, by which CEO connections can affect the cost of equity are not mutually exclusive and can operate simultaneously. The net effect of CEO connections on a firm's cost of equity is therefore ambiguous. In this paper, we estimate the empirical relation using measures of CEO's connectedness to business executives in other firms and measures of a firm's implied cost of equity. We also examine whether each of the channels are more likely to operate in certain segments of firms. We build our measure of CEO connections following Engelberg, Gao, and Parsons (2013) by counting the number of executives and directors that the CEO is connected to via common employment, education, and social activities outside the boundary of the focal firm. We calculate the cost of equity implied by analyst's earnings forecasts and current stock price using the four accounting-based valuation models of Claus and Thomas (2001), Gebhardt, Lee, and Swaminathan (2001), Easton (2004), and Ohlson and Juettner-Nauroth (2005). Following Hail and Leuz (2006, 2009) and Houston, Lin, and Xie (2015), we average the values from the four models in excess of the risk-free rate to obtain the implied cost of equity measure as the main dependent variable.

We find that the size of a CEO's network is significantly and positively associated with the implied cost of equity after controlling for the standard controls from extant literature, including proxies for systematic and idiosyncratic risks. The effect is not only statistically significant, but also economically meaningful. A one standard deviation increase in the number of CEO's connections leads to an incremental higher cost of equity by 23.2 basis points, which translates to 4% higher cost relative to the average cost of equity. The average firm in our sample has outstanding equity of $3,371.12 million, so this translates into additional costs of $7.82 million for firms financing using equity.

We implement several tests to alleviate endogeneity concerns relating to omitted variables bias. First, the results are robust to additional controls for CEO tenure, age, compensation, and ability. Second, we control for firm governance characteristics and board characteristics to alleviate concerns that the CEO network size might proxy for the effectiveness of the firm's corporate governance and we reach similar conclusions. Third, additional control variables relating to firm distress risk, investments, asset structure, and analyst coverage also do not affect the inference of a positive relation between CEO network size and cost of equity. The results are also robust to controlling for firm fixed effects, CEO fixed effects, and industry-year fixed effects. Finally, we also implement a propensity score matched sample analysis to control for observable differences between firms with highly connected CEOs and less-connected CEOs and reach similar conclusions.

To address issues relating to reverse causality, we implement difference-in-differences tests surrounding CEO turnovers. We find that a change in CEO network size due to the appointment of a new CEO is positively related to future changes in cost of equity capital but past changes in the cost of equity is not associated with current changes in CEO network size, suggesting that the direction of causality runs from CEO connectedness to cost of equity.

We conduct additional tests to identify the specific channels through which social connections impact cost of equity. The results show that the positive impact of CEO connections on capital cost is predominantly among firms with weak governance where the potential for agency issues is higher, providing support for the agency channel. In addition, using a simple regression discontinuity design (RDD) setting, we find that cost of equity is reduced upon the passing of shareholder proposals to improve internal corporate governance, consistent with agency problems affecting the cost of equity. Importantly, the reduction in cost of equity is only evident among the firms with low CEO connectedness, providing further support for the agency channel.

We also test for the presence of the risk-taking channel. We find a steeper positive CEO connections-cost of equity relation among younger CEOs with more career concerns, consistent with connections encouraging risk-taking behavior by expanding the outside options of the CEO to insure against firing costs. We find a stronger positive relation between CEO connections and cost of equity where the connections are more likely to contain industry-relevant information such as connections to industry rivals and to upstream or downstream firms, consistent with CEO connections providing better access to relevant information so that CEOs can better identify and exploit risky investment opportunities. Consistent also with increased risk-taking, we document positive relations between CEO network size and various proxies of firm risks and risk-taking behavior.

Finally, we also test whether CEO connections facilitate information flow between the firm and outsiders. Informationally-opaque firms should benefit most from the information flow with outsiders that a highly-connected CEO can facilitate. Therefore, the agency and risk-taking costs of having a highly-connected CEO on the cost of equity may be offset by the benefits of increased information flow. Indeed, we find that the positive relation between CEO connections and cost of equity is attenuated for informationally-opaque firms, suggesting that CEO network might be useful in reducing information asymmetry for certain segments of firms.

This study contributes to the accounting literature in the following ways. We add CEO connections as a new determinant of the cost of equity capital. Previous studies on the determinants of cost of equity focused on firm-level characteristics. These include information risk (Easley and O'hara, 2004; Francis, LaFond, Olsson, and Schipper, 2005; El Ghoul, Guedhami, Ni, Pittman, and Saadi, 2013), voluntary disclosure and disclosure quality (Chen, Miao, and Shevlin, 2015; Cao, Myers, Tsang, and Yang, 2017), corporate tax avoidance (Goh, Lee, Lim, and Shevlin, 2016), shareholder taxes and financial constraints (Dai, Shackelford, Zhang, and Chen, 2013), firm reputation (Cao, Myers, Myers, and Omer, 2015), corporate social responsibility performance (El Ghoul, Guedhami, Kwok, and Mishra, 2011), financial restatements as a measure of reporting quality (Graham, Li, and Qiu, 2008), and governance (Chen, Chen, and Wei, 2009, 2011; Lin, Ma, Malatesta, and Xuan, 2013).

Despite the growing literature on the importance of CEO characteristics in influencing firm behavior, few studies examine how CEO characteristics are associated with the cost of equity. Mishra (2014) shows that generalist CEOs are associated with a higher cost of equity whereas we study CEO social connections. Engelberg *et al.* (2012) and Ferris *et al.* (2017b) study social connections to financiers only whereas we examine connections to a broader community of all outside firms. We also examine and show both the adverse and beneficial effects of CEO connections on the cost of equity. In particular, we attempt to isolate when beneficial or adverse effects are likely to dominate in additional cross-sectional tests, such as the importance of CEO connections in reducing information asymmetry for reducing cost of equity especially among the informationally-opaque firms.

This paper relates also to the literature on corporate governance effects on cost of equity. These studies find that the cost of equity is lower for firms with good governance (Ashbaugh-Skaife *et al.*, 2004), no internal control deficiencies (Ashbaugh-Skaife, Collins, and Lafond, 2009), with strong shareholder rights (Chen *et al.*, 2011), and in countries with good legal protection (Chen *et al.*, 2009). In addition, Lambert, Leuz, and Verrecchia (2007) shows that higher quality accounting information and governance structures can reduce cost of equity by reducing managerial misappropriation of the firm's cash flow and improve production and/or investment decisions. Our evidence shows that the effect of CEO connectedness on the cost of equity is incremental to corporate governance effects, as well as interacts with corporate governance effects. We find that CEO connectedness increases cost of equity after controlling for corporate governance variables, and that CEO connectedness increases cost of equity especially in companies with weaker corporate governance.

Lastly, we contribute to the literature on economic effects of social networks. Previous studies have related CEO ties to the firm's directors or bank lenders, whereas we examine CEO ties to the broad community outside the firm. The previous studies that examine CEO ties to the broader community have focused on ex post outcomes for investment and firm value. In contrast, we are interested in how CEO ties to the broader community affect the firm's ex ante implied cost of equity through effects on information asymmetry, agency costs, and risk-taking channels. Each of these channels predict a different impact of CEO connectedness on cost of equity. Previous studies only provide piecemeal indirect evidence on how CEO connectedness can potentially affect the cost of equity. The overall impact of CEO connectedness on cost of equity is unclear. We show the size of CEO's social network has a positive net impact on firm's financing cost but this impact differs depending on the extent of agency problems within the firm and the information environment of the firm.

The remainder of this paper is as follows. Section 2 describes the sample and variable construction and the empirical model used in the regressions. Section 3 presents the main empirical results and analysis. Section 4 discusses potential endogeneity issues and section 5 looks at additional test results and examines the mechanisms through which CEO connections affect the cost of equity. Finally, section 6 concludes the paper.

2. Data and methodology

We start with the list of firms and CEOs on Execucomp. We obtain data on CEO characteristics and personal connections from Boardex database by Management Diagnostic Limited. Boardex provides detailed biographical information on executives and directors of public companies, private companies, and not-for-profit companies. The information includes their work, education, and social information as well as their personal profile. The information on CEO compensation is from Execucomp, financial data from Compustat, stock return and pricing information from Center for Research in Security Prices (CRSP), and analyst forecast information from Institutional Broker's Estimate System (IBES).

The main sample consists of firm-year observations in the intersection of Boardex, Execucomp, Compustat, CRSP, and IBES. We begin our sample from 2003 as the coverage in Boardex is incomplete prior to 2003. The last year of the data is 2014. The sample includes 10,507 firm-year observations from 1,943 unique firms that have non-missing values for the main regression variables. In addition, we collect data on anti-takeover provisions, board structure data, and shareholder voting results from ISS (formerly RiskMetrics) databases, and the institutional holdings data are taken from the Thomson Reuters 13F institutional ownership database.

2.1 Variable definitions

a. Measures of implied cost of equity

We estimate the cost of equity that is implied in the current stock prices and the consensus of individual analysts' forecasts as provided by IBES. We adopt the four accounting-based valuation models by Claus and Thomas (2001), Gebhardt *et al.* (2001), Easton (2004), and Ohlson and Juettner-Nauroth (2005).[3] These four models make different use of analyst's earnings forecasts, forecast horizon, and have different assumptions regarding the long and short-term growth rates.

To compute the implied cost of equity for each of the models, we extract the analyst forecasts on one-year-ahead and two-year-ahead earnings per share (EPS) and long-term growth rate forecast from IBES. We require the forecasts to be positive. We further require each firm-year observation to have information on book value of equity, shares outstanding, earnings, and dividends from Compustat, and stock price information from CRSP. Following Gebhardt *et al.* (2001), we use the median values of analyst forecasts as of June each year. This ensures that the financial information from the previous fiscal year is reflected in the stock price at the time of estimation and that the information is publicly available.[4] We constrain each estimate of implied cost of equity to be positive, and treat observations as missing if the observations have negative values.

[3] CT, GLS, MPEG, and OJ models, respectively.

[4] We have tried restricting our sample to the firms with December fiscal year-end, and also excluded firms with April or May fiscal year-ends and run our main regressions. The results are qualitatively the same.

There is little consensus on which model performs best, thus we follow the previous literature and take the average of the four estimates (Hail and Leuz, 2006, 2009). This can mitigate the possible measurement errors associated with a particular model. We calculate the average cost of equity only for firm-year observations that are not missing any of the four estimates. We also show results separately for the cost of equity estimate from each of the models. Finally, from the average estimate and each individual model estimates, we subtract the risk-free rate, as proxied by the 10-year US treasury bond yield in June of each year, to generate implied equity risk premiums. We use these implied equity risk premiums as the dependent variables.

Estimating the firm's *ex-ante* cost of equity using accounting valuation models has advantages over conventional approach that relies on realized stock returns to calculate the cost of equity. Elton (1999) suggests that realized return is a poor proxy for the cost of equity. As argued by Hail and Leuz (2006, 2009), the implied cost of equity is useful because the accounting-based valuation models separately incorporate growth and cash flow estimates making them suitable for isolating changes in the cost of equity. In addition, accounting-based valuation models can estimate cost of equity without using the time-series of past returns, therefore they are forward looking and are more likely to closely mimic investors' expected returns (Hail and Leuz, 2006; Pástor, Sinha, and Swaminathan, 2008; Hail and Leuz, 2009). The details on the computation of each model can be found in Appendix A.

These measures of implied cost of equity are not without limitations. Hou, van Dijk, and Zhang (2012) (HDZ) argue that the cost of equity estimated from analyst forecasts are not reliable since analysts tend to be overly optimistic. They suggest a new approach to forecast earnings by estimating a cross-sectional model using accounting numbers and then use these forecasted earnings in place of earnings forecasted by analysts in the four cost of equity models. They find that their cost of equity estimates better predict future stock returns than the traditional cost of equity estimates generated using analyst forecasts. Therefore, following HDZ, we also re-estimate the four individual cost of equity estimates using the earnings forecasts from the cross-sectional regression models. We then take the average of these four models and subtract the risk-free rate to arrive at a HDZ cost of equity estimate. Following their paper, we only require one non-missing individual cost of equity estimates to come up with the composite measure to maximize coverage.[5] Details on how to estimate the cross-sectional earnings forecast models can be found in Appendix B.

b. Measures of CEO's connections

We match firms in Boardex to Compustat and CRSP using both manual and computer matching (Kamiya, Kim, and Park, 2016). The matched Boardex-Compustat-CRSP universe of firm-years is the basis for the construction of our network connections. Next, we match the CEO names in Execucomp with those in Boardex in order to obtain the social profile and network of the CEO. We are able to match about 95% of all CEOs in Execucomp, and the final sample that we use consists of 2,863 unique CEOs after requiring non-missing control variables and the cost of equity capital estimates.

Following Engelberg *et al.* (2013), we calculate the size of CEOs' personal connections as the total number of executives and directors in the matched Boardex-Compustat-CRSP universe to whom the CEO has an employment, university, or other social connection. Hence, connection is not counted for the individuals in private companies that are not in Compustat and CRSP or

[5] We have also followed Li and Mohanram (2014) in using the earnings persistence model and residual income model to predict future earnings when computing the implied cost of equity capital and find similar results.

firms that are not covered by Boardex. Also, we follow Faleye *et al.* (2014) and assume that once a connection is established, the two individuals are connected in the following years.[6]

The CEO is connected to an individual via employment links if both worked at or sat on the board of another company at the same time during or before the current year. We exclude connections initiated from the CEO's current employment. A university connection is established when two individuals attended the same university and graduated within one year of each other with the same degree type.[7] We follow Cohen *et al.* (2008) and categorize the degree descriptions into six types: (1) undergraduate, (2) masters, (3) MBA, (4) Doctor, (5) Law, and (6) Others. We require that the graduation date to be before the given year of observation. A social connection exists when two individuals are active members of the same social organization, such as clubs, associations, and charities. As the starting and ending date of joining such social organizations are mostly missing in Boardex, we do not impose restrictions on the date that an individual has joined or left the organization when defining social connections similar to past literature.

c. Control variables

We control for the standard variables that are documented to be important in determining the cost of equity. Firm size is calculated as the natural logarithm of the market value of common equity; leverage is measured as the ratio of long-term debt to the market value of equity; and book to market ratio equals the natural logarithm of the ratio of book value of equity to the market value of equity. We also include market beta and idiosyncratic risk calculated from historical daily

[6] However, individuals may drop out of the Boardex database because of death instead of data error. Therefore, we also drop this assumption and reconstruct the CEO connections variable and find similar results.
[7] The institution ID in Boardex reflects multiple schools within the same university, therefore, these IDs are aggregated into a single university ID. For example, the institution ID for "Harvard University" is 764747769, "Harvard Business School" is 755756849, and "Harvard Law School" is 756006873. These are merged into "Harvard University" and given a new university ID.

returns. In particular, beta is estimated using the market model with CRSP value-weighted return and the stock's daily returns over the 12 months prior to the time of implied cost of equity estimation. Idiosyncratic risk is the standard deviation of the residuals from the market model.

Following Dhaliwal, Judd, Serfling, and Shaikh (2016), we include two additional variables, price momentum and analyst forecast dispersion, to account for the potential sluggishness when analysts process information from stock prices and to mitigate any impact of forecast errors on the cost of equity estimates, respectively. We define momentum as the natural logarithm of one plus the compounded daily stock returns over the previous 12 months and analyst forecast dispersion as the standard deviation of analysts' estimates of one year ahead earnings per share forecast. Additionally, consistent with Chen *et al.* (2011) and Cao *et al.* (2015), we add the median analysts' long-term growth forecast from IBES to control for the potential bias in the cost of equity estimate that can arise from analysts' forecast optimism. All control variables in the regressions are winsorized at 1% and 99%, unless the variable is an indicator variable. All independent variables are standardized to have mean of zero and standard deviation of one unless noted otherwise. The detailed definitions of all variables are in Appendix B.

d. Summary statistics

Table 1 shows the descriptive statistics for CEO connections (Panel A), the implied equity risk premium, and other main control variables (Panel B). A CEO has an average of about 135 total connections, out of which 53 are employment connections, 9 are education connections, and 72 are social connections. We observe that the standard deviations of the connections measures are quite large. These numbers are consistent with previous literature such as Engelberg *et al.* (2013)

The average implied cost of equity estimate across the four models is 5.75%. The CT and GLS models have relatively lower equity premiums (4.38% and 4.03%, respectively) compared to OJ and MPEG models (7.34% and 6.84%, respectively). This observed pattern is consistent with previous documentations, such as Gode and Mohanram (2003) and Dhaliwal, Heitzman, and Zhen Li (2006), which shows that OJ model provides the upper bound and GLS model provides the lower bound to costs of capital estimates. The HDZ model also gives a relatively higher number at 6.12%.

2.2. Empirical methodology

To examine the relation between the size of CEO connection and the cost of equity, we estimate the following panel regression model at the firm-year level as the baseline regression:

$$
\begin{aligned}
Cost\ of\ Equity &\\
&= \alpha + \beta \cdot CEO\ connections + \gamma_1 \cdot Firm\ size + \gamma_2 \cdot Book\ to\ market + \gamma_3\\
&\cdot Leverage + \gamma_4 \cdot Momentum + \gamma_5 \cdot Forecast\ dispersion + \gamma_6\\
&\cdot Long\ term\ growth + \gamma_7 \cdot Beta + \gamma_8 \cdot Idiosyncratic\ risk\\
&+ Year\ fixed\ effect + Industry\ fixed\ effect + \varepsilon
\end{aligned}
$$

where the dependent variable is the implied cost of equity of a firm as of June in each year. *CEO connections* and financial statement items are measured for the most recent fiscal year ending before the estimation month of the dependent variable. The analyst-related and risk items are measured in the contemporaneous year as the dependent variable. Throughout the paper, unless noted otherwise, we include year fixed effects and industry fixed effects at the two-digit SIC level, and cluster standard errors at the firm level.

3. Empirical analysis and results

3.1. CEO connections and cost of equity

We begin our analysis by examining whether the size of the CEO's personal network impacts the firm's cost of equity capital. The results are presented in Table 2. The dependent variable in Columns 1 to 3 is the average implied cost of equity. We show results with and without the risk measures, beta and idiosyncratic risk, as CEO connections could impact cost of equity through its impact on firm risk-taking and controlling for risk might attenuate the effects of CEO connections. In Column 1, where we do not control for risk, we find that CEO connections positively and significantly affect a firm's cost of equity capital. The result is economically meaningful as well. A one standard deviation increase in the CEO social connections is associated with a cost of equity that is about 23.2 basis points higher. This translates to about 4% rise in the cost of equity relative to the sample mean. The average firm in our sample has outstanding equity of $3,371.11 million, a 23.2 basis point increase in its cost of equity implies $7.82 million additional cost every year for the firm to finance with equity. [8]

Following prior literature, we control for systematic and idiosyncratic risks in Columns 2 and 3. The positive effects of CEO connections on cost of equity is slightly attenuated though by not much. To be conservative, we use the specifications in Column 3 for the rest of our paper. As expected, both measures of risks are positively related to the cost of equity. The signs on the other control variables are consistent with prior literature. Bigger firms have lower costs though this is likely to be due to the impact of size on firm risks as the significance of the coefficient on firm size disappears in Columns 2 and 3 after controlling for beta and idiosyncratic risk. Consistent

[8] We also use the net equity issuance defined by Baker and Wurgler (2002) as the dependent variable and find evidence that the firms with higher CEO connections have lower equity issuance, suggesting that these firms experience difficulty accessing financial market.

with prior literature, the cost of equity is also positively related to *Book to market*, *Leverage, Forecast dispersion, and long-term growth rates* and negatively related to *Momentum*.

Columns 4 to 7 are regression results using individual cost of equity model estimates as the dependent variable. Except for the GLS model in Column 5, the coefficients of *CEO connections* are all positively and statistically significant at the 1% level. The economic significance are also similar to that in Column 1. Therefore, no single model is driving the results in Columns 1 to 3.

To mitigate the concern for optimism bias in analysts' earnings forecast, we follow Hou *et al.* (2012) and use earnings forecasts generated from a cross-sectional model to estimate the implied cost of equity. The regression result is shown in Column 8 and we still find largely similar result. Overall, the results in Table 2 show that a firm with larger CEO network has higher cost of equity. These results are consistent with the agency channel and risk-taking channel.

3.2. Alternative specifications for CEO connections

Table 3 shows regression results with alternative specifications for the connectivity measure. Column 1 uses the residual from regressing *CEO connections* on firm size to ensure that the result is not driven by the correlation between *CEO connections* and firm size. Column 2 takes the natural logarithm of CEO connections to account for outliers. In Column 3, we use the percentile ranking of *CEO connections* rather than the raw number of CEOs' social ties (Engelberg *et al.*, 2013). Finally, we use CEOs' centrality measure in the last column, which is the number of a CEO's connection scaled by the gross number of all CEOs' connections in each given year (Hochberg, Ljungqvist, and Lu, 2007). The positive relation between cost of equity and CEO connections is robust to all these alternative specifications.

4. Addressing potential endogeneity

The results presented in the previous section is consistent with CEO connections having a positive impact on the cost of equity capital. However, the relation between CEO network and the cost of equity is not free from potential endogeneity problems. The main concern for endogeneity problem arises from omitted variables which can cause the simultaneity bias. To address this issue we control for additional variables and also use different fixed effects to control for unobservable firm and CEO characteristics in a linear framework. However, *CEO connections* might be picking up nonlinear effects of these linear control variables. Therefore we also use a propensity score matching approach where we match on observed firm and CEO characteristics. Finally, we implement a difference-in-differences methodology surrounding CEO turnover to reduce reverse causality and CEO selection concerns.

4.1. Additional control variables

We first address the omitted variables problem with additional control variables and also various fixed effects. We present the results in Appendix C. Note that by including additional control variables, we might be biasing against us as some of the additional control variables control for the effects of *CEO connections* itself. The size of a CEO's network may be related to several CEO characteristics and compensation structure which prior studies have found to affect firm risk-taking and agency issues and in turn, the firm's cost of equity. Therefore, we control for CEO age and tenure (e.g., Berger, Ofek, and Yermack, 1997; Serfling, 2014), cash compensation, and compensation structure as proxied by CEO portfolio delta and vega (Guay, 1999; Ang, Cole, and Lin, 2000; Coles, Daniel, and Naveen, 2006). We also control for CEO ability by including the general ability index from Custódio, Ferreira, and Matos (2013) and a dummy variable indicating whether the CEO is from an Ivy League school. In addition, we include an indicator variable for CEO overconfidence to control for CEO's risk-taking behavior (Hirshleifer, Low, and Teoh, 2012). *CEO connections* continue to be significant at the 1% level with similar economic magnitude after including these additional control variables.

Papers have shown that a firm's level of agency problems affect the cost of equity capital (e.g., Ashbaugh *et al.* 2004). In Column 2, we control for board and governance-related variables. We include as additional control variables the number of blockholders, institutional ownership percentage, the existence of monitoring intensive board (Faleye, Hoitash, and Hoitash, 2011), board size, audit committee size to board size (Lin, Li, and Yang, 2006), CEO ownership, existence of internal control deficiency (Ashbaugh-Skaife *et al.*, 2009), and the number of independent directors in his own firm the CEO is socially connected to (e.g., Hwang and Kim, 2009). We also follow Larcker *et al.* (2013) to control for board connectedness. We also control for CEO power as proxied by CEO pay slice (Bebchuk, Cremers, and Peyer, 2011), whether the CEO is the only insider on the board (Adams, Almeida, and Ferreira, 2005), and whether the CEO is also the chairman of the board and president (Adams *et al.*, 2005). After controlling for the various board and governance-related variables, *CEO connections* is still positively significant.

Next, we include additional variables related to firm characteristics that might affect a firm's cost of equity. We control for squared firm size to capture any quadratic relation between firm size and cost of equity; firm age to control for firm life-cycle dynamics; *Altman's Z* to control for default risk; *PPE* to control for tangible assets; *Log(CAPEX)* and standard deviation of ROA to capture investment and firm risk, respectively; R&D expense and discretionary accruals to control for information asymmetry; *Number of segments* to control for the complexity of firm structure; and *Free cash flow* to control for financial flexibility (e.g. Almeida, Campello, and

Weisbach, 2004). *CEO connections* continue to be significant. Next, we control for analyst coverage, as proxied by the number of analysts covering the firm, and analysts' forecast bias and the results continue to be robust. Finally, we also control for all the CEO, board, governance, firm, and analyst-related variables in a single regression and *CEO connections* continue to be significant at the 1% level.

We also control for various fixed effects, such as firm fixed effects instead of industry fixed effects to exploit within-firm variation in the *CEO connections* variable. Next, we add CEO fixed effects in addition to industry fixed effects and year fixed effects. Our results continue to hold. We also control for industry-year fixed effects and find similar results. Therefore, the positive relation between CEO network size and cost of equity capital is unlikely to be driven by time-invariant firm and CEO characteristics or industry time trends.

4.2. Propensity score matching

We have controlled for various additional CEO and firm characteristics in a linear regression, however, if the linear control variables used in the regressions do not fully capture the differences between firms with varying CEO network size, the *CEO connections* measure can pick up the non-linear effects of the control variables (Dhaliwal *et al.*, 2016). Therefore, we use propensity score matching to alleviate such non-linearity concerns and concerns of endogenous selection on observable variables (Rosenbaum and Rubin, 1983; Roberts and Whited, 2013).

First, we form two groups with respect to the size of CEO's network. The treatment group is the group with above median *CEO connections* while the control group is the group with below median *CEO connections*. Next, we run a logit regression model where the dependent variable is an indicator variable equals to one if the firm belongs to the high *CEO connections* group and zero if the firm belongs to the low *CEO connections* group. We use two sets of matching covariates. The first set includes the control variables used in the baseline regression in Table 2 Column 3. The second set includes additional CEO characteristics and pay structure as matching covariates. We obtain the propensity score, which is the predicted probability that firm has a highly connected CEO from the logit regression. Next, we match each treated firm (high CEO connections) to a control firm (low CEO connections) with the closest propensity score from the same year and from the same industry. We use kernel matching and nearest neighbor matching without replacement. The match is done within the same 2-digit industry and same year.

The results are presented in Table 4. In Panel A, we compare the means of the matching covariates for the sample matched using kernel matching with bandwidth 0.0005 and where we include additional CEO matching covariates. The resulting sample consists of 1,124 pairs of firms with high and low connected CEOs. The means of all matched variables are insignificantly different from zero between the treated and matched sample, except for CEO age. Therefore the matching is generally successful. The comparison of the matching covariates for the other specifications are not reported for brevity but the untabulated results show that the match is robust to using one-to-one nearest neighbor matching without replacement, and with and without CEO covariates.

Panel B compares the cost of equity between the high *CEO connections* group and low *CEO connections* group for different match specifications. Specification (1) compares the cost of equity between high *CEO connections* and low *CEO connections* group for the match done using kernel match with bandwidth of 0.00025 and standard control variables from Table 2 Column 3.[9] Specification (2) corresponds to the matches for the specification used in Panel A (Kernel

[9] We use different bandwidths to minimize the difference in matched covariates between treatment and control groups.

matching with additional CEO matching covariates). Both specifications show that firms with highly connected CEOs have 36 basis points higher cost of equity capital compared to firms with CEOs that are relatively less connected. The differences are significant at the 5% level.

Specifications 3 and 4 show the results of nearest neighbor matching without replacement. Specification 3 includes only firm characteristics as matching covariates while specification 4 includes both firm and CEO characteristics.[10] Again, we find that firms with highly connected CEOs have higher cost of equity capital compared to firms with less connected CEOs.

4.3. Reverse causality and selection issues

We argue that a bigger CEO social network causally affects cost of equity. However, changes in cost of equity may affect a CEO's social network. For example, firms which became financially distressed may experience an increase in cost of equity, these firms may then hire a CEO with a large social network as the CEO potentially can tap into his vast resource network to engineer a turnaround for the firm. If this is the case, we should see that an increase in the cost of equity precede an increase in CEO connectedness surrounding CEO turnover. The increase in CEO connectedness would then be followed by a decrease in cost of equity if the highly-connected CEO manages to stage a turnaround. To rule out such CEO selection issues, we implement a difference-in-differences (DiD) test to examine how changes in CEO connectedness surrounding CEO turnover affects lead and lag changes in cost of equity.

We first start with a sample of 620 CEO turnovers in our sample. We compare CEO names in consecutive years to determine whether a turnover takes place or not. Next, we calculate the

[10] We require the propensity score to be within +/-0.0085 of each other in specification 3 and +/- 0.025 of each other in specification 4. The use of different calipers is because some covariates fail to match when we use the same caliper in both specifications.

change in *CEO connections* around the CEO turnover and then partition the sample of turnovers into quartiles based on the size of CEO connection change. Those turnovers that fall in the top quartile has the highest increase in CEO connections while those turnovers that fall in the bottom quartile has the lowest increase (largest decrease) in CEO connections. On average, the top quartile experience an increase in *CEO connections* by 138 and the bottom quartile experience a decrease in *CEO connections* by 153. Next, we compare the average change in cost of equity for the top and bottom quartile to calculate the DiD estimates of the cost of equity.

Table 5 shows the result from the DiD tests. Panel A shows the effect of CEO connections changes over *T*-1 to *T* (turnover year) on changes in cost of equity post-turnover, i.e., *T* to *T*+1 while Panel B examines longer-term changes in cost of equity from *T* to *T*+2. The average change in cost of equity is reported for the top quartile CEO connections change group and the bottom quartile CEO connections change group. When we examine the shorter-term changes in Panel A, we find that the average cost of equity decreases for both groups of firms and the average changes are not significantly different from each other across the two groups. However, when we examine the longer-term change in Panel B, we find that the average cost of equity drops by 29 basis points for firms with the biggest decrease in CEO connections while the average cost of equity increases by 40 basis points for the firms with the biggest increase in CEO connections. The average changes in cost of equity are significantly different from each other across the two groups at the 5% level. It is unclear when the market incorporates the impact of the new CEO into stock prices. Investors may have partially revised their expectations immediately following the turnover, thereby cost of equity would have changed already at time *T*. This would bias downwards our estimates of the change in cost of equity. Therefore, we further present the changes in cost of equity from *T*-1 to

T+1 in Panel C and *T*-1 to *T*+2 in Panel D. The results are qualitatively the same as Panels A and B, respectively, although the DiD estimates are bigger as expected.

Next, in Panel E, we show that changes in CEO connections due to the turnover is independent of the change in cost of equity prior to the turnover. The sample of turnovers are divided into 4 groups based on the change in cost of equity prior to the turnover, i.e., *T*-2 to *T*-1. We next compare the change in CEO connections from the old CEO to the new CEO, i.e., *T*-1 to *T*, between the bottom quartile group and top quartile group. The result shows that past changes in implied cost of equity do not significantly impact the selection of new CEO with larger social network.

Therefore, the documented positive relation between CEO connections and cost of equity is unlikely to be due to firms with higher cost of equity selecting CEOs with bigger networks. These results are more consistent with changes in CEO connections causally affecting cost of equity and also suggest that the information on CEOs' network size changes takes time to be fully reflected in the cost of equity.[11]

5. Additional tests

In this section we provide further analyses of the relation between CEO connections and the cost of equity. First, we examine the types of connections that are most relevant in determining a firm's cost of equity. We then attempt to identify the channels through which CEO connections influence a firm's cost of equity. We consider three channels with which CEO connections can affect the cost of equity – agency channel, risk-taking channel, and information asymmetry channel.

[11] We also look at connection changes over *T*-2 to *T* and its impact on cost of equity changes from *T* to *T*+1 and *T* to *T*+2. The results are only significant for the longer-term change, supporting the finding that information about CEO connection changes propagates slowly into the cost of equity.

Note that these three channels are not entirely mutually exclusive. Therefore, our goal is not to preclude one channel in favor of another but simply to provide evidence to show that all channels are at work in the data, if indeed this is the case.

5.1. Regression by individual components of CEO connections

Which types of connections are the most important in determining the cost of equity capital? We split the connections of the CEO into the three subgroups - employment, education, and other social connections in Table 6. We include the standard control variables in the baseline regression.

Columns 1 and 3 show that connections arising from prior employment and other social activities, respectively, positively affects the cost of equity. However, in Column 2, university connections negatively affects cost of equity. Some of the largest educational networks in our data come from the top U.S. schools. Therefore, one possible explanation for the negative relation between number of university connections and cost of equity could be that university connections proxy for the latent ability or skill of the CEOs and high-ability CEOs may be able to manage the firm better leading to lower costs of capital (Engelberg *et al.*, 2013). In Columns 5 to 7, we divide the education connections into those arising from Ivy League schools and those arising from non-Ivy League schools to examine more directly whether education connections captures CEOs' latent ability. We find that only connections arising from Ivy League schools are significant and negative in predicting cost of equity. Putting these evidences together, it seems that the negative coefficient of education connections is driven by connections from a few elite schools which may be partially correlated with CEOs' managerial ability.[12]

[12] Alternatively, the mechanism through which education connections affect cost of equity may be different from the mechanism through which employment and other social connections affect cost of equity. It could be the case that the information transfer between parties with the same education background is more effective which reduces information asymmetry between the firm and outsiders, leading to lower cost of equity (Diamond and Verrecchia,

5.2. Evidence for agency channel

a. Cross-section results by governance measures

Prior research finds that agency problem increases with the size of CEOs' network (Kirchmaier and Stathopoulos, 2008; Kramarz and Thesmar, 2013; El-Khatib *et al.*, 2015). Therefore, if CEO network affects cost of equity through the agency channel, the impact of CEO connections would be more evident when the potential for agency problem is higher. More specifically, the need to monitor a highly-connected CEO by outside investors would be higher for firms with more room for potential agency problem. This leads to an increase in monitoring cost by outside investors which will be reflected in the implied cost of equity. Furthermore, the risk of expropriation by a powerful, unfettered CEO would also be higher causing investors to price-protect themselves through a higher required rate of return.

In Table 7, we use several proxies for the existence of agency problems. For Column 1, following Faleye *et al.* (2011), we create an indicator variable, *Intense monitor,* to indicate more intense monitoring by the independent directors and therefore less potential agency issues. *Intense monitor* is an indicator variable that equals one if the majority of independent directors serve on at least two of three monitoring-intensive committee (i.e. audit, compensation, and nominating). Column 2 interacts *CEO connections* with the indicator variable for small board size, *Small board*. The general consensus is that smaller boards are more effective at monitoring due to lesser free-rider issues (Yermack, 1996). In Column 3, similar to Lin *et al.* (2006), we use the ratio of audit committee size to board size as a proxy for governance. If this ratio is high, the firm is probably focusing more on monitoring activities and improving corporate governance. *High Audit* is an

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1991; Francis *et al.*, 2004; Cao *et al.*, 2015; Chen, Li, and Zou, 2016). There is supporting evidence that communication is more effective when the parties share more similarities (Rogers and Bhowmik, 1970) and that the relationships established in schools are more alike, socially and culturally, than those established in non-schools settings (Kalmijn and Flap, 2001).

indicator variable equals to one if the ratio is greater than the median, and zero otherwise. In Column 4, *High CEO own.* is an indicator variable equals to one if CEO percentage ownership is greater than the median, and zero otherwise. Core, Holthausen, and Larcker (1999) find that firms with higher CEO ownership percentage has more effective governance structure, leading to reduced CEO compensation. *ICD* is an indicator variable that equals to one if the firm has any internal control deficiency. Ashbaugh-Skaife *et al.* (2009) document a positive association between internal control deficiency and cost of equity. *CEO-Dir Indicator* equals to one if CEO has any social connections to his own independent directors. Hwang and Kim (2009) show that CEO connections to independent directors can increase agency problems.

Consistent with the agency channel, all the interaction terms are negative and significant at least at the 5% level, except for *ICD* and *CEO-Dir Indicator*, indicating that the impact of *CEO connections* is weaker when there is less potential agency problems, i.e., when there is more intense monitoring from board members. In firms with stronger governance, the risk of expropriation by a powerful, well-connected CEO is lesser and the need for extra monitoring by outside investors are also lesser.

b. Passage of shareholder governance proposals

Evidence from previous literature suggests that passing shareholder-sponsored corporate governance proposals improve internal corporate governance, thus increasing shareholder value (Cuñat, Gine, and Guadalupe, 2012). Therefore, we should expect the passage of corporate governance proposals to reduce the cost of equity. However, this reduction would be attenuated in firms with better-connected CEOs if CEOs' social network is the source of agency problem. Following Cuñat *et al.* (2012), we implement a regression discontinuity design (RDD) using data from shareholder-sponsored governance proposals that seek to improve internal corporate governance. This empirical strategy essentially compares the change in the cost of equity for proposals that pass by a small margin to the change in cost of equity for proposals that fail by a small margin. For these close-call votes, passing of the proposal is very close to an independent, random event and is unlikely to be affected by firm characteristics. Put in another way, firms which pass the proposal by 50.1% votes should be quite similar to firms which fail the proposal by 49.9% votes but this small difference in the voting percentage generates a discontinuity in the likelihood that the provisions will be implemented. Firms are more likely to make improvements in corporate governance if the proposal is passed compared to firms which fail the proposal, even by a little.

We obtain data on shareholder-sponsored proposals and their voting outcomes from ISS. In all, we find 2,455 shareholder proposals that can be matched to our sample. To implement the RDD, we follow Cuñat *et al.* (2012) and estimate the following regression $y_{i,t+1} = \alpha \cdot Pass_{i,t} + Polynomials_{i,t} + Year\ fixed\ effects + u_{i,t}$, where the dependent variable is implied cost of equity and the independent variable is an indicator variable *Pass* which equals to one if shareholders' proposal to improve internal governance has passed the threshold level, and zero otherwise. *Polynomials* are on each side of the threshold and they are calculated as the vote results of each proposals in percentages minus the threshold percentage required to pass the proposal (i.e., vote result for each proposal – 0.5). The order of polynomials included is limited up to second order because Gelman and Imbens (2014) argue that estimating causal effects based on higher order polynomials can be misleading and recommend using linear or quadratic polynomials. We include year fixed effects and cluster standard errors at the firm level. We estimate the model for the full sample and also for subsamples divided based on median *CEO connections*.

Table 8 reports the results. Column 1 shows results for the full sample. The coefficient on the *Pass* indicator variable is negative and significant, suggesting that passing a governance proposal which seeks to improve internal governance leads to a decrease in the cost of equity capital. Therefore, agency cost has a positive impact on the cost of equity. In Columns 2 and 3, we separate the sample into those with below median *CEO connections* and those with above median *CEO connections*, respectively. The coefficient of *Pass* is significantly negative for the low CEO connectedness group while it is insignificant for the high CEO connections group. Furthermore, the coefficient of *Pass* is larger in magnitude in the low CEO connectedness group compared to the high CEO connectedness group (-1.119 versus -0.710). To the extent that CEOs with high social connections enjoy significant power or suffer from high agency problems, we should observe more muted response to the passage of governance proposals for firms with powerful CEOs. Therefore, consistent with the findings in previous section, our result from the RDD further suggests that CEOs' personal connections increase agency problems leading to higher cost of equity and that good corporate governance can moderate its' impact.

5.3. Evidence for risk-taking channel

CEOs' network size can increase their risk-taking incentives as social networks facilitate relevant information transfer about potential investment opportunities (Hong *et al.*, 2018) and also improves re-employment options in the event that the risky venture fails and the CEO gets fired (Faleye *et al.*, 2014; Liu, 2014; Ferris *et al.*, 2017a). Therefore, a bigger CEO network can lead to an increase in cost of equity capital through its impact on aggregate corporate risk-taking. We examine this possibility in Table 9.

CEOs who are nearer to retirement have less career concerns and less worry about losing their job. Therefore, the expanded outside options provided by a bigger social network should matter less for older CEOs' risk-taking incentives. If so, we expect the impact of CEO connections on cost of equity will be attenuated for the sample of older CEOs. In Panel A, we divide the sample of CEOs into two groups based on the median CEO age in the sample. Consistent with our expectations, the impact of CEO connections on cost of equity is stronger among the sample of younger CEOs. The coefficient of *CEO connections* for the younger CEOs is bigger in magnitude and also more significant, and it is significantly different at the 1% level from the corresponding coefficient for the older CEOs.

We next examine the possibility that CEO connections allow them to access relevant network information, which allows them to better identify investment opportunities, thereby reducing their risk aversion towards *ex-ante* risky projects. We identify types of connections which are most likely to contain investment-relevant information. We argue that connections to rival firms which are in the same industry as the focal firm and firms in the upstream or downstream industries are most likely to contain information relevant for the CEO. Rival firms are defined as firms that operate in the same three-digit SIC industry as the focal firm. To identify potential customer-supplier firms, we follow Fan and Goyal (2006) and use the 2007 Use Table of Benchmark Input-Output (IO) compiled by the Bureau of Economic Analysis (BEA) for the U.S. Economy to identify vertically-related industries.[13]

[13] The table records the commodity flows between each pair of over 400 different IO industries. We calculate the vertical relatedness coefficient of each industry pair and identify vertically-related industries by requiring the coefficient to be greater than 5%. Then we match IO industry codes to the SIC codes using the concordance table provided by the BEA. Finally, we merge the identified vertically-related industry pairs with our data to identify the upstream and downstream industries of each firm and also to compute the number of connections to the firms in vertically-related industries.

Table 9, Panel B, presents the regression results. *Rival connections* (*Non-rival connections*) is the number of executives and directors working in or sitting on the boards of rival firms (non-rival firms) that the CEO is connected to via employment, education, and other social activities. *Customer-supplier connections* and *Non-customer-supplier connections* are defined similarly but for connections to firms in upstream and downstream industries. The variables in Panel B are not standardized so that we can compare the size of coefficients across different variables. Columns 1 to 3 show the regression results for rival and non-rival firm connections and Columns 4 to 6 show the results for customer-supplier and non-customer-supplier firm connections. All coefficients are positively significant consistent with the previous results. However, as expected, we find that the coefficient of *Rival connections* in Column 1 is much bigger in magnitude compared to the coefficient of *Non-rival connections* in Column 2. The two coefficients are also significantly different from each other at the 1% level as evidenced by the Chi-Square value of 10.01. In Column 3, when we put both types of connections together, we find that *Rival connections* is more important and its coefficient is significantly different from that of *Non-rival connections* with *p*-value 0.081. Similarly, we find that connections to upstream/downstream industries are more important compared to connections to other less relevant industries. The two coefficients in Column 6 are significantly different from each other at the 5% level.

Results in Panel B are also consistent with the idea that a bigger CEO social network lead to expanded outside options for the CEO which in turn increases their incentives to engage in risk-taking. The CEO's working experience in the current firm is likely to be a useful attribute for other firms in the same industry or for upstream or downstream firms. For example, executives with similar industry experience are highly sought after as directors (see e.g.,Wang, Xie, and Zhu, 2015; Corporate Board Member, 2016). Thus, CEOs who are more connected to rival firms or to customer or supplier firms are likely to have better labor market consequences from receiving more job offers from these firms than a CEO who is less connected to related firms.[14]

In Panel C, we examine directly the relation between *CEO connections* and several proxies of firm risk-taking. Our proxies for risk-taking include stock return volatility, earnings volatility, natural log of R&D spending, and *Log(CAPEX)*. If a bigger social network incentivizes the CEO to engage in risk-taking, we should see a positive impact of CEO connections on these proxies of risk-taking. Note however that prior literature often consider capital expenditure to be a safer form of investment compared to R&D (Coles *et al.*, 2006), therefore, CEO connections might have a negative impact on capital expenditures instead. We use the specifications from the baseline regression in Table 2 but do not include beta and idiosyncratic risk in the regressions. In Columns 1 to 4, we find statistically significant coefficient with expected signs for *CEO connections* suggesting that CEO connections positively impact firm risk-taking.

In Column 5, we use *accrual* to proxy for earnings management (see e.g., Healy, 1985; DeAngelo, 1986). Highly-connected CEOs have better outside options in case of failure, therefore, they may be more willing to take on risk and be more willing to engage in aggressive financial reporting. However, for similar reason, it is also possible that highly-connected CEOs have less incentive to engage in earnings management since they can easily find a new job if they get fired for underperformance. Therefore, it is left as an empirical question whether highly-connected CEOs increase or reduce earnings management. The result in Column 5 presents significantly positive coefficient for *CEO connections* suggesting that highly-connected CEOs engage in more earnings management activities.

[14] It is possible that CEO social connections to important stakeholders can help foster better relationships and more stable operations, reducing cost of equity. However, on average, the net effect of CEO connections to potential suppliers and customers is positive in the data.

Finally, in Columns 6 and 7, we regress firm beta and idiosyncratic risk on *CEO connections*, respectively. We find that the coefficient of CEO connections is positive but not significantly related to systematic risk (*t*-value of 0.74), while it is positive and significantly related to idiosyncratic risk (*t*-value of 2.73).[15]

An important question to address here is whether the observed risk-taking behavior of connected CEOs is driven by the connectedness of the CEOs or whether firms with projected risk-taking activities appoint the CEOs with larger network to tap into their network. Similar to Hirshleifer *et al.* (2012), we test whether our risk-taking results hold for the sub-sample of long-tenured CEOs. The effect from firm-CEO matching is likely to be more important when the CEO is first assigned to the firm. And should diminish as CEO tenure increases. Therefore, we limit the sample of CEOs to those with tenure over four years and six years and re-run the tests from Panel C. In untabulated result, the overall results are qualitatively the same as in Panel C; CEO connections increase risk-taking behavior even for long-tenured CEOs. In Panel D, we show that the CEO connections variable is still positively significant when predicting cost of equity even for the subsets of firm-years for which CEO has long tenure. Therefore our results are unlikely to be due solely to selection of highly-connected CEOs by firms which are expected to increase their risk-taking but the results are at least partially driven by highly-connected CEOs engaging in more risk-taking.

[15] The results are at odds with what can be expected from the traditional asset pricing models. However, there is a growing strand of literature documenting the pricing of firm-specific risk, which may result from market imperfections and failure of investors to fully diversify their portfolios due to exogenous reasons; such as taxes, limited attention, transaction costs, private information, as well as behavioral biases (see e.g., Fu, 2009). Our findings suggest that the positive relation between CEOs' network size and the implied cost of equity could be driven by firm-specific risk. However, as in previous literature on implied cost of equity (e.g., Hail and Leuz, 2006, 2009; Chen *et al.*, 2011; Dhaliwal *et al.*, 2016), both beta and idiosyncratic risk are controlled for in the regressions throughout the paper. Given that we continue to find a positive relation between CEO connections and cost of equity even after controlling for beta and idiosyncratic risk, the positive pricing of CEOs' ties must be beyond what can be explained by the included risk measures.

5.4. Evidence for information asymmetry channel

We find a positive relation between cost of equity and CEO network size which eliminates the possibility that on average, CEO connectedness helps to reduce information asymmetry. However, it is possible that this information asymmetry channel is at work in certain segments of firms, in particular, those informationally-opaque firms which would particularly benefit from the advantageous information flow conferred by a highly-connected CEO. We examine this possibility in Table 10.

In Panel A, we include various proxies for information asymmetry in the regressions and interact them with *CEO connections*. *Small size* is an indicator variable equals to one if the firm's market value of equity is below the sample median, and zero otherwise. Firm size is often used as a proxy for information asymmetry as smaller firm is more informationally opaque while information is readily available for bigger firms since they have more channels, such as media exposure and conference calls, through which information can be distributed (see e.g., Aboody and Lev, 2000; Cao *et al.*, 2017). *High accrual* is an indicator variable equals to one if *accrual* is higher than sample median and zero otherwise. Earnings management is predominantly done through the manipulation of accruals, and investors are heterogeneous in their ability to process earnings information. So poor earnings quality can exacerbate information asymmetry by differently informing investors (Diamond and Verrecchia, 1991). *High bid-ask* is an indicator variable equals to one if the bid-ask spread is higher than the sample median, and zero otherwise. *Few analysts* is an indicator variable equals to one if the number of analysts following the firm is below the sample median, and zero otherwise. *High volatility* is an indicator variable equals to one if the stock return volatility is above sample median, and zero otherwise. Firms with high bid-ask spread, with low analyst coverage, and higher stock return volatility have higher information asymmetry (Lang and Lundholm, 1993; Armstrong, Core, Taylor, and Verrecchia, 2011; Cao *et al.*, 2015).

While the coefficients on the standalone *CEO connections* variable are all positive and significant, most of the coefficients on the interaction terms, other than the one on *High accrual*, are negative and significant, suggesting that the positive relation between *CEO connections* and cost of equity is attenuated among informationally-opaque firms. The results are consistent with the hypothesis that CEO connections induce better information flow between the firm and outsiders, which mitigates information asymmetry and helps reduce the cost of equity, especially among the informationally-opaque firms. At the bottom of Panel A, we provide the *p*-values which test the null hypothesis that the sum of the coefficients on the standalone *CEO connections* and the interaction term is equals to zero. The null hypothesis is mostly not rejected except for the *High accrual* interactions, suggesting that the adverse effect of agency and risk channels can be offset by better information flow through CEO network for the opaque firms.

In Panel B, we also look at the connections to capital providers to examine whether the information asymmetry channel is driven specifically by connections to capital providers. We follow Engelberg *et al.* (2012) and Ferris *et al.* (2017b) to define connections to banks and financiers. *Bank connections* (*Non-bank connections*) is the number of directors and executives who are working (not working) in banks or sitting (not sitting) on the boards of banks connected to the CEO via employment, university and other social links. Similarly, *Financier connections* (*Non-financier connections*) is the number of connections between the CEO and executives and directors who are working (not working) or sitting (not sitting) on boards of financier firms, which are classified as ‘banks’, ‘investment companies’, ‘private equity’, or ‘specialty and other finance’ in Boardex, through their past employment, university and other social links. There are some evidence showing that connections to banks lead to a lower cost of equity capital while connections to non-banks increase the cost of equity, however, these results are only significant for the specification with firm fixed effects. The weak results highlight the possibility that the beneficial impact of reduced information asymmetry between firms and potential financiers may be offset by the adverse effects of increased information asymmetry among investors. Cai *et al.* (2016) find that CEO connections to investment firms increase the likelihood of informed trading and thereby lead to higher costs of trading.

6. Conclusion

This study examines the relation between the size of the CEOs' social network and the implied cost of equity. We find that the *ex-ante* cost of equity increases with the number of CEO connections. The result is robust to different model specifications with various sets of control variables and alternative measures of CEO connections and cost of equity. We also alleviate concerns of endogeneity by using propensity score matching and difference-in-differences tests surrounding CEO turnover.

Additional tests also identify three potential channels through which social connections influence the cost of equity. First, highly connected CEOs may have higher agency issues which leads to increased cost of equity capital. Using several governance measures, we find cross-sectional evidence that the size of CEOs' network has a larger impact for the firms with weaker corporate governance. This finding is further supported by using a regression discontinuity design to examine the impact on cost of equity following the passage of shareholder proposals to improve internal corporate governance.

Second, a big social network can incentivize the CEO to engage in riskier projects, thereby increasing the cost of equity. A big social network facilitates the CEO to take on riskier projects as it increases the outside options for the CEO following a potential job loss due to project failure. Furthermore, a highly-connected CEO can have access to investment-relevant information through his network which enhances his ability to identify good projects, thereby reducing the risk of failure on an *ex-ante* basis. We find support for this risk-taking channel as results are stronger for younger CEOs more prone to career concerns issues and we also find a greater impact of connections that are more likely to contain investment-relevant information. CEO connections are also positively related to various risk-taking measures.

Third, personal network can be conduits of information between the firm and outside investors. We examine whether CEO personal connections can help alleviate information asymmetry issues for informationally-opaque firms and thereby reducing the cost of equity for these firms. We find some support for this information asymmetry channel as we find that the positive impact of CEO connections is attenuated for firms which has high information asymmetry.

Past papers have shown that CEO's personal connections to capital providers can lower information asymmetry and thereby the firm's cost of equity. Our study differs from these studies by examining the CEO's connectedness to the general business population. By doing so, we find that the impact of CEO's personal connections on cost of equity are more nuanced. CEO's connectedness to the general business population increases the cost of equity on average due to increase in agency issues and risk-taking. However, for certain segments of firms which are informationally-opaque, CEO's general connections act as conduits of information and helps lower information asymmetry between the firm and outside investors.

Appendix A. Models of individual cost of capital estimates

In this appendix, we describe in detail the cost of equity models used in the paper to estimate the implied cost of capital. All cost of capital estimates are estimated for June of year *t*. We obtain stock price information from CRSP, financial data from Compustat, and analyst-level data from IBES. In order to estimate the cost of capital for all models, we require each firm-year observation to have information on stock price in June of year *t* (P_t), dividend payout ratio (d_{t-1}), book value per share at the beginning of fiscal year (B_t), earnings forecasts one-year-ahead ($FEPS_{t+1}$) and two-years-ahead ($FEPS_{t+2}$) that are positive, as well as long-term growth forecast (*LTG*). However, some models require the use of earnings forecast beyond year two. Thus, we impute the forecast from the previous year's forecast and the long-term growth forecast if the forecast is not available (i.e. $FEPS_{t+i} = FEPS_{t+i-1}(1+LTG)$). The median analyst forecast of earnings and stock prices used are from June of each year *t* to ensure that the financial information from previous fiscal year is reflected in the stock price. The risk-free rate (r_f) equals to the yield on 10-year Treasury note in June of year *t*.

Once we have the implied cost of capital estimates, we constrain the individual cost of capital estimates to be positive and subtract the risk-free rate from each estimates to attain risk-premium. For the observations without any missing individual cost of capital estimates, we follow previous studies, such as Hail and Leuz (2006, 2009), and take the average of the four estimates in order to reduce the measurement error by individual models.

ICOC	Valuation equations and assumptions	Source
CT	$$P_t = B_t + \sum_{i=1}^{5} \frac{(FEPS_{t+i} - k_{CT} \cdot B_{t+i-1)})}{(1+k_{CT})^i} + \frac{(FEPS_{t+5} - k_{CT} \cdot B_{t+4}) \cdot (1+g)}{(k_{CT} - g) \cdot (1+k_{CT})^5}$$ where, k_{CT} = the implied cost of capital estimates that solves the equation, P_t = market price of stock in June of year t, B_t = book value of equity at beginning of fiscal year t, $B_{t+i} = B_{t+i-1} + FEPS_{t+i} \cdot (1-d)$, $FEPS_{t+i}$ = median analysts forecasts i-year ahead, $FEPS_{t+i} - k_{CT} \cdot B_{t+i-1}$ = residuals earnings at t+i which is the difference between forecasted earnings and cost of capital charged for book value of equity previous fiscal year end, d_{t-1} = dividend payout ratio. If earnings are positive, it equals to the dividends from previous fiscal year divided by earnings. If earnings are negative, it equals to the dividends over 0.06 × total assets. Replace payout ratio with zero if it is less than zero, and replace it with one if it is greater than one, $g = r_f - 3\%$.	Claus and Thomas (2001)
GLS	$$P_t = B_t + \sum_{i=1}^{11} \frac{(FEPS_{t+i} - k_{GLS} \cdot B_{t+i-1)})}{(1+k_{GLS})^i} + \frac{(FEPS_{t+12} - k_{GLS} \cdot B_{t+11})}{(1+k_{GLS})^{11}}$$	Gebhardt *et al.* (2001)

	where, k_{GLS} = the implied cost of capital estimates that solves the equation, P_t = market price of stock in June of year t, B_t = book value of equity at beginning of fiscal year t, $B_{t+i} = B_{t+i-1} + FEPS_{t+i} \cdot (1-d)$, $FEPS_{t+i}$ = median analysts forecasts i-year ahead, After year t+3, *FEPS* mean revert linearly to median industry ROE (*FROE*) by 12th year, where industry is defined at two-digit SIC. Median ROE is computed using all profitable firms over the past 10 years. Where the forecasted return on equity is calculated as: $FROE_{t+i} = \frac{FEPS_{t+i}}{B_{t+i-1}}$, $FEPS_{t+i} - k_{CT} \cdot B_{t+i-1}$ = residuals earnings at t+i. Same as previously defined, d_{t-1} = dividend payout ratio. Same definition as in the previous model, $g = r_f - 3\%$.	
OJ	$k_{OJ} = A + \sqrt{A^2 + \frac{FEPS_{t+1}}{P_t} \cdot \big(g - (\gamma - 1)\big)}$ where, k_{OJ} = the implied cost of capital estimates, $A = \frac{1}{2} \cdot \left((\gamma - 1) + \frac{DPS_{t+1}}{P_t}\right)$ $FEPS_{t+i}$ = median analysts forecasts i-year ahead, $DPS_{t+1} = DPS_0$, dividend per share. Assumed to be constant, $STG = \frac{FEPS_{t+2} - FEPS_{t+1}}{FEPS_{t+1}}$, $g = \frac{STG + LTG}{2}$, short term growth rate, $(\gamma - 1) = r_f - 3\%$, the perpetual growth rate.	Ohlson and Juettner-Nauroth (2005)
MPEG	This model is a special case of OJ model. The model requires one-year ahead and two-year ahead earnings forecast and positive change in earnings forecast. After the explicit forecast horizon, the abnormal earnings constantly grows in perpetuity. $P_t = \frac{(FEPS_{t+2} + DPS_{t+1} \cdot k_{ES} - FEPS_{t+1})}{k_{ES}^2}$ where, k_{ES} = the implied cost of capital estimates, $FEPS_{t+i}$ = median analysts forecasts i-year ahead, DPS_{t+1} = the expected dividends per share in year t+1, equals to $FEPS_{t+1} \cdot d$, d_{t-1} = dividend payout ratio. Same definition as in the previous model,	Easton (2004)

Appendix B. Variable definitions

Variable	Definitions	Source
Accrual	Discretionary accruals component of total accruals estimated using the modified Jones model	Dechow, Sloan, and Sweeney (1995) Compustat, CRSP
Altman's Z	1.2*Working Capital/Total Assets + 1.4*Retained Earnings/Total Assets + 3.3*EBIT/Total Assets+ 0.6*Market value of Equity/Total Liabilities+0.999* Sales/Total Assets	Compustat
Analysts' forecast bias	Actual realized earnings minus one year ahead consensus forecast, scaled by stock price one-month prior the forecast announcement date	Compustat, CRSP, IBES
Analyst forecast dispersion	Standard deviation of one year ahead earnings per share forecast	IBES
Audit percentage	The ratio of the number of audit committee to the size of the board	ISS (Riskmetric)
Bank (Non-bank) connections	The number of executives and directors working or sitting on the boards of banks (non-banks) that the CEO is connected to via employment, university, and other social connections	Execucomp, Boardex
Beta	A proxy for the systematic risk of a firm. Estimated using the market model with daily returns over the 12 months prior to the time of cost of capital estimation	CRSP
Board network	The total number of executives and directors the board is connected to	Boardex
Board size	The number of directors sitting on the board	ISS (Riskmetric)
Book to market	Natural log of the book value of equity to the market value of equity	Compustat
Busy board	Dummy variable that takes the value of one if board is busy. Board is considered busy when the majority of independent directors serve on more than three outside public boards	Fich and Shivdasani (2006) ISS (Riskmetric)
CAPEX	Capital expenditure divided by lagged sales	Compustat
CEO cash compensation	Natural log of the sum of salary plus bonus	Execucomp
CEO connections	The number of executives and directors the CEO is connected to via professional connection, education connection, and social connection.	Engelberg *et al.* (2013) Execucomp, Boardex
CEO delta	The sensitivity of the CEO's equity portfolio to a 1% change in stock price	Coles *et al.* (2006) Execucomp
CEO-Dir Indicator	An indicator variable that equals to one if CEO is connected to at least one independent director on the board, and zero otherwise	Execucomp, Boardex

CEO-Independent Dir	The number of independent directors of his current company the CEO is connected to	Execucomp, Boardex
CEO ownership	The percentage of CEO's ownership in the firm	Execucomp
CEO title concentration	An indicator variable that equals to one if the CEO is both the chairman of the board and president, or the CEO is chairman and the firm does not have president or COO, and zero otherwise	Adams *et al.* (2005) Execucomp
CEO vega	The sensitivity of the CEO's equity portfolio to a 1% change in stock return volatility	Coles et al. (2006) Execucomp
CPS	CEO pay slice. CEO's total pay over the sum of the five highest paid executives' pay in a firm	Bebchuck *et al.* (2011) Execucomp
Customer-supplier (Non-customer-supplier) connections	The number of executives and directors working (not working) in customer or supplier industries that the CEO is connected to	Execucomp, Boardex
Earnings volatility	Standard deviation of earnings over the past 5 years. Earnings is defined as income before extraordinary items divided by the average of total assets of current and previous year	Dichev and Tang (2009) Compustat
Employment connections	The number of connections from the CEO's prior work and professional experience	Execucomp, Boardex
Few analysts	An indicator variable equals to one if the number of analysts following the firm is below the sample median for the year, and zero otherwise	IBES
Financier (Non-financier) connections	The number of executives and directors working in financier firms (non-financier firms) the CEO is connected to. Financier firms are the firms classified as 'banks', 'investment companies', 'private equity', or 'specialty and other finance' in Boardex.	Ferris *et al.* (2017), Execucomp, Boardex
Firm size	Natural log of market value of equity, adjusted for CPI to 2015 dollars	Compustat
Free-cash-flow	(Net cash flow from operating activities – cash dividends) divided by lagged total assets	Compustat
General ability index	Skills of CEOs that are transferrable across firms and industries. Common component extracted using principal components analysis from number of positions, number of firms, number of industries, CEO experience at other firm, CEO experience from conglomerate	Custódio *et al.* (2013) BoardEx, Execucomp, Compustat
High accrual	An indicator variable that equals to one if the accruals is higher than sample median for the year, and zero otherwise	Compustat
High audit	An indicator variable that equals to one if the percentage of audit committee to board size is higher than the sample median for the year, and zero otherwise	ISS (Riskmetrics)
High bid-ask	An indicator variable that equals to one if the bid-ask spread is higher than the sample median for the year, and zero otherwise	Corwin and Schultz (2012), CRSP
High CEO own.	An indicator variable that equals to one if the percentage of CEO ownership is above the sample median for the year and zero otherwise	Execucomp

High volatility	An indicator variable that equals to one if the stock return volatility is above sample median for the year and zero otherwise	CRSP
ICD	An indicator variable that equals to one if the firm has any internal control deficiencies and zero otherwise	Audit Analytics
Idiosyncratic risk	The standard deviation of the residual daily returns from the market model estimated with daily returns over the 12 months prior to the time of cost of capital estimation	CRSP
Implied cost of capital (ICOC)	The average of implied cost of capital. It is the mean value of four individual cost of capital estimates based on Clause and Thomas (2001), Gebhardt *et al.* (2001), Ohlson and Jeuttner(2005), and Easton (2004) minus the risk free rate that is the 10 year treasury yield on the month of cost of capital estimation	Compustat, CRSP, IBES
Implied cost of capital (ICOC) - HDZ	The average of four implied cost of capital measures that are estimated using earnings forecasted from running the following pooled cross-sectional regression. $E_{i,t+\tau} =$ $\alpha_0 + \alpha_1 A_{i,t} + \alpha_2 DPT_{i,t} + \alpha_3 DP_{i,t} + \alpha_4 E_{i,t} + \alpha_5 Neg\ E_{i,t} + \alpha_6 ACC_{i,t,} + \varepsilon_{i,t,+\tau}$ where, $E_{i,t+\tau}$ = earnings of firm *i* in year t+τ, where τ ranges from one to five. Income before extraordinary items from Compustat, $A_{i,t}$ = total assets, $DPT_{i,t}$ = dividend payment, $DP_{i,t}$ = an indicator variable that equals to one if the firm pays dividends and zero otherwise, $Neg\ E_{i,t}$ = an indicator variable that equals to one for firms with negative earnings and zero otherwise, $ACC_{i,t}$ = accruals calculated using balance sheet method. We estimate the alphas of the cross-sectional model using previous ten years of data using the entire Compustat/CRSP universe. For each year's earnings, we use one to five years lagged independent variables to run five independent regressions and obtain five different sets of alpha coefficients. We obtain one to five years earnings forecasts by multiplying the most recent fiscal-year-end accounting variables with the alphas estimated from the regressions. We use this forecast estimates to compute the cost of capitals. Following Hou *et al.* (2012), we only require a firm to have at least one non-missing cost of capital estimates to compute the composite measure to maximize coverage.	Hou *et al.* (2012) Compustat, CRSP, IBES
Institutional ownership	The percentage of shares owned by institutional investors	Thomson Reuters, 13F
Intense monitor	An indicator variable that equals one when the majority of independent directors sit on two or more monitoring-intensive committees (audit, compensation, and nominating).	Faleye *et al.* (2011) ISS (Riskmetrics)
Ivy League	An indicator variable that equals to one if the CEO has attended an Ivy League school, and zero otherwise	Boardex

Ivy (Non-Ivy) League connections	The number of CEO's education connections established from Ivy (Non-Ivy) league schools, including undergraduate, masters, MBA, PhD, law, and other degrees	Execucomp, Boardex
Leverage	Ratio of long-term debt to the market value of equity	Compustat
Log (CAPEX)	Natural log of one plus *CAPEX*.	Compustat
Log (CEO age)	Natural log of CEO's age in years	Execucomp
Log (Firm age)	Natural log of the number of years since the firm first appeared in Compustat or CRSP, whichever is earlier	Compustat, CRSP
Log (R&D)	Natural log of one plus R&D expenses	Compustat
Log (Tenure)	Natural log of CEO tenure in years	Execucomp
Long-term growth	Analysts' long-term earnings growth forecast	IBES
Momentum	Natural log of one plus the compounded stock return over the previous 12 months	CRSP
Number of analysts	The number of analysts following and making forecasts	IBES
Number of blockholders	The number of blockholders that own more than 5% of firm's outstanding common shares	Thomson Reuters, 13F
Number of segments	The number of business segments of a firm	Compustat
Other social connections	The number of connections from the CEO's social activities. Included only if the individuals have 'active roles' other than mere membership, except clubs	Execucomp, Boardex
Overconfidence	An indicator variable that equals to 1 if a CEO holds options that are more than 67% in the money and zero otherwise	Execucomp
PPE	Property, plant, and equipment scaled by lagged sales	Compustat
Rival (Non-rival) connections	The number of executives and directors working in rival firms (non-rival firms) that the CEO is connected to via employment, university, and other social connections. Rival firms are defined as those in the same three-digit SIC industry as the focal firm	Execucomp, Boardex
Single insider	An indicator variable that equals to one if the CEO is the only insider director on a firm's board of directors, and zero otherwise	Execucomp
Small board	An indicator variable that equals to one if the board size is below the sample median for the year, and zero otherwise	ISS (Riskmetrics)
Small size	An indicator variable that equals to one if the firm size is smaller than the sample median for the year, and zero otherwise. Firm size is measured using the natural log of market value of equity.	Compustat
Standard deviation of ROA	Standard deviation of return on assets during the past five years Return on assets is defined as operating income before depreciation divided by total asset	Compustat
Stock return volatility	Standard deviation of the natural logarithm of daily returns over the past year	CRSP
University connections	The number of connections from the CEO's education, including undergraduate, masters, MBA, PhD, law, and other degree	Execucomp, Boardex

Appendix C. Endogeneity test – Controlling for additional variables

This table provides regression results from adding additional variables to the baseline regression and different fixed effects to test for the robustness of the findings. The dependent variable is *Cost of equity – Mean*, the average of implied cost of equity estimates calculated following the four methodologies presented in Claus and Thomas (2001) (CT), Gebhardt *et al.* (2001) (GLS), Easton (2004) (MPEG), and Ohlson and Juettner-Nauroth (2005) (OJ) and is in excess of the 10-year treasury yield. *CEO connections* is the number of executives and directors that the CEO is connected to via employment, university, and other social connections. Column 1 controls for CEO-related variables. Column 2 controls for board-related variables and governance variables. Column 3 adds other firm-related variables. Column 4 controls for additional analyst-related variables. Column 5 includes all the additional control variables. Column 6 uses firm fixed effect instead of industry fixed effect. Column 7 adds CEO fixed effects to the baseline model. Column 8 uses industry-year fixed effect. All variable descriptions can be found in Appendix B. All independent variables are standardized to have mean zero and standard deviation one. All specifications include the control variables from Table 2 Column 3, year fixed effects, and industry fixed effects unless noted otherwise. Industries are defined at the 2-digit SIC level. The *t*-statistics with standard errors clustered at the firm level are reported in parentheses. *, **, and *** denote significance at 10%, 5%, and 1%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
CEO connections	0.246***	0.123*	0.115**	0.219***	0.155***	0.356*	0.484*	0.232***
	(3.06)	(1.82)	(2.12)	(3.05)	(3.03)	(1.68)	(1.72)	(3.19)
Log(Tenure)	-0.160***				-0.0768			
	(-2.88)				(-1.50)			
Log(CEO age)	0.077*				-0.0453			
	(1.74)				(-0.86)			
CEO delta	0.009				0.000213			
	(0.07)				(0.00)			
CEO vega	0.002				-0.00150			
	(0.02)				(-0.02)			
CEO cash compensation	0.214***				0.147***			
	(3.27)				(2.72)			
General ability index	0.077				0.0449			
	(1.34)				(1.02)			
Ivy League	-0.368***				0.0113			
	(-2.81)				(0.08)			
Overconfidence	-0.408***				-0.170**			
	(-3.57)				(-2.10)			
Number of blockholders		-0.105			-0.0910*			
		(-1.58)			(-1.81)			
Institutional ownership		-0.178***			-0.0666			
		(-2.70)			(-0.89)			
Intense monitor		0.024			0.0231			
		(0.46)			(0.49)			
Board size		0.291***			0.0228			
		(3.78)			(0.33)			
Audit percentage		0.072			-0.0105			
		(1.06)			(-0.19)			
CEO ownership		-0.133**			-0.0747			
		(-2.55)			(-1.03)			
ICD		0.972			-0.255			
		(0.93)			(-1.19)			
CEO-Independent Dir		-0.100*			-0.0638			
		(-1.84)			(-1.51)			
Board network		0.010			0.0252			
		(1.39)			(0.48)			
CPS		-0.023			-0.0534			
		(-0.54)			(-1.24)			

Single insider		0.090			0.127			
		(0.85)			(1.59)			
CEO title concentration		0.075			0.207*			
		(0.80)			(1.91)			
Size^2			1.395***		0.560			
			(3.32)		(1.14)			
Log(Firm age)			0.292***		0.189**			
			(4.40)		(2.51)			
Altman's Z			-0.320***		-0.263***			
			(-7.58)		(-4.42)			
PPE			-0.0269		-0.0188			
			(-1.01)		(-0.68)			
Log(CAPEX)			-0.0125		-0.0703*			
			(-0.42)		(-1.68)			
Log (R&D)			0.0850		0.104			
			(1.02)		(1.38)			
Standard deviation of ROA			0.315***		0.375***			
			(6.73)		(7.29)			
Accrual			0.00464		0.0454			
			(0.10)		(0.90)			
Number of segments			0.0105		0.00336			
			(0.21)		(0.05)			
Free-cash-flow			-0.294***		-0.270***			
			(-4.70)		(-4.07)			
Number of analysts				-0.142**	-0.0338			
				(-2.16)	(-0.45)			
Analyst forecast bias				-0.523***	-0.255***			
				(-4.80)	(-4.26)			
Observations	8,696	6,737	7,196	10,507	4,005	10,507	10,507	10,507
Adjusted R-squared	0.434	0.504	0.445	0.417	0.575	0.747	0.838	0.418

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Table 1. Summary statistics

This table provides the summary statistics of dependent and independent variables. All continuous control variables are winsorized at the 1st and 99th percentiles. Panel A shows the summary statistics for the CEO connections while Panel B provides the statistics for variables relating to the costs of equity and other control variables. The sample consists of 10,507 firm-year observations from 2003 to 2014. *Cost of equity – Mean* is the average of implied cost of equity estimates calculated following the four methodologies presented in Claus and Thomas (2001) (CT), Gebhardt *et al.* (2001) (GLS), Easton (2004) (MPEG), and Ohlson and Juettner-Nauroth (2005) subtracted by the 10-year treasury yield. *Cost of equity – HDZ* is the implied cost of equity estimates calculated following Hou *et al.* (2012). *CEO connections* is the number of directors and executives with whom the CEO is connected to via employment, university, or social connections. *Employment connections* is the number of CEO's pre-existing connections from his previous job positions; *Education connections* is the number of CEO's connections from educational institutions; and *Other social connections* is the number of connections from charities, clubs etc. *Firm size* is the natural log of market value of equity. *Book to market* is the natural log of book value of equity to market value of equity. *Leverage* is long-term debt divided by the market value of equity. *Momentum* is the natural log of one plus the compounded stock return over the previous 12 months. *Beta* is estimated from the market model regressing daily stock returns over the prior 12 months on the corresponding CRSP value-weighted market returns. *Idiosyncratic risk* is the standard deviation of the residuals from the market model. *Forecast dispersion* is the standard deviation of one year ahead earnings per share forecast. *Long-term growth* is the long-term growth rate forecasted by analysts.

	Mean	**S.D.**	**P25**	**Median**	**P75**
Panel A. CEO connections					
CEO connections	135.048	153.199	37.000	75.000	170.000
- Employment connections	52.761	59.568	23.000	37.000	59.000
- Education connections	9.104	20.251	0.000	0.000	10.000
- Other social connections	72.286	117.568	1.000	23.000	89.000
Panel B. Cost of equity variables and controls					
Cost of equity - Mean	5.745	3.812	3.729	5.255	7.022
Cost of equity - CT	4.377	3.209	2.549	4.052	5.745
Cost of equity - GLS	4.030	2.808	2.125	3.824	5.565
Cost of equity - OJ	7.341	3.473	5.093	6.788	8.858
Cost of equity - MPEG	6.840	4.137	4.199	6.154	8.597
Cost of equity – HDZ	6.479	6.290	2.793	4.951	8.360
Firm size	8.123	1.465	7.040	7.966	9.085
Book to market	-0.934	0.650	-1.313	-0.875	-0.486
Leverage	0.278	0.386	0.022	0.149	0.367
Momentum	0.111	0.290	-0.050	0.125	0.280
Beta	1.024	0.364	0.757	0.996	1.255
Idiosyncratic risk	0.017	0.008	0.012	0.016	0.021
Forecast dispersion	0.081	0.105	0.030	0.050	0.090
Long-term growth	13.398	6.410	10.000	12.500	15.750

Table 2. CEO connections and cost of equity

This table provides regression results relating CEO connections to the cost of equity capital for 10,507 firm-year observations from 2003 to 2014. The dependent variable in Columns 1 to 3 is *Cost of equity – Mean*, the average of implied cost of equity estimates calculated following the four methodologies presented in Claus and Thomas (2001) (CT), Gebhardt *et al.* (2001) (GLS), Easton (2004) (MPEG), and Ohlson and Juettner-Nauroth (2005) (OJ) and is in excess of the 10-year treasury yield. The dependent variables in Columns 4 to 7 are the cost of equity estimates, in excess of the risk-free rate, from CT, GLS, OJ, and MPEG respectively. Column 8 uses the implied cost of equity following Hou *et al.* (2012) as the dependent variable. *CEO connections* is the number of executives and directors that the CEO is connected to via employment, university, and other social connections. All other variable descriptions can be found in Appendix B. All independent variables are standardized to have mean zero and standard deviation one. All specifications include year fixed effects and industry fixed effects. Industries are defined at the 2-digit SIC level. The *t*-statistics with standard errors clustered at the firm level are reported in parentheses. *, **, and *** denote significance at 10%, 5%, and 1%, respectively.

	Dependent variable =							
	Cost of equity – Mean			CT	GLS	OJ	MPEG	HDZ
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
CEO connections	0.232***	0.227***	0.223***	0.238***	0.062	0.300***	0.293***	0.669***
	(3.16)	(3.08)	(3.03)	(2.70)	(0.78)	(4.51)	(3.29)	(7.83)
Firm Size	-0.192***	-0.057	-0.008	0.115	0.027	-0.059	-0.116	-2.626***
	(-2.59)	(-0.76)	(-0.10)	(1.21)	(0.34)	(-0.63)	(-1.20)	(-20.43)
Book to market	0.433***	0.425***	0.436***	0.338***	0.775***	0.238***	0.395***	0.0628
	(7.96)	(7.83)	(7.98)	(5.65)	(11.62)	(3.26)	(5.69)	(0.59)
Leverage	0.570***	0.512***	0.496***	0.481***	0.340***	0.633***	0.530***	0.765***
	(8.18)	(7.45)	(7.20)	(6.34)	(5.39)	(7.45)	(5.71)	(6.23)
Momentum	-0.736***	-0.753***	-0.746***	-0.695***	-0.529***	-0.910***	-0.849***	-0.934***
	(-18.67)	(-19.31)	(-18.76)	(-15.03)	(-16.14)	(-17.85)	(-14.81)	(-11.68)
Forecast dispersion	1.210***	1.179***	1.168***	1.208***	1.026***	1.020***	1.416***	0.363***
	(6.40)	(6.22)	(6.10)	(5.43)	(5.28)	(6.82)	(6.33)	(3.92)
Long-term growth	0.344***	0.290***	0.266***	0.362***	-0.111*	0.508***	0.305***	-0.418***
	(5.65)	(4.66)	(4.11)	(4.87)	(-1.76)	(7.10)	(3.91)	(-5.10)
Beta		0.410***	0.355***	0.289***	0.201***	0.357***	0.574***	0.0628
		(8.77)	(7.51)	(5.17)	(4.59)	(6.09)	(8.82)	(0.55)
Idiosyncratic risk			0.163**	0.074	0.056	0.054	0.469***	0.924***
			(2.23)	(0.89)	(0.82)	(0.54)	(4.85)	(6.01)
Observations	10,507	10,507	10,507	10,507	10,507	10,507	10,507	10,495
Adjusted R-squared	0.392	0.399	0.400	0.310	0.402	0.326	0.363	0.322

Table 3. Regression with alternative specifications of CEO connections

This table reports results using alternative specifications for CEO connections. The dependent variable is *Cost of equity – Mean*, the average of implied cost of equity estimates calculated following the four methodologies presented in Claus and Thomas (2001) (CT), Gebhardt *et al.* (2001) (GLS), Easton (2004) (MPEG), and Ohlson and Juettner-Nauroth (2005) (OJ) and is in excess of the 10-year treasury yield. *CEO connections* is the number of executives and directors that the CEO is connected to via employment, university, and other social connections. *Residual CEO connections* is the residual from regressing *CEO connections* on firm size. Column 2 uses the natural log of *CEO connections* as the main independent variable. Column 3 uses the percentile rank of *CEO connections* as the main independent variable. Column 4 uses the scaled percentage of *CEO connections*, which is the number of CEO connections divided by the total of connections across all CEOs for a given year, as the main independent variable. All independent variables are standardized to have mean zero and standard deviation one. All specifications include the control variables listed in Table 2 Column 3, year fixed effects, and industry fixed effects. Industries are defined at the 2-digit SIC level. All variable descriptions can be found Appendix B. The *t*-statistics with standard errors clustered at the firm level are reported in parentheses. *, **, and *** denote significance at 10%, 5%, and 1%, respectively.

	(1)	(2)	(3)	(4)
Residual CEO connections	0.181***			
	(3.03)			
Log(CEO connections)		0.129**		
		(2.09)		
Percentile CEO connections			0.128**	
			(2.19)	
Scaled CEO connections				0.098*
				(1.79)
Controls	Yes	Yes	Yes	Yes
Observations	10,507	10,507	10,507	10,507
Adjusted R-squared	0.400	0.398	0.398	0.398

Table 4. Endogeneity test: Propensity score matching

This table presents results for the propensity score matched sample analysis where firms in the above median *CEO connections* are matched to firms in the below median group. The matching starts with a logit regression in which the dependent variable is an indicator equals one if the firm-year falls in the above median *CEO connections* group and zero otherwise. We use two sets of matching covariates – the first set consists of the explanatory variables in the baseline regression in Table 2, Column 3, the second set further includes CEO characteristics and CEO pay structure. Then, using the estimated predicted probabilities from the logit regressions, we match to each high *CEO connections* observation a low *CEO connections* observation. We employ kernel matching and one-to-one nearest neighbor matching without replacement. The match is done within the same industry and same year. Panel A reports the mean comparison of covariates for the matching specification that includes additional CEO matching covariates and using kernel matching with bandwidth of 0.0005. Panel B compares the average cost of equity for the high *CEO connections* group and low *CEO connections* group matched using various matching methods and specifications. (1) compares the cost of equity for the samples matched using kernel matching with bandwidth 0.00025 and without CEO covariates. (2) compares the cost of equity for the samples matched using kernel matching with bandwidth of 0.0005 and including CEO characteristics as additional matching covariates. (3) compares the cost of equity for the samples matched using one-to-one nearest neighbor matching without replacement and without additional CEO covariates and we require the propensity score to be within +/- 0.0085 of each other. (4) compares the cost of equity for the samples matched using one-to-one nearest neighbor matching without replacement with additional CEO covariates and require the propensity score of each matched pair to be within +/- 0.025 of each other. The *t*-statistics tests whether the difference between the two groups of firms are significantly different from zero. Industries are defined at 2-digit SIC level. All matching covariates are standardized to have mean zero and standard deviation one. All variable descriptions can be found in Appendix B. *, **, and *** denote significance at 10%, 5%, and 1%, respectively.

Panel A. Covariate comparison

Variable	**High Conn.**	**Low Conn.**	**Diff.**	***t*-statistics**
Propensity score	0.5118	0.5116	0.0002	0.02
Firm size	-0.0188	-0.0421	0.0232	0.68
Book to market	0.0498	0.0657	-0.0159	-0.38
Leverage	-0.0050	0.0279	-0.0328	-0.82
Momentum	0.0092	-0.0217	0.0309	0.78
Analyst forecast dispersion	-0.0797	-0.0749	-0.0048	-0.13
Long-term growth	-0.0715	-0.0738	0.0023	0.06
Beta	-0.0263	-0.0713	0.0450	1.11
Idiosyncratic risk	-0.0929	-0.1024	0.0094	0.25
Log (Tenure)	-0.0182	0.0147	-0.0329	-0.82
Log (CEO age)	-0.0197	-0.0935	0.0738	1.76*
CEO delta	-0.0939	-0.0609	-0.0330	-1.12
CEO vega	0.0351	0.0090	0.0260	0.59
Cash compensation	0.0014	-0.0210	0.0225	0.61
General ability index	0.0653	0.0334	0.0319	0.76
Ivy	0.0934	0.0970	-0.0036	-0.29
Overconfidence	0.3345	0.3287	0.0058	0.29

Panel B. Test of difference in cost of equity for matched samples

Cost of equity (1)	5.7710	5.4113	0.3597	2.28**
Cost of equity (2)	5.7359	5.3785	0.3574	2.40**
Cost of equity (3)	5.7009	5.3569	0.3440	1.95*
Cost of equity (4)	5.7331	5.4124	0.3207	2.04**

Table 5. Endogeneity test: Test of causality around CEO turnover

This table presents the results of difference-in-difference tests to address reverse causality concerns. We focus on the time surrounding CEO turnovers, where Year *T* is the year containing the turnover. Panels A to D examine how future cost of equity changes when CEO network size changes due to turnover events. Panel A looks at the cost of equity change from *T* to *T*+1 and Panel B from *T* to *T*+2. Panel C looks at the cost of equity change from *T-1* to *T*+1 and Panel D from *T-1* to *T*+2. The sample of turnovers are divided into four quartiles based on the change in *CEO connections* from *T*-1 to *T*. Panel E presents the effect of implied cost of equity changes from *T*-2 to *T*-1 on CEO's connections changes arising from CEO turnover. All variable descriptions can be found in Appendix B. *, **, and *** denote significance at 10%, 5%, and 1%, respectively.

Panel A: Effect of CEO connections change (*T*-[*T*-1]) on future change in cost of equity ([*T*+1] – *T*)

Dependent variable: Δ Cost of equity ([*T*+1] -*T*)				
CEO connections change quartile groups	Obs	Mean	Diff-in-Diff	T-Stat
Δ CEO's connections (*T*-[*T*-1]) ≤ 25%	135	-0.1830	0.0027	0.0097
Δ CEO's connections (*T*-[*T*-1]) ≥ 75%	134	-0.1803		

Panel B: Effect of CEO connections change (*T*-[*T*-1]) on future change in cost of equity ([*T*+2] – *T*)

Dependent variable: Δ Implied Cost of equity ([*T*+2] -*T*)				
CEO connections change quartile groups	Obs	Mean	Diff-in-Diff	T-Stat
Δ CEO's connections (*T*-[*T*-1]) ≤ 25%	101	-0.2885	0.6946	1.9624**
Δ CEO's connections (*T*-[*T*-1]) ≥ 75%	104	0.4062		

Panel C: Effect of CEO connections change (*T*-[*T*-1]) on future change in cost of equity ([*T*+1] – [*T*-1])

Dependent variable: Δ Cost of equity ([*T*+1] –[*T*-1])				
CEO connections change quartile groups	Obs	Mean	Diff-in-Diff	T-Stat
Δ CEO's connections (*T*-[*T*-1]) ≤ 25%	98	-0.2583	0.5688	1.5416
Δ CEO's connections (*T*-[*T*-1]) ≥ 75%	97	0.3106		

Panel D: Effect of CEO connections change (*T*-[*T*-1]) on future change in cost of equity ([*T*+2] – [*T*-1])

Dependent variable: Δ Implied Cost of equity ([*T*+2] –[*T*-1])				
CEO connections change quartile groups	Obs	Mean	Diff-in-Diff	T-Stat
Δ CEO's connections (*T*-[*T*-1]) ≤ 25%	63	0.1795	1.0218	2.1105 **
Δ CEO's connections (*T*-[*T*-1]) ≥ 75%	75	1.2013		

Panel E: Effect of past cost of equity change ([*T*-1]-[*T*-2]) on change in CEO connections (*T*-[*T*-1])

Dependent variable: Δ CEO's connections (*T*-[*T*-1])				
Cost of equity change quartile groups	Obs	Mean	Diff-in-Diff	T-Stat
Δ Implied Cost of equity ([*T*-1]-[*T*-2]) ≤ 25%	115	-11.2261	9.5202	0.4961
Δ Implied Cost of equity ([*T*-1]-[*T*-2]) ≥ 75%	119	-1.7059		

Table 6. Additional tests – Individual CEO connections components

This table shows the regression results of regressing the cost of equity on the various types of CEO connections. The dependent variable is *Cost of equity – Mean*, the average of implied cost of equity estimates calculated following the four methodologies presented in Claus and Thomas (2001) (CT), Gebhardt *et al.* (2001) (GLS), Easton (2004) (MPEG), and Ohlson and Juettner-Nauroth (2005) (OJ) and is in excess of the 10-year treasury yield. *Employment connections* is the number of CEO's pre-existing connections from his previous job position. *Education connections* is the number of CEO's connections from educational institution. *Other social connections* is the number of connections from charities, clubs etc. *Non-Ivy League connections* is the number of CEO's education connections arising from non-Ivy League educational institution. *Ivy League connections* is the number of CEO's education connections arising from Ivy League educational institution. All independent variables are standardized to have mean zero and standard deviation one. All specifications include the control variables from Table 2 Column 3, year fixed effects, and industry fixed effects unless noted otherwise. Industries are defined at the 2-digit SIC level. All variable descriptions can be found in Appendix B. *t*-statistics with standard errors clustered at the firm level are reported in parentheses. *, **, and *** denote significance at 10%, 5%, and 1%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Employment connections	0.229**			0.213**			
	(2.50)			(2.28)			
Education connections		-0.138***		-0.162***			
		(-2.68)		(-3.09)			
Other social connections			0.179***	0.172**			
			(2.69)	(2.52)			
Non-Ivy League connections					-0.027		-0.042
					(-0.44)		(-0.69)
Ivy League connections						-0.125***	-0.130***
						(-2.83)	(-2.89)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	10,507	10,507	10,507	10,507	10,507	10,507	10,507
Adjusted R-squared	0.400	0.399	0.399	0.403	0.398	0.399	0.399

Table 7. Additional tests – Support for agency channel

This table shows the cross-sectional regression results by governance measures. The dependent variable is *Cost of equity – Mean*, the average of implied cost of equity estimates calculated following the four methodologies presented in Claus and Thomas (2001) (CT), Gebhardt *et al.* (2001) (GLS), Easton (2004) (MPEG), and Ohlson and Juettner-Nauroth (2005) (OJ) and is in excess of the 10-year treasury yield. CEO connections is the number of executives and directors that the CEO is connected to via employment, university, and other social connections. *Intense monitor* is an indicator variable equals to one if the majority of independent directors serves on at least two of three monitoring intensive committee (audit, compensation, and nominating) following Faleye *et al.* (2011), and zero otherwise. *Small board* is an indicator variable equals to one if the board size is smaller than the median for the year, and zero otherwise. *High audit* is an indicator variable equals to one if the number of audit committee members to board size is greater than the median for the year, and zero otherwise. *High CEO own.* is an indicator variable equals to one if the CEO ownership percentage is greater than the median for the year, and zero otherwise. *ICD* is an indicator variable that equals to one if the firm has any internal control deficiencies, and zero otherwise. *CEO-Dir Indicator* is an indicator variable equals to one if the CEO is socially connected to at least one independent director on the board and zero otherwise. All variable descriptions can be found in Appendix B. All continuous independent variables are standardized to have mean zero and standard deviation one. All specifications include the control variables listed in Table 2 Column 3, year fixed effects, and industry fixed effects unless noted otherwise. Industries are defined at 2-digit SIC level. The *t*-statistics with standard errors clustered at the firm level are reported in parentheses. *, **, and *** denote significance at 10%, 5%, and 1%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
CEO connections (a)	0.262***	0.207***	0.297***	0.330***	0.209***	0.242***
	(3.81)	(2.77)	(3.52)	(3.79)	(2.70)	(3.02)
Intense monitor	-0.093					
	(-0.87)					
(a) X Intense monitor	-0.486***					
	(-2.78)					
Small board		-0.300***				
		(-3.19)				
(a) X Small board		-0.255**				
		(-2.17)				
High audit			0.033			
			(0.41)			
(a) X High audit			-0.310**			
			(-2.37)			
High CEO own.				-0.429***		
				(-4.33)		
(a) X High CEO own.				-0.273**		
				(-2.17)		

ICD					0.561	
					(0.84)	
(a) X ICD					0.820	
					(0.84)	
CEO-Dir Indicator						-0.021
						(-0.43)
(a) X CEO-Dir Indicator						-0.037
						(-1.35)
Observations	8,552	8,552	7,183	10,395	10,507	10,507
Adjusted R-squared	0.446	0.445	0.499	0.405	0.401	0.400

Table 8. Additional tests - Passage of governance proposals and subsample by CEO connections

This table reports the regression-discontinuity design for the passage of governance-improving proposals following Cuñat *et al.* (2012). The regression takes the form of $y_{i,t+1} = \alpha \cdot Pass_{i,t} + Polynomials_{i,t} + Year\ fixed\ effects + u_{i,t}$. The dependent variable is *Cost of equity – Mean,* the average of implied cost of equity estimates calculated following the four methodologies presented in Claus and Thomas (2001) (CT), Gebhardt *et al.* (2001) (GLS), Easton (2004) (MPEG), and Ohlson and Juettner-Nauroth (2005) (OJ) and is in excess of the 10-year treasury yield. The main independent variable *Pass* is an indicator variable that equals to one if the shareholder's proposal to improve corporate governance has received more than the threshold percentage of vote, and zero otherwise. Polynomials are computed as the vote results for each proposals in percentages minus the threshold percentage to pass the proposal. Polynomials up to 2nd order are included in the regression specification. Column 1 uses the entire sample. Column 2 uses the group of firms with below median *CEO connections*. Column 3 shows the result for the group of firms with above median *CEO connections*. All specifications include year fixed effect. The *t*-statistics with standard errors clustered at the firm level are reported in parentheses.*, **, and *** denote significance at 10%, 5%, and 1%, respectively.

	Full Sample	Low CEO connections	High CEO connections
	(1)	(2)	(3)
Pass	-0.877**	-1.119**	-0.710
	(-2.23)	(-2.18)	(-1.31)
Controls	No	No	No
Polynomials	2	2	2
Year Fixed Effects	Yes	Yes	Yes
Observations	2,455	1,243	1,212
Adjusted R^2	0.085	0.165	0.048

Table 9. Additional tests - Support for risk-taking channel

This table provides evidence in support of the risk-taking channel impact of CEO connections. In Panel A, we divide the sample into two groups based on the median age of the CEOs and run the baseline regression in Table 2 Column 3. The *Chi*^{2} test whether the coefficients of *CEO connections* are significantly different across the two subsamples. Panel B shows the regression results where cost of equity is regressed on the CEO's connections to rival firms, non-rival firms, customer-supplier firms, and non-customer-suppler firms. The regression specification follows that in Table 2 Column 3. *Rival connections* (*Non-rival connections*) is the number of executives and directors working in rival firms (non-rival firms) that the CEO is connected to via employment, university, and other social connections. Rival firms are defined as those in the same three-digit SIC industry as the focal firm. *Customer-supplier connections* (*Non-customer-supplier connections*) is the number of executives and directors working (not working) in customer or supplier industries that the CEO is connected to via employment, university, and other social connections. Panel C shows results where we regress proxies for risk-taking against *CEO connections*. The risk-taking proxies are rescaled to show less decimal points. The control variables include the ones used in Table 2 Column 1 where systematic and unsystematic risks are excluded. Panel D presents the regression results of CEO connections on cost of equity for the subsample of long-term tenured CEOs. All variable descriptions can be found in Appendix B. All independent variables are standardized to have mean zero and standard deviation one, except for the main independent variables in Panel B. All specifications include the control variables listed in Table 2 Column 3, year fixed effects, and industry fixed effects unless noted otherwise. Industries are defined at 2-digit SIC level. The *t*-statistics with standard errors clustered at the firm level are reported in parentheses. *, **, and *** denote significance at 10%, 5%, and 1%, respectively.

Panel A. Impact of CEO age

	(1) Young CEOs	(2) Old CEOs
CEO connections	0.343***	0.127*
	(3.81)	(1.66)
Chi^2	7.7***	
Observations	4,926	5,581
Adjusted R-squared	0.412	0.398

Panel B. CEO connections to competitors/customer-suppliers

	(1)	(2)	(3)	(4)	(5)	(6)
Rival connections	0.012***		0.007**			
	(3.30)		(2.16)			
Non-rival connections		0.001**	0.001**			
		(2.93)	(2.42)			
Customer-supplier connections				0.024***		0.019**
				(3.50)		(2.69)
Non-customer-supplier connections					0.001**	0.001*
					(2.87)	(1.95)
Chi^2	10.01***			11.42***		
F-Statistics			3.05*			6.17**
Observations	10,507	10,507	10,507	10,507	10,507	10,507
Adjusted R-squared	0.399	0.400	0.400	0.400	0.400	0.401

Panel C. CEO connections and risk-taking behavior

	Stock Return Volatility (x100)	**Earnings Volatility (x100)**	**Log (R&D)**	**Log (CAPEX) (x100)**	**Accrual (x100)**	**Systematic Risk (x100)**	**Idiosyncratic Risk (x100)**
CEO connections	0.024**	0.196**	0.201***	-0.298**	0.203**	0.395	0.027***
	(2.31)	(2.54)	(4.25)	(-2.33)	(2.33)	(0.74)	(2.73)
Observations	10,507	9,654	10,507	10,507	9,054	10,507	10,507
Adjusted R-squared	0.674	0.170	0.676	0.508	0.050	0.383	0.576

Panel D. Separating by CEO tenure

	(1) CEO Tenure > 4 Years	(2) CEO Tenure > 6 Years
CEO connections	0.191***	0.141**
	(2.67)	(2.02)
Observations	6,939	5,236
Adjusted R-squared	0.407	0.433

Table 10. Additional tests – Support for information asymmetry channel

This table presents the results supporting information asymmetry channel of CEO connections. Panel A shows the cross-sectional regression results by information asymmetry measures. The dependent variable is *Cost of equity – Mean*, the average of implied cost of equity estimates calculated following the four methodologies presented in Claus and Thomas (2001) (CT), Gebhardt *et al.* (2001) (GLS), Easton (2004) (MPEG), and Ohlson and Juettner-Nauroth (2005) (OJ) and is in excess of the 10-year treasury yield. CEO connections is the number of executives and directors that the CEO is connected to via employment, university, and other social connections. *Small size* is an indicator variable equals to one if the market value of equity is below the sample median for the year, and zero otherwise. *High accrual* is an indicator variable equals to one if the accrual is higher than sample median for the year and zero otherwise. *High bid-ask* is an indicator variable equals to one if the bid-ask spread is higher than the sample median for the year, and zero otherwise. *Few analysts* is an indicator variable equals to one if the number of analysts following the firm is below the sample median for the year, and zero otherwise. *High volatility* is an indicator variable equals to one if the stock return volatility is above sample median for the year, and zero otherwise. Panel B shows the regression results for bank (non-bank) connections and financier (non-financier) connections as the explanatory variable. *Bank (non-bank) connections* are CEO connections to executives and directors working (not working) in the banking industry. *Financier (non-financier) connections* are CEO connections to executives and directors working (not working) in the firms classified as 'banks', investment companies', 'private equity', or 'specialty and other finance' in Boardex. All variable descriptions can be found in Appendix B. All independent variables are standardized to have mean zero and standard deviation one. All specifications include the control variables listed in Table 2 Column 3, year fixed effects, and industry fixed effects unless noted otherwise. Industries are defined at 2-digit SIC level. The *t*-statistics with standard errors clustered at the firm level are reported in parentheses. *, **, and *** denote significance at 10%, 5%, and 1%, respectively.

Panel A. Cross-sectional regression results by information asymmetry measures

	(1)	(2)	(3)	(4)	(5)
CEO connections: (a)	0.344***	0.272***	0.316***	0.304***	0.304***
	(4.01)	(3.07)	(4.29)	(3.60)	(3.49)
Small size	-0.124				
	(-0.72)				
(a) X Small size	-0.458***				
	(-3.57)				
High accrual		0.169***			
		(2.61)			
(a) X High accrual		-0.073			
		(-1.06)			
High bid-ask			0.106		
			(1.46)		
(a) X High bid-ask			-0.276**		
			(-2.10)		
Few analysts				0.175*	
				(1.83)	
(a) X Few analysts				-0.231**	
				(-2.00)	
High volatility					0.014
					(0.14)
(a) X High volatility					-0.266**
					(-1.97)
(a) + Interaction (*p*-value)	0.2956	0.0059	0.7598	0.4806	0.7352
Observations	10,507	9,057	10,277	10,507	10,507
Adjusted R-squared	0.402	0.445	0.406	0.401	0.401

Panel B. Bank (non-bank) connections

	(1)	(2)	(3)	(4)
Bank connections	0.119	-0.635*		
	(0.74)	(-1.79)		
Non-bank connections	0.083	0.801**		
	(0.57)	(2.05)		
Financier connections			0.150	0.358
			(1.16)	(1.63)
Non-financier connections			0.079	-0.063
			(0.69)	(-0.26)
Firm FE	No	Yes	No	Yes
Industry FE	Yes	No	Yes	No
Year FE	Yes	Yes	Yes	Yes
Observations	10,507	10,507	10,507	10,507
Adjusted R-squared	0.399	0.748	0.400	0.747

When to ally? Labor protection and firm growth strategies

ABSTRACT

We study how increases in employment protection through the passage of state laws affect strategic alliance formation and firm's choice of growth strategy. We show that, following the adoption of these laws, there is a significant increase in strategic alliance activities, especially among high growth firms. More importantly, there is a shift away from capital-intensive investments, such as internal capital expenditures and M&As towards the more flexible strategic alliance. We also find that firms that form strategic alliances following the adoption of the law have higher innovation output. Overall, our findings are consistent with employment protection making investments within the firm more irreversible and leading them to seek alternative growth strategies by moving investments outside their boundaries through strategic alliance formation.

"The greatest change in the way business is being conducted is the accelerating growth of relationships based not on ownership but on partnership."

Peter Drucker, Keynote Speech, Collaborative Commerce Summit, June 2001.

1. Introduction

Firms can grow in a multitude of ways – internal organic investments, external mergers and acquisitions (M&As), and entering into strategic alliances with other companies. How do firms trade off among these growth strategies and thereby determine their boundaries? We propose that employment protection is an important determinant of firms' strategic growth choices. Past empirical findings suggest that labor protection is intricately associated with firm growth. However, less is understood about how increased labor protection affect the *choice* of growth strategy and how labor laws affect the ways firms choose to construct their boundaries. To fill this gap in the literature, we use the staggered adoption of Wrongful Discharge Laws (WDLs) by U.S. state courts that increases the cost of discharging employees and show that increased employee protection leads firms to move their investments outside their firm boundaries through entering into strategic alliances with other firms. At the same time, the *same* firms are substituting away from internal capital investments and M&As.

There are several ways for a firm to grow. A firm can grow through internal organic growth, such as capital expenditures, and through non-organic M&As or strategic alliances (Bodnaruk, Massa, and Simonov, 2013). While each of these growth strategies pursue firm growth, the choice among internal capital expenditures, M&As, and strategic alliances are considered as alternative ways for firms to grow (e.g., Kogut and Singh, 1988; Mathews and Robinson, 2008; Robinson, 2008; Bodnaruk *et al.*, 2013), each with their own costs and benefits.[1] Yet, there is very little empirical work on understanding how firms grow and what affects their choice of growth strategies (Bodnaruk *et al.*, 2013). Furthermore, most papers have focused on examining the determinants of internal capital expenditures and external M&As. In contrast, less is done to understand the determinants of strategic alliances. Previous works document that strategic alliances not only generate firm value (e.g., Chan, Kensinger, Keown, and Martin, 1997; Bodnaruk *et al.*, 2013) but also require relatively smaller investments (e.g., Kogut and Singh, 1988) that are easily reversible with low cost (Balakrishnan and Koza, 1993). Therefore, even though relatively overlooked thus far by researchers, alliances can be attractive means for firms to pursue growth.

Strategic alliance is not without limitations and it has potential negative downsides to it. Although strategic alliances allow for sharing of risks among the entities involved, the benefits generated from the strategic alliance operation would also have to be shared (PWC, 2016). In addition, there has to be careful coordination and execution among the multiple management teams involved, otherwise overall operations from the strategic alliance may slow down. Bonatti and Hörner (2011) point out that free-riding could become a problem in collaborating work between partners and it can also lead to procrastination. Finally, there are potential hold-up problems that can arise from incomplete contracts between the strategic alliance parties. According to Coase (1937), firms choose their boundaries to minimize transaction costs, and previous works, such as Klein, Crawford, and Alchian (1978) and Williamson (1979) suggest that vertical integration rather than entering into contractual agreements can minimize hold-up issues. Therefore, due to these issues, bringing operations within the boundaries of the firm may be preferred.

[1] Dyer, Kale, and Singh (2004) conducted a survey in 2002 targeting executives from 200 U.S. companies on their views about acquisitions and strategic alliances. 82% of executives responded that they view acquisitions and strategic alliances as alternative ways to achieve the same growth goals.

A firm's resource is finite, thus, it needs to decide on how to make the best use of its limited assets in order to sustain growth and to expand operations. Most often the investment decision accompanies hiring or reallocation of labor forces, which is unarguably one of the most critical components of firm operations and often form the largest proportion among firm expenses. In this paper, we examine the relation between employee firing costs and firm growth through strategic alliance. Employee firing costs constrain a firm from discharging their employees when needed, especially when the investment turns out badly (Serfling, 2016).

Previous research document that increases in firing costs lead to reduction in capital investment and sales growth (Bai, Fairhurst, and Serfling, 2017) and decreases in M&A activities (Chatt, Gustafson, and Welker, 2017).[2] These findings are consistent with firing costs increasing the irreversibility of projects undertaken through internal investments and M&As. The irreversibility of projects makes it more costly and more difficult for firms to scale down on projects and also reduces the net present values (NPVs) of the projects from lower recovery values (e.g., Bernanke, 1983; Pindyck, 1991; Bertola and Caballero, 1994; Abel, Dixit, Eberly, and Pindyck, 1996; Abel and Eberly, 1996). In contrast to internal investments and M&As, non-organic strategic alliances require relatively smaller investments and tend to be easily reversible in case of failure (e.g., Kogut and Singh, 1988; Balakrishnan and Koza, 1993). For example, KPMG International (2017) noted that "… strategic alliances have become an increasingly attractive and flexible alternative – especially for businesses that cannot afford large investments, or at least want to stagger their financial outlays." PWC (2016) makes a similar observation, "A lack of available investment capital or a low appetite for M&A risk is another big motive behind

[2] Chatt *et al.* (2017) writes that the firing costs for mergers are likely to be higher because of the higher likelihood of multiple lawsuits from a large number of employee turnover following mergers.

JVs and alliances." Therefore, we hypothesize that internal capital expenditures and external growth through M&As become less attractive growth options after exogenous increases in employee firing costs, and companies would find strategic alliances as an attractive alternative to circumvent the situation and spur growth.

Similar to Acharya, Baghai, and Subramanian (2014) and Serfling (2016), we use the staggered adoption of WDLs as a natural experiment to identify the effect of employment protection on firm's choice of growth strategies with particular focus on strategic alliance activity. WDLs increase the success rate of fired employees winning lawsuits against their former employers, as a consequence, increasing the costs associated with discharging or firing employees. The laws consist of three exceptions to the employment-at-will doctrine that are designed to protect employees against unjust discharge of workers: good faith, implied contract, and public policy exceptions. Our focus is on the good faith exception, which allows the workers discharged for 'bad cause' to file lawsuits under both contract and tort law. Therefore, the good faith exception enables employees to recover contractual losses as well as punitive damages (i.e., for emotional distress). In many cases, compensation for punitive damages outweigh that of contractual losses. Thus, the good faith exception is deemed the most far reaching among the three exceptions and it has substantial effect on firms (e.g., Dertouzos and Karoly, 1992; Kugler and Saint-Paul, 2004).

We use the difference-in-differences approach on a panel of 73,999 firm-year observations from 1985 to 2003 to test the impact of employment protection on strategic alliance activities. We find that the adoption of the good faith exception is followed by a 3.67% increase in strategic alliance activities. This result continues to hold after controlling for various firm, industry, and state level characteristics. We also find that following the increase in employee firing costs due to the adoption of the good faith exception, firms replace internal investments and M&As with strategic alliances. Firms increase their alliance activities especially when they have higher investment opportunities, suggesting that firms are making use of strategic alliances to capitalize on growth opportunities. These findings are consistent with firms trading off the benefits and costs of each growth strategy, and after the law change, the positives of strategic alliances outweigh the negatives, compared to the other two types of strategies.

To infer the causal relationship from difference-in-differences specifications, it is crucial that both treated and control firms do not violate parallel trends assumption prior to the adoption of the good faith exception. It could also be problematic if the adoption of the good faith exception has been influenced by underlying political or economic factors. We show that the parallel trend assumption is satisfied. Furthermore, a reading of the circumstances surrounding WDL adoptions suggests that WDLs are likely to be adopted based on judicial decisions rather than political or economic considerations (e.g., Acharya *et al.*, 2014; Serfling, 2016). Moreover, we also show that strategic alliance activity increases only after (not before) the adoption of the good faith exception, reducing the concern for reverse causality. Lastly, the staggered adoption of good faith exception in different states at different points in time naturally creates multiple treatment and control groups reducing bias and noise associated with a single shock (Roberts and Whited, 2013).

To ensure balanced covariates between treatment firms (firms that are subject to the good faith exception) and control firms, we also use propensity score matching to select control firms. The results from the difference-in-differences analysis using the matched samples are stronger and show that strategic alliance activities increase after the law has been adopted.

As a further robustness check, we run cross-sectional tests using triple-difference regression models for firms with high cash flow volatility and firms with a single segment. The intuition is that we should see the greatest impact of the law change on firms that are most likely to discharge employees pre-law adoption. The likelihood of firms discharging employees increase with cash flow volatility (Cuñat and Melitz, 2012). Firms with a single segment may not be able to avoid adjusting employment in response to negative shocks as they cannot shift workers from one segment to another segment (Tate and Yang, 2015). Consistent with our expectations, we find the increase in alliance deals to be mainly among firms with high cash flow volatility or single segment firms after passage of the law.

We try to reconcile our findings to the theoretical mechanisms through which employment protection increases strategic alliance, namely the investment irreversibility channel. If the adoption of the good faith exception makes it more costly to scale down and fire employees, we should see decreased likelihood of employee downsizing in response to negative shocks post-law adoption. Consistent with our expectations and Bai *et al.* (2017), we find that poorly performing firms are likely to decrease the number of employees but this sensitivity reduces if the firm is headquartered in a state that has adopted the good faith exception. This channel is further corroborated by the finding that innovative firms engage in more alliances after the law passage. Innovative firms engage in risky, longshot projects with higher chances of failure. If these firms choose to do research and development (R&D) internally, they may have to discharge employees in case of the project failure. Therefore, for these innovative firms strategic alliances become a much more viable option after the law change.

We also test for whether limited access to capital is driving the increase in strategic alliance post-law adoption. Good faith exception makes labor costs more fixed in nature, therefore it may raise financial distress costs by increasing firm operating leverage (Serfling, 2016; Bai *et al.*, 2017). If so, we expect to see the increase in strategic alliance activities post-law adoption mainly for the financially constrained firms as strategic alliance is likely to become relatively cheaper and thus a more attractive and plausible form of investment, compared to internal capital expenditures and M&As. Our results do not support this alternative channel.

Finally, we also look at the value implications with respect to strategic alliance formation and the passage of the law. As investments become irreversible, the cost for firms to commit large amounts of investments increases, especially for risky, longshot projects with high chances of failure. Thus, firms may choose to work on risky projects using strategic alliance and less-risky projects internally in order to share risk and avoid dismissing employees when the projects fail.[3] So we expect the adoption of the good faith exception to increase strategic alliance activities followed by increases in innovative output, which can generate firm value (Hall, Jaffe, and Trajtenberg, 2005).[4] Consistent with Acharya *et al.* (2014), we find that firm innovative output increases following the adoption of the good faith exception. In particular, we find that the increase in innovation is significantly larger for the firms that engage in strategic alliance activities following good faith exception adoption. Therefore, the results suggest that labor protection from wrongful termination law increases the usage of strategic alliances as a growth option and it adds value to the firms through amplified innovative capability.

Our paper contributes to several strands of literature. First, we provide evidence of the effect of labor market friction (i.e., firing cost) on firms' decisions to invest and grow. WDLs impact employment decisions (e.g., Dertouzos and Karoly, 1992; Autor, Donohue III, and Schwab, 2006; Autor, Kerr, and Kugler, 2007), innovation (Acharya *et al.*, 2014), and capital structure (Serfling, 2016). In addition, recent papers have shown how employment protection affects M&A

[3] Robinson (2008) notes that strategic alliances may be a more conducive organizational form for longshot innovative projects. Consistent with this, Chemmanur, Shen, and Xie (2016) and Li, Qiu, and Wang (2018) document that strategic alliances accelerate corporate innovation.
[4] Acharya *et al.* (2014) document an increase in innovation output after the adoption of WDLs. They argue that as employees become more immune to being discharged, they are more willing to exert firm-specific effort leading to increase in firm innovation outputs.

activity (Chatt *et al.*, 2017) and internal investment activity (Bai *et al.*, 2017). However, to the best of our knowledge, this paper is the first paper to provide comprehensive evidence that stronger employment protection can induce firms to form more strategic alliances as their preferred growth strategy relative to other options, such as, internal investment and M&As.

Our paper is also related to the literature on the determinants of strategic alliance. Relative to the literature on M&As and capital expenditures, the literature examining the determinants of strategic alliances are much lesser and also just emerging. Extant empirical works find the determinants that spur strategic alliance formation include inter-firm managerial social ties (Yang, Zhu, and Santoro, 2017), governance (Bodnaruk *et al.*, 2013), common equity blockholders (Chemmanur *et al.*, 2016), and technological conglomeration (Li *et al.*, 2018). Our study adds to this emerging literature by documenting that labor protection is an important determinant for firms to choose strategic alliance as a form of growth strategy.

In addition, we contribute to the literature on organization form, firm boundary, and innovation. Robinson (2008) argues that strategic alliances may be more suitable for innovative and high R&D firms, and this argument has been empirically supported in previous research (e.g., Chan *et al.*, 1997; Gomes-Casseres, Hagedoorn, and Jaffe, 2006; Chemmanur *et al.*, 2016; Li *et al.*, 2018). Seru (2014) shows that acquired firms in diversifying mergers experience diminished research incentives and produce less output, and therefore acquirers tend to perform R&D activities outside their firm boundaries using strategic alliances. Our paper contributes to this strand of literature by using a quasi-natural experiment and thereby providing cleaner evidence to show that the formation of strategic alliances due to increased employment protection leads to higher innovative output.

2. Wrongful Discharge Laws

2.1 Institutional background

Traditionally, U.S. states defined the relationship between employer and employee by the "employment-at-will" doctrine. Under this doctrine, employers can freely discharge employees for any reason at any time without the burden of legal liability. However, courts and legislative bodies started viewing the relationship between employer and employees as not being equal, and they started to realize that employers often have structural and economic high ground on employment negotiations (Muhl, 2001). It led many states to develop exceptions to the employment-at-will rule starting in the late 1950s and with massive adoptions from the 1970s. These are typically known as "wrongful discharge laws." They are adopted by court rulings at the state level and allow employees to sue employer for wrongful dismissal. These exceptions mainly protect workers without written contractual agreements or those not covered by the federal laws that aim to safeguard particular types of workers, such as union members, racial minorities, women, the aged, and the disabled (Miles, 2000). These laws developed into three exceptions: good faith, implied contract, and public policy exceptions.

The good faith exception is applicable when an employer discharges an employee without "just cause" and prohibits termination of employees out of bad faith or motivated by malice.[5] There is no clear definition of "just cause" stipulated by law, however, the case of *Enterprise Wire Co. and Enterprise Independent Union* (46 LA 359, 1966) established seven tests to evaluate whether the employer had 'just cause."[6]

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[5] The good faith exception also prohibits employers from depriving employees of the benefits of employment. For example, employer cannot discharge workers just before pensions vest or before their entitled bonus is due.

[6] Employer is deemed to have "just cause" for termination of employment if the following criteria are all satisfied: 1) the employer informed and forewarned the employee advanced notice of disciplinary consequences; 2) the enforced rule or managerial order is reasonable; 3) the employer made effort to discover employee actually violates the rule prior to disciplinary action; 4) the employer's investigation was fair and objective; 5) the employer has evidence of

Implied contract exception applies in situations where the employer has implicitly guaranteed employment unless there is good cause for termination. Firms can avoid lawsuits under the implied contract exception by inserting disclaimers into their handbooks stating that employment-at-will doctrine is applied (Miles, 2000). Lastly, public policy exception prohibits employers from terminating employees for rejecting to violate public policy or refusing to commit legal-wrongdoing. Courts typically limit the application of public policy exception to termination of employment where the employer violated a clearly identifiable legal stipulation (Autor *et al.*, 2007).[7]

The good faith exception represents the largest departure from employment-at-will doctrine, therefore the good faith exception is deemed to be the most far reaching among the three exceptions (e.g., Dertouzos and Karoly, 1992; Miles, 2000; Kugler and Saint-Paul, 2004). In addition, the tort law applicability of the law lets employees recover for punitive damages, which can significantly increase employer's litigation liability with high uncertainty. Also, as prior works suggest, the latter two exceptions may have limited effects on firms. Therefore, following Serfling (2016) our focus of analysis is on the good faith exception and the other two exceptions are treated as additional control variables.

We make an important assumption that the presence of wrongful discharge laws, specifically the good faith exception, increases the probability of winning the lawsuits against the employers, leading to increases in potential legal liability (i.e., firing cost) for firms and that firms pay attention to such increase in firing costs. Prior research has documented various evidences

employee's guilt; 6) the employer has enforced its rules and orders to all employees without discrimination; and 7) the degree of discipline is reasonable given the seriousness of proven offense.

[7] Employers can still face wrongful termination claims for economically justified layoffs if employees believe that their employments have been terminated wrongfully. See *Coelho v. Posi-Seal International, Inc.*, 208 Conn. 106, 544 A.2d 504 (1988).

consistent with this assumption (e.g., Autor *et al.*, 2007; Serfling, 2016; Bai *et al.*, 2017; Chatt *et al.*, 2017); firms seem to adjust financial and investment policies in response to the law change. The direct financial impact of potential lawsuits are also found to be large enough to put a burden on the targeted firm. Jung (1997) examines the verdicts of WDL cases and show that the plaintiffs won nearly half of the cases between 1992 and 1996 and were awarded $1.29 million on average in 1996. The amount recovered for punitive damage accounted for more than half the amount, indicating that punitive damage can be costly. In a more recent work, Boxold (2008) documents that the average amount awarded to the plaintiffs is $0.59 million, with a maximum amount of $5.4 million. Furthermore, in the recent case of *Robert Ward et al. v. Cadbury Schweppes Bottling Group et al.* [8], the management team came up with a discriminatory policy to force older workers out of their jobs. They implemented their policy and harassed the old employees for many years. The court ruled against Cadbury Schweppes Bottling Group and awarded $18.3 million to the six plaintiffs. The amount may not be large enough to have a material impact on large firms, however, there is the possibility of multiple litigations that can significantly increase their legal liabilities (Serfling, 2016). And it is also possible that large legal fees and high settlements may influence the risk-averse managers' behavior (Dertouzos, Holland, and Ebener, 1988).

2.2. The adoption of wrongful discharge laws

The adoption of wrongful discharge laws is based on the precedent-setting cases by the state courts since this law is made not by the legislature but by the judicial decision. Therefore, we follow Autor *et al.* (2006) to identify the precedent-setting cases for the recognition of wrongful discharge laws. However, we recognize Utah as adopting the good faith exception starting in 1989

[8]See *Robert Ward et al. v. Cadbury Schweppes Bottling Group et al.*, Case No. 2:09-cv-03279.

following Walsh and Schwarz (1996), Littler (2009), and Serfling (2016). We use separate indicator variables for the good faith, implied contract, and public policy exceptions to specify whether a state's appellate or Supreme Court sustained the decision to adopt these exceptions to the employment-at-will doctrine. These variables equal to one for the years after the state has adopted the corresponding wrongful discharge laws and zero otherwise. Following previous works, we match these indicator variables to states where each firm's headquarter is located (e.g., Acharya *et al.*, 2014; Serfling, 2016; Bai *et al.*, 2017).[9]

3. Data and empirical methods

3.1. Sample selection

Our strategic alliance sample starts from 1985, the year SDC started providing coverage on strategic alliances, and the sample period ends in 2003, five years after the last passage of the good faith exception in Louisiana.[10] We include all strategic alliance deals from Securities Data Corporation Platinum (SDC) database. Strategic alliances refer to all types of business arrangements made between two or more firms to achieve mutual objectives by sharing and utilizing their resources (Bodnaruk *et al.*, 2013). Therefore strategic alliances include non-R&D related alliances such as marketing alliances, R&D related alliances (RDA) and joint ventures

[9] Compustat provides only the most recent headquarters locations. Serfling (2016) argues that since the majority of plaintiffs in the WDL lawsuits hold important positions within the firm (Dertouzos *et al.*, 1988), using the headquarter state in the test will capture a large portion of the increase in firing costs. Furthermore, using the most recent headquarter states biases against finding any results.

[10] We follow Bai *et al.* (2017) to end the sample period in 2003. The main result continues to hold if we end the sample period in other years, such as 1999, 2000, 2001, or 2002.

(JV).[11] We require the strategic alliance deals to be completed and involve at least one non-financial U.S. firm that can be matched to Compustat.[12]

Our final sample includes all U.S. firms (financial firms are excluded) from the CRSP/Compustat merged database with publicly traded stocks.[13] Firms with no strategic alliance deals recorded in SDC are considered to have not made any deals. The data on U.S. innovation comes from Kogan, Papanikolaou, Seru, and Stoffman (2017), financial data from Compustat, and stock price information from CRSP.[14] Observations are required to have non-missing values for the main variables used in the regressions. Our final sample consists of 73,999 firm-year observations from 10,173 distinct firms, which made 17,587 strategic alliance over our sample period.

The distribution of strategic alliance deals by year and by Fama-French 17 industries classification is presented in Table 1. In Panel A, the number of strategic alliance deals increases over time and peaks in the mid-1990s and declines in the early 2000s. The observation is similar looking at the percentage of firms with at least one strategic alliance deals for the year as shown in Column (3). In Panel B, looking at the number of strategic alliance deals and the percentage of firms engaging in at least one strategic alliance deals across the industries, strategic alliance activities are mostly concentrated in the drugs, chemicals, and machinery and business equipment industries.

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[11] RDA is alliance deals related to R&D activity; JV is an agreement among two or more firms to form a joint venture where a new separate entity is created to achieve a common objective. Outsourcing and leases are not included as these are contractual agreements with monetary payments.

[12] We focus on strategic alliance deals with the status of "Completed/Signed." Schilling (2009) suggests that using both completed and pending strategic alliance can yield a data pattern that may be different from the pattern obtained using completed strategic alliances. Therefore, in untabulated tests, we include the "Pending" deals and find similar results. In another test, we include all strategic alliance deals, including those with unclear status (such as "Letter of intent" or "Rumor"), the results remain similar.

[13] We follow Li *et al.* (2018) to exclude financial firms from our sample. However, our main findings remain unchanged if we also exclude utilities firms.

[14] We thank Kogan *et al.* (2017) for making the data available online at https://iu.app.box.com/v/patents.

3.2. Empirical methods

We adopt a difference-in-differences research design to investigate the relation between the increase in firing cost from the recognition of the good faith exception and strategic alliance activities. We estimate the following regression as the baseline specification:

$$
\begin{aligned}
Log(SA)_{i,s,t} = {} & \alpha_1 GF_{s,t} + \alpha_2 IC_{s,t} + \alpha_3 PP_{s,t} + \beta_1 Firm\ characteristics_{i,s,t-1} \\
& + \beta_2 Industry\ characteristics_{i,s,t-1} + \beta_3 State\ characteristics_{s,t-1} \\
& + Industry\ fixed\ effect + Year\ fixed\ effect + \varepsilon_{i,s,t}
\end{aligned}
$$

where the dependent variable is the natural logarithm of one plus the number of strategic alliance deals for firm i headquartered in state s for a given year t. The variables *GF*, *IC*, and *PP* are indicator variables that take the value of one if state *s* adopts the good faith, implied contract, and public policy exceptions by year *t* and zero otherwise, respectively. We include industry fixed effects at the 2-digit SIC level and year fixed effects, and cluster standard errors by the headquarter state following the suggestion by Bertrand, Duflo, and Mullainathan (2004). We also check for the robustness of our results using industry-year fixed effects and firm and year fixed effects.

We include control variables for firm and industry characteristics that are frequently used in strategic alliance regressions (e.g., Bodnaruk *et al.*, 2013; Chemmanur *et al.*, 2016; Li *et al.*, 2018). They are *Log(Assets), R&D, Cash, Sales growth, Log(Firm age), ROA, Fixed assets, Leverage, Capex, Tobin's Q, HHI index, and Market share*. We also include several state-level characteristics to control for the state's economic and political conditions following Serfling (2016). These variables include *State GDP per capita*, *State GDP growth*, *Democrats*, *State unemployment rate,* and *Circuit state's GF*. The appendix provides detailed descriptions of the variables used.

The staggered adoption of WDLs by the U.S. state courts at different states at different times has an added advantage. It allows firms to be in the control group, i.e., the firms headquartered in the states that have not adopted the good faith exception, at one point in time and in the treatment group, i.e., the firms headquartered in the states that have adopted the good faith exception, at other times. Therefore, the staggered adoption reduces the concern about big differences between treatment and control groups (Serfling, 2016). The key identifying assumption is that the average change in strategic alliance activities would evolve similarly for both treatment and control firms if it were not for the adoption of the law, and the identification comes from comparing the firms headquartered in states that adopt the law against the firms headquartered in states that have not adopted the law.

The summary statistics are presented in Table 2. All continuous variables (except state-level variables) are winsorized at the 1st and 99th percentiles, and all dollar values are adjusted for CPI to 2004 dollars. Panel A shows the summary statistics for the full sample, and Panel B makes the comparison of means for the firms headquartered in states that adopt the good faith exception at some point in time and the firms headquartered in states that never adopt this law. On average, a firm in the treatment group tends to be smaller with higher R&D spending. All variables are significantly different between treatment and control samples, therefore, we include these variables as controls in our regressions.

4. Empirical results

4.1. The timing of the passage of the good faith exception

Our tests rely on the assumption that the adoption of the good faith exception is not related to the prior year's strategic alliance activities of the firms headquartered in that state and state-level political and economic factors. If the adoption of the law is systematically driven by state-level political and economic conditions, then the parallel trends assumption would be violated. The parallel trends assumption states that the strategic alliance activities of firms headquartered in states that adopt WDL and those that do not adopt should evolve similarly in the absence of the WDL adoption. However, since the adoption of WDLs is based on judicial decisions rather than legislature, it is likely to be driven by the merits of the case rather than state political and economic factors. The court decisions also show that the judges did not have any intention to influence the strategic alliance activities of the firms, but rather to enhance fairness of employment relationships and to maintain consistency with contract law principles (Walsh and Schwarz, 1996). Nonetheless, we examine the determinants of the good faith exception to address the endogeneity concerns on reverse causality.

We follow Acharya *et al.* (2014) and Serfling (2016) and estimate Weibull Hazard models, where the "failure event" is the recognition of the good faith exception. States are excluded from the sample once they adopt this law. All explanatory variables are lagged by one year. *Log(Strategic Alliance deals)* is the natural logarithm of one plus the number of all strategic alliance deals in a state. We also control for other state-level variables, including *State unemployment rate, Log(per capita GDP), Implied contract, Public policy, Changes in state unemployment rate, State GDP growth, Circuit state's GF, Circuit state's IC, Circuit state's PP, Democrats,* and *Right-to-work*. All continuous explanatory variables are standardized to have mean zero and standard deviation one.

The results are shown in Table 3. We do not any find statistically significant coefficients for *Log(Strategic alliance deals)* indicating that the adoption of the good faith exception is not related to preexisting strategic alliance deals. The fraction of states in the federal circuit with public policy exception and the right-to-work law are the only variables that load positively and significantly in the regression. The result is fairly consistent with Serfling (2016). Therefore, the results supports our assumption that the change to this law is likely to be at least in part unanticipated event to the firms headquartered in these states so that the adoption of the law is not driven by these state-level economic and political factors.

4.2. Main results

We first examine the effect of the good faith exception on strategic alliance. We hypothesize that the good faith exception increases the cost of firing employees thereby making strategic alliance an attractive option for firm growth. If this is the case, we expect to observe an increase in strategic alliance deals for firms headquartered in states that pass the good faith exception. Figure 1 shows that the number of strategic alliances increases in the three years after the adoption of the good faith exception, compared to before the adoption. This increase becomes the most significant two years after adopting the law.

We run a formal test and present the results in Table 4. In Panel A, we use the ordinary least square regressions (OLS) specification. The regressions use *Log(SA)* as the dependent variable. The main independent variable is the good faith indicator, *GF*. The coefficient of 0.0367 in Column 1 where we only include the WDL indicator variables indicates that the adoption of the good faith exception increases the strategic alliance activities of firms in the affected states by 3.74 percentage points relative to the control firms. In Column 2, we include additional firm characteristics; Column 3 adds industry-related characteristic; and Column 4 additionally includes state-level characteristics. We use Column 4 as the baseline regression specification throughout the paper. Column 5 controls for industry-year fixed effects instead of year fixed effects and industry fixed effects so as to take into account any temporary industry factors that can affect strategic alliance activities and the likelihood of a state adopting the good faith exception at the same time (Bai *et al.*, 2017). The good faith coefficients are all positively significant with similar economic significance. For Column 6, we include firm fixed effects instead of industry fixed effects from the baseline regression to ensure that the result is not driven by omitted time-invariant firm characteristics. We still find positive coefficient with similar economic significance.

We also test for the robustness of the results to alternative specifications. In Column 1, to control for the unobservable propensity of the firm to engage in strategic alliances, we include the first five years (from 1985 to 1989) historical average of strategic alliance deals as an additional control variable in the baseline specification and find that our results are unaffected. When including the historical average, the sample starts in 1990 instead. Some may argue that joint ventures (JVs) are distinct from alliances as the former requires more investment and are less flexible compared with the latter. [15] Therefore, in Column 2, we exclude JVs from *Log(SA)* to use as the dependent variable and re-run the same regression from Panel A. The results are mostly consistent.[16] As our dependent variables are log values rather than the raw values of strategic alliance deals and have many zeros, in Columns 3 and 4, we use the raw counts of strategic alliance deals and run negative binomial and Poisson regressions to test for the robustness of the result. We

[15] Joint ventures typically require the formation of a separate legal entity and operate independently of the parents. Therefore, a contractual agreement must exist between the entities involved, which is a less flexible arrangement. Also, the investment required to form joint ventures is higher than forming strategic alliances, which typically utilizes the resources at hand to generate synergies. Therefore, it would be more difficult for firms to recover investment from joint ventures than from alliances when things do not work out well. Consistent with these arguments, we find that the results are relatively weaker when we focus only on joint ventures.

[16] Most papers do not distinguish between alliances and joint ventures. For example, a survey paper on strategic alliances by Kwan (2016) uses strategic alliance or alliance to indicate all types of pure alliances and joint ventures. In addition, PWC (2016) writes that the motivation for firms to engage in alliances and joint ventures is the unavailability of investment capital and to avoid risky M&As. This indicates that joint ventures are probably still less capital-intensive or risky compared to internal investments or M&As.

also run logit regressions with the dependent variable set to one if the firm has any strategic alliance deals at all and zero otherwise. We continue to find positive and significant coefficients for *GF*.

4.3. Econometric concerns

4.3.1 Pre-treatment trends

It is important that the parallel trend assumption is satisfied for us to use the difference-in-differences research design (Roberts and Whited, 2013). The concern is that states may adopt the good faith exception during the periods when there are increases in strategic alliance activity leading to issues of reverse causality and also violation of the parallel trend assumption. As shown in Table 2 already, we find that the level of strategic alliance activities in a state do not predict the enactment of good faith exception. Nevertheless, in this section, we also test whether there is a trend of increasing strategic alliance activity before the law has been adopted.

We re-estimate our regressions by replacing the *GF* dummy with the following indicator variables for separate time periods: *GF (-1), GF (0), GF (1), and GF (2+). GF (-1)* equals to one if the firm is headquartered in a state that will pass the law in the following year and is zero otherwise; *GF (0)* equals to one if the firm is headquartered in a state that adopts the law during the current year and is zero otherwise; *GF (1)* equals to one if the firm is headquartered in a state that has adopted the law during the past year and is zero otherwise; and *GF (2+)* equals to one if the firm is headquartered in a state that has adopted the law two years and more and is zero otherwise.

Table 5 shows the results. All columns include the control variables from Table 4 Panel A Column 4 (the baseline specification). Columns 1 and 2 include industry fixed effects and year fixed effects; Columns 3 and 4 include industry-year fixed effects; and Columns 5 and 6 include firm fixed effects and year fixed effects. Additionally the even-numbered columns include state-specific time trends allowing each state to have different trends in strategic alliance deals that could coincide with the law passage (Serfling, 2016). We do not find any significant trend before the adoption of the good faith exception. The increase in strategic alliance deals occur only after the passage of the good faith exception. The consistent results across different specifications confirm that the result is not specification-specific. Overall, the findings suggest that there are no reverse causality issues and that the passage of the good faith exception is unlikely to be anticipated.

4.3.2 Propensity score match

Roberts and Whited (2013) suggest that firm covariates must be balanced across the treatment and control groups. This is less of an issue in our setting as the adoption of the good faith is staggered at different times, therefore, firms enter into the control and treatment groups at different times, i.e., control firms will become treatment firms after good faith is adopted in their states. Nevertheless, we test for the robustness of our findings by conducting a matched sample analysis to control for firm characteristics differences between treatment and control firms.

Treatment firms are the firms headquartered in states that adopt the good faith exception the following year (year *t*), and control firms are firms headquartered in states that never adopt the good faith exception. Similar to Serfling (2016), we restrict our sample to all treatment and control firm observations surrounding the year of the good faith adoption. Both treatment and control firms are required to have at least one observation within three years before the treatment year and one observation within three years after the treatment year.

We use the observations from *t*-1 to run logistics regressions to estimate the propensity scores and create two matched samples using different firm characteristics. For the first match, we include *Log(Assets), R&D, Cash, Sales growth, Fixed assets,* and *Tobin's Q*. We further include *Log(Firm age), ROA, Leverage,* and *Capex* for the second match. We kernel match each treated firm observation from *t*-1 to a control firm that are from the same year, same 2-digit SIC industry, and with bandwidth 0.00005. Therefore, the matches are done within each industry-year pair. Panel A of Table 6 shows that the match is successful as the treatment and control firms are similar along all observable firm characteristics.

In Panel B, we show the effects of the adoption of the good faith exception on strategic alliance deals using the matched samples. *Treatment* is an indicator variable that equals to one if the firm is headquartered in a state that adopts the good faith exception and zero otherwise, and *Post* is an indicator variable that equals to one for the years after the adoption of the good faith exception and zero otherwise. Columns 1 and 4 use the baseline specification in Table 4; Columns 2 and 5 include industry-year fixed effects instead of other fixed effects; and Columns 3 and 6 control for firm fixed effects in place of industry fixed effects. The results indicate that treatment firms increase strategic alliance deals relative to control firms following the adoption of the good faith exception.

4.3.3 Robustness tests - Heterogeneous treatment effects

Certain types of firms are more likely to be affected by the adoption of the good faith exception. We utilize triple-difference regressions to test for the cross-sectional variation impact. Using triple-difference allows us to include state-year fixed effects. Therefore, the identification will then come from comparing firms within each treated state that are potentially more affected by the law change against firms that are less affected. This reduces the concern that our results are driven by spurious correlation with other unobserved factors that may affect firms headquartered in states that do and do not adopt the good faith exception differently.

According to Cuñat and Melitz (2012), firms in industries with volatile cash flow require higher flexibility with their labor forces, meaning that firms may be required to adjust employment more often in response to cash flow changes. Also, firms with a single segment cannot respond to negative shocks by deploying workers from one segment to another (Tate and Yang, 2015). As De Meuse, Marks, and Dai (2011) note, strategic alliance formation has minimal impact on firm structure and on labor forces and it also provides flexibility to the labor force by enabling the utilization of existing labor. Therefore, we expect to see firms with more volatile cash flows and single segment firms engaging more in strategic alliances after the good faith adoption compared to firms with relatively stable cash flows and multi-segment firms, respectively.

The results of the triple-difference approach are presented in Table 7.[17] We interact our *GF* dummy with an indicator variable that equals to one if the firm is in a 2-digit SIC industry with cash flow volatility above the industry median for the year (*Ind. CF volatility*) or if the firm has a single segment (*Single segment*), and zero otherwise. We find positive coefficients for the interactions of high cash flow volatility firms and single segment firms with the *GF* dummy, and most coefficients are significant. Therefore, our results are consistent with the expectations that firms with high industry cash volatility and firms with a single business segment increase utilizing strategic alliances to provide flexibility to their existing labor force when it becomes more costly for these firms to fire employees.[18]

[17] For all triple-difference results, the results are also robust to including just industry-year fixed effects and industry-year fixed effects together with state-year fixed effects. The results are not tabulated to conserve space.
[18] We also examine the firms that rely more on human capital, such as those with large number of employees and those in service industries (2-digit SIC between 70 and 89). The results are generally consistent with our expectation that labor intensive firms engage in more strategic alliances after the adoption of the good faith exception.

4.4. The choice between growth options – strategic alliance versus capital expenditures versus M&As

We have shown so far that the adoption of the good faith exception increases strategic alliance activities, however, strategic alliance formation is not the only way for a firm to grow. A firm can grow through an organic growth strategy of internal investments or through non-organic external M&As and strategic alliances (Bodnaruk *et al.*, 2013). Bai *et al.* (2017) and Chatt *et al.* (2017) show that increases in firing costs reduce the incentives for firms to make investments in capital expenditures and mergers and acquisitions. We examine whether firms are substituting such permanent and irreversible investments with the relatively flexible strategic alliances.

Similar to the tests in Bodnaruk *et al.* (2013), we test for the choice between strategic alliance and capital expenditure and choice between strategic alliance and M&A. A direct comparison of the growth strategies by looking at the trade-off between growth options can provide insights on how labor protection affects firms' investment decisions. We report the results in Table 8. In panel A, the dependent variable in Columns 1 to 3 is the natural logarithm of one plus the ratio of number of strategic alliance deals to capital expenditures (in millions of dollars). The dependent variable in Columns 4 to 6 is the natural logarithm of one plus the ratio of the number of strategic alliance deals to the number of completed M&A deals. We restrict our sample to those with non-zero capital expenditures and M&As, respectively. The coefficients on *GF* are mostly significant and positive, suggesting that strategic alliances are favored over internal investments and M&As after firing costs increase. It is possible that the firms which reduce their M&A activities and capital expenditures are a different subset of firms from those which increase their strategic alliance activities. To ensure that this is not the case, we restrict our sample to firms which engage in at least one strategic alliance during the sample period and find that our results remain similar.

In Panel B, we include an indicator variable for withdrawn M&As and its interaction with *GF* to test whether the firms with withdrawn M&As engage in more strategic alliances after adopting the good faith exception. We find significant result supporting that this indeed is the case. Overall, these findings support our hypothesis that the increase in firing costs from stronger employment protection make strategic alliances a preferred growth option over internal investment or M&As.[19]

4.5. The good faith exception and investment opportunities

The good faith exception increases the cost of firing, potentially leading firms to give up on valuable investment opportunities as they worry about costly exit if the investment project fails. For example, Bai *et al.* (2017) document that capital expenditures are less sensitive to investment opportunities after the adoption of the good faith exception. We next examine the responsiveness of strategic alliance deals to changes in investment opportunities to see whether firms substitute strategic alliance for internal capital expenditures to avoid the potential problem of costly firing in case of project failure. We interact the *GF* indicator variable with two indicator variables that proxy for firms with high investment opportunities. *High Q (High SG*) is an indicator variable equals to one if the firm's *Tobin's Q (Sales growth)* is above the yearly median and zero otherwise. If high firing costs make other irrevocable growth strategies (i.e., capital expenditure and M&As) relatively more expensive, we expect increases in strategic alliance deals, which are more flexible and subsequently relatively less costly especially for high growth firms.

[19] Due to the limited number of firms with withdrawn M&As, results with firm fixed effects are not significant.

The results in Table 9 show that the findings are consistent with our expectations. The interaction term between the indicators of high investment opportunities and *GF* are mostly significantly positive, indicating that strategic alliance deals are more responsive to growth opportunities after the adoption of the good faith exception.

5. Potential mechanisms – irreversibility channel

We argue that the good faith exception increases the cost of firing employees in the event that investment projects fail. This leads to firms seeking growth strategies such as strategic alliances, which is more flexible and relatively reversible compared to internal investments and M&As. If our results are driven by the irreversibility of investment channel, we should observe that firms located in states with the good faith exception would be less likely to terminate employment following poor performance.

We test for the irreversibility channel in Table 10 following Bai *et al.* (2017). We create two measures that capture the degree of employment reduction. *Large decrease in employees* in Columns 1 to 4 is an indicator variable that equals to one if the percentage decrease in employees over the year is greater than 15% and zero otherwise. *Emp. decrease* is the percentage decrease in employees over a year and is set to zero if the change is positive. We interact the *GF* indicator variable with an indicator variable, *Low profitability*, which equals to one if the changes in *cash flow* from *t*-1 to *t* is below the sample median for the year and zero otherwise.

The OLS results show that poorly-performing are more likely to discharge workers. The result from Column 1 suggests that before the adoption of the good faith exception, firms with below median profitability has 2.49 percentage points higher probability of discharging workers. However, this sensitivity declines by nearly 39% (0.0098/0.0249) once the state adopts the good faith exception. Similarly, in Column 5, the low profitability firms reduce employment by 0.6814 percentage points but the positive coefficient of 0.3504 on the interaction term suggest that the adoption of the law reduces this sensitivity by 51% (0.3504/0.6814). We also control for state-year fixed effects in addition to the industry fixed effects in Columns 2 and 6; firm fixed effects and year fixed effects in Columns 3 and 7; and firm fixed effects and state-year fixed effects in Columns 4 and 8. The results continue to hold in most cases. Overall, we find some evidence that greater employment protection makes projects more irreversible.

In addition, we test whether innovative firms are more likely to form strategic alliance after the good faith exception adoption. Innovation necessarily involves risk and if firms undertake the innovation in-house, they may end up having to fire workers if the project ends up badly. This cost is likely to increase post-good faith adoption. Therefore, strategic alliance is the natural choice for risky longshot projects (Robinson, 2008) and especially after the good faith exception adoption, which increases the cost of innovating in-house. We use the following proxies for high innovation firms: 1) *High R&D*, which equals to one if the firm has above median R&D expense to total assets for a given year and zero otherwise; 2) *Innovative firm,* which equals to one if the firm has been awarded at least one patent over 1950 to 2003 and zero otherwise; and 3) *LQW,* which equals to one if the firm has above the yearly median value of firm-to-economy technological proximity and zero otherwise (Li *et al.*, 2018).

The results are presented in Table 11. We find that the interaction of *GF* with the proxies for innovative firms are mostly significantly positive, indicating that the innovative firms increase strategic alliances more than those non-innovative firms after the adoption of the good faith exception.

These evidences support the irreversibility mechanisms through which the increase in employment protection affect strategic alliance activity. Higher labor protection makes investments more irreversible by making it more difficult to discharge workers in case the projects produce bad outcomes. Therefore, our findings suggest that the increases in firing costs promote more strategic alliance deals by making internal investments and M&As more irreversible.

6. Alternative hypothesis

In this section, we explore an alternative mechanism which may also explain our results. If the good faith exception distresses firms by raising operating leverage (labor costs becomes relatively fixed) and crowding out financial leverage, firms would have more difficult time accessing capital for investments. Therefore, strategic alliances may become an attractive alternative to huge capital expenditures or M&As. If this is the case, we should expect the impact of the law change to be greater for financially constrained firms.

Similar to Bai *et al.* (2017), we construct different proxies for financial constraint and create an indicator variable *High financial constraint*, which equals to one if a firm is considered highly financially constrained according to the proxy. We then interact this financial constraint indicator variable with the good faith dummy. We expect this interaction term to be significantly positive if the financing channel is at work. Table 12 shows the results. In Column 1, *High financial constraint* equals to one if a firm is considered to be dependent on external finance and zero otherwise (Rajan and Zingales, 1998). A firm is dependent on external capital if it has higher capital expenditure than its operating cash flow, where operating cash flow is defined following Byoun (2008). In Columns 2 to 4, we use the financial constraint indices by Kaplan and Zingales (1997), Whited and Wu (2006), and Hadlock and Pierce (2010), respectively. Firms are considered highly constrained if each of the index is above the sample median of the year. In Columns 5 and 6, we define those firms without a dividend and those with firm size below the sample median of the year as highly constrained companies, respectively.

Most of the results show consistently positive and significant coefficient for the *High financial constraint* variable indicating that firms with financial difficulties choose to form more strategic alliances.[20] The interaction of *GF* and *High financial constraint* show negatively significant coefficients for all columns but one. The untabulated results show consistent findings after controlling for state-year fixed effects. Therefore, there is no evidence to support the alternative hypothesis that the increase in strategic alliances post-law change is due to financing difficulties.

7. Additional test: Strategic alliance outcomes

Previous works have shown that strategic alliances are value increasing (e.g., Chan *et al.*, 1997; Bodnaruk *et al.*, 2013) and that it leads to increased innovative output (Chemmanur *et al.*, 2016; Li *et al.*, 2018). Furthermore, Hall *et al.* (2005) show that innovations can be value generating. Therefore, we examine whether the strategic alliances formed in states with the good faith exception are associated with improved innovation. We create an indicator variable *Alliance* that equals to one if the firm engages in strategic alliance deals in a year and zero otherwise. We interact this variable with the good faith dummy to examine whether firms that form strategic alliances in states with the good faith exception produce higher innovation output relative to firms in states without the good faith law.

[20] We additionally control for the financial constraint proxies in the baseline specification from Table 4. The result remains significant.

The results are presented in Table 13. We use innovative outcome variables as the dependent variables. The coefficients for *GF* are positive and significant, which is consistent with the findings of Acharya *et al.* (2014) that the adoption of the good faith exception leads to higher innovation. In particular, we find that the coefficients on our main variable of interest, the interaction of *GF* with *Alliance*, are positive and significant for nearly all specifications, implying that part of the increase in innovation post-law adoption is done through strategic alliances. The results show that firms that form strategic alliances post-law change produce patents that are more valuable and innovative. These firms also become more efficient in producing high quality patents with respect to the number of employees, and they make more investments in R&D.[21] We also control for state-year fixed effects in untabulated results and reach similar conclusions.

Overall, we find evidence that the good faith exception and strategic alliances increase firm value by increasing innovation. And innovative output is significantly enhanced for the strategic alliance forming firms that are headquartered in states that adopt the good faith exception. Thus, these findings suggest that strategic alliances spur innovation and that the firms headquartered in states with the good faith exception may choose strategic alliances as a growth strategy to create value.

8. Conclusion

This paper uses the staggered adoption of the good faith exception as an exogenous shock to state-level labor protection to examine how employee firing costs impact firm investment and growth strategy. We find evidence that stronger employment protection induces firms to move

[21] We try using three years aggregate patents, citations, and patent value as the dependent variables and obtain similar results.

outside of their boundaries by engaging in more strategic alliance deals. In particular strategic alliances are favored over other relatively irreversible growth strategies (i.e. internal capital expenditures and M&As). The effect of the law is more significant for firms with stronger investment opportunities and also for firms involved in risky, longshot projects. Lastly, we find significantly larger innovative output for the firms that form strategic alliance following the law change.

Our findings are consistent with the hypothesis that greater employment protection increases strategic alliances by making investments such as capital expenditures and M&As more irreversible. Strategic alliance, which is relatively more flexible, becomes a better alternative for firms to sustain growth. Overall, our findings provide insights into how employment protection law affects firms' choice of growth strategies.

Appendix. Variable definitions

Variable	Description	Data source
Alliance	An indicator variable that equals to one if the firm has at least one strategic alliance deal for the year and zero otherwise	SDC Platinum
Capex	Capital expenditures over total assets	Compustat
Cash	Cash and short-term investments over total assets	Compustat
Cash flow	Profitability proxy defined as the ratio of income before extraordinary items plus depreciation and amortization to total assets.	Compustat
Change in state's unemployment rate	Change in unemployment rate of a state over the fiscal year	Bureau of Labor Statistics
Circuit state's GF	Fraction of other states in the same federal circuit region as the firm that have passed the Good Faith exception by year *t*	Computed by authors
Circuit state's IC	Fraction of other states in the same federal circuit region as the firm that have passed the Implied Contract exception by year *t*	Computed by authors
Circuit state's PP	Fraction of other states in the same federal circuit region as the firm that have passed the Public Policy exception by year *t*	Computed by authors
Democrats	Fraction of a state's congress members in the U.S. House of Representatives that belong to the Democratic party in a given year	History, Art & Archives, U.S. House of Representatives
Employee	The number of employees of the firm in thousands	Compustat
Emp. decrease	Percentage decrease in employees over a year. It is set to zero if the change is positive	Hanka (1998) Compustat
External dependence	An indicator variable that equals to one if capital expenditure is greater than operating cash flow, which is defined following Byoun (2008), for the year and zero otherwise	Compustat
Fixed assets	Total property, plant, and equipment over total assets	Compustat
GF	An indicator variable that equals to one if the state has adopted the Good Faith exception and zero otherwise	Serfling (2016)
GF (+1)	An indicator variable that equals to one if the state has adopted the Good Faith exception during last year and zero otherwise	Serfling (2016)

GF (+2)	An indicator variable that equals to one if the state has adopted the Good Faith exception more than two years ago and zero otherwise	Serfling (2016)
GF (0)	An indicator variable that equals to one if the state adopts the Good Faith exception during the current year and zero otherwise	Serfling (2016)
GF (-1)	An indicator variable that equals to one if the state will adopt the Good Faith exception within a year and zero otherwise	Serfling (2016)
High Q	An indicator variable that equals to one if *Tobin's Q* is above the yearly median value and zero otherwise	Compustat
High R&D	An indicator variable that equals to one if *R&D* is greater than the yearly sample median and zero otherwise	Compustat
High SG	An indicator variable that equals to one if *Sales growth* is above the yearly sample median and zero otherwise	Compustat
HHI index	Herfindahl index of sales at a 2-digit SIC industry and year	Compustat
HP index	-0.737*Size + 0.043*Size^2 - 0.040*Age Size = natural logarithm of total assets. The total assets is maxed at $4.5 billion Age = the number of years the firm has non-missing stock price in Compustat	Hadlock and Pierce (2010) Compustat
IC	An indicator variable that equals to one if the state has adopted the Implied Contract exception and zero otherwise	Serfling (2016)
Ind. CF volatility	An indicator variable that equals to one if the firm is in a 2-digit SIC industry where the industry cash flow volatility is above the median across all industries for the year and is zero otherwise. Industry cash flow volatility is defined as the average cash flow volatility of all firms in a 2-digit SIC industry and year. A firm's cash flow volatility is the standard deviation of *Cash flow* over *t*-10 to *t*-1	Compustat
Innovative firm	An indicator variable that equals to one if the firm has been awarded at least one patent over the period 1950 to 2003	Kogan *et al.* (2017) Li *et al.* (2018)
KZ index	-1.001909*((*ib* + *dp*)/lag(*ppent*)) + .2826389*((*at* + *csho***prcc_f* - *ceq* - *txdb*)/*at*) + 3.139193*(*dltt* + *dlc*)/*seq* - 39.3678*((*dvc* + *dvp*)/lag(*ppent*)) - 1.314759*(*che*/lag(*ppent*))	Lamont et al. (2001) Compustat
Large decrease in employees	An indicator variable that equals to one if the percentage decrease in employees over the year is greater than 15% and zero otherwise	Compustat
Leverage	Short-term debt plus long-term debt over total assets	Compustat
Log(Assets)	Natural logarithm of one plus total assets in 2004 millions of dollars	Compustat

Log(Citations)	Natural logarithm of one plus the number of citations of patents filed in the year	Kogan *et al.* (2017)
Log(Citations/Employee)	Natural logarithm of citations per thousand employees	Kogan *et al.* (2017)
Log(Citations/Patent)	Natural logarithm of the ratio of citations to patents	Kogan *et al.* (2017)
Log(Firm age)	Natural logarithm of firm age in years using the first observation from Compustat or CRSP	Compustat CRSP
Log(Patents/Employee)	Natural logarithm of the patents that are filed in a year per one thousand employees	Kogan *et al.* (2017) Compustat
Log(Patent value)	Natural logarithm of one plus the total value of all patents filed in the year, where patent value is in 2004 millions of dollars. The value of a patent is estimated as the product of the estimated stock return from patent issuance, adjusted for potential measurement error, times the market capitalization of the firm that is issued a patent on the day before the announcement of the patent issuance.	Kogan *et al.* (2017)
Log(Patents)	Natural logarithm of one plus the number of patents filed in the year	Kogan *et al.* (2017)
Log(per capita GDP)	Natural logarithm of GDP per capita, which is GDP of state divided by total population of state in 2004 dollars	Bureau of Economic Analysis
Log(R&D)	Natural logarithm of the ratio of R&D expenditure to total assets for the given year	Compustat
Log(SA)	Natural logarithm of one plus the number of strategic alliance deals in the year	SDC Platinum
Log(Strategic alliance deals)	Natural logarithm of one plus the number of all strategic alliance deals in a state for a given year	SDC Platinum
Low profitability	An indicator variable that equals to one if the change in cash flow from *t*-1 to *t* is negative, and zero otherwise	Compustat
LQW	An indicator variable that equals to one if firm-to-economy technological proximity is above the sample median for the year and zero otherwise	Li *et al.* (2018) Kogan *et al.* (2017)
Market share	Market share of the firm within a 2-digit SIC industry and year. Sales over total 2-digit SIC industry-year sales	Compustat
No dividend	An indicator variable that equals to one if the firm does not pay any dividend for the year and zero otherwise	Compustat
PP	An indicator variable that equals to one if the state has adopted the Public Policy exception and zero otherwise	Serfling (2016)
R&D	R&D expenditure over total assets	Compustat
Right-to-work	An indicator variable that equals to one if the state has adopted the right-to-work law by year *t*	Department of Labor

ROA	Income before extraordinary items over total assets	Compustat
SA/Capx	Natural logarithm of one plus the ratio of the number of strategic alliances to the capital expenditures	SDC Platinum Compustat
SA/MA	Natural logarithm of one plus the ratio of the number of strategic alliances to the number of completed M&A deals	SDC Platinum
Sales growth	Sales over lagged sales	Compustat
Single segment	An indicator variable that equals to one if the firm has a single business segment in the year and zero otherwise	Compustat
Small size	An indicator variable that equals to one if the size of the firm is below the sample median in the year and zero otherwise	Compustat
State GDP growth	GDP growth rate of a state over a fiscal year	Bureau of Economic Analysis
State unemployment rate	The percentage of state unemployment of March each year as provided by Current Population Survey	Bureau of Labor Statistics
Tobin's Q	(*at* + (*csho***prcc_f*) - *ceq*)/*at*.	Compustat
Withdrawn	An indicator variable that equals to one if the firm has any withdrawn M&A deals in the year and zero otherwise.	SDC Platinum
WW index	-0.091*(*ib*+*dp*)/*at* - 0.062*Positive dividend + 0.021**dltt*/*at* - 0.044*(log(*at*)) + 0.102*Industry sales growth - 0.035*Sales growth Positive dividend = 1 if *dvc* + *dvp* is positive and zero otherwise Industry sales growth = Average industry sales growth at the 3-digit SIC level and year Sales growth = *sale*/lag(*sale*)-1	Whited and Wu (2006) Compustat

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Figure 1. Strategic alliances around the adoption of the good faith exception
This figure shows the average number of strategic alliances in the years before and after the adoption of the good faith exception. The sample is restricted to the firms headquartered in states that adopt the good faith exception during our sample period and have at least one observation three years before and after the adoption of the good faith law. The y-axis plots the average number of strategic alliances for the given years, and the x-axis shows the years relative to the adoption of the good faith exception.

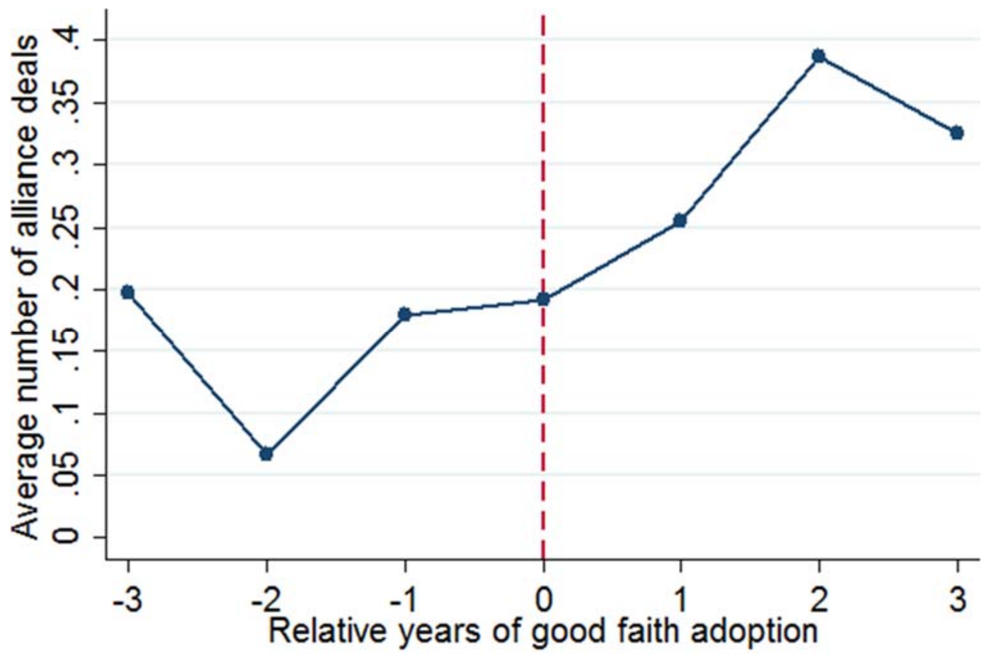

Table 1. Distribution of strategic alliance deals by year and by industry

This table reports the distribution of strategic alliance deals by year and by Fama-French 17 industries classification. Panel A presents the distribution of strategic alliances by year and Panel B presents the distribution of strategic alliances by Fama-French 17 industries classification.

Panel A. Distribution of strategic alliance deals by year

Year	Number of strategic alliances	% firms with SA	Obs.
1985	35	0.97%	3,495
1986	70	1.83%	3,502
1987	59	1.59%	3,517
1988	120	2.72%	3,639
1989	107	2.48%	3,705
1990	699	9.80%	3,672
1991	1,193	13.95%	3,664
1992	1,761	17.74%	3,630
1993	1,623	16.11%	3,774
1994	1,882	19.14%	3,961
1995	1,817	19.38%	4,194
1996	1,277	15.56%	4,422
1997	1,838	18.62%	4,507
1998	1,493	16.75%	4,568
1999	1,456	16.97%	4,344
2000	866	11.27%	4,065
2001	434	7.19%	3,896
2002	421	7.16%	3,854
2003	436	8.83%	3,590

Panel B. Distribution of strategic alliance deals by Fama-French 17 industries classification

Fama-French 17 industries	Number of strategic alliances	% firms with SA	Obs.
Food	261	7.60%	2,565
Mining and Minerals	72	7.10%	789
Oil and Petroleum Products	386	7.52%	3,605
Textiles, Apparel & Footware	207	7.57%	1,982
Consumer Durables	461	8.29%	2,858
Chemicals	436	14.07%	1,478
Drugs, Soap, Perfumes, Tobacco	1,219	21.51%	2,720
Construction and Construction Materials	180	3.96%	3,231
Steel Works Etc.	114	7.59%	1,292
Fabricated Products	58	5.42%	923
Machinery and Business Equipment	4,735	13.12%	12,686
Automobiles	301	9.93%	1,209
Transportation	477	8.46%	2,753
Utilities	273	7.05%	3,177
Retail Stores	402	5.72%	5,434
Other	8,005	14.17%	27,297

Table 2. Summary statistics

This table reports the summary statics for dependent and independent variables. Panel A presents the summary statistics for the full sample. Panel B reports the comparison of the means between firms headquartered in states that adopt the good faith exception at some point in time (treatment firms) and firms headquartered in states that never adopt the good faith exception (control firms). The sample consists of all Compustat firms (excluding financial industries) from 1985 to 2003 and includes 73,999 firm-year observations. All continuous variables, except state-level variables, are winsorized at the 1st and 99th percentiles, and dollar values are adjusted to 2004 dollars. *SA* is the number of strategic alliances the firm has entered during a fiscal year. *Patents, citations,* and *Patent value* are the number of patents, citations and patent value in millions of 2004 dollars, respectively. The value of each patent is estimated as the product of the estimated stock return from patent issuance, adjusted for potential measurement error, times the market capitalization of the firm that issued the patent on the day before the announcement of the patent issuance. *Patent value* is the sum of the values to all patents in the year. The innovation data on patents, citations and patent value is from Kogan *et al.* (2017). *Citations/Patent* is the ratio of the number of citations to the number of patents. *Patents/Employee* is the number of patents per one thousand employees; *Citations/Employee* is the number of citations per one thousand employees; *SA/Capx* is the natural logarithm of one plus the number of strategic alliances divided by capital expenditures; and *SA/MA* is the natural logarithm of one plus the ratio of the number of strategic alliances to the number of completed mergers and acquisitions. *GF* is an indicator variable that takes value of one if the state where the firm is headquartered in has adopted the good faith exception by year *t* and is zero otherwise. *IC* and *PP* are indicator variables set to one if the state where the firm is headquartered in has adopted the implied contract and public policy exceptions by year *t* and is zero otherwise. *Assets* is the book value of assets in millions of 2004 dollars. *R&D* is the ratio of R&D expenditures to total assets. *Cash* is cash and short-term investments over total assets. *Sales growth* is the ratio of sales to lagged sales. *Firm age* is the number of years since the firm first appeared in Compustat or CRSP, whichever is earlier. *ROA* is income before extraordinary items scaled by total assets. *Fixed assets* is the ratio of total property, plant, and equipment to total assets. *Leverage* is short-term debt plus long-term debt divided by total assets. *Capex* is capital expenditures over total assets. *Tobin's Q* is the ratio of total assets plus common shares outstanding times fiscal year-end stock price minus total common equity to total assets. *HHI index* is the Herfindahl index of sales in each 2-digit SIC industry and year. *Market share* is the ratio of sales over a 2-digit SIC industry total sales for a year. *State GDP per capita* is the natural log of a state's GDP divided by total population. *State GDP growth* is the growth of a state's GDP over last year's GDP. *Democrats* is the fraction of a state's congress members in the U.S. House of Representatives who belong to the Democratic Party in a given year. *State unemployment rate* is the percentage of state unemployment of March each year as provided by the Current Population Survey. *Circuit state's GF* is the fraction of other states in the same federal circuit region as the firm that have passed good faith exception by the year.

Panel A. Summary statistics for full sample

Variable name	Obs.	Mean	S.D.	P25	Median	P75
Dependent variables						
SA	73,999	0.19	0.68	0.00	0.00	0.00
Patents	73,999	23.73	220.23	0.00	0.00	1.00
Citations	73,999	294.55	3,293.86	0.00	0.00	0.00
Patent value	73,999	439.66	5,028.84	0.00	0.00	0.06
Citations/Patent	20,217	13.01	17.34	2.74	8.00	16.00
Patents/Employee	71,674	6.18	24.25	0.00	0.00	0.36
Citations/Employee	71,674	72.70	335.89	0.00	0.00	0.05
SA/Capx	72,201	0.04	0.21	0.00	0.00	0.00
SA/MA	12,943	0.13	0.34	0.00	0.00	0.00
Explanatory and control variables						
GF	73,999	0.26	0.44	0.00	0.00	1.00
IC	73,999	0.00	0.39	1.00	1.00	1.00
PP	73,999	0.00	0.40	1.00	1.00	1.00
Assets	73,999	1,294.97	3,946.62	34.30	133.39	39,805.50
R&D	73,999	0.04	0.09	0.00	0.00	0.05
Cash	73,999	0.15	0.19	0.02	0.07	0.21
Sales growth	73,999	1.23	0.72	0.98	1.09	1.27
Firm age	73,999	18.43	15.15	7.00	13.00	26.00
ROA	73,999	-0.04	0.24	-0.04	0.03	0.07
Fixed assets	73,999	0.32	0.24	0.13	0.25	0.46
Leverage	73,999	0.25	0.21	0.06	0.22	0.38
Capex	73,999	0.07	0.07	0.02	0.05	0.09
Tobin's Q	73,999	1.92	1.71	1.05	1.35	2.04
HHI index	73,999	0.09	0.09	0.04	0.06	0.09
Market share	73,999	0.01	0.03	0.00	0.00	0.01
State GDP per capita	73,999	35.78	5.65	31.65	35.37	39.18
State GDP growth	73,999	0.03	0.03	0.01	0.03	0.05
Democrats	73,999	0.56	0.17	0.50	0.57	0.63
State unemployment rate	73,999	0.06	0.02	0.05	0.06	0.07
Circuit state's GF	73,999	0.22	0.26	0.00	0.00	0.50

Panel B. Comparison of sample means for treatment and control firms

	Treatment sample (Obs. = 20,973)	Control Sample (Obs. = 53,026)	Difference	(p-value)
Dependent variables				
SA	0.255	0.167	0.088	0.000
Patents	31.932	20.484	11.448	0.000
Citations	400.734	252.554	148.180	0.000
Patent value	575.876	385.779	190.097	0.000
Citations/Patent	0.255	0.167	0.088	0.000
Patents/Employee	11.937	3.908	8.029	0.000
Citations/Employee	139.442	46.420	93.022	0.000
SA/Capx	0.060	0.031	0.029	0.000
SA/MA	0.171	0.115	0.056	0.000
Control variables				
IC	0.886	0.781	0.105	0.000
PP	0.962	0.742	0.220	0.000
Assets	904.456	1449.425	-544.969	0.000
R&D	0.076	0.032	0.044	0.000
Cash	0.212	0.127	0.085	0.000
Sales growth	1.267	1.221	0.046	0.000
Firm age	15.164	19.720	-4.556	0.000
ROA	-0.072	-0.021	-0.051	0.000
Fixed assets	0.280	0.332	-0.052	0.000
Leverage	0.210	0.260	-0.050	0.000
Capex	0.068	0.070	-0.002	0.003
Tobin's Q	2.199	1.805	0.394	0.000
HHI index	0.078	0.089	-0.011	0.000
Market share	0.007	0.012	-0.005	0.000
State GDP per capita	38.144	34.847	3.297	0.000
State GDP growth	0.032	0.029	0.003	0.000
Democrats	0.574	0.558	0.016	0.000
State unemployment rate	0.059	0.057	0.002	0.000
Circuit state’s GF	0.384	0.151	0.223	0.000

Table 3. The timing of passage of the good faith exception: The duration model

This table reports the estimates from a Weibull hazard model, where the "failure event" is the adoption of the good faith exception in a state. States are dropped from the sample once they adopt the good faith exception. All explanatory variables are lagged by one year and all continuous variables are standardized to have mean zero and standard deviation of one. *Log(Strategic alliance deals)* is the natural logarithm of one plus the number of all strategic alliance deals in a state for a given year. Variable definitions are provided in the appendix. The sample spans from 1985 to 2003. Standard errors are clustered by state. The *t*-statistics are reported in parenthesis. *, **, and *** denote significance at 10%, 5%, and 1%, respectively.

	(1)	**(2)**
Log (Strategic alliance deals)	-0.6671	-0.5695
	(-1.49)	(-1.47)
State unemployment rate		0.0252
		(0.07)
Log(per capita GDP)		-0.0310
		(-0.04)
Implied contract		-1.2976
		(-1.13)
Public policy		-0.0836
		(-0.03)
Change in state unemployment rate		-0.7386
		(-1.34)
State GDP growth		-0.2027
		(-0.35)
Circuit states' good faith		1.3014
		(1.29)
Circuit states' implied contract		0.1104
		(0.12)
Circuit states' public policy		22.7514***
		(5.59)
Democrats		-0.3068
		(-0.47)
Right-to-work		4.2860*
		(1.81)
Observations	687	687

Table 4. The good faith exception and strategic alliances

This table provides the regression results relating the enactment of the good faith exception to the strategic alliance activities for 73,999 firm-year observations spanning from 1985 to 2003. Panel A reports the results from using OLS regression. The dependent variable is *Log(SA)*, the natural logarithm of one plus the number of strategic alliances deals. The main independent variable is *GF* which is an indicator variable equals to one if the state in which the firm is headquartered in has adopted the good faith exception, and zero otherwise. Panel B reports the regression results for alternative regression specifications. Column 1 includes the five years historical average of strategic alliances as a control variable to the baseline specification in Column 4, Panel A. The sample period starts from 1990 for this regression. Column 2 uses the natural logarithm of one plus the number of strategic alliances, excluding joint ventures, as the dependent variable; and Columns 3 to 5 are the results for the Negative Binomial, Poisson regressions and Logit regressions. Only the coefficient and associated *t*-statistics on the *GF* indicator variable is shown. The control variables follows that of Panel A column 4. For the Negative Binomial and Poisson regressions, the dependent variable is the number of strategic alliance deals done by the firm in the year. For the logit regressions, the dependent variable is an indicator variable equals to one if the firm has completed at least one strategic alliance deal and zero otherwise. The Appendix provides the variable definitions. Industries are defined at the 2-digit SIC level. Standard errors are clustered by state. The *t*-statistics are reported in parenthesis. *, **, and *** denote significance at 10%, 5%, and 1%, respectively.

Panel A. OLS regressions

	(1)	(2)	(3)	(4)	(5)	(6)
GF	0.0367***	0.0262***	0.0265***	0.0186**	0.0184**	0.0316*
	(3.94)	(3.49)	(3.54)	(2.48)	(2.59)	(1.79)
IC	0.0225***	0.0213***	0.0209***	0.0127*	0.0140**	0.0165
	(3.36)	(4.65)	(4.48)	(1.86)	(2.18)	(1.22)
PP	-0.0121**	-0.0269***	-0.0267***	-0.0202***	-0.0208***	-0.0196***
	(-2.17)	(-6.10)	(-6.01)	(-3.85)	(-4.15)	(-2.75)
Log(Assets)		0.0503***	0.0472***	0.0470***	0.0475***	0.0300***
		(13.53)	(12.79)	(12.91)	(12.38)	(10.96)
R&D		0.4173***	0.4113***	0.4101***	0.4054***	0.1550***
		(16.14)	(16.28)	(16.07)	(15.02)	(5.24)
Cash		0.0347**	0.0375***	0.0356**	0.0397***	-0.0082
		(2.53)	(2.77)	(2.63)	(2.86)	(-0.67)
Sales growth		0.0037*	0.0036*	0.0036*	0.0039*	-0.0001
		(1.70)	(1.70)	(1.68)	(1.83)	(-0.02)
Log(Firm age)		-0.0105**	-0.0121***	-0.0120***	-0.0130***	-0.0633***
		(-2.51)	(-2.85)	(-2.90)	(-2.84)	(-7.50)
ROA		0.0007	0.0048	0.0069	-0.0033	0.0198***
		(0.05)	(0.37)	(0.51)	(-0.35)	(3.44)
Fixed assets		-0.0590***	-0.0561***	-0.0561***	-0.0562***	-0.0184

		(-5.04)	(-5.12)	(-5.11)	(-5.31)	(-1.28)
Leverage		-0.0499***	-0.0468***	-0.0465***	-0.0460***	-0.0105
		(-4.90)	(-4.70)	(-4.66)	(-4.60)	(-1.21)
Capex		0.1139***	0.1141***	0.1181***	0.1306***	-0.0223
		(5.23)	(5.33)	(5.50)	(5.90)	(-1.40)
Tobin's Q		0.0154***	0.0150***	0.0150***	0.0146***	0.0079***
		(8.73)	(8.36)	(8.35)	(7.48)	(7.18)
HHI index			-0.0041	-0.0040	0.0000	-0.0027
			(-0.16)	(-0.16)	(.)	(-0.14)
Market share			0.4450***	0.4488***	0.4748***	-0.2016
			(3.21)	(3.24)	(3.12)	(-1.43)
State GDP per capita				0.0391	0.0384	-0.2179**
				(1.24)	(1.24)	(-2.39)
State GDP growth				-0.0551	0.0543	-0.2012
				(-0.42)	(0.53)	(-1.62)
Democrats				-0.0177	-0.0097	-0.0303
				(-1.21)	(-0.68)	(-1.49)
State unemployment rate				0.8135***	0.6037**	0.9150**
				(2.75)	(2.52)	(2.63)
Circuit state's GF				0.0085	0.0113	0.0135
				(0.61)	(0.86)	(0.70)
Industry FE	Yes	Yes	Yes	Yes	No	No
Industry-Year FE	No	No	No	No	Yes	No
Firm FE	No	No	No	No	No	Yes
Year FE	Yes	Yes	Yes	Yes	No	Yes
Observations	73,999	73,999	73,999	73,999	73,999	73,999
Adjusted R-squared	0.0832	0.1700	0.1710	0.1721	0.1896	0.3437

Panel B. OLS regressions with alternative specifications

	(1) Including historical average	(2) Excluding joint ventures	(3) Negative binomial	(4) Poisson	(5) Logit
GF	0.0131*	0.0180**	0.1731***	0.1978**	0.1614***
	(1.79)	(2.39)	(2.94)	(2.16)	(2.71)
Industry FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Observations	30,573	73,999	73,999	73,999	70,384
Adjusted R-squared	0.2917	0.1628	N/A	N/A	N/A

Table 5. The effect of the adoption of the good faith exception on strategic alliance deals

This table reports the regression results relating strategic alliances to the adoption of the good faith exception. The dependent variable is *Log(SA)*, the natural logarithm of one plus the number of strategic alliance deals. *GF (-1)* is an indicator variable set to one if the firm is headquartered in a state that will pass the good faith exception in a year and zero otherwise; *GF (0)* is an indicator variable that takes the value of one if the firm is headquartered in a state that adopts this law during current year and zero otherwise; *GF (1)* is an indicator variable that equals to one if the firm is headquartered in a state that passed the law one year ago and zero otherwise; *GF (2+)* is an indicator variable equals to one if the firm is headquartered in a state that adopted the law two or more years ago and zero otherwise. Columns 1 and 2 include industry fixed effects and year fixed effects; Columns 3 and 4 include industry-year fixed effects; and Columns 5 and 6 include firm fixed effects and year fixed effects. The even-numbered columns further include state-specific time trends. The Appendix provides detailed variable definitions. All specifications include the control variables listed in Column 4, Panel A, Table 4. Industries are defined at the 2-digit SIC level. Standard errors are clustered by state. The *t*-statistics are reported in parenthesis. *, **, and *** denote significance at 10%, 5%, and 1%, respectively.

	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
GF (-1)	0.0402	0.0401	0.0384	0.0382	0.0309	0.0318
	(1.14)	(1.13)	(1.31)	(1.30)	(1.27)	(1.28)
GF (0)	0.0354	0.0354	0.0240	0.0237	0.0543*	0.0545*
	(1.44)	(1.43)	(1.00)	(0.99)	(1.73)	(1.71)
GF (1)	0.0305**	0.0305**	0.0199	0.0197	0.0461**	0.0461**
	(2.27)	(2.25)	(1.51)	(1.50)	(2.16)	(2.13)
GF (2+)	0.0181**	0.0177*	0.0183**	0.0167*	0.0342*	0.0347*
	(2.39)	(1.84)	(2.57)	(1.88)	(1.96)	(1.95)
Industry FE	Yes	Yes	No	No	No	No
Industry-Year FE	No	No	Yes	Yes	No	No
Firm FE	No	No	No	No	Yes	Yes
Year FE	Yes	Yes	No	No	Yes	Yes
State-Year Time Trends	No	Yes	No	Yes	No	Yes
Observations	73,999	73,999	73,999	73,999	73,999	73,999
Adjusted R-squared	0.1721	0.1721	0.1896	0.1896	0.3437	0.3437

Table 6. Propensity score matched sample and univariate test

This table reports the impact of the good faith exception on strategic alliance activities of firms using propensity score matched samples. We limit the sample to all observations +/- 3 years around the adoption of the good faith exception and require at least one observation before and after the adoption of the good faith exception in year *t*. The treatment group consists of firms headquartered in states that adopt the good faith exception in the following year. The control group consists of firms headquartered in states that never adopt the good faith exception. We estimate the propensity scores using logistics regression based on observations from year *t*-1. We make the first matched sample by estimating propensity scores using *Log(Assets), R&D, Cash, Sales growth, Fixed assets,* and *Tobin's Q*. We include *Log(Firm age), ROA, Leverage,* and *Capex* as additional variables for the second match. For both matches, we kernel match each treatment firm in year *t*-1 to a control firm from the same 2-digit SIC industry and year, and require the bandwidth of 0.00005. Panel A shows the means of the covariates used in the matching for treatment and control groups in year *t*-1. Panel B presents the results from difference-in-differences regressions using the matched samples. Columns 1 to 3 show the result for matched sample 1 and Columns 4 to 6 show the result using matched sample 2. *Treatment* is an indicator variable that equals to one if the firm is headquartered in a state that adopts the good faith exception and zero otherwise; *Post* is an indicator variable that equals to one in the years after the adoption of the good faith exception and zero otherwise. We do not include in sample the year in which a state adopts the good faith exception. The Appendix provides detailed variable definitions. All specifications include the control variables listed in Column 4, Panel A, Table 4. Industries are defined at the 2-digit SIC level. Standard errors are clustered by state. The *t*-statistics are reported in parenthesis. *, **, and *** denote significance at 10%, 5%, and 1%, respectively.

Panel A. Comparison of means

	Matched sample 1		**Matched sample 2**	
	Treatment	**Control**	**Treatment**	**Control**
Propensity score	0.0098	0.0098	0.0079	0.0079
Log(Assets)	5.2715	5.2169	5.6661	5.9370
R&D	0.0229	0.0268	0.0244	0.0155
Cash	0.0948	0.1115	0.0947	0.1134
Sales growth	1.2138	1.2321	1.1593	1.1714
Fixed assets	0.4609	0.4692	0.4141	0.4345
Tobin's Q	1.6277	1.4781	1.5058	1.5409
Log(Firm age)			2.9676	3.0932
ROA			0.0011	0.0356
Leverage			0.2574	0.2955
Capex			0.0683	0.0685

Panel B. The adoption of the good faith exception and strategic alliance

	Matched sample 1			Matched sample 2		
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Treatment	0.0600***	0.0340		-0.0099	-0.0030	
	(2.85)	(1.55)		(-0.20)	(-0.06)	
Treatment x Post	0.0810*	0.1181**	0.0764*	0.1432**	0.1034	0.1510**
	(2.04)	(2.75)	(1.96)	(2.47)	(1.57)	(2.52)
Post	-0.0580	-0.1009*	-0.0717*	-0.0353	0.0147	0.0184
	(-1.49)	(-1.95)	(-1.84)	(-0.81)	(0.26)	(0.39)
Industry FE	Yes	No	No	Yes	No	No
Industry-Year FE	No	Yes	No	No	Yes	No
Firm FE	No	No	Yes	No	No	Yes
Year FE	Yes	No	Yes	Yes	No	Yes
Observations	557	557	557	604	604	604
Adjusted R-squared	0.3169	0.3188	0.5018	0.4390	0.4389	0.6352

Table 7. Robustness tests – Heterogeneous treatment effects

This table presents the robustness test results. The dependent variable is *Log(SA)*, the natural logarithm of one plus the number of strategic alliances deals. *Ind. CF volatility* equals to one if the firm is in a 2-digit SIC industry where the cash flow volatility of the industry is above all industry median of the year and zero otherwise. Industry cash flow volatility is defined as the average cash flow volatility of all firms in a 2-digit SIC industry and year. The cash flow volatility of the firm is the standard deviation of *Cash flow* of the firm over *t*-10 to *t*-1, where *cash flow* is defined as the ratio of income before extraordinary items plus depreciation and amortization to total assets; *Single segment* equals to one if the firm has a single business segment in a year and zero otherwise. The Appendix provides detailed variable definitions. All specifications include the control variables listed in Column 4, Panel A, Table 4. Industries are defined at the 2-digit SIC level. Standard errors are clustered by state. The *t*-statistics are reported in parenthesis. *, **, and *** denote significance at 10%, 5%, and 1%, respectively.

	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
GF	-0.0328***	-0.0388	0.0119	-0.0309	0.0067	0.0026	0.0140	-0.0258
	(-2.97)	(-0.63)	(0.66)	(-0.56)	(0.80)	(0.04)	(0.81)	(-0.46)
Ind. CF volatility $_{t-1}$	-0.0085*	-0.0077*	-0.0022	-0.0010				
	(-1.96)	(-1.78)	(-0.52)	(-0.22)				
GF x Ind. CF volatility $_{t-1}$	0.0335***	0.0312***	0.0139**	0.0090				
	(6.46)	(5.70)	(2.10)	(1.46)				
Single segment $_{t-1}$					0.0004	0.0021	-0.0085	-0.0053
					(0.10)	(0.51)	(-1.51)	(-1.09)
GF x Single segment $_{t-1}$					0.0173***	0.0063	0.0304***	0.0122**
					(3.07)	(1.01)	(3.18)	(2.05)
Industry FE	Yes	Yes	No	No	Yes	Yes	No	No
Firm FE	No	No	Yes	Yes	No	No	Yes	Yes
Year FE	Yes	No	Yes	No	Yes	No	Yes	No
State-Year FE	No	Yes	No	Yes	No	Yes	No	Yes
Observations	73,877	73,877	73,877	73,877	73,999	73,999	73,999	73,999
Adjusted R-squared	0.1727	0.1779	0.3437	0.3461	0.1722	0.1774	0.3438	0.3462

Table 8. The good faith exception and choice between firm growth strategies

This table reports the relation between the adoption of the good faith exception and the choice between firm growth strategies. Panel A reports the choice between strategic alliances and capital expenditures, and the choice between strategic alliances and completed M&As. The dependent variable in Columns 1 to 3 is the natural logarithm of one plus the number of strategic alliances divided by capital expenditures (*log(1+SA/Capx)*). The dependent variable in Columns 4 to 6 is the natural logarithm of one plus the number of strategic alliances divided by the number of completed M&A deals (*log(1+SA/M&A)*). Panel B presents the results for the regression of *Log(SA)* on the interaction of *Withdrawn* dummy with *GF*, where *Withdrawn* equals to one if the firm has at least one withdrawn M&A deal during the year, and zero otherwise. The Appendix provides detailed variable definitions. All specifications include the control variables listed in Column 4, Panel A, Table 4. Industries are defined at the 2-digit SIC level. Standard errors are clustered by state. The *t*-statistics are reported in parenthesis. *, **, and *** denote significance at 10%, 5%, and 1%, respectively.

Panel A. Choice between strategic alliances, organic growth and M&As

	(1)	(2)	(3)	(4)	(5)	(6)
		Strategic Alliances vs. Capital Expenditures			Strategic Alliances vs. M&As	
GF	0.0058*	0.0058*	0.0077	0.0197*	0.0210**	0.1081*
	(1.70)	(1.91)	(0.93)	(1.94)	(2.12)	(1.92)
Industry FE	Yes	No	No	Yes	No	No
Industry-Year FE	No	Yes	No	No	Yes	No
Firm FE	No	No	Yes	No	No	Yes
Year FE	Yes	No	Yes	Yes	No	Yes
Observations	72,201	72,201	72,201	12,943	12,943	12,943
Adjusted R-squared	0.0931	0.1072	0.2108	0.1953	0.1896	0.2558

Panel B. Strategic alliance deals for firms with withdrawn M&As

	(1)	(2)	(3)
GF	0.0202***	0.0193***	0.0072
	(2.71)	(2.73)	(0.12)
Withdrawn $_t$	0.0029	0.0059	0.0019
	(0.33)	(0.61)	(0.23)
GF x Withdrawn $_t$	0.0550***	0.0520**	0.0546**
	(2.74)	(2.46)	(2.64)
Industry FE	Yes	No	Yes
Industry-Year FE	No	Yes	No
Year FE	Yes	No	No
State-Year FE	No	No	Yes
Observations	73,999	73,999	73,999
Adjusted R-squared	0.1716	0.1894	0.1775

Table 9. The good faith exception and investment opportunities

This table presents the cross-sectional variations by investment opportunities. The dependent variable is *Log(SA)*, the natural logarithm of one plus the number of strategic alliances deals. *High Q* is an indicator variable that equals to one if the firm's *Tobin's Q* is above the median value for the year and zero otherwise. *High SG* is an indicator variable that equals to one if the firm's *Sales growth* is greater than the median value for the year and zero otherwise. The appendix provides detailed variable definitions. All specifications include the control variables listed in Column 4, Panel A, Table 4. Industries are defined at the 2-digit SIC level. Standard errors are clustered by state. The *t*-statistics are reported in parenthesis. *, **, and *** denote significance at 10%, 5%, and 1%, respectively.

	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
GF	0.0025	-0.0083	0.0263	-0.0247	0.0077	-0.0037	0.0258	-0.0237
	(0.37)	(-0.14)	(1.43)	(-0.44)	(0.82)	(-0.06)	(1.48)	(-0.41)
Tobin's Q $_{t-1}$	0.0138***	0.0142***	0.0075***	0.0083***				
	(7.25)	(7.36)	(6.34)	(6.86)				
GF x High Q $_{t-1}$	0.0299***	0.0299***	0.0135*	0.0140**				
	(5.55)	(4.76)	(1.83)	(2.24)				
Sales growth $_{t-1}$					0.0018	0.0019	-0.0012	-0.0009
					(0.77)	(0.86)	(-0.60)	(-0.45)
GF x High SG $_{t-1}$					0.0214**	0.0224*	0.0139	0.0143
					(2.03)	(1.91)	(1.42)	(1.37)
Industry FE	Yes	Yes	No	No	Yes	Yes	No	No
Firm FE	No	No	Yes	Yes	No	No	Yes	Yes
Year FE	Yes	No	Yes	No	Yes	No	Yes	No
State-Year FE	No	Yes	No	Yes	No	Yes	No	Yes
Observations	73,999	73,999	73,999	73,999	73,999	73,999	73,999	73,999
Adjusted R-squared	0.1726	0.1779	0.3437	0.3462	0.1724	0.1777	0.3438	0.3463

Table 10. The good faith exception and employment reduction

This table presents the results of cross-sectional effects of decrease in firm profitability on employment outcomes. The dependent variable in Columns 1 to 4 is *Large decrease in employees*, which is an indicator variable that equals to one if the percentage decrease in employees over the year is greater than 15% and zero otherwise. Columns 5 to 8 use *Emp. decrease,* which is the percentage decrease in employees over a year, and it is set to zero if the change is positive. *Low profitability* is set to one if the change in *Cash flow* from *t*-1 to *t* is below the sample median of the year and zero otherwise, where *Cash flow* is defined as the ratio of income before extraordinary items plus depreciation and amortization to total assets. The Appendix provides detailed variable definitions. All specifications include the control variables listed in Column 4, Panel A, Table 4. Industries are defined at the 2-digit SIC level. Standard errors are clustered by state. The *t*-statistics are reported in parenthesis. *, **, and *** denote significance at 10%, 5%, and 1%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Large decrease in employees				Emp. decrease (x 100)			
GF	0.0145**	-0.0366	0.0222	-0.0417	-0.6939***	1.3211	-0.6062	0.3577
	(2.32)	(-0.81)	(1.34)	(-0.57)	(-3.31)	(0.51)	(-0.82)	(0.10)
Low profitability $_t$	0.0249***	0.0233***	0.0134***	0.0121***	-0.6814***	-0.6166***	-0.2998*	-0.2452
	(6.21)	(6.00)	(3.14)	(2.86)	(-3.98)	(-3.60)	(-1.76)	(-1.44)
GF x Low profitability $_t$	-0.0098**	-0.0077*	-0.0112**	-0.0085	0.3504*	0.2730	0.3682*	0.2796
	(-2.26)	(-1.83)	(-2.32)	(-1.66)	(1.76)	(1.39)	(1.78)	(1.29)
Industry FE	Yes	Yes	No	No	Yes	Yes	No	No
Firm FE	No	No	Yes	Yes	No	No	Yes	Yes
Year FE	Yes	No	Yes	No	Yes	No	Yes	No
State-Year FE	No	Yes	No	Yes	No	Yes	No	Yes
Observations	71,131	71,131	71,131	71,131	71,131	71,131	71,131	71,131
Adjusted R-squared	0.0908	0.0918	0.1683	0.1671	0.1101	0.1104	0.2206	0.2192

Table 11. The good faith exception and innovative firms

This table shows the results for the cross-sectional differences of the effect of the good faith exception on strategic alliances using various firm and industry level variables. *High R&D* is equal to one if the firm's *R&D* is greater than the sample median of the given year and zero otherwise; *Innovative firm* equals to one if the firm has been awarded at least one patent over 1950 to 2003; *LQW* is equal to one if the firm-to-economy technological proximity measure by Li *et al* (2018) is above the sample median for the given year and zero otherwise. Appendix provides the variable definitions. All specifications include the control variables listed in Column 4, Panel A, Table 4. Industries are defined at the 2-digit SIC level. Standard errors are clustered by state. The *t*-statistics are reported in parenthesis. *, **, and *** denote significance at 10%, 5%, and 1%, respectively.

	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**	**(11)**	**(12)**
	High R&D				**Innovative firm**				**LQW**			
GF	0.0040	0.0027	0.0278	-0.0198	0.0034	-0.0047	-0.0068	-0.0404	0.0095	-0.0665*	0.0360	-0.0376
	(0.71)	(0.04)	(1.53)	(-0.35)	(0.57)	(-0.07)	(-0.38)	(-0.78)	(1.01)	(-1.81)	(1.16)	(-0.60)
Innovative $_{t-1}$	0.0397***	0.0396***	-0.0048	-0.0043	0.0194***	0.0205***	-0.0228	-0.0236	0.0124	0.0139*	-0.0003	0.0001
	(6.67)	(7.01)	(-0.59)	(-0.58)	(3.90)	(4.14)	(-0.79)	(-0.77)	(1.44)	(1.74)	(-0.07)	(0.03)
GF x Innovative $_{t-1}$	0.0250***	0.0258***	0.0130	0.0112	0.0266***	0.0240***	0.0775*	0.0675	0.0316**	0.0269**	0.0189**	0.0161*
	(3.52)	(3.32)	(0.84)	(0.73)	(3.11)	(2.73)	(1.91)	(1.40)	(2.07)	(2.06)	(2.13)	(1.73)
Industry FE	Yes	Yes	No	No	Yes	Yes	No	No	Yes	Yes	No	No
Firm FE	No	No	Yes	Yes	No	No	Yes	Yes	No	No	Yes	Yes
Year FE	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No
State-Year FE	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Observations	73,999	73,999	73,999	73,999	73,999	73,999	73,999	73,999	37,721	37,721	37,721	37,721
Adjusted R-squared	0.1745	0.1798	0.3437	0.3461	0.1734	0.1786	0.3438	0.3462	0.2286	0.2366	0.3913	0.3953

Table 12. Alternative hypothesis - The good faith exception and financial constraints

This table reports the results of cross-sectional effects of financial constraints on strategic alliances. The dependent variable is *Log(SA)*, the natural logarithm of one plus the number of strategic alliance deals in the year. *GF* is an indicator variable that equals to one if the firm is headquartered in a state that has adopted the good faith exception by the year and zero otherwise. *High financial constraint* is an indicator variable that equals to one if the firm does not have enough financial slack or is financially constrained and zero otherwise. In Column 1, *High financial constraint* is equal to one if the firm has higher capital expenditures than its operating cash flow and zero otherwise. For Columns 2 to 4, we follow Farre-Mensa and Ljungqvist (2016) to define KZ index, WW index, and HP index and set *High financial constraint* to one if the value of the index is above the sample median and zero otherwise. In Column 5, *High financial constraint* is equal to one if the firm pays zero dividend in a given year and zero otherwise. Column 6 measures the degree of financial constraint by dividing the sample using firm size and *High financial constraint* is equal to one if the firm's assets is b*elow* the sample median in a given year and zero otherwise. The Appendix provides detailed variable definitions. All specifications include the control variables listed in Column 4, Panel A, Table 4. Industries are defined at the 2-digit SIC level. Standard errors are clustered by state. The *t*-statistics are reported in parenthesis. *, **, and *** denote significance at 10%, 5%, and 1%, respectively.

	(1) External dependence	**(2) KZ index**	**(3) WW index**	**(4) HP index**	**(5) No dividend**	**(6) Small size**
GF	0.0408***	0.0283***	0.0410***	0.0410***	0.0192	0.0481***
	(3.78)	(2.80)	(2.72)	(2.68)	(1.38)	(2.88)
High financial constraint $_{t-1}$	0.0128**	0.0032	0.0627***	0.0741***	0.0437***	0.0886***
	(2.40)	(0.46)	(7.78)	(9.74)	(6.07)	(10.77)
GF x High financial constraint $_{t-1}$	-0.0306***	-0.0220***	-0.0402**	-0.0394**	-0.0032	-0.0528**
	(-5.08)	(-2.95)	(-2.34)	(-2.26)	(-0.26)	(-2.60)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	73,999	71,269	73,808	73,995	73,999	73,999
Adjusted R-squared	0.1725	0.1669	0.1757	0.1764	0.1744	0.1779

Table 13. The good faith exception and strategic alliances outcomes

This table presents the results of regressions relating strategic alliances outcome variables to the adoption of the good faith exception. The dependent variables are the proxies for innovation. *Log(Patent)* is the natural logarithm of one plus the number of patents filed in the year; *Log(Citations)* is natural logarithm of one plus the total number of citations belonging to the patents filed in the year; *Log(Patent value)* is the natural logarithm of one plus the total value of all patents filed in the year, where value is estimated as the product of the estimated stock return from patent issuance, adjusted for potential measurement error, times the market capitalization of the firm that is issued a patent on the day before the announcement of the patent issuance and it is in millions of 2004 dollars; *Log(Citations/Patent)* is natural logarithm of the ratio of citations to patents filed in the year; *Log(Patents/Employee)* is natural logarithm of the number of patents filed in the year divided by the number of employees (in thousands); *Log(Citations/Employee)* is natural logarithm of the number of citations per employee; *Log(R&D)* is natural logarithm of the ratio of R&D expenditures to total assets for the given year. *Alliance* is equal to one if the firm has at least one strategic alliance deal for the given year and zero otherwise. The Appendix provides detailed variable definitions. All specifications include the control variables listed in Column 4, Panel A, Table 4. Industries are defined at the 2-digit SIC level. Standard errors are clustered by state. The *t*-statistics are reported in parenthesis. *, **, and *** denote significance at 10%, 5%, and 1%, respectively.

	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**
	Log(Patent)	***Log(Citations)***	***Log(Patent value)***	***Log(Citations /Patent)***	***Log(Patents /Employee)***	***Log(Citations /Employee)***	***Log(R&D)***
GF	0.0950***	0.1281***	0.1099***	-0.0134	0.0961***	0.1355**	0.0027***
	(3.35)	(2.81)	(3.41)	(-0.43)	(3.26)	(2.63)	(2.92)
Alliance $_t$	0.4562***	0.6600***	0.7098***	0.1220***	0.1919***	0.3945***	0.0039***
	(8.48)	(8.05)	(7.98)	(4.12)	(4.55)	(5.50)	(7.77)
GF x Alliance $_t$	0.1078	0.2072*	0.1993*	-0.0448	0.1803***	0.3059**	0.0030***
	(1.65)	(1.98)	(1.85)	(-0.98)	(2.70)	(2.39)	(5.09)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	73,999	73,999	73,999	20,217	71,674	71,674	73,999
Adjusted R-squared	0.4240	0.3829	0.4218	0.2930	0.3496	0.3134	0.7825

Financial constraints and firm growth strategies

ABSTRACT

We study the effect of financial constraints on firms' decision on the choice of growth strategies. We show that financial constraints are positively associated with strategic alliance activities, and negatively associated with mergers and acquisitions. The finding is mixed for internal capital expenditures. We argue that the disciplinary role of financial constraints and the need for financing drive our results. We also present that financially constrained firms use strategic alliances as preferred growth strategy over internal investments and mergers and acquisitions.

1. Introduction

All firms strive to grow and to create value in order to stay in the market competition. The firms must make investments of various forms in positive NPV projects to achieve this goal. In general, a firm can grow through an organic growth (internal capital expenditures) or through non-organic mergers and acquisitions (M&As) or strategic alliances (Bodnaruk, Massa, and Simonov, 2013). Making investment can be very costly so it is important that firms have enough financial resources in hand not to miss out on attractive investment opportunities. When firms are financially constrained, financial frictions prevent them from raising external funds. Therefore, constrained firms may not be able to invest in all value-enhancing future projects, thereby losing their chances to grow further.

A large number of previous research has examined the impact of financial constraints on firm internal capital expenditures (e.g., Fazzari, Hubbard, and Petersen, 1988; Almeida and Campello, 2007; Denis and Sibilkov, 2009; Campello, Graham, and Harvey, 2010) and generally find that financial constraints negatively impact firms' abilities to invest organically. However, less is known about how financial constraints affect M&A and strategic alliance and in particular how such constraints may affect a firm's choice of growth strategy. Therefore, our goal in this paper is to answer how financial constraints shape firm boundary and determine firms' choice of growth strategies with our primary focus on firm strategic alliance activities.

Both organic and non-organic growth options share the same goal of sustaining growth, and they are considered as alternative strategies (e.g., Kogut and Singh, 1988; Mathews and Robinson, 2008; Robinson, 2008; Bodnaruk *et al.*, 2013).[1] While these growth options all aim to

[1] A 2002 survey of 200 U.S. company executives conducted by Dyer, Kale, and Singh (2004) show that 82% of executives view acquisitions and alliances as alternative growth options.

generate firm value, each has their own characteristics that are relevant in addressing our research question. First of all, strategic alliances are typically less capital-intensive relative to M&As (e.g., Kogut and Singh, 1988; Bodnaruk *et al.*, 2013), costs little to reverse investments (Balakrishnan and Koza, 1993), and create firm value (e.g., Chan, Kensinger, Keown, and Martin, 1997; Bodnaruk *et al.*, 2013). However, strategic alliances also have downsides. For example, firms that form alliances can experience free-rider problems between collaborating partners and experience delays in projects (e.g., Bonatti and Hörner, 2011; Campbell, Ederer, and Spinnewijn, 2014). On the other hand, M&As are generally considered as value decreasing, especially for firms with high agency problems (e.g., Jensen, 1986; Jensen, 1987; Harford, 1999). Lastly, internally organized projects are subject to agency issues arising from resource commitment within a firm. According to previous works, such as Robinson (2008) and Bodnaruk *et al.* (2013), the firms have incentives to move resources from low-profitability projects to high-profitability projects in order to maximize firm value. And firms may engage in this "winner-picking" regardless of managers' efforts, thus the managers may choose to shirk. Robinson (2008) and Bodnaruk *et al.* (2013) have shown that alliances can address and overcome this agency problem.

We make hypothesis on how financial constraints determine a firm's decision on investments and growth strategies. First, financially constrained firms cannot easily raise external financing as financial constraints raise the cost of capital of the firm and reduce available resources for investments. Therefore, financial constraints limit firms' ability to make investments in desirable projects. As a consequence, a model of decreasing returns to scale predicts these firms to make decisions to optimally utilize their limited resources and invest in growth strategies that are cost efficient. Alternatively, the free-cash-flow argument of Jensen (1986) predicts that firms with large free-cash-flow are embedded with agency problems that they are more likely to invest in value decreasing projects. Under the this argument, Almeida, Hsu, and Li (2013) show that financial constraints have disciplinary benefit that can force firms to make optimal investment decisions and to make efficient use of capital by alleviating agency problem. Therefore, we hypothesize that financially constrained firms engage in higher level of strategic alliance deals as they are considered a cheaper alternative and a growth option for firms with less agency problems.

These two mechanisms or channels are not mutually exclusive as they are very closely related. From the first channel, we can hypothesize that financially constrained firms are more likely to increase strategic alliances and reduce M&As and internal investments, as the latter two are considered as more expensive growth options than the first one (e.g., Luypaert and Huyghebaert, 2007; Alshwer, Sibilkov, and Zaiats, 2011; Bodnaruk *et al.*, 2013). Recently industry reports also state that strategic alliances are an attractive investment option for firms that cannot afford large investments (PWC, 2016; KPMG International, 2017).[2] The agency mechanism also expect similar outcome. If financial constraints discipline firms, we should expect to observe increase in alliances, and decrease in M&As and internal capital expenditure.

We use the ordinary least squares (OLS) regressions to test for these hypothesis. We use the *Log(SA), Log(M&A),* and *Investments* as the proxies for strategic alliances, M&As, and internal investments, respectively. We measure financial constraints by *No-dividend, Payout, KZ index* (Kaplan and Zingales, 1997)*, WW index* (Whited and Wu, 2006)*, HP index* (Hadlock and Pierce, 2010)*,* and *Size*. We sort these financial constraint proxies into median and create indicator variables for financially constrained firms. *Constrained* equals to one when a firm is categorized

[2] KPMG International (2017) report their survey result that most alliances do not require upfront investment (80%), and when the other 20% made an upfront investment, the amount exceeds $100 million. This is much lower in comparison to the average investment amount of $416 million for M&As.

as financially constrained when samples are divided into median, and zero otherwise. All variables are defined in the Appendix.

We first examine whether financially constrained firms increase strategic alliance activities. We find that most of the coefficients are positive and significant suggesting that constrained firms significantly engage in more alliance deals. The relation is also economically meaningful as well. The constrained firms form 1.25% to 7.94% more alliances than unconstrained firms depending on the measure of financial constraints. Next, we test how financial constraints impact the level of M&A deals. All significant financial constraint measures, except for *HP index*, are negative and significant supporting our hypothesis. Lastly, for internal investments regression, we find mixed results. The coefficients for *No-dividend, Payout*, and *HP index* are positively significant. We argue that the positive coefficients for first two measures are due to the firms using retained earnings to make internal investments instead of paying out as dividend. And *HP index* may capture the lifecycle of the firm rather than dimensions of financial constraints because it only takes firm size and age to construct the index. The findings are robust to industry-year fixed effects and the results are similar.

We also try to address the endogeneity concerns from omitted variables and provide some supporting evidence for causal relationship by using the junk bond market collapse in 1989 as the exogenous shock to the financial constraints. We use the shock to run the difference-in-differences regression and compare the average changes in strategic alliance activities from pre- to post-event period for the junk bond issuers and the average changes in strategic alliances from the pre- and post-event period for unrated firms. We find evidence that the junk bond issuers increase strategic alliances after the junk bond market collapse. However, we do not find any evidence for M&As and capital expenditures.

In order to identify the channels, we interact financial constraint dummies with an indicator variable *FCF* that equals to one if the firm has high free-cash-flow, and zero otherwise. Previous research has shown that firms with high free-cash-flow are likely to make bad investment decisions due to agency problems (e.g., Jensen, 1986, 1987; Harford, 1999; Almeida *et al.*, 2013). If the disciplining effect of financial constraints is the driving force for our findings, we would expect to find stronger results for firms that are likely to experience higher agency problem as constrained firms would not make wasteful investments. In contrast, if constrained firms make investment decisions based on their available resources, we would observe attenuated results for cash-rich firms. We find evidence that is consistent with the agency channel for strategic alliances and M&As. The constrained firms with large free-cash-flow are associated with significantly larger alliance activities and significantly lower M&As. However, for internal investments, we find evidence supporting the other hypothesis. We observe the increase in internal investments for constrained firms with large free-cash-flow. Therefore, our findings suggest that the financial constraints can work as a disciplinary tool for making decisions on non-organic external growth strategies but it is representative of poor financial status of the firm for organic internal investments decisions.[3]

Lastly, we examine how financial constraints affect firm's decision on the choice between growth strategies. We directly compare the choice between strategic alliance and internal investment and choice between strategic alliance and M&As by regressing *SA/Capx* and *SA/MA* on financial constraint measures and control variables. We observe significantly positive

[3] Lang, Walkling, and Stulz (1991) suggest that firms with high free-cash-flow and low investment opportunities suffer the most from the agency cost of free-cash-flow. We tried running subsample tests with respect to the investment opportunities for alliances M&As, and capital expenditure. Both high and low investment opportunities show the same pattern. This finding is similar to Harford (1999), where he finds both high and low Tobin's Q firms with large free-cash-flow exhibit agency issues.

coefficients for both regressions. Few measures show negative coefficients but without significance. The findings support our hypothesis that financially constrained firms prefer strategic alliances as the growth strategy over internal investment or M&As.

This paper makes the following contributions. First, this paper makes contribution to the literature on financial constraints and real decisions by showing that constrained firms prefer to form strategic alliances over engaging in M&As or investing in internal investments. There are previous research that show financial constraints may have implications for M&As and investments (e.g., Fazzari *et al.*, 1988; Harford, 1999; Almeida and Campello, 2007). However, up to our best knowledge, no other paper has provided evidence linking financial constraints to all organic and non-organic growth options and to firm's choice on growth strategies.

Our findings also contribute to the literature on the determinants of firm boundaries, particularly strategic alliance. There are scant research that looks at the factors that determine alliance formation including firm governance (Bodnaruk *et al.*, 2013), common blockholders (Chemmanur, Shen, and Xie, 2016), and firm-to-economy technological proximity (Li, Qiu, and Wang, 2018). Our finding adds to the literature by providing evidence that financial flexibility is an important factor that determines firm's decision to form alliance.

Furthermore, we complement the findings of Almeida *et al.* (2013) on the disciplinary role of financial constraints. We show evidence that financial constraints can serve a disciplinary role that is strong enough to influence firm's decision on growth strategies and that more alliances and less M&As are formed as a result of reduced agency problem.

2. Data and empirical methods

2.1. Sample selection

We retrieve the data on strategic alliances from the Securities Data Corporate (SDC) Platinum database. We define strategic alliance as all agreements made between two or more firms to achieve mutually beneficial objectives (Bodnaruk *et al.*, 2013). SDC Platinum started providing coverage on alliances from 1985, therefore, our sample starts from 1985 and ends in 2017. Our sample includes all types of alliance deals recorded on SDC database (i.e., R&D related alliance and joint ventures). We also collect data on M&As from SDC. The data on firm financials is from Compustat and stock price information is from CRSP. We restrict our sample to all publicly traded industrial U.S. firms (excluding financial firms and utilities firms) from CRSP/Compustat merged database. We require that the alliance deal involve at least one non-financial U.S. firms that can be matched to a firm in Compustat.[4] For the firm-year observations without any alliance deals recorded in SDC database, we assume them to have not made any deals. We also restrict observations to have non-missing values for the main control variables used in the regressions. Our sample consists of 104,947 firm-year observations. However, the number of observation varies by regression specifications due to missing values for the various financial constraint measures.

We present the distribution of alliance deals by year and by Fama-French 17-industry classification in Table 1. In Panel A, we observe very apparent pattern of increasing alliance activities over time and they are the highest during the entire 1990s, marking the peak in the mid-

[4] We use alliance deals with the status of "Completed/Signed." Many alliance deals have the unclear status, such as "Pending" or "Letter of intent." As Schilling (2009) suggests that data pattern can be different when using both completed and pending alliance and when using completed alliances only, in untabulated tests, we add the "Pending" deals and find similar results. We also try using all alliance deals, including those with unclear status, the results are very similar.

1990s, and then there is downturn since the beginning of the 21st century. This pattern is fairly consistent with the pattern observed in Schilling (2009) Appendix 1. In Panel B, we document the distribution by industry. The number of alliances are especially high in the Drugs, Soap, Perfumes, and Tobacco industry, Machinery and Business Equipment industry, and also in the 'Other' industries.

2.2. Empirical methods

To test for the relationship between financial constraint and the levels of various growth strategies, we estimate the following Ordinary Least Squares (OLS) regression models as the baseline specifications:

$$(1)\ Y_{i,t} = \alpha_1 Constrained_{i,t-1} + Controls_{i,t-1} + Industry\ fixed\ effects + Year\ fixed\ effects + \varepsilon_{i,t}$$

where the dependent variable *Y* is *Log(SA), Log(M&A),* or *Investment*. *Log(SA)* is the natural logarithm of one plus the number of strategic alliance deals; *Log(M&A)* is the natural logarithm of one plus the number of completed M&A deals; and *Investment* is the ratio of capital expenditure over total assets. The subscript *i* denotes the firm and *t* stands for the year of observation. All right-hand side variables are lagged by one year. The financial constraint proxies that we use are *No-dividend, Payout, KZ index, WW index, HP index,* and *Size. Constrained* in the first regression model is an indicator variable that equals to one if the firm does not pay any dividend, *Payout* and *Size* is below the sample median, and *KZ index, WW index,* and *HP index* is above the sample median. It equals to zero otherwise. We include industry fixed effects at the 2-digit SIC industry level, and year fixed effects, and cluster standard errors at the firm level.

We control for the variables that are often used in strategic alliance literatures (e.g., Bodnaruk *et al.*, 2013; Chemmanur *et al.*, 2016; Li *et al.*, 2018). These include *Size, R&D, Cash, Sales growth, Log(Firm age), ROE, Fixed assets, Leverage, Capex, Tobin's Q, HHI index, Market share, PE ratio, Institutional ownership,* and *Free-cash-flow*. All variables are defined as in the Appendix. All continuous variables are winsorized at 1st and 99th percentiles, and all dollar values are adjusted for CPI to 2015 dollars. Table 2 presents the characteristics of the sample used.

3. Empirical results

3.1. Main results

We start by examining the effects of financial constraints on strategic alliance activities. Almeida *et al.* (2013) argue that financial constraints have disciplinary benefit and that it can force firms to make optimal investment decisions and improve capital efficiency. Alternatively, they also state that financial constraints increase a firm's cost of capital and reduce its' available resources for investment, thereby making firms to invest in more cost efficient projects. Furthermore, other papers document that strategic alliances tend to require smaller investment than M&As and better governed firms form more alliances (Bodnaruk *et al.*, 2013), and the alliances investment can be reversed with relatively lower cost in case of failure (Balakrishnan and Koza, 1993). Therefore, we make the hypothesis that the firms experiencing difficulty raising external capital (i.e., financially constrained firms) may choose to engage in higher level of strategic alliance deals.

We run the OLS regression models defined in the previous section to formally test for this hypothesis. The results are presented in Table 3. Consistent with our hypothesis, we find positive and significant coefficients for most of the proxies for financial constraints. Financially constrained firms have 1.56% to 4.03% higher strategic alliance activities relative to unconstrained firms depending on different specifications.[5] This finding supports the prediction that financially constrained firms form more alliances.[6]

Next, we test the hypothesis that financially constrained firms reduce M&A activities. The previous literatures consider alliances and M&As as alternatives (e.g., Kogut and Singh, 1988; Mathews and Robinson, 2008), and the agency story suggests that most acquisitions are value destroying. Bodnaruk *et al.* (2013) also states that M&As are more costly than strategic alliances in general. So, to the extent financial constraints have disciplinary benefit and reduce agency problem or to the extent M&As are cheaper than strategic alliances, we expect to observe negative coefficients for financially constrained firms. The results are shown in Table 4, and they are somewhat consistent with our prediction. Financially constrained firms have 1.45% to 5.11% lower M&A activities.[7] *HP index* is the only proxy with significantly positive coefficient for constrained firm dummy. This could be because different constraint measures may capture other aspects of firms.

Lastly, in Table 5, we use *Investment* as the dependent variable. Internally undertaking projects exposes the firm to agency issues on resource commitment (Bodnaruk *et al.*, 2013). Fazzari *et al.* (1988) document that constrained access to external capital can lead firms to decrease investment. Therefore, we expect to observe decrease in internal capital expenditure for financially constrained firms. However, we observe mixed results for the constraint proxies and all

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[5] We have also tried logit regression with industry fixed effects and year fixed effects, and also with industry-year fixed effects for *Log(SA)* and *Log(M&A)* as the dependent variable since most of our dependent variable is 0. The result is also fairly similar when using Poisson regression using the number of alliance and M&A deals as the dependent variable.

[6] I have also tried using the number of strategic alliances deals excluding the number of joint ventures as the dependent variable. The results are qualitatively the same.

[7] We use total M&A value as the dependent variable and find that M&A value tends to be lower for the constrained firms.

coefficients are positive except for *WW index* in Panel A. This finding can be explained by the Denis and Sibilkov (2009) that financially constrained firms with high cash holdings can increase capital expenditure by undertaking positive net present value projects. Also, for the positive coefficients of *No-dividend* and *Payout* measures, we argue that the results could demonstrate that the firms that did not payout any dividend or firms with low payout ratio use their retained earnings to fund for internal investment needs. And the firms with high *HP index* also portrait positive coefficient. We interact the financial constraint dummy with *High cash* dummy variable to test whether constrained firms with high cash increase capital expenditures. The result in Panel B shows that *Constraint* dummy is now mostly negative while *Constrained x High cash* are all positively significant. This supports the view of Denis and Sibilkov (2009). All our findings in these tables are robust to using industry-year fixed effects to control for year specific industry factors.[8]

3.2 Endogeneity concerns: Difference-in-differences test

There is possibility that the findings are could be driven by omitted variables that may influence both the dependent and independent variables. In order to address the potential endogeneity issues from omitted variables we control for various firm-level and industry-level variables in the main regression. In addition, we control for industry fixed effects and year fixed effects. However, we still cannot rule out the possibility that the omitted variables problem could be driven by a firm-level omitted variable even though we control for several firm-level control variables that are commonly used in the previous studies. Therefore, to address this issue, we

[8] We observe the wave of alliance activities in 1990s in Table 1 and adding industry-year fixed effects may account for it.

follow the previous papers (e.g., Lemmon and Roberts, 2010; Almeida *et al.*, 2013) and utilize the junk bond market collapse in 1989 as an exogenous shock to run a difference-in-differences (DID) regression. Lemmon and Roberts (2010) write that the firms that issue junk-grade bond lost access to liquidity when there was a development in the corporate bond market in 1989. Therefore, these firms would have experienced tightening financial constraints more than other firms that do not finance using the junk bond issuance.

The event window spans from 1986 to 1993 and assigned as pre-event period for the years before 1990 and post-event period on or after 1990. The sample for the test is limited to the junk bond issuers and unrated firms. We use S&P long-term domestic issuer credit rating for the credit rating. The firms that are rated lower than or equal to BB+ are junk bond issuers and firms without any rating are considered unrated. We also require at least one observation for both pre- and post-event period, and unrated firms to stay unrated and junk-grade bonds to stay within the junk-grade during the event period. The results can be found in Table 6.

The coefficient of interest is Junk x Post interaction variable. We find that the coefficient is positive and significant for all three columns. The findings imply that the junk bond market collapse tightens financial constraints for the junk bond issuers more than for the unrated firms, and it leads these firms to increase strategic alliance activities. The findings from this table alleviates the concern for omitted variables problem and also help establish the causal relationship between financial constraints and strategic alliances.[9]

[9] We do not tabulate the results for M&As and internal capital expenditures. We do not find any evidence suggesting that tighter financial constraints impact these growth options.

3.3 Financial constraints and disciplinary benefit

Our evidence suggest that financial constraints tend to increase strategic alliances, reduce M&As, and mixed finding for internal capital expenditure. If our results are driven by reduction in agency problem from tighter financial constraints, we should expect to see greater effect where agency cost is high. Jensen (1986) argues that firms with large free-cash-flow are likely to suffer from agency problems so these firms may invest in unproductive projects that are not in the interest of shareholders, and in Jensen (1987), he writes that the agency cost of free-cash-flow reduces firm value and that the agency cost can be mitigated by reducing cash flow available for managers to spend. Moreover, Harford (1999) finds that cash-rich firms tend to make value decreasing investment decisions. Therefore, we expect to find stronger effect when the constrained firms have higher free-cash-flow.

We test for this hypothesis in Table 7. The dependent variables used are *Log(SA), Log(M&A),* and *Investment* for Panels A, B, and C, respectively. We interact the indicator variables for financially constrained firms with high free-cash-flow dummy variable *FCF* and use it as our main variable of interest. In Panel A, the coefficient of *FCF* is negative as expected, suggesting reduction in alliance deals. This is consistent with Bodnaruk *et al.* (2013), where firms with high agency problems are less likely to engage in strategic alliance deals. *Constrained* coefficients are still positive. Consistent with our prediction, *Constrained x FCF* and *High FC x FCF* coefficients are mostly positive even though only two proxies show significance supporting our agency prediction that financially constrained firms with high free-cash-flow are more likely to increase alliance activities.

Harford (1999) documents evidence that cash-rich firms engage in value decreasing mergers and acquisitions, supporting the agency cost of free-cash-flow explanation. Therefore, we can expect negative coefficients for highly constrained firms with high free-cash-flow. Panel B shows that all coefficients for *FCF* are positive and mostly highly significant, consistent with agency cost of free-cash-flow story. And the coefficients for interaction terms are negative and significant as expected, except for *External dependent* measure. The result is very strong. This suggests that financial constraints may reduce the agency costs of free-cash-flow, thereby reducing value destroying investments.

Under our assumption that financial constraints have disciplinary benefit, the interaction terms are likely to show negative coefficients, while it is also possible to observe positive coefficients if the constrained firms merely needed financial flexibility in order to make capital expenditures. Therefore, we cannot make clear prediction and it is left as an empirical question. The results in Panel C show that constrained firms with high free-cash-flow increase capital expenditures. This is suggestive that firms with tight constraints invest in capital expenditures when they have enough internally generated resources. This finding is consistent with the arguments of Denis and Sibilkov (2009) that financially constrained firms with high cash holdings can increase internal capital expenditure by utilizing internal resources.

Overall, the findings from this table are consistent with the idea that financial constraints can motivate firms to make optimal investment decisions by mitigating free-cash-flow agency problems of the firm and also by the availability of resources that can be utilized.

3.4 Financial constraints and the choice between growth options

We have found that the lack of financial slack is positively associated with alliance formation, lower M&A deals, mixed relation with internal capital expenditures. Bodnaruk *et al.* (2013) writes that strategic alliance is not the only way for firms to sustain growth and that firms can use internal investments or external M&As as an alternative growth strategy. In this section, we further examine whether alliances are used as a preferred growth option for financially constrained firms by making direct comparison of the choice between the growth strategies.

We follow Bodnaruk *et al.* (2013) and test whether strategic alliances are preferred growth strategy over M&As and capital expenditures when a firm is financially constrained. The authors argue that internally organized projects are vulnerable to agency issues arising from the incentive problem and that alliances can alleviate this issue. Also, M&As tends to require higher investment than alliances, which are also considered financially more flexible (e.g., Bodnaruk *et al.*, 2013). Taking these into account, we anticipate that alliances would be a preferred form of investment to M&As for financially constrained companies. The prediction is not clear for the choice of investment between strategic alliances and capital expenditures.

We create the dependent variables *SA/Capx* as the natural logarithm of one plus the ratio of the number of strategic alliance deals scaled by capital expenditures, and *SA/MA* is the natural logarithm of one plus the ratio of the number of strategic alliance deals to the number of completed M&As. Observations with zero capital expenditures or zero M&A deals are excluded from our sample. The regression results are presented in Table 8. Panel A presents the result for *SA/Capx* as the dependent variable. As in previous section, the results are mixed, suggesting that the choice between strategic alliances and internal capital expenditure is not so obvious for financially constrained companies. Panel B reports the results for *SA/MA* and the result is consistent with our expectation with significance. All results show positive coefficient and most are strongly significant. The findings partly support our hypothesis that strategic alliance is a preferred growth strategy over other growth options when firms have difficulty raising external capital.

4. Conclusion

This paper studies the link between financial constraints and investments and growth strategies. We argue that financially constrained firms are likely to portrait different behaviors toward different types of investment options. We find that financial constraints increase strategic alliance activities and reduce M&As. The finding is unclear for internal investments. Our findings provide evidence suggesting that financially constrained firms expand their boundary and sustain growth by forming alliances. In addition, the constrained firms with high free-cash-flow show stronger results for alliances and M&As. So we identify the disciplinary benefit of financial constraint as the potential mechanism to explain our findings. We also document that financial constraints lower resources available for internal investment, leading to reduction in more capital intensive internal investments. This is evidenced from increases in internal investments when financially constrained firms have high cash or free-cash-flow. And we also find some evidence that alliances are a favored form of growth strategies over other growth options when a firm is constrained. Overall, our paper shows that financial constraints are important factor for a firm's decisions on investments and growth strategies.

Appendix. Variable definitions

Asset	The book value of total assets in millions of 2015 dollars	Compustat
Cash	The ratio of cash to total assets. Che/at	Compustat
Capex	Capital expenditures over total assets during previous fiscal year t-1	Compustat
Fixed assets	Total property, plant, and equipment over total assets	Compustat
FCF	An indicator that equals to one if the firm has above the sample median free-cash-flow for the year, and zero otherwise	Compustat
Free-cash-flow	An indicator variable for high free-cash-flow, where free-cash-flow is defined as (ib+dp-delta(invt+rect+aco-lco)-capx) divided by market value of assets (dltt+dlc+ csho*prcc_f)	Compustat
HHI index	Herfindahl index of sales at 2-digit SIC industry and year	Compustat
High cash	An indicator variable that equals to one if the firm has above the sample median cash for the year, and zero otherwise.	Compustat
HP index	$-0.737*\text{Size} + 0.043*\text{Size}^2 - 0.040*\text{Age}$ Size = log of total assets. The total assets is maxed at $4.5 billion Age = the number of years the firm has non-missing stock price in Compustat	Hadlock and Pierce (2010) Compustat
Institutional ownership	The percentage of shares owned by institutional investors	Thomson Reuters 13F
Investment	Capital expenditures over total assets in year t	Compustat
KZ index	-1.001909*((*ib* + *dp*)/lag(*ppent*)) + .2826389*((*at* + *csho***prcc_f* - *ceq* - *txdb*)/*at*) + 3.139193*(*dltt* + *dlc*)/*seq* - 39.3678*((*dvc* + *dvp*)/lag(*ppent*)) - 1.314759*(*che*/lag(*ppent*))	Lamont et al. (2001) Compustat
Leverage	Short-term debt plus long-term debt over total assets	Compustat
Log(Firm age)	Natural logarithm of firm age in years using the first observation from Compustat and CRSP	Compustat CRSP
Log(M&A)	Natural logarithm of one plus the number of completed mergers and acquisitions	SDC Platinum
Log(SA)	Natural logarithm of one plus the number of strategic alliance deals	SDC Platinum
Market share	Market share of a firm within 2-digit SIC industry and year. Sales over 2-digit SIC industry-year average sales	Compustat
No-dividend	An indicator variable that equals to one if the firm does not pay any dividend, and zero otherwise	Compustat

Payout ratio	The ratio of dividends and common stock repurchases to operating income (dvc+dvp+prstkc)/at	Compustat
PE ratio	Ratio of stock price to earnings per share	Compustat
R&D	R&D expenditure over total assets. 0 if missing.	Compustat
ROE	Ratio of earnings to average equity	Compustat
SA/Capx	Natural logarithm of one plus the ratio of the number of strategic alliances to the capital expenditures	SDC Platinum Compustat
SA/MA	Natural logarithm of one plus the ratio of the number of strategic alliances to the number of completed M&A deals	SDC Platinum
Sales growth	Sales over lagged sales	Compustat
Size	Natural logarithm of one plus total assets in 2015 millions of dollars	Compustat
Tobinq	Ratio of total assets plus common shares outstanding times fiscal year-end stock price minus total common equity to total assets. (at+(csho*prcc_f)-ceq)/at	Compustat
WW index	-0.091*(*ib*+*dp*)/*at* - 0.062*Positive dividend + 0.021**dltt*/*at* - 0.044*(log(*at*)) + 0.102*Industry sales growth - 0.035*Sales growth Positive dividend = 1 if *dvc* + *dvp* is positive and zero otherwise Industry sales growth = Average industry sales growth at 3-digit SIC level and year Sales growth = *sale/*lag(*sale)*-1	Whited and Wu (2006) Compustat

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Table 1. Distribution of strategic alliance deals by year and by industry

This table reports the distribution of strategic alliance deals by year and by Fama-French 17 industries classification. Panel A presents the distribution of alliances by year and Panel B presents the distribution of alliances by Fama-French 17 industries classification.

Panel A. Distribution of strategic alliance deals by year

Year	Number of alliance	Mean	N
1985	36	0.0122993	2,927
1986	68	0.0222005	3,063
1987	59	0.0189650	3,111
1988	116	0.0359578	3,226
1989	110	0.0331226	3,321
1990	692	0.2073098	3,338
1991	1,192	0.3536043	3,371
1992	1,813	0.5513990	3,288
1993	1,701	0.4799661	3,544
1994	1,942	0.5137566	3,780
1995	1,838	0.4575554	4,017
1996	1,291	0.2996055	4,309
1997	1,876	0.4167963	4,501
1998	1,535	0.3304629	4,645
1999	1,482	0.3299199	4,492
2000	895	0.2081395	4,300
2001	437	0.1044955	4,182
2002	435	0.1032029	4,215
2003	448	0.1116372	4,013
2004	377	0.0974916	3,867
2005	423	0.1153846	3,666
2006	581	0.1619287	3,588
2007	540	0.1580796	3,416
2008	417	0.1243662	3,353
2009	83	0.0249549	3,326
2010	54	0.0172855	3,124
2011	141	0.0472837	2,982
2012	177	0.0600815	2,946
2013	182	0.0630412	2,887
2014	214	0.0752726	2,843
2015	38	0.0134991	2,815
2016	218	0.0766526	2,844
2017	211	0.1815835	1,162

Panel B. Distribution of strategic alliance deals by Fama-French 17 industries classification

Fama-French 17 industries	Number of alliance	Mean	N
Food	362	0.0884437	4,093
Mining and Minerals	108	0.0467533	2,310
Oil and Petroleum Products	509	0.0789270	6,449
Textiles, Apparel & Footware	261	0.0938849	2,780
Consumer Durables	588	0.1523316	3,860
Chemicals	519	0.2000000	2,595
Drugs, Soap, Prfums, Tobacco	1,685	0.3297456	5,110
Construction and Construction Materials	207	0.0444588	4,656
Steel Works Etc	138	0.0658711	2,095
Fabricated Products	67	0.0527975	1,269
Machinery and Business Equipment	5,580	0.2794611	19,967
Automobiles	366	0.1788856	2,046
Transportation	583	0.1126352	5,176
Retail Stores	504	0.0632371	7,970
Other	10,145	0.2301184	44,086

Table 2. Summary statistics

This table reports summary statics for the dependent and independent variables. The sample consists of all Compustat firms (excluding financial industries and utilities industries) from 1985 to 2017 and includes 104,947 firm-year observations. All continuous variables, except indicator variables, are winsorized at 1st and 99th percentiles, and dollar values are adjusted to 2015 dollars. *SA* is the number of strategic alliances the firm has entered during a fiscal year. *M&A* is the number of completed mergers and acquisitions during the fiscal year. *Investment* is the ratio of capital expenditures to the total assets; *SA/Capx* is the natural log of one plus the number of strategic alliances divided by capital expenditures; and *SA/MA* is the log of one plus the ratio of strategic alliances to the number of completed mergers and acquisitions. *External dependent* is an indicator variable that equals to one if capital expenditure is greater than the operating cash flow as computed following Byoun (2008), and zero otherwise; *No-dividend* is an indicator variable that equals to one if the firm does not pay any dividend, and zero otherwise; *Payout ratio* is the ratio of dividends and common stock repurchases to operating income; *KZ index, WW index,* and *HP index* are indexes for financial constraints defined following Farre-Mensa and Ljungqvist (2016). *Assets* is the book value of assets in millions of 2015 dollars. *R&D* is the ratio of R&D expenditures to total assets. *Cash* is the cash and short-term investments over total assets. *Sales growth* is the ratio of sales to lagged sales. *Firm age* is the number of years since the firm first appeared in Compustat or CRSP, whichever is earlier. *ROE* is the ratio of earnings to average equity for prior fiscal year. *Fixed assets* is the ratio of total property, plant, and equipment to total assets. *Leverage* is short-term debt plus long-term debt divided by total assets. *Capex* is capital expenditures over total assets. *Tobin's Q* is the ratio of total assets plus common shares outstanding times fiscal year-end stock price minus total common equity to total assets (*(at+(csho*prcc_f)-ceq)/at*). *HHI index* is the Herfindahl index of sales at 2-digit SIC industry and year. *Market share* is the ratio of sales over 2-digit SIC industry average sales for year. *PE ratio* is the ratio of stock price to earnings per share. *Institutional ownership* is the percentage of shares owned by institutional investors.

Variable	N	Mean	S.D.	P25	Mdn	P75
Dependent variables						
SA	104,947	0.17	0.64	0	0	0
M&A	104,947	0.58	2.14	0	0	0
Investment	104,515	0.06	0.06	0.02	0.04	0.07
SA/Capx	103,935	0.02	0.14	0	0	0
SA/MA	20,143	0.11	0.30	0	0	0
Explanatory and control variables						
No-dividend	104,947	0.66	0.47	0	1	1
Payout ratio	97,566	0.02	0.04	0	0	0.02
KZ index	100,363	-6.83	25.73	-4.99	-0.79	0.99
WW index	104,513	-0.22	0.29	-0.34	-0.24	-0.15
HP index	104,946	-3.1	0.84	-3.68	-3.14	-2.55
Asset	104,947	3437.77	12039.72	71.67	301.65	1487.1
R&D	104,947	0.04	0.09	0	0	0.04
Cash	104,947	0.18	0.21	0.03	0.1	0.26

Sales growth	104,947	1.14	0.47	0.96	1.07	1.21
Firm age	104,947	19.01	15.79	8	14	25
ROE	104,947	-0.04	0.61	-0.07	0.08	0.17
Fixed asset	104,947	0.28	0.23	0.1	0.21	0.41
Leverage	104,947	0.22	0.21	0.03	0.19	0.35
Capex	104,947	0.06	0.06	0.02	0.04	0.08
Tobin's Q	104,947	2.01	1.66	1.09	1.47	2.22
HHI index	104,947	0.09	0.13	0.04	0.05	0.09
Market share	104,947	0.07	7.36	0	0	0.01
PE ratio	104,947	13.99	54.33	-2.5	11.84	23.04
Institutional ownership	104,947	0.4	0.30	0.11	0.35	0.65
Free-cash-flow	104,947	-0.04	0.19	-0.08	0	0.04

Table 3. Financial constraints and strategic alliance deals

This table presents the ordinary least squares regression results of strategic alliance deals on financial constraints measures during our sample period of 1985 to 2017. The dependent variable is *Log(SA)*, which is the natural logarithm of one plus the number of strategic alliance deals. *Constrained* is a dummy variable equal to one if the firm is categorized as financially constrained. Column 1 uses *No-dividend* as the main variable that equals to one if the firm does not pay any dividend, and zero otherwise. From Columns 2-6, we use *Payout, KZ index, WW index, HP index,* and *Size* as the explanatory variable. We divide these variables at the median. For *Payout* and *Size*, we assign the firms below the sample median to the constrained group (*Constrained*). For rest of the financial constraint proxies, we assign the firms to the constrained group if the firm is above the sample median. All variables are as defined in Appendix. All specifications include industry fixed effects and year fixed effects unless noted otherwise. Industries are defined at the 2-digit SIC industries. *t*-statistics are reported in parenthesis and standard errors are clustered at the firm level. *, **, and *** denote significance at 10%, 5%, and 1%, respectively.

	(1) **No-dividend**	(2) **Payout**	(3) **KZ index**	(4) **WW index**	(5) **HP index**	(6) **Size**
Constrained	0.0403***	0.0156***	0.0040	0.0353***	0.0305***	0.0398***
	(11.01)	(6.48)	(1.26)	(10.25)	(6.75)	(8.34)
Size	0.0794***	0.0716***	0.0694***	0.0829***	0.0798***	0.0868***
	(20.36)	(18.96)	(19.18)	(20.07)	(18.96)	(18.45)
R&D	0.0185***	0.0221***	0.0188***	0.0197***	0.0190***	0.0190***
	(11.18)	(11.88)	(11.29)	(11.50)	(11.38)	(11.39)
Cash	0.0054***	0.0051***	0.0069***	0.0056***	0.0059***	0.0058***
	(3.25)	(2.98)	(3.81)	(3.31)	(3.49)	(3.45)
Sales growth	0.0006	0.0005	0.0005	0.0006	0.0005	0.0005
	(0.52)	(0.42)	(0.47)	(0.48)	(0.47)	(0.48)
Log(Firm age)	0.0063***	0.0045**	0.0014	0.0025	0.0066***	0.0014
	(2.96)	(2.14)	(0.70)	(1.18)	(2.59)	(0.66)
ROE	-0.0050***	-0.0051***	-0.0053***	-0.0057***	-0.0060***	-0.0059***
	(-5.51)	(-5.32)	(-5.82)	(-6.29)	(-6.58)	(-6.49)
Fixed asset	-0.0079***	-0.0098***	-0.0101***	-0.0091***	-0.0095***	-0.0098***
	(-3.86)	(-4.76)	(-4.99)	(-4.45)	(-4.68)	(-4.84)
Leverage	-0.0131***	-0.0109***	-0.0098***	-0.0109***	-0.0101***	-0.0094***
	(-8.66)	(-7.35)	(-6.52)	(-7.43)	(-6.95)	(-6.51)
Capex	0.0064***	0.0063***	0.0066***	0.0068***	0.0064***	0.0065***

	(5.15)	(5.07)	(5.44)	(5.44)	(5.19)	(5.26)
Tobin's Q	0.0260***	0.0233***	0.0239***	0.0265***	0.0252***	0.0259***
	(13.70)	(12.40)	(12.92)	(13.67)	(13.22)	(13.51)
HHI index	0.0016	0.0017	0.0013	0.0015	0.0018	0.0017
	(1.03)	(1.08)	(0.83)	(0.97)	(1.11)	(1.06)
Market share	0.0110***	0.0119***	0.0104***	0.0094***	0.0097***	0.0091***
	(3.58)	(3.81)	(3.33)	(3.09)	(3.21)	(3.02)
PE ratio	-0.0004	-0.0005	-0.0006	-0.0008	-0.0008	-0.0008
	(-0.45)	(-0.47)	(-0.56)	(-0.81)	(-0.80)	(-0.79)
Institutional ownership	0.0028	0.0041**	0.0051***	0.0066***	0.0062***	0.0078***
	(1.47)	(2.06)	(2.66)	(3.47)	(3.26)	(4.17)
Free-cash-flow	-0.0030***	-0.0029***	-0.0031***	-0.0032***	-0.0035***	-0.0037***
	(-3.92)	(-3.68)	(-4.00)	(-4.11)	(-4.57)	(-4.78)
Observations	114,462	114,462	106,737	109,411	113,854	114,460
Adjusted R-squared	0.1386	0.1414	0.1363	0.1353	0.1411	0.1402

Table 4. Financial constraints and mergers and acquisitions

This table presents the ordinary least squares regression results of mergers and acquisitions deals on financial constraints measures during our sample period of 1985 to 2017. The dependent variable is *Log(M&A)*, which is the natural logarithm of one plus the number of completed M&A deals. *Constrained* is a dummy variable equal to one if the firm is categorized as financially constrained. Column 1 uses *No-dividend* as the main variable that equals to one if the firm does not pay any dividend, and zero otherwise. From Columns 2-6, we use *Payout, KZ index, WW index, HP index,* and *Size* as the explanatory variable. We divide these variables at the median. For *Payout* and *Size*, we assign the firms below the sample median to the constrained group (*Constrained*). For rest of the financial constraint proxies, we assign the firms to the constrained group if the firm is above the sample median. All variables are as defined in Appendix. All specifications include the control variables from Table 3, industry fixed effects and year fixed effects unless noted otherwise. Industries are defined at the 2-digit SIC industries. *t*-statistics are reported in parenthesis and standard errors are clustered at the firm level. *, **, and *** denote significance at 10%, 5%, and 1%, respectively.

	(1) No-dividend	**(2) Payout**	**(3) KZ index**	**(4) WW index**	**(5) HP index**	**(6) Size**
Constrained	0.0101	-0.0214***	-0.0511***	-0.0145**	0.0604***	0.0103
	(1.28)	(-4.33)	(-8.18)	(-2.25)	(7.78)	(1.17)
Observations	112,372	104,798	107,576	111,922	112,371	112,372
Adjusted R-squared	0.0944	0.0935	0.0944	0.0944	0.0956	0.0944

Table 5. Financial constraints and investment

This table presents the ordinary least squares regression results of investment on financial constraints measures during our sample period of 1985 to 2017. The dependent variable is *Investment*, which is the capital expenditures over total assets. *Constrained* is a dummy variable equal to one if the firm is categorized as financially constrained. Column 1 uses *No-dividend* as the main variable that equals to one if the firm does not pay any dividend, and zero otherwise. From Columns 2-6, we use *Payout, KZ index, WW index, HP index,* and *Size* as the explanatory variable. We divide these variables at the median. For *Payout* and *Size*, we assign the firms below the sample median to the constrained group (*Constrained*). For rest of the financial constraint proxies, we assign the firms to the constrained group if the firm is above the sample median. In Panel A, we provide the OLS results of *Investment* on *Constrained* variable. In Panel B, we add the interaction of *Constrained* and *High cash* indicator variable, where *High cash* equals to one if the firm has above the sample median cash for the year, and zero otherwise. *All* variables are as defined in Appendix. All specifications include the control variables from Table 3, industry fixed effects and year fixed effects unless noted otherwise. Industries are defined at the 2-digit SIC industries. *t*-statistics are reported in parenthesis and standard errors are clustered at the firm level. *, **, and *** denote significance at 10%, 5%, and 1%, respectively.

Panel A. Constrained firms and investment

	(1) No-dividend	**(2) Payout**	**(3) KZ index**	**(4) WW index**	**(5) HP index**	**(6) Size**
Constrained	0.0018***	0.0014***	0.0010**	-0.0013***	0.0027***	0.0005
	(4.31)	(4.04)	(2.34)	(-2.84)	(5.18)	(0.93)
Observations	111,895	104,351	107,110	111,445	111,894	111,895
Adjusted R-squared	0.5246	0.5258	0.5218	0.5265	0.5246	0.5245

Panel B. Cash holding for constrained firms and investment

	(1) No-dividend	**(2) Payout**	**(3) KZ index**	**(4) WW index**	**(5) HP index**	**(6) Size**
Constrained	0.0002	-0.0005	-0.0008	-0.0024***	-0.0000	-0.0004
	(0.37)	(-1.18)	(-1.61)	(-4.37)	(-0.02)	(-0.67)
Constrained x High cash	0.0043***	0.0041***	0.0046***	0.0030***	0.0051***	0.0026***
	(7.85)	(7.18)	(7.45)	(5.15)	(8.44)	(4.49)
Observations	104,515	97,164	99,941	104,081	104,514	104,515
Adjusted R-squared	0.5391	0.5408	0.5367	0.5407	0.5391	0.5386

Table 6. Endogeneity test – Junk bond market collapse

This table presents difference-in-differences regression results during the event period of 1986 to 1993. We assign 1986 to 1989 as the pre-event and 1990 to 1993 as the post-event period. *Junk* equals to one if the credit rating of the firm is equal to or lower than BB+ from S&P's long-term domestic issuer credit rating, and zero otherwise. *Post* equals to one if the observation is from the post-event period and zero otherwise. The dependent variable is *Log(SA)*, which is the natural logarithm of one plus the number of strategic alliance deals. All other variables are as defined in Appendix. All control variables from Table 3 are included. Column 1 controls for industry fixed effects and year fixed effects; Column 2 controls for industry-year fixed effects; and Column 3 controls for firm fixed effects and year fixed effects. Industries are defined at the 2-digit SIC industries. *t*-statistics are reported in parenthesis and standard errors are clustered at the firm level. *, **, and *** denote significance at 10%, 5%, and 1%, respectively.

	(1)	(2)	(3)
Junk x Post	0.0801***	0.1056***	0.0804***
	(3.17)	(4.12)	(3.13)
Junk	-0.0138	-0.0352***	
	(-1.05)	(-2.64)	
Post	0.0039	0.0020	-0.0172
	(0.63)	(0.34)	(-1.39)
Industry FE	Yes	No	No
Year FE	Yes	No	Yes
Industry-Year FE	No	Yes	No
Firm FE	No	No	Yes
Observations	12,564	12,564	12,564
Adjusted R-squared	0.1630	0.1662	0.3567

Table 7. Financial constraints and free-cash-flow

This table presents the cross-sectional results of financial constraints and free-cash-flow. Panel A shows the results using *Log(SA)*as the dependent variable, Panel B uses *Log(M&A),* and Panel C uses *Investment* as the dependent variable. *Constrained* is defined as in previous tables. *FCF* is an indicator variable that equals to one if the firm's free-cash-flow is above the yearly sample median, and zero otherwise. *Constrained x FCF* is the interaction of *Constrained* and *FCF*. All variables are as defined in Appendix. All specifications include the control variables from Table 3, industry fixed effects and year fixed effects unless noted otherwise. Industries are defined at the 2-digit SIC industries. *t*-statistics are reported in parenthesis and standard errors are clustered at the firm level. *, **, and *** denote significance at 10%, 5%, and 1%, respectively.

Panel A. Strategic alliances

	(1) **No-dividend**	**(2)** **Payout**	**(3)** **KZ index**	**(4)** **WW index**	**(5)** **HP index**	**(6)** **Size**
Constrained	0.0413***	0.0160***	0.0036	0.0351***	0.0296***	0.0371***
	(10.40)	(6.28)	(1.05)	(9.64)	(6.23)	(7.39)
Constrained x FCF	0.0036	0.0049***	0.0015	0.0057***	-0.0001	0.0014
	(1.26)	(3.14)	(0.94)	(2.77)	(-0.06)	(0.70)
FCF	-0.0063**	-0.0062***	-0.0042***	-0.0077***	-0.0035**	-0.0048***
	(-2.30)	(-4.62)	(-3.17)	(-4.03)	(-2.40)	(-2.64)
Observations	104,947	97,566	100,363	104,513	104,946	104,947
Adjusted R-squared	0.1424	0.1374	0.1358	0.1417	0.1405	0.1408

Panel B. M&As

	(1) **No-dividend**	**(2)** **Payout**	**(3)** **KZ index**	**(4)** **WW index**	**(5)** **HP index**	**(6)** **Size**
Constrained	0.0141*	-0.0224***	-0.0537***	-0.0121*	0.0642***	0.0091
	(1.69)	(-4.33)	(-8.17)	(-1.77)	(7.91)	(0.99)
Constrained x FCF	-0.0216***	-0.0101***	-0.0084***	-0.0220***	-0.0248***	-0.0304***
	(-4.02)	(-3.59)	(-2.99)	(-5.88)	(-8.02)	(-8.70)
FCF	0.0242***	0.0124***	0.0078***	0.0222***	0.0227***	0.0279***
	(4.74)	(5.11)	(3.27)	(6.24)	(8.29)	(8.68)
Observations	104,947	97,566	100,363	104,513	104,946	104,947
Adjusted R-squared	0.0934	0.0922	0.0934	0.0934	0.0949	0.0938

Panel C. Investments

	(1) No-dividend	(2) Payout	(3) KZ index	(4) WW index	(5) HP index	(6) Size
Constrained	0.0021***	0.0015***	0.0011**	-0.0009**	0.0024***	0.0008
	(4.40)	(4.11)	(2.55)	(-1.98)	(4.93)	(1.52)
Constrained x FCF	0.0002	0.0011***	0.0029***	0.0009*	0.0014***	0.0013***
	(0.33)	(2.70)	(8.14)	(1.83)	(3.67)	(2.88)
FCF	0.0025***	0.0020***	0.0008**	0.0020***	0.0017***	0.0017***
	(3.68)	(5.03)	(2.48)	(3.86)	(4.70)	(3.63)
Observations	104,515	97,164	99,941	104,081	104,514	104,515
Adjusted R-squared	0.5386	0.5404	0.5367	0.5406	0.5387	0.5385

Table 8. Financial constraints and the choice between growth strategies

This table presents the relation between financial constraints proxies and the choice between strategic alliances and capital expenditures, and the choice between strategic alliances and M&As. The dependent variable in Panel A is the natural logarithm of one plus the number of strategic alliances divided by capital expenditures (*SA/Capx)*. The dependent variable in Panel B is the natural logarithm of one plus the number of strategic alliances divided by the number of M&As (*SA/MA)*. Column 1 uses *No-dividend* as the main variable that equals to one if the firm does not pay any dividend, and zero otherwise. From Columns 2-6, we use *Payout, KZ index, WW index, HP index,* and *Size* as the explanatory variable. We divide these variables at the median. For *Payout* and *Size*, we assign the firms below the sample median to the constrained group (*Constrained*). For rest of the financial constraint proxies, we assign the firms to the constrained group if the firm is above the sample median. All variables are as defined in Appendix. All specifications include the control variables from Table 3, industry fixed effects and year fixed effects unless noted otherwise. Industries are defined at the 2-digit SIC industries. *t*-statistics are reported in parenthesis and standard errors are clustered at the firm level. *, **, and *** denote significance at 10%, 5%, and 1%, respectively.

Panel A. SA/Capx

	(1) **No-dividend**	**(2)** **Payout**	**(3)** **KZ index**	**(4)** **WW index**	**(5)** **HP index**	**(6)** **Size**
Constrained	0.0046***	0.0020*	0.0049***	-0.0021*	-0.0079***	-0.0019
	(5.65)	(1.95)	(3.88)	(-1.68)	(-6.01)	(-1.27)
Observations	103,935	96,628	99,455	103,512	103,934	103,935
Adjusted R-squared	0.0709	0.0680	0.0712	0.0706	0.0711	0.0708

Panel B. SA/MA

	(1) **No-dividend**	**(2)** **Payout**	**(3)** **KZ index**	**(4)** **WW index**	**(5)** **HP index**	**(6)** **Size**
Constrained	0.0361***	0.0140***	0.0139**	0.0216***	0.0072	0.0220***
	(5.75)	(2.89)	(2.17)	(3.32)	(0.99)	(2.63)
Observations	20,143	18,704	18,926	20,112	20,142	20,143
Adjusted R-squared	0.1599	0.1531	0.1577	0.1592	0.1579	0.1583