THESIS IN CORPORATE POLICIES

By

ZIHAO YUAN

A thesis submitted to the University of Birmingham for the degree of
DOCTOR OF PHILOSOPHY

Department of Finance
Birmingham Business School
College of Social Sciences
University of Birmingham
September 2023

ABSTRACT

What forces are responsible for shaping firm's corporate policies? In the thesis, we attempt to address this question by focusing on two important corporate policies of a firm, labor investment and dividend smoothing. In particular, we investigate three potential drivers, social capital, board co-option and stock market liquidity, to labor investment and dividend smoothing. Drawing a large sample of US public listed firms, we show that firms located in areas with higher social capital level, and having fewer co-opted directors on the board present less inefficient labor investment. Moreover, firms with more liquid shares tend to smooth their dividends more. The results are unchanged to multiple robustness tests, difference-in-difference design, and instrumental variable analysis. Our findings shed new light on the determinants of a firm's labor investment and dividend smoothing policies.

ACKNOWLEDGEMENT

I would like to express my heartfelt gratitude to the individuals and groups who have played an important role in my journey of completing the thesis. First, I extend my deep appreciation to my supervisors, Dr. Malika Hamadi and Dr. Anandadeep Mandal. During my PhD journey, they not only provided me with extensive feedback to refine my research, but also encouraged me to deepen my subject knowledge. Our frequent discussions to different subjects have been motivating me in taking more complex research projects. Without their persistent help and support, this thesis would not have been possible.

I would also like to express my thanks to my family. The challenges by the Covid-19 pandemic brought me about huge uncertainty and emotional turmoil. During this difficult time, my family provided significant encouragement and emotional support, which motivated me to continue moving forward in my academic journey.

My gratitude extends to my fellow PhD peers at the Birmingham Business School: Arisyi Fariza Raz, Seyit Gokmen, Xia Li, Yang Gao, Jiayi Yuan, Jing Liu, Yichen Xi, Yutan Li, and Yucen Jiang. Over the four-year PhD programme, we shared the study space, which enhanced our networking. Although we worked in different research areas, our collective discussions on subject knowledge and mutual support in the study space cultivated a positive environment that fostered my academic growth.

With deepest thanks,
Zihao Yuan

Contents

List of Tables

Chapter 1

GENERAL INTRODUCTION

Corporate policy is crucial for a firm. Effective corporate policies help align a firm's activities and decision-making processes with its goals and interests among stakeholders. A key question that draws the attention of academic researchers in corporate finance is particularly concerned with the understanding the forces responsible for shaping a firm's corporate policies. Prior theoretical literature has shed light on how agency conflicts and information asymmetry affect corporate policy decisions (e.g., Miller and Modigliani, 1961; Jensen and Meckling, 1976; Bhattacharya, 1979; Miller and Rock, 1985; Jensen, 1986). In the thesis, we start by relaxing some conditions related to perfect capital markets (PCM) and considering real world with market frictions (e.g., principal-agent conflicts and asymmetric information between corporate insiders and outsiders). Within this framework, we specifically focus on firm's labor investment and dividend smoothing policies.

Labor investment is one of the critical strategic decisions for a firm. With efficient investment in labor, firms are considered more productive and have greater competitive advantages within the product market (Becker, 1964). As a result, the firm gains increased potential for profitability and enhanced corporate value (e.g., Pfeffer, 1994; Hansson, Johanson and Leitner, 2004; Merz and Yashiv, 2007). However, inefficient labor investment can be detrimental to the corporate value, as firms with sub-optimal labor investment policy may present problems related to excess capacity or insufficient growth (Stein, 1989). Previous literature posits that sub-optimal labor investment arises from the agency costs of the separation of ownership and control within a firm. If agents are not subjected to effective monitoring, they are likely to engage in self-serving behaviors, leading to conflicts of interest between agents and principals (Jensen and Meckling, 1976). These agency conflicts can manifest in two types of inefficient labor investment (e.g., over-investment and under-investment).

On the one hand, over-investment may arise when firms are susceptible to free cash flow problems, managers can use these free cash flows inconsistent with shareholder's interest (Jensen, 1986). For example, managers with large amounts of excess cash are likely to engage in the practices of over-hiring employees to establishing their empire to obtain greater power, influence, security, and reputation within the firm (e.g., Williamson, 1963; Stein, 2003). Moreover, without sufficient monitoring of the principal, the agent may have fewer incentives to engage in actions that maximize corporate value and choose to enjoy their 'quiet life' (Bertrand and Mullainathan, 2003). Under the 'quiet life' hypothesis, managers may avoid making hard decisions or undertaking difficult tasks, such as dismissing of under-performed employees. This results in another form of over-investment: under-firing.

On the other hand, under-investment can occur in the presence of information asymmetry. Firms with asymmetric information may have difficulty in accessing external capital. Under this situation, managers tend to under-invest in the labor force to save costs and enhancing cash flow (Campello, Graham and Harvey, 2010). In addition, since the entry of short-term investors may exacerbate managerial myopia, managers are tempted to under-invest in labor to meet current earnings targets (Ghaly, Dang and Stathopoulos, 2020). Managers can also under-invest in labor if they prefer to pursue a 'quiet life'. This may occur because poorly monitored managers are reluctant to make hiring decisions to expand firm's business (Stein, 2003). Moreover, under-investment can be related to the extent to which managers are willing to take risks. Managers with risk-averse preference may reduce hiring activities even if firm's economic fundamentals indicate under-capacity (Jung, Lee and Weber, 2014), because they are worried about unpredictable productivity of new employees and increased business costs associated with hiring (Sualihu, Rankin and Haman, 2021).

To understand what drives inefficient investment policy in labor, we consider two factors ignored in previous empirical studies: social capital and board co-option. Social capital, a concept that originated from the fields of sociology and politics, is defined as a society's values and norms that encourage cooperation and reciprocity, and constraint opportunism (see, e.g., Putnam, 1995; Guiso, Sapienza and Zingales, 2011). Prior work shows that it can be beneficial to economic well-being and firm's policies. For example, social capital has been found to facilitate economic development, enhances capital market participation, limit tax avoidance, reduce the costs of audit fees, reduce cost of debt capital, foster innovation, or constraint managerial rent extraction in CEO compensation (e.g., Guiso, Sapienza and Zingales, 2004; Francois and Zabojnik, 2005; Jha and Chen, 2015; Hasan, Hoi, Wu and Zhang, 2017a; Hasan, Hoi, Wu and Zhang, 2017b; Gupta, Raman and Shang, 2020). We aim to extend these literature by investigating the influence of social capital on labor investment.

Social capital can be good for labor investment through acting as informal governance and monitoring mechanisms. Social capital can cultivate dense social networks, and social norms of cooperation and reciprocity in a community over time. Specifically, dense social networks are beneficial for information exchange and interactions among corporate stakeholders (e.g., Putnam, 1995; Guiso et al., 2011; Jha and Chen, 2015). Such social connections among a firm's stakeholders can translate into effective monitoring (Wu, 2008). In addition to social networks, cooperative norms help constraint agent's self-serving actions, because they expect higher opportunity costs for deviating from such prescribed norms where they reside, such as social sanctions (e.g., Coleman, 1988; Hoi, Wu and Zhang, 2019; Hasan, Hoi, Wu and Zhang, 2020). The agents are then less likely to take opportunistic actions at the expense of other corporate stakeholders. Accordingly, we predict that higher social capital disciplines manager's behaviors in labor investment decision-making processes reducing sub-optimal labor investment.

Another potential force we propose to explore in the context of labor investment is board co-option. The concept 'board co-option' refers to the appointment of directors to a firm's board after the CEO has taken office (Coles, Daniel and Naveen, 2014). The directors who have been co-opted may attempt to align with and show loyalty to the incumbent CEO since their appointment and nomination processes are directly or indirectly influenced by the CEO. The primary role of a board of directors concerns overseeing and monitoring the management of the firm. However, in firms characterised by higher board co-option, the CEO can capture the board, compromising its ability to effectively carry out monitoring duties (Khanna, Kim and Lu, 2015). According to Coles et al. (2014), having more co-opted directors on the board tends to make board oversight less effective. Their evidence shows that firms that have a larger percentage of co-opted directors on their board tend to engage in over-invest activities and pay their executives at a higher level.

Previous empirical evidence has documented that in firms with greater board co-option managers are tempted to take value-destroying actions. Khanna et al. (2015) find that this appointment-based CEO-director connection increases the likelihood of corporate fraud and decreases the likelihood of detecting such fraud. Moreover, the increase in co-opted directors can result in a greater likelihood of financial misstatement (Cassell, Myers, Schmardebeck and Zhou, 2018), more covenant restriction in the loan contracts (Lim, Do and Vu, 2020), lower credit ratings and larger credit spreads (Sandvik, 2020), higher default risk (Baghdadi, Nguyen and Podolski, 2020), and more corporate misconduct (Zaman, Atawnah, Baghdadi and Liu, 2021). Overall, these empirical findings suggest that board co-option can undermine the board's oversight, hence exacerbating conflicts of interest between the agent and the principal.

In the presence of board co-option, the CEO is expected to exert significant influence over the board, result in decrease in the board's effectiveness in monitoring activities, accordingly in inefficient labor investment. This influence can empower CEOs with greater behavioral latitude and managerial discretion, such as engaging in over-investment and empire-building actions (Coles et al., 2014). Fracassi and Tate (2012) argue that the management under weak board monitoring can have greater managerial opportunism, leading to sub-optimal investment policies. Given that CEOs can also make labor investment decisions (Khedmati, Sualihu and Yawson, 2020), firms with a higher proportion of co-opted directors on the board may exhibit less efficient labor investment practices.

The last issue we attempt to explore is corporate dividend smoothing, which is a well-identified practice in a firm's dividend policy. This phenomenon was observed in early survey evidence by Lintner (1956). Instead of making significant changes in dividends, managers tend to smooth their dividends with gradual growth even if earnings change substantially, as they believe that shareholders prefer a stable dividend policy and that the outside markets put a premium on such stability. Existing theoretical models on the payout level are associated with information asymmetry and agency conflicts. These theories have also been argued to explain why managers smooth the dividends.

The principal-agent theory posits that dividends can function as a mechanism for mitigating agency costs arising from the separation of ownership and control (e.g., Easterbrook, 1984; Jensen, 1986; Fluck, 1999; Myers, 2000). According to this perspective, paying high and steady dividends, which reduces excess cash under the management's control, benefits outside shareholder's interest. Moreover, La Porta, Lopez-de Silanes, Shleifer and Vishny (2000) introduce two models associated with the relation between agency problems and dividends, the outcome model and the substitute model. The outcome model predicts that managers are forced to disgorge free cash flows through dividends when the shareholder rights are strong. This implies that paying regular and high dividends is an outcome of effective governance. The substitute model suggests that dividend smoothing could be viewed as a substitute for governance. Under this view, managers should establish a reputation for shareholder-friendly treatment by paying high and smooth dividends. This reputation-building can be critical when managers seek to raise external capital on more favorable terms in the future. Accordingly, the substitute model implies that building this reputation through dividends becomes especially important when shareholder protection is weak.

In the context of asymmetric information, dividend smoothing can be attributed to manager's signalling efforts or their precautionary savings motives. The signalling model predicts that managers use dividends as the means of delivering private information about firm's earnings and future cash flows to the outside market (e.g., Bhattacharya, 1979; John and Williams, 1985; Miller and Rock, 1985; Kumar, 1988). If dividend smoothing is generated as a consequence of manager's signalling behaviors, this action should prevail among the firms facing higher degree of asymmetric information. This is because the benefit of signalling can be limited for less opaque firms. Additionally, dividend smoothing may result from manager's precautionary savings motives. When firms are financially constraint, managers face higher costs of external financing, and prefer to save cash inside the firm in response to potential adverse shocks in the future (e.g., Almeida, Campello and Weisbach, 2004; Bates, Kahle and Stulz, 2009). Under this view, managers choose to maintain lower level of dividends, therefore leading to a smoothing pattern dividend policy.

To better understand mechanisms behind dividend smoothing policy, we aim to consider the impact of one specific force within the financial markets (stock market liquidity). We seek to show the effect of stock liquidity on dividend smoothing. We expect that stock liquidity can have opposing effects on dividend smoothing. From agency theories, it is posited higher stock liquidity can help reduce agency conflicts through two mechanisms, encouraging large shareholders monitoring actions (Maug, 1998), and enhancing the credibility of exit threats (e.g., Edmans, 2009; Admati and Pfleiderer, 2009), leading to good corporate governance. Therefore, dividend smoothing and stock liquidity could be considered as substitutes or complements mechanisms for controlling agency costs. Specifically, based on the outcome view, higher stock liquidity serves as a disciplining force on managerial behavior, hence inducing them to pay high and stable dividends to disgorge free cash. In contrast, based on the substitute view, since free cash problem is already constraint in highly liquid firms, manager's reputation-building actions through paying dividends are less needed, leading to less dividend smoothing.

Stock liquidity may also affect the practice of dividend smoothing by mitigating information asymmetry between corporate managers and outside investors. Informed investors are motivated to acquire more information and to trade on high liquid shares, because they can obtain higher gains through trading based on their private information (e.g., Holden and Subrahmanyam, 1992; Holmström and Tirole, 1993; Subrahmanyam and Titman, 2001). The price of highly liquid shares therefore becomes more informativeness. Corporate managers then can learn from what is reflected in the firm's share prices, and factor these information into their strategic decision-making processes (e.g., Durnev, Morck and Yeung, 2004; Luo, 2005; Bakke and Whited, 2010). If stock liquidity enhances informativeness of the share prices, managers are less likely to engage in signalling actions, such as paying a steady dividend stream, because the benefit of such behavior could be very limited for firms with high liquid stocks.

We examine labor investment policy in Chapter 2 and Chapter 3, and we examine dividend smoothing policy in Chapter 4. In Chapter 2, our analysis focuses on the relationship between social capital and labor investment. Using a sample of 52,268 firm-year observations, representing 5,957 US public firms in 1992-2015, our evidence shows that firms located areas characterized by high levels of social capital present less sub-optimal labor investment. In relation to its economic significance, a one standard deviation increase in social capital is associated with a 6.9% (4.0%) decrease in labor investment inefficiency relative to the sample median (mean). We construct an instrumental variable depending on the geographical distance between the firm's location in the county and the Canadian border in order to account for potential endogeneity. Lastly, we employ a difference-in-difference design based on a firm's relocation event.

The effect of social capital on labor investment inefficiency remains significant. Our findings align with the argument that social capital can play an important role in mitigating agency conflicts in corporate labor investment.

Chapter 3 of the thesis investigate the relationship between board co-option and labor investment. We conduct our analysis based on a sample of 2,040 unique US publicly listed firm from 1996 to 2014, representing 16,743 firm-year observations. Our main results show that firms with more board co-option exhibit greater inefficient labor investment. This finding holds economic significance. A one standard deviation increase in co-option leads to approximately a 3.1% (4.9%) increase in abnormal net hiring relative to the sample mean (median). To validate the robustness of our results and account for potential endogeneity, we employ a difference-in-difference analysis, considering the implementation of the Sarbanes-Oxley Act of 2002 (SOX), and then use an instrumental variable constructed as the industry mean of the firm's co-option. Our findings support the view that the presence of co-opted directors on the board tends to weaken the monitoring and exacerbate agency conflicts, leading to greater corporate labor investment inefficiency.

In Chapter 4, we tests whether stock liquidity induces managers to smooth dividends. We draw a sample of 1,254 US public firms between 1993 and 2022. The baseline results show a positive relation between stock liquidity and dividend smoothing. The effect is also economically significant: a one standard deviation increase in stock liquidity leads to a 6.0% increase in dividend smoothing. To better identify the causal effect of stock liquidity on dividend smoothing, we implement a difference-in-difference analysis based on 2001 decimalization in the US. We next conduct an instrumental variable approach to mitigate potential omitted variable bias. The IV is calculated by using the median of stock liquidity in the industry. Our results from DID and IV regressions further confirm the baseline findings, implying that, in highly liquid firms, managers are forced to use dividend smoothing to alleviate the problems of free cash flows.

This thesis sheds new light on the forces driving two specific firm policies, labor investment and dividend smoothing. An increasing number of empirical studies show that the quality of financial reporting (Jung et al., 2014), the informativeness of stock prices (Ben-Nasr and Alshwer, 2016), the connections between CEOs and board members (Khedmati et al., 2020), the treatment of employees by firms (Cao and Rees, 2020), the long-term horizons of institutional investors (Ghaly et al., 2020), equity compensation (Sualihu, Rankin and Haman, 2021), market competition (Boubaker, Dang and Sassi, 2022), and the liquidity of stocks (Ee, Hasan and Huang, 2022) can have an impact on corporate labour investment. We build upon this literature and provide fresh evidence that community social capital and board co-option can significantly influence the efficiency of labor investment within firms.

Furthermore, the thesis contributes a novel perspective to understanding the factors influencing dividend smoothing. Our research in dividend smoothing is related to Michaely and Roberts (2012). Their evidence shows that publicly listed firms tend to smooth their dividends more than their private counterparts, indicating that the scrutiny of the capital markets can be critical in driving dividend smoothing. However, their study does not present evidence of the specific forces within capital markets contributing to dividend smoothing. We extend their work by exploring the impact of stock market liquidity as a potential driver of dividend smoothing behaviors

The structure of the thesis is organized as follows. Chapter 2 thoroughly analyses on the association between social capital and labor investment. In Chapter 3, we continue to investigate labor investment but consider a different potential factor, that is, board co-option. Chapter 4 focuses on a distinct firm policy, dividend smoothing. Our goal is to examine how stock market liquidity shapes such practices. Chapter 5 concludes.

Chapter 2

SOCIAL CAPITAL AND LABOR INVESTMENT

2.1. Introduction

The influence of social capital in geographical regions on organizations and corporations has been widely discussed in different fields of social sciences (see, e.g., Guiso et al., 2011). Recent research suggests that social capital, defined as a set of values and norms that encourage cooperation and constraint opportunism (see, e.g., Putnam, 1995; Guiso et al., 2011), plays a role redas an informal corporate governance mechanism to alleviate agency problems in different corporate settings. For example, social capital is found to have an effect in limiting tax avoidance, reducing the costs of audit fees, reducing the cost of equity, fostering innovation, reducing the use of trade credit, lowering bank loan spread as well as at-issue bond spreads, constraining financial adviser misconduct, improving financial reporting quality, and limiting managerial rent extraction in CEO compensation (Hasan et al., 2017a; Jha and Chen, 2015; Gupta, Raman and Shang, 2018; Gupta et al., 2020; Hasan et al., 2020; Hasan and Habib, 2019; Hasan et al., 2017b; Bai, Shang, Wan and Zhao, 2021; Jha, 2019; Hoi et al., 2019). However, despite evidence from the literature that agency conflicts and information asymmetry between managers and outsiders lead to inefficient levels of investment (see, e.g., Hubbard, 1998; Stein, 2003), whether social capital helps reduce inefficient labor investment levels is still a research question to be investigated.

In this paper we extend this literature and examine whether social capital mitigates labor investment inefficiency[1]. This topic is worth investigating given that firms with efficient labor investment are more competitive in the product markets (Pfeffer, 1994). Moreover, recent studies show that firms overinvesting in labor face higher wage bill payment and other related costs to cover the excessive staff. On the other hand, firms underinvesting may suffer less productivity (Sualihu, Yawson and Yusoff, 2021). Besides, in contrast to the classical labor economics view that labor investment is free of adjustment costs, suggesting that employment decisions are free of financing frictions due to information asymmetry, studies have shown that these costs exist not only for capital investment but for labor investment too. When managers adjust their labor demand by hiring or laying off-employees adjustment costs, including a fixed component, are incurred (see e.g., Oi, 1962; Hamermesh, 1996; Dixit, 1997)[2]. These labor-related adjustment costs suggest that firms may need external financing, which generates frictions affecting employment decisions; as such, asymmetry of information between managers and outside finance suppliers can create inefficiencies. Therefore, asymmetries of information and agency costs are attached to labor investments as much as to capital investments. Self-interested managers can undertake suboptimal levels of labor investment not justified by firm's economic fundamentals. Managers could overinvest because they are more interested in empire-building and entrenching themselves (see e.g., Stein, 2003; Shleifer and Vishny, 1989). Alternatively, they may adopt a lazy attitude and prefer enjoying a 'quiet life' (Hicks, 1935) that results in either overinvesting or underinvesting. There is an overinvestment type of outcome if managers refrain, for

[1]We use labor investment inefficiency, abnormal net hiring, and abnormal labor investment interchangeably though out the paper.

[2]These costs are related to search, advertising, selection, hiring, training, or firing costs

instance, from shutting down non-performing divisions. Conversely, there is underinvestment when managers are less prone to undertake new projects, open new plants, or change the existing balance of power between managers within the firm; in addition, managers preferring to enjoy a quiet life end up paying higher wages to employees (see e.g., Bertrand and Mullainathan, 2003).

However, a society with a high level of social capital may inhibit the opportunistic behaviors of managers, given that social capital incorporates dense social networks and strong norms of cooperation and reciprocity. Specifically, social networks can encourage interactions and information exchanges between stakeholders, leading to more effective monitoring (see e.g., Wu, 2008; Jha, 2019). In addition to social networks, behaviors contradictory to co- operative norms in a society with high social capital can result in imposing social sanctions (Coleman, 1988). Thus, agents expect higher opportunity costs for deviating from such prescribed norms and tend to act more seriously in line with their obligations (e.g., Hoi, Wu and Zhang, 2019; Hasan, Hoi, Wu and Zhang, 2020), which leads managers, for instance, to more efficient investments corresponding to the firm's fundamentals.

We examine how social capital affects labor investment inefficiency in order to test our hypothesis. The non-explained component of labor investment by a firm's economic fundamentals is considered as a proxy for labor investment inefficiency. This is captured by the absolute value of residuals from regressions of percentages changes in the number of employees on their normal determinants (see e.g., Pinnuck and Lillis, 2007; Jung et al., 2014). For social capital, we use US county-level social capital statistics from Rupasingha, Goetz and Freshwater (2006). This data set includes two essential components of social capital, social networks and cooperative norms. The construction of the social capital variable involves the principal component analysis, which is based on social networks and cooperative norms (see e.g., Rupasingha et al., 2006; Hasan et al., 2017a; Hasan et al., 2017b).

We draw on a comprehensive sample of 52,268 firm-year observations, representing 5,957 US public firms for the years 1992-2015 and test our conjecture. Our key result is that firms in counties with higher social capital have significantly less labor investment inefficiency. The effect is economically significant. A one standard deviation increase in social capital is associated with approximately 6.9% (4.0%) decrease in hiring inefficiency relative to the median (mean) in the sample. This negative relation between social capital and hiring inefficiency continues to hold after addressing the endogeneity concerns using various exercises. First, to capture unobservable firm-specific heterogeneity and to control for the time-invariant differences across state-industry, we use the state fixed effects model and high-dimensional industry fixed effect models, respectively. As an additional control we also use firm fixed effects. Moreover, in order to examine whether our findings are driven by the systematic variations in firm-specific characteristics across high and low social capital counties, or driven by chance, we use the propensity score matching (PSM) approach. The results further confirm the negative relation between social capital and inefficient hiring. However, social capital and a firm's abnormal hiring may still be simultaneously determined by unobserved factors. To mitigate this concern, we use an instrumental variable (IV) estimation. In particular, we exploit Putnam's (2001) argument that the distance to the Canadian border is a good predictor of social capital in the US, we follow Hasan et al. (2017a) and construct an instrumental variable for social capital based on the distance between firm's US county location and the Canadian border. The IV results further confirm the baseline findings. As an additional test, we use a difference-in-difference analysis based on the firm's change in exposure to social capital because of relocation into a new county. To account for the fact that this decision could be an endogenous choice, we use the entropy-balancing method to re-weight the covariates in the first, second, and third moments. The results are consistent with our main findings.

In addition, we run a battery of other sensitivity tests. In our main tests, labor investment inefficiency is estimated from the the absolute value of residuals from regressions of percentages changes in the number of employees on a series of firm characteristics

(Pinnuck and Lillis, 2007). Larger absolute values of these residuals suggest greater labor investment inefficiency. To capture whether discretionary hiring is used to over or under invest in labor because managers have incentives to do so, we use signed measures of labor inefficiency and split the sample into two sub-samples, the labor over investment sample and the labor under investment one. Then, we further detail the sources of inefficiency because over-investment (under-investment) can be the result of over-hiring and/or under-firing (under-hiring and/or over-firing). Therefore, we further split these two sub-samples into four sub-samples, namely, over-hiring, under-firing, under-hiring, over-firing. Our findings show that higher social capital reduces all of the sub-optimal investment in labor.

We also run our baseline model augmented with additional controls to rule out any confounding factors effects. In a further test, we consider alternative proxies for labor investment inefficiency, such as the difference between a firm's actual hiring and median value of hiring within the firm's industry, the first stage reduced form model that included only sales, and the first stage augmented model with additional factors as in Pinnuck and Lillis (2007). In addition, we use different proxies for social capital. Our results from these various tests confirm our main finding that social capital has a negative effect on inefficient labor investment.

Furthermore, we also run tests to examine governance mechanisms through which social capital can affect labor investment inefficiency. In particular, we find that the relation between social capital on labor investment inefficiency is more pronounced when firms are more susceptible to hostile takeovers or followed by less financial analysts.

Our analysis adds to the previous literature in two ways. First, our study makes a valuable contribution to the existing body of literature on labor investment. Growing empirical studies have documented that corporate labor investment is related to financial reporting quality (Jung et al., 2014), stock price informativeness (Ben-Nasr and Alshwer, 2016), CEO ties to independent board members (Khedmati et al., 2020), firms' employee-friendly treatment (Cao and Rees, 2020), long-term horizon of investment

(Ghaly et al., 2020), equity compensation (Sualihu, Rankin and Haman, 2021) or stock liquidity (Ee et al., 2022). Our study extends this literature by showing how social capital constraints inefficient labor investment.

Second, we contribute to the literature on the role played by social capital in the corporate setting. Studies have shown that social capital in regions surrounding firm's headquarters where firms reside can provide an environment that is beneficial to the firms. For instance by constraining financial adviser misconduct (Bai et al., 2021), deterring corporate tax avoidance (Hasan et al., 2017a), reducing the costs of debt (Hasan et al., 2017b), lowering the costs of equity (Gupta et al., 2018), improving financial reporting quality (Jha, 2019), or promoting corporate innovation practices (e.g., Gupta et al., 2020; Hasan et al., 2020). Our study links two strands of literature, namely, social capital and corporate labor investment, and shows that social capital reduces labor investment not explained by firm's economic fundamentals.

The remainder of this paper is structured as follows. In section 2, we discuss the literature related to social capital and inefficient labor investment, and then develop the main hypothesis. We give the detail about data and research method in section 3. Section 4 presents the empirical results. Section 5 discusses potential endogeneity concerns. Section 6 presents analysis of the governance mechanism. Section 7 concludes.

2.2. Literature Review and Hypothesis Development

2.2.1. What Is Social Capital?

Different theoretical concepts have been developed to delineate the notion of social capital. Basically, two alternative dimensions of social capital have been suggested: social capital as a private good and as a public good. The private good view of social capital contends that it is a resource for individuals and is usually discussed in sociology; while the public good view relates to the benefits for the public and is often used in economics and politics (Scrivens and Smith, 2013).

Early studies describe social capital based on the individual level by focusing on personal relationships and networks, as well as resources and supports stemming from the networks (e.g., Bourdieu, 1986; Boxman, De Graaf and Flap, 1991; Coleman, 1988; Portes, 1998). Specifically, Bourdieu (1986) defines social capital as the sum of resources associated with a persistent connection of more or less institutionalized mutual acquaintance and recognition. In this view, social capital mainly focuses on the resources (such as status and power) that people can acquire through their membership in their personal social network, as well as the quality of those resources. Similarly, Coleman (1988) describes social capital as ‘a variety of different entities, they all consist of some aspect of social structures and encourage certain actions of individual and corporate actors within that structure’. Boxman et al. (1991) refer to social capital as specific social structure (i.e. people’s networks) and a resource that derives from the networks that people can use to pursue their interests. Further, Portes (1998) defines social capital as the ability of members in a community to garner benefits through social networks and other social structures.

Social capital as a public good, on the other hand relates to social norms and connections between individuals and wider communities (e.g., Fukuyama, 1997; Putnam, Leonardi and Nanetti, 1993; Putnam, 1995; Uphoff and Wijayaratna, 2000; Guiso et al., 2004; Guiso, Sapienza and Zingales, 2006; Guiso et al., 2011). Putnam (1995) defines social capital as ‘networks, trust and norms that enable members within a society to act together more effectively in pursuing shared objectives’. In the view of Putnam, social capital is more about the connections between individuals and the life of their communities, as opposed to the ties between individuals. Fukuyama (1995) and Fukuyama (1997) view social capital as a set of shared beliefs and norms among people within a community. This subjective form of social capital can foster cooperation, norms of trust and reciprocity. In addition, Uphoff and Wijayaratna (2000) provide interpretation to the structural aspect of social capital, it originates from various aspects of social relationships, such as collective activities and social networks that establish patterns of social interactions. Guiso et al. (2004) and Guiso et al. (2011) provide a more specific definition of social capital. They define it as the norms and networks that encourage cooperation and mutual trust, mitigate opportunistic behaviours and limit free-riding problems (Guiso et al., 2011).

In our study, the definition of social capital follows much of the prior literature concerned with the public good aspect of social capital (e.g., Putnam, 1995; Fukuyama, 1997; Guiso et al., 2006; Guiso et al., 2011). Accordingly, we define social capital, in the community, as social networks and shared norms that promote collaboration, limit opportunistic behaviors and curb self-interest. It should be noted that the notion of social networks, in our study, is not meant for the ties among individuals who know each other, such as family and friends, but it is rather intended to capture the 'civic engagement'. Civic engagement is a term specified in Putnam (1995) and Putnam (2000) to refer to the connections between people and their community life established through social organizations.

2.2.2. Agency Conflicts and Inefficient Investment in Labor

Investment in labor is considered to be one of the most important corporate investment activities, as efficient investment in labor tends to increase the competitiveness of a firm (Becker, 1964), increase productivity and earnings (Hansson et al., 2004), and enhance firm's market value (Merz and Yashiv, 2007). However, the existence of adjustment costs for labor demand by managers (see e.g., Oi, 1962; Dixit, 1997) and/or agency conflicts may result in inefficient investment.

One of the most important corporate investment activities is labour investment, since effective labour investment tends to boost a firm's competitiveness (Becker, 1964), productivity and earnings (Hansson et al., 2004), and market value (Merz and Yashiv, 2007). However, the existence of adjustment costs for labor demand by managers (see e.g., Oi, 1962; Dixit, 1997) and/or agency conflicts may result in sub-optimal investment in labor. This can manifest as reduced productivity due to over-investment or inadequate growth due to under-investment (Stein, 1989).

On the one hand, over-investment can be associated with over-hiring practices, resulting from manager's self-interest and opportunism to increase the firm size (i.e. the number of employees) for empire building purposes and gaining greater influence within the firm (Stein, 2003). Sualihu, Rankin and Haman (2021) argue that it can be easier for managers to expand the number of employees rather than making investments in fixed assets. Williamson (1963) also states that managers can behave opportunistically (i.e. over-hiring labor force) to gain more power, security, status and reputation. Besides, over-investment in labor force can also be due to under-firing when the economic conditions of the firm requires such adjustments but managers refrain from taking action. For instance, in poorly governed firms, managers prefer to enjoy 'a quiet life' and not exerting costly efforts or making difficult decisions such as shutting down poorly performing divisions and dismissing workers (Bertrand and Mullainathan, 2003).

On the other hand, manager's 'quiet life' preference can also lead to under-investment. For example, entrenched managers may be less inclined to make the necessary effort to expand firm's businesses (Stein, 2003), resulting in under-hiring. Beyond the 'quiet life' hypothesis, it has been argued that myopic investors, who base their trading decisions on the short-term performance of a stock, can exert pressure on a firm's management. Such pressure may lead to managerial concerns about the short-term stock price, potentially resulting in the decrease in valuable long-term investments (Bushee, 1998). Similarly, Graham, Harvey and Rajgopal (2005) contend that, in order to achieve short-term targets, managers are prepared to forgo long-term investments that are expected to be profitable. When managers are more concerned about shot-term results, they are likely to reduce investment in labor for increasing short-term earnings (Ghaly et al., 2020). In addition, under-investment may also be caused by managers' risk preference. Risk-averse managers could be reluctant to hire more employees, despite firm's economic fundamentals that may indicate under-capacity (Jung et al., 2014). Further, Sualihu, Rankin and Haman (2021) state that hiring could be a risky activity because of unpredictable productivity of new employees and increased business cost from hiring. Overall, suboptimal levels of investments tend to be value destroying (Ben-Nasr and Alshwer, 2016), leading to the failure of achieving expected returns for shareholder (Khedmati et al., 2020).

2.2.3. Hypothesis Development

It has been argued in the literature that in the presence of information asymmetries with weak and costly monitoring, managers have higher incentives to act in their own interest (Jensen and Meckling, 1976), and hence resulting in inefficient investments (e.g., Hubbard, 1997; Stein, 2003). However, in high social capital regions, managers can incur higher opportunity costs when deviating from the accepted social values and norms within their community or social network. As such, social capital could be considered as an informal governance and monitoring mechanism alleviating agency problems between managers and external investors, and hence reducing inefficient investment in labor. We argue that there are two potential channels through which social capital could affect labor investment efficiency: social networks and cooperative norms. Prior studies have documented that dense social networks encouraging good behaviours is a key characteristic of high social capital in a community (e.g., Posner, 1980; Putnam, 2000; Scrivens and Smith, 2013). Further, a dense social network in a region means frequent interactions and more information exchange among individuals (e.g., Putnam, 1995; Guiso et al., 2011; Jha and Chen, 2015). This suggests that, in a such environment, firm's different stakeholders, such as shareholders, managers, institutional investors and bankers, are more likely to be socially connected either directly or indirectly through interactions among members in the community. Therefore, one could expect that, when social capital level is high in a community, dense social networks facilitating interactions and increasing information exchanges among the firm's stakeholders may help in providing effective monitoring (Wu, 2008) and deters corporate manager's opportunistic behaviors resulting in a labor investment corresponding to firm's economic fundamentals.

Furthermore, the persistence of strong social networks in societies over a long period can build shared social norms and values that encourage cooperation and reciprocity (e.g., Portes, 1998; Putnam, 2000). In essence, cooperative norms tend to be strong in a community with high social capital inducing firm's managers, in a such community, to be more inclined to take actions consistent with the accepted social norms. Accordingly, managers are less likely to take conflicting actions with their values, such as practices that could benefit shareholders at the expense of other stakeholders (e.g., Hasan et al., 2017b; Hoi et al., 2019; Jha, 2019). Scrivens and Smith (2013) argue that agent's behaviors are not only affected by individual preferences but also by the prescribed norms and values in a society where they reside. Akerlof (2007) argues that people care about how they and others should behave. They are satisfied when they live up to their values and are at an unease when they fail to do so. He maintains that in modelling agents' preferences researchers should account for the opportunity costs of the behaviors that deviate from one's values. This is reasonable, given that the actions, such as narrow self-interest and opportunistic behaviors, are viewed as contradictory to the reciprocity and cooperative norms in a community leading to social sanctions. Social sanctions can include social ostracism (Putnam et al., 1993) and stigmatization (Posner, 2000), while informal punishment can include anger, disapproval and reputation damage (Halpern, 2005). In this case, agents in high social capital communities face higher marginal costs when their behaviors are contradictory to the prescribed values associated with cooperative norms in the communities (Hoi et al., 2019). The norms, therefore, may serve as an informal type of governance to discipline agent's behaviours (Bai et al., 2021). Accordingly, one could anticipate that strong cooperative norms in high social capital community may discipline the behaviors of firm's managers, and encourage them to take their obligations more seriously, hence giving them the incentives to engage in less inefficient labor investment.

Because social capital, embedded in both dense social networks and cooperative norms, may act as an external and informal governance and a monitoring device that mitigates agency problems in labor investment activities, we can expect a decrease in labor investment inefficiency with high social capital. This leads to our main hypothesis:

Hypothesis 1. *Firms headquartered in areas with higher levels of social capital have lower levels of inefficient labor investment.*

2.3. Empirical Methodology

2.3.1. Sample Selection

Our sample consists in all US publicly listed firms for the period 1992-2015. This time frame is justified by the coverage of county social capital data set. We combine firms' financial data and stock returns from Compustat/CRSP Merged (CCM), county social capital from the Northeast Regional Centre for Rural Development (NRCRD) at the Pennsylvania State University, counties demographics information from US Census Bureau, states unionization data from Union Membership and Coverage database, and governance variables from Boardex. After excluding financials and observations with missing values, our final sample used to estimate our baseline model consists of 52,268 firm-year observations, representing 5,957 unique firms. We winsorize all continuous variables at the 1^{st} and 99^{th} percentiles of their distributions to mitigate the effect of outliers.

2.3.2. Measuring Social Capital

To construct the variable on social capital, we use Rupasingha et al. (2006) U.S. county data available from the Northeast Regional Centre for Rural Development (NR-CRD) at Pennsylvania State University. The NRCRD database provides county information on voter turnouts in presidential elections (PVOTE), county-level response rates to the Census Bureau's decennial census (RESPN), the total numbers of non-profit organizations (NCCS) and the total numbers of social organizations (ASSN). The NRCRD reports three waves of data. The first covers the periods 1990, 1997, and 2005 (old data), the second updates 1997 and 2005, and adds 2009, and the last one covers 2014 (new data).

We use PVOTE and RESPN to proxy for social norms fostering cooperative behaviors. This is based on the literature advocating that social capital is enhanced by people voluntary participation in societal activities and public organizations favoring civic engagement (see e.g., Putnam et al., 1993; Rupasingha et al., 2006). Further, according to Guiso et al. (2004) and Guiso et al. (2011), they argue that since there are no direct economic incentives or legal constraints associated with voting or participating in a census survey, these two indicators are more likely to reflect the degree to which individuals within a community are willing to comply with social norms that emphasize cooperative behaviors (see, e.g., Guiso et al., 2004; Guiso et al., 2011; Funk, 2010; Knack, 2002; Hasan et al., 2017a). NCCS and ASSN, on the other hand, are used to capture county-level social networks density, they include the level of horizontal social interactions across many non-profit and other social organizations (see, e.g., Guiso et al., 2011; Hasan et al., 2017a; Hasan et al., 2017b). In the view of Putnam (1995) social organizations are primary means of being civically engaged. Moreover, extensive face-to-face social interactions between people has the potential to promote cooperation and strengthen personal social networks (Coleman, 1988).

To construct a single index for social capital, we follow Rupasingha et al. (2006) and implement a principal component analysis (PCA) based on PVOTE, RESPN, NCCS and ASSN. Therefore, our social capital variable variable (Social Capital) is the first principal component from a PCA. PVOTE is the percentage of voters who voted in presidential elections. RESPN is the response rate to the Census Bureau's decennial census. We then divided NCCS and ASSN, like in Hasan et al. (2017a) and Hasan et al. (2020), by population per 10,000 and population per 100,000 respectively.

We also make an additional adjustment to the 1990 NCCS and ASSN. We use the new data 1997, 2005, 2009, and 2014 and adjust the 1990 NCCS and ASSN which were recorded differently in the old data 1990, 1997, 2005. Specifically, the old wave of data includes additional social organizations (such as recreation clubs) and additional non-profit organizations with an international reach. Thus, we calculate the total number of non-profit organizations (NCCS) in 1990 as in Hasan et al. (2017a) by dividing the NCCS in 1997 by one plus the average of percentage change in NCCS from 1997-2005, 2005-2009 and 2009-2014. And we calculate the total number of social organizations (ASSN) in 1990 by using ten types of social organizations reported in the NRCRD data set (including religious organizations, bowling centres, physical fitness facilities, civic associations, business associations, political organizations, labor organizations, public golf courses, professional organizations and sports clubs). These organizations are recorded for all the years.

Finally, we use linear interpolation as in Jha and Chen (2015) to complete the date for the missing years. Further, in a robustness test, we rely on a back-filling procedure, as in Hasan et al. (2020) and Hoi et al. (2019), and complete data for missing years with the data from the preceding year for which data are available.

2.3.3. Measuring Labor Investment Inefficiency

Labor investment inefficiency is determined by regressing the percentage change in the number of employees on firm-specific fundamental factors that determine firm's optimal level of labor use. The residuals are interpreted as an indicator of the abnormal labor investment. Residuals with higher values are interpreted as an indicator of labor investment inefficiency. Following prior research (e.g., Ben-Nasr and Alshwer, 2016; Ghaly et al., 2020; Khedmati et al., 2020; Cao and Rees, 2020) we rely on the absolute value of the residuals. Absolute values reflect both negative and positive residuals, allowing us to capture overall inefficiencies stemming both over-investing and under-investing practices. In additional tests, we use signed abnormal labor investment to distinguish labor over-investing (positive abnormal labor investment) from labor under-investing (negative abnormal labor investment). It should be noted that over-investment may be due to over-hiring or under-firing of workers, while under-investment may stem from under-hiring or over-firing (Ben-Nasr and Alshwer, 2016; Jung et al., 2014). Accordingly, we run tests where we first split the full sample into over-investing and under-investing subsamples, and subsequently, the over-investing sample is subdivided into over-hiring and under-firing subsamples, then the under-investing sample is split into under-hiring and over-firing subsamples. Abnormal labor investment is the residual, ε_{it}, obtained from the following regression as suggested in Pinnuck and Lillis (2007):

$$\begin{aligned} Net\ Hiring_{it} = \beta_0 &+ \beta_1 Sales\ Growth_{it-1} + \beta_2 Sales\ Growth_{it} + \beta_3 \Delta ROA_{it-1} + \beta_4 \Delta ROA_{it} \\ &+ \beta_5 ROA_{it} + \beta_6 Return_{it} + \beta_7 Size_{it-1} + \beta_8 Quick_{it-1} + \beta_9 \Delta Quick_{it-1} \\ &+ \beta_{10} \Delta Quick_{it} + \beta_{11} Leverage_{it-1} + \sum_{l=0}^{5} \theta_l LossBin_{lit-1} + \delta_j + \gamma_t + \varepsilon_{it}, \end{aligned} \tag{2.1}$$

Where the subscripts i and t refer to firm i and year t respectively, $Net\ Hiring_{it}$ is the percentage change in a firm's staff number. $Sales\ Growth_{it}$ is the percentage change in sales. As in Pinnuck and Lillis (2007) we also include prior year sales growth to account for the potential time lag in the adjustment for labor demand. ΔROA_{it} is the change in return on assets to capture the hiring activities due to the change in earnings. Prior year change in ROA is also included, to account for the time for labor demand to adjust, as well as the level return on assets ROA_{it}, to account for the profitability (Pinnuck and Lillis, 2007). $Return_{it}$ is the accumulated 12-month stock return to capture future expected growth (Pinnuck and Lillis, 2007). $Size_{it-1}$ is prior firm's market value in log. $Quick_{it-1}$ is short-term investment and cash divided by current debt. It captures short-term liquidity that may affect changes in employment (Jung et al., 2014). $\Delta Quick_{i,t}$ is the percentage change in the quick ratio, as a further control for liquidity. Prior year change in the quick ratio is also included. $Leverage_{it-1}$ is the leverage ratio, which Leverage controls for financing needs that may affect the hiring decisions (Pinnuck and

Lillis, 2007). $LossBin$ are five dummy variables controlling for the occurrence of losses as firms making losses are more likely to reduce labor force. Each $LossBin$ dummy variable takes on the value of one if ROA in previous year is in a certain interval width. Following previous studies, we consider 0.005 as the interval of ROA (e.g., Jung et al., 2014; Ben-Nasr and Alshwer, 2016; Khedmati et al., 2020). For example, LossBin1 takes the value of one if ROA in previous year is between -0.005 and 0 and zero otherwise, LossBin2 takes the value of one if ROA in previous year is between -0.010 and -0.005 and zero otherwise, LossBin3 takes the value of one if ROA in previous year is between -0.015 and -0.010 and zero otherwise, and so on for the other LossBins. Pinnuck and Lillis (2007) state that firms are likely to cut down their labor force when making losses. The regression includes both industry and year fixed effects to control for unobserved omitted factors across industry and year.

For robustness and to rule out measurement problems, we use two alternative models to measure abnormal labor investment. First, we consider the argument in Biddle, Hilary and Verdi (2009) that sales growth is the key measure for strong growth opportunities that determines firms' investment levels. Following this idea, sales growth may affect a firm's hiring decisions, because firms with higher sales growth tend to hire more employees to increase productivity (Sualihu, Rankin and Haman, 2021). Therefore, following Jung et al. (2014) and Sualihu, Rankin and Haman (2021) we estimate the fallowing regression by including sales growth, $SalesGrowth_{it-1}$, as the only explanatory variable:

$$Net\ Hiring_{it} = \beta_0 + \beta_1 Sales\ Growth_{it-1} + \delta_j + \gamma_t + \varepsilon_{it}, \tag{2.2}$$

As for Equation 2.1, the absolute value of the residuals is the proxy for inefficient investment in labor.

The second alternative model we estimate is based on Ben-Nasr and Alshwer (2016) and Cao and Rees (2020). It is argued that additional factors could influence a firm's hiring decision such as, R&D expenditures, capital expenditures, acquisition expenditures, unionization, natrual logarithm of state GDP (millions of current dollars). We therefore estimate the following regression:

$$\begin{aligned} Net\ Hiring_{it} = {} & \beta_0 + \beta_1 Sales\ Growth_{it-1} + \beta_2 R\&D_{it-1} + \beta_3 CAPEX_{it-1} \\ & + \beta_4 Acquisitions_{it-1} + \beta_5 Union_{t-1} + \beta_6 Ln(GDP)_{t-1} + \delta_j + \gamma_t + \varepsilon_{it}, \end{aligned} \tag{2.3}$$

Similar to the above equation the absolute value of residuals is the proxy for labor investment inefficiency.

Moreover, following Harvey, Lins and Roper (2004), instead of using residuals from a regression, we consider the industry median level of net hiring in a given year as the optimal level of hiring for that firm-year. This follows the idea that managers of a firm are likely to herd towards their peers within the same industry when making investment decisions (Scharfstein and Stein, 1990). Thus, if a firm's labor investment deviates from its industry level, it is therefore viewed as inefficient. Accordingly, the difference between a firm's actual hiring and its industry level is used as the measure for labor investment inefficiency. First-stage variables in equations (2.1), (2.2), and (2.3) are defined in Table 2.2 in the Appendix, and the corresponding first-stage regressions are in columns (1), (2), and (3) in Table 2.3 in the Appendix.

2.3.4. Baseline Model

Our baseline model to explore the relation between social capital and labor investment inefficiency is as follows:

$$\begin{aligned} Abnormal\ Net\ Hiring_{ict} = {} & \beta_0 + \beta_1 Social\ Capital_{ct-1} + \beta_2 MTB_{ict-1} \\ & + \beta_3 Size_{ict-1} + \beta_4 Quick_{ict-1} + \beta 5 Leverage_{ict-1} \\ & + \beta_6 Dividend_{ict-1} + \beta_7 Std\ Cash_{ict-1} \\ & + \beta_8 Std\ Sale_{ict-1} + \beta_9 Tangibility_{ict-1} + \beta_{10} Loss_{ict-1} \\ & + \beta_{11} Labor\ Intensity_{ict-1} + \beta_{12} Ab.non-LaborInvest_{ict-1} \\ & + \beta_{13} Income_{ct-1} + \beta_{14} Education_{ct-1} + \delta_j + \gamma_t + \varepsilon_{ict}, \end{aligned} \tag{2.4}$$

where the subscripts i, c, j, and t denote firm i, county c, industry j, and year t respectively. The dependent variable $Abnormal\ Net\ Hiring_{ict}$ is our measure for labor investment inefficiency, estimated as the absolute residuals from the Model 2.1. The main independent variable $SocialCapital_{ct-1}$ is the social capital measure. We also include multiple firm-level fundamentals based on previous studies (e.g., Biddle et al., 2009; Ghaly et al., 2020; Jung et al., 2014). In particular, we control for market-to-book ratio, firm size, leverage, dividend payouts, cash flow as well as sales volatility, tangibility, losses, and labor intensity. Following Jha and Chen (2015) and Rupasingha et al. (2006), we consider county-level demographics to ensure that the effect social capital is not confounded by these factors, such as per capita personal income and education level in counties. Finally, we control for industry (δ_j) and year fixed effects (γ_t) for isolating the effects of unknown factors across industries and across years.

We present descriptive statistics in Table 2.1 for all variables in Eq. (2.4) [3]. The mean and standard deviation of abnormal hiring are 0.147 and 0.197 respectively, indicating that the firm's actual hiring practices, on average, deviates from the expected level by 14.7%. This is consistent with Ghaly et al. (2020). County-level social capital has a negative mean of -0.550, with standard deviation 0.831. This is in line with Hasan et al. (2017a) and Jha and Chen (2015). Statistics for other control variables are broadly in line with prior research (e.g., Ben-Nasr and Alshwer, 2016; Jung et al., 2014).

2.4. Empirical Results

2.4.1. Baseline Results

Table 2.2 reports our baseline results of Eq. (2.4) on the relation between sub-optimal labor investment and social capital. In column (1) we exclude all control variables and estimate the baseline model with our main explanatory variable $Social\ Capital$ only. The result in column (1) shows a negative and significant relation between $Abnormal\ Net\ Hiring$ and $Social\ Capital$, indicating that higher levels of social capital reduce firm's

[3] Variables of first-stage estimations in equations (2.1), (2.2), and (2.3) are defined along with their descriptive statistics in Table 2.2 of the Appendix. The corresponding first-stage estimations of equations (2.1), (2.2), and (2.3) are shown in Table 2.3 in the Appendix too.

abnormal hiring activities. Column (2) shows results for Eq (2.4). The estimated coefficient is negative and significant at 1% level, which confirms the previous result and suggests that even if most of these control variables are significant their omission is not a source of important biases in the coefficient of our main explanatory variable. The results are economically significant. A one-standard-deviation increase in *Social Capital* is associated with approximately 6.9% (4.0%) decrease in *Abnormal Net Hiring* relative to the median (mean) [4]. Control variables results are consistent with previous literature (e.g., Ghaly et al., 2020; Khedmati et al., 2020; Jung et al., 2014).

In columns (3), (4) and (5) of Table 2.2, we re-examine Eq (2.4) and run estimations by including different level fixed effects. Column (3) is the reproduction of the results of column (2), for ease of comparison with the other columns. In column (3), we add state-level fixed effects to control for unobserved omitted factors across states, such as wrongful discharge laws and geographic differences that could affect labor investment decisions (Serfling, 2016). In column (4), we control for industry-year interactive fixed effects to account for omitted factors across industries and years, suggested by Gormley and Matsa (2014). Lastly, we include firm fixed effect in column (5) to control for unknown firm-level factors. Across all these models, the qualitative results are very similar, presenting a negative relation between social capital and abnormal labor investment. These findings are in line with our main hypothesis that firms headquartered in areas with higher levels of social capital have lower levels of inefficient labor investment.

---

[4] The mean and median of *Abnormal Net Hiring* are 0.147 and 0.084 respectively. The coefficient on *Social Capital* is -0.007, and its standard deviation is 0.831. Therefore, a one-standard-deviation increase in *Social Capital* leads to a decrease in *Abnormal Net Hiring* by approximately 6.9% relative to the median ((-0.007*0.831)/0.084=-0.069)), and 4.0% relative to the mean ((-0.007*0.831)/0.147=-0.040))

2.4.2. Labor Over-Investment and Under-Investment

In this section, we extend the main analysis by investigating the relation between social capital and specific types of inefficient labor investment. In particular, we examine whether social capital affects over- and/or under-investment in labor. Because it is likely that over-investment (under-investment) may stem from over-hiring and/or under-firing (under-hiring and/or over-firing) (see, e.g., Ben-Nasr and Alshwer, 2016; Jung et al., 2014; Sualihu, Rankin and Haman, 2021), we use signed abnormal net hiring obtained from equation (2.1) and further decompose over-investment (under investment). We split the full sample as follows:

- **Over-investment in labor sample** contains observations with positive abnormal net hiring (this is denoted as *Abnormal Labor*$^{+}$). Then this is further split in two additional subsamples:
  - **Over-hiring sample** contains observations with positive abnormal net hiring, and positive expected net hiring (this is denoted as *Over-hiring*$^{+}$).
  - **Under-firing sample** contains observations with positive abnormal net hiring, and negative expected net hiring (this is denoted as *Under-firing*$^{+}$).
- **Under-investment in labor sample** contains observations with negative abnormal net hiring (this is denoted as *Abnormal Labor*$^{-}$). Then this is further split in two additional subsamples:
  - **Under-hiring sample** contains observations with negative abnormal net hiring, and positive expected net hiring (this is denoted as *Under-hiring*$^{-}$).
  - **Over-firing sample** contains observations with negative abnormal net hiring, and negative expected net hiring (this is denoted as *Over-firing*$^{-}$).

We use these subsamples and re-estimate our baseline model. Table 2.3 reports the results. Column (1) shows that social capital can help reduce abnormal net hiring for firms with over-investing. Columns (2) and (3) show that social capital is negatively associated with over-hiring and under-firing respectively, suggesting that social capital mitigates over-investing and over-investing stemming from over-hiring or under-firing. We reach a similar conclusion for under-investment. In column (4) we find that social capital reduces the inefficient investment in labor for under-investing firms. Columns (5) and (6) also shows a negative association between social capital and under-hiring as well as over-firing. Overall, results from columns (1)-(6) suggest that social capital tends to help mitigating all types of inefficient labor investments.

2.4.3. Controlling for Additional Factors

To further check the robustness of our baseline results, we implemented several robustness tests by adding several controls to rule out any confounding effects.

Firstly, we take into account the effect of labor union. Unionized labor may increase the firm's costs of adjusting labor stock and also affect its hiring decisions, because collective bargaining agreements can impose frictions that make wages sticky and layoffs more costly (e.g., Chen, Kacperczyk and Ortiz-Molina, 2011; Hamermesh, 1996; Jung et al., 2014). Therefore, we re-estimate the baseline model by controlling for the state-level union, $Union$, defined as the rate of state level union coverage. The union data are collected from Union Membership and Coverage Database. Column (1) in Table 2.4 shows the results when the variable $Union$ is included in the estimation. The relation between social capital and labor investment inefficiency remains negative and significant at the 1% level after controlling for the labor union.

Secondly, it should be noted that investment in labor tends to be costly. labor investment often incurs significant adjustment costs, such as transferring costs and replacement of the labor force (Hamermesh, 1996). Moreover, given that labor is a quasi-fixed factor, investment in labor may involve huge spending on hiring and training employees (Benmelech, Bergman and Seru, 2021). Such costs usually require financing. If firms are stuck in financial difficulties, they are likely to make inefficient investment in labor. Campello et al. (2010) argue that firms with financial constraints tend to cut the labor force aimed at saving costs and enhancing cash flow. Therefore, to mitigate the concern that the main results could be driven by the factor relating to financing, we control for the degree of financial constraints. To this end, following Foucault and Frésard (2012), the dependence on external capital is used to measure for financial constraints. It is measured as the industry median value of the difference between capital expenditures and cash flow from operations, divided by capital expenditures. If a firm's external financing dependence is greater than the industry median value, the firm in this industry is more likely to have financial constraints. Therefore, we use an indicator variable, $FinancialConstraints$, that equals one if firm's external financing dependence value is greater than its industry median, and zero otherwise. The results are presented in column (2) of Table 2.4. The negative and significant estimated coefficient on $Social\ Capital$ indicates that the results are not affected by the financial constraints.

Thirdly, previous studies have documented that organization capital of a firm, as one of the most important intangible assets, contributes to better firm performance, higher market value, more productivity, higher expected stock return and better M&A performance (e.g., Atkeson and Kehoe, 2005; Eisfeldt and Papanikolaou, 2013; Leung, Mazouz, Chen and Wood, 2018; Lev, Radhakrishnan and Zhang, 2009; Li, Qiu and Shen, 2018). Better firm performance may lead to the potential future success, this tends to allow firms more likely to attract and retain talents and hence may affect firm's labor hiring decisions (e.g., Attig and Cleary, 2014; Le and Tran, 2022). To take into account this possibility, we control for firm-level organization capital. Details of $Organization\ Capital$ variable construction is presented in Appendix C. Regression results when $Organization\ Capital$ is included are reported in column (3) of Table 2.4. The coefficient on social capital, $Social\ Capital$, remains negative and significant at the 1% level, indicating that the baseline findings are not affected by the inclusion of firm-level organization capital.

Lastly, one concern that the negative relation between social capital and labor investment inefficiency could be driven by omitted governance variables. A firm with weak governance tends to have more agency conflicts and more information asymmetry, and hence driving firm's investment efficiency deviating from the optimal level (e.g., Ghaly et al., 2020; Jung et al., 2014). To mitigate this concern, we control for the $Duality$, which is defined as a dummy variable equals to one if a firm's CEO also takes the role of the board chair, and zero otherwise. We also control for $Independent\ Directors$, which is defined as the percentage of the independent directors on the board. Results with this additional controls are reported in Table 2.4. Column (4) controls for $Duality$ and $Independent\ Directors$, and shows a negative and significant coefficient on $Social\ Capital$. These results suggest that the negative relation between social capital and labor investment inefficiency hold after controlling for additional governance variables.

2.4.4. Alternative Proxies for Labor Investment Inefficiency

In this subsection, several alternative measures for labor investment efficiency are considered. Firstly, following Harvey et al. (2004), we consider the median level of net hiring in a firm's industry in a given year as the optimal level of hiring for that firm-year. This follows the idea that managers of a firm attempt to follow their peers within the industry when making investment decisions (Scharfstein and Stein, 1990). Hence, the difference between a firm's actual hiring and its industry level is used as the measure for labor investment inefficiency. The greater deviation from a firm's industry level, the more inefficient investment in labor. Results are shown in Table 2.5 in column (1). The coefficient remains negative and significant at the 1% level.

Secondly, Biddle et al. (2009) state that sales growth is a key measure for strong growth opportunities. Following this idea, sales growth may affect a firm's hiring decisions, because firms with higher sales growth tend to hire more employees to increase productivity (Sualihu, Rankin and Haman, 2021). Therefore, following Jung et al. (2014) and Sualihu, Rankin and Haman (2021) we re-estimate equation (2.1) as equation (2.2) by only including sales growth, $SaleGrowth_{it-1}$, as the independent variable, and use the absolute value of residuals as the proxy for inefficient investment in labor. Column (2) of Table 2.5 presents the results. The results remain qualitatively the same as the baseline regressions.

Thirdly, Ben-Nasr and Alshwer (2016) argue that a number of additional factors could influence a firm's hiring decision, such as R&D expenditures, capital expenditures, GDP and acquisition expenditure. Therefore, following Ben-Nasr and Alshwer (2016) and Cao and Rees (2020), we re-estimate equation (2.1) that we adjust as equation (2.3) by including additional variables: unionization, R&D expenditures, capital expenditures, natural logarithm of state GDP, and acquisition expenditures. Then the absolute value of residuals is the proxy for labor investment inefficiency. As shown in column (3) in Table 2.5, the results are also qualitatively the same as the baseline findings. Overall, the results are robust to different proxies for labor investment inefficiency.

2.4.5. Alternative Proxies for Social Capital

In this subsection, alternative social capital measures are introduced to test the robustness of the negative relation between social capital and labor investment inefficiency. First, following Gupta et al. (2020), we consider voter turnout rates in US elections, obtained from United States Elections Project, as another proxy for social capital (McDonald, 2014). The NRCRD voter turnout $PVOTE$ (Rupasingha et al., 2006) we use to construct Social Capital variable in our baseline estimations refers to the percentage of voters in presidential elections, instead, McDonald's (2014) voter turnout includes both the vote for the highest office in the presidential election years as well as non-presidential election years [5]. Voter turnout can reflect the civic engagement

[5]Voter turnout data can be obtained from United States Election Project (McDonald, 2014). Recall that the social capital data in our baseline regressions are obtained from the NRCRD (Rupasingha et al., 2006), and include voter turnout. The voter turnout in NRCRD refers to percentage of voter in presidential

of individuals in a region, higher voter turnout suggests more civic engagement (Guiso et al., 2004). The voter turnout variable, $Vote$, is defined as the percentage of voting-age population voted for the highest office in a state in a given election year. The voting-age population is defined by the Bureau of the Census as people residing in the United States, age 18 and older.

Second, recall that the main independent variable, $Social\ Capital$, in the baseline model is constructed based on social network and cooperative norms. We examine the effects of $Social\ network$ and $Cooperative\ norms$ separately on abnormal hiring in order to confirm the validity of our baseline results. $Social\ network$ is measured as the first principal component from a PCA analysis based on ASSN and NCCS, and $Cooperative\ norms$ is obtained using a similar procedure based on PVOTE and RESPN.

Third, as mentioned in Section 2.3.2, the missing values for social capital index are replaced by linear interpolation. However, other studies, such as Hasan et al. (2020) and Hoi et al. (2019), use back-filling approach to construct social capital index, because social capital is relatively sticky and stable overtime (e.g., Anheier, Gerhards and Romo, 1995; Hoi, Wu and Zhang, 2018). Therefore, we rely on back-filing procedure to estimate missing year data in social capital, this leads to an additional proxy for social capital, $Back-filling$.

Fourth, to ensure that our baseline results are not affected by using the method of Hasan et al. (2017a) and the adjustments made to construct our social capital variable $Social\ Capital$ [6], we re-estimate our main model by using the raw social capital index of Rupasingha et al. (2006), SK, which is available in 1997, 2005, 2009 and 2014 (without interpolation or backfilling). Note that we do not use social capital data in 1990 because Rupasingha et al. (2006) include additional social organizations and additional non-

elections. However, the voter turnout obtained from McDonald (2014) includes both the vote for highest office in presidential election years and non-presidential election years. Therefore, we consider the data provided by McDonald (2014) as alternative source for social capital measure.

[6] Presented in Section2.3.2.

profit organizations with an international reach in 1990. However, these organizations are not included in later years. Therefore social capital data in 1990 are not compatible with that in later years.

Regression results of using each alternative proxies of social capital discussed above are presented in Table 2.6. Across all regressions, the coefficient on each alternative social capital measure is negative and significant at either 1% or 5% levels, indicating that the relation between social capital and labor investment inefficiency holds when employing different proxies of social capital.

2.4.6. Propensity Score Matching

Our baseline results in Table 2.2 are robust after controlling for several time-invariant factors and time-varying factors, such as industry, year, state or industry-year high-dimensional fixed effects. However, these results could be biased if social capital is affected by the potential confounding characteristics. Therefore, in this section, we employ propensity score matching (PSM) analysis to reduce the impact of omitted (observable) variables on the results.

To implement the PSM technique, we first rank social capital data, from the whole sample period within the same year for all firms, and extract firm-year observations above 75^{th} percentile line and below 25^{th} percentile line. We define a treatment dummy variable, $HighSocialCapital$, that equals to one for firm-years above 75^{th} percentile line (treatment group) and zero for those under 25^{th} percentile line (control group). From this setting, the subsample contains 12,728 firm-year observations for treatment group ($High\,Social\,Capital = 1$) and 13,162 firm-year observations for control group ($High\,Social\,Capital = 0$).

Next, we calculate the propensity score by estimating a Probit model with the dependent variable, $HighSocialCapital$. The covariates used as the independent variables are firm-level characteristics specified in the baseline model, including market-to-book ratio, firm size quick ratio, leverage, dividend, volatility in cash flow and sales, tangibility, losses, labor intensity, and abnormal non-labor investment. To ensure that firms in the treatment group and control group are comparable, we then use nearest neighbour matching approach, with replacement, and require that the difference in propensity scores between the treatment and the control does not exceed 1% in absolute value. This procedure ensures that firms with treatment is matched to those with control by finding the closest propensity score. To assess the quality of the match. We re-estimate the Probit model for post-match sample. Columns (1) and (2) of Table 2.7 present results estimated by the Probit model from pre-match and post-match samples respectively. Column (1) shows that, for the pre-match sample, estimates on volatility in cash flow, losses, labor intensity and dividend are all significant at the 1% level. In column (2), for the post-match sample, all estimated coefficients become insignificant, suggesting that firms in treatment and those in control do not present distinguishable characteristics. The Pseudo R-squared also drops significantly after matching, from 0.139 to 0.006. In a good match, the independent variables should not well explain the outcome (treatment status), hence the Pseudo R-squared is lower. In addition, we verify the quality of the match by comparing the differences in all firm-specific characteristics between the treatment and control using univariate t-test. Panel A of Table 2.8 reports results for the t-test. For pre-match sample, as expected, there are significant differences in most firm characteristics. For post-match sample, except that difference in social capital is significant, the univariate difference test statistics on firm characteristics are insignificant, indicating that the difference between treatment and control is only driven by social capital, as opposed to other firm-level observables. Therefore, above diagnostic tests suggest that the matching is efficiently done.

Panel B of Table 2.8 reports the results where we use $HighSocialCapital$, instead of $Social\ Capital$ as our main independent variable and re-estimate our baseline model. Consistent with the main finding, the results indicate that firms with higher social capital tend to have less inefficient investment in labor. Note that we also use quintile or decile as the cutoffs to define treatment group and control group in PSM, the findings are unchanged [7].

2.5. Endogeneity Concerns

2.5.1. Instrumental Variable Analysis

Our results so far suggest a causal effect of social capital on inefficient investment in labor. In our baseline estimation, we have included different time-invariant controls, in addition to as many county, state and firm-level controls as possible. However, social capital and firm's abnormal hiring may still be simultaneously determined by unobserved factors. To mitigate this concern we use an instrumental variable (IV) estimation. Our instrumental variable is the distance between a county and the Canadian boarder.

The use of this IV is motivated by Putnam (2001) who shows that the distance to the US-Canada boarder is a good indicator for the level of social capital in US states. In particular, the more closer to the Canadian boarder means higher level of social capital [8]. This is because the current social capital is strongly associated with the American history of slavery in the 19^{th} century. He emphasises that the slavery system and post-slavery reconstruction period destroyed the social capital among the Blacks, and the social connections between the Blacks and poor Whites (Putnam, 2001).

Following Putnam's insight, we introduce the instrument $Distance$. This IV satisfies the exclusion restriction. It is not likely that the a county's distance to the Canadian boarder affects abnormal net hiring except through social capital in the county where the firm is situated. $Distance$ is the natural logarithm of the closest distance between the county where a firm is headquartered and the Canadian boarder. Our instrument is similar to the IV adopted in recent empirical work on social capital (see e.g., Hasan et al., 2017a; Hasan et al., 2017b; Gupta et al., 2020). In line with Putnam (2001)

[7] These results are not tabulated.

[8] This is very well shown in the Appendix. This figure is reproduced from Putnam (2001).

prediction we expect *Distance* to be negatively correlated with social capital.

The results for instrumental variable regression are reported in Table 2.9. We first regress *Social capital* on *Distance* and all other control variables specified in the baseline model. Column (1) shows the estimation. As expected, the coefficient on the IV is negative and statistically significant at 1% level, consistent with the findings of Putnam (2001). The estimation for the second stage is reported in column (2). The coefficient on *Social capital* is negative and significant at the 1% level, suggesting that the relation between social capital and labor investment inefficiency is not influenced by the potential omitted variable bias.

2.6. Evidence from Firm's Relocation Event

Our social capital data are based on the county where the firms are headquartered. However, it is likely that some firms during our sample period can relocate their headquarters, leading to the changes in firm's exposure to social capital. As an additional analysis in this section, we focus on firm's relocation events and follow Hasan et al. (2017a) to conduct a difference-in-difference analysis. If higher social capital can reduce corporate inefficient labor investment, one could expect that firms after relocation to the US county with higher social capital should have less labor investment inefficiency. In contrast, firms after relocation to the US county with lower social capital should have more labor investment inefficiency. Therefore, we compare the changes in labor investment inefficiency, before and after the relocation, across firms with relocation to higher social capital against firms with relocation to lower social capital.

To conduct such analysis, we rely on US Securities and Exchange Commissions (SEC) 10-K filings to identify firm's headquarter addresses. The relocation event occurs if a firm records addresses in two different US counties in 10-k filings in two consecutive years. We then define 3 years before and 3 years after the relocation event as pre-relocation window and post-relocation window respectively. We require firms should have at least one year data in both pre-relocation window and post-relocation window. Moreover, we exclude firms with multiple relocation events (i.e. firms relocate their headquarters more than once). Note that the electronic SEC filings initiated in 1993. Therefore, our sample period used for the DID analysis starts from 1993. Finally, We identify 323 unique firms that experience relocation during our sample period representing 1,518 firm-year observations. Among these, 165 firms relocate to counties with lower level of social capital while 158 firms move to counties with higher level of social capital.

To conduct our DID analysis, we run following regression:

$$\begin{aligned} Abnormal\ net\ hiring_{ict} = {} & \beta_0 + \beta_1 Treat * Post + \beta_2 MTB_{it-1} + \beta_3 Size_{it-1} + \beta_4 Quick_{it-1} \\ & + \beta 5 Leverage_{it-1} + \beta_6 Dividend_{it-1} + \beta_7 Std\ cash_{it-1} + \beta_8 Std\ sale_{it-1} \\ & + \beta_9 Tangibility_{it-1} + \beta_{10} Loss_{it-1} + \beta_{11} \textsf{Labor intensity}_{it-1} \\ & + \beta_{12} Ab.\ non-labor\ invest_{it-1} + \beta_{13} income_{ct-1} \\ & + \beta_{14} Education_{ct-1} + Industry\_FE + Year\_FE + County\_FE + \varepsilon_{it}, \end{aligned} \tag{2.5}$$

where the subscripts i, c, and t denote firm i, county c, and year t respectively.

In equation (2.5), we replace our *Social Capital* variable with the interaction term, $Treat * Post$. $Treat$ is a dummy variable that equals one if the firm moves to a county with higher social capital and zero otherwise. $Post$ is a dummy variable that equals one if firm-year observations are from the post-relocation time and zero otherwise. The coefficient on the interaction term, $Treat * Post$, is our primary interest because it captures the DID effects on the changes in labor investment inefficiency across firms with the relocation of social capital increasing and that of social capital decreasing for post and pre-relocation periods.

Despite the DID exercise, firm relocation could be an endogenous choice. To account for this, we follow Hainmueller (2012) and use the entropy-balancing method to re-weight the covariates in the moments (mean, variance, skewness) for firms with social capital increasing and with social capital decreasing before the relocation. In Table 2.10, we show that there are no differences in mean, variance and skewness across these two groups. We present the regression results in Table 2.11. The coefficient on

$Treat * Post$ is negative and statistically significant at the 1% level, indicating that firms relocating to a county with higher social capital have less inefficient labor investment after the relocation event. However, we note that the magnitude of this coefficient is larger than that of our main result. This could be due to sampling error because of the very reduced sample size of firms relocation.

2.7. Evidence of Governance Mechanism Based on Takeover Threats

In this section, we explore the channel through which social capital affects labor investment. Given that agency problems are pervasive in publicly list firms, the presence of agency conflicts can lead to abnormal investment in labor. Regarding the role played by social capital, the evidence shows that social capital can help cultivate a social culture to deter manager opportunism (Hasan et al., 2017a), and to reduce agency conflicts (Hoi et al., 2019). Following our hypothesis and main results, if the decrease in labor investment inefficiency is because social capital serves as informal governing mechanism that discipline manager's behaviors and reduce agency problems in labor investment activities, one could expect that the negative relation between social capital and abnormal net hiring are more pronounced when firms have weak corporate governance. To test this conjecture, we employ Cain, McKeon and Solomon's (2017) takeover index, which measures a firm's susceptibility to takeover. According to Cain et al. (2017), a higher value of takeover index suggests that firms face greater hostile takeover threats and are more likely to be taken over, hence the firms tend to have weaker managerial entrenchment and stronger corporate governance. Therefore, we use a dummy variable, $LowTakeoverIndex$, that takes on the value of one if firm-year observations are below the 25^{th} percentile of takeover index value, and zero otherwise, and then re-estimate the baseline regressions by including $LowTakeoverIndex$ and interaction term between $Social\ Capital$ and $LowTakeoverIndex$.

The regressions results are reported in Table 2.12. Consistent with the above conjecture, the coefficient on the interaction term, $SocialCapital * LowTakeoverIndex$, is negative and significant at the 5% level, indicating that the negative relation between social capital and inefficient labor investment is more pronounced when firms are less susceptible to hostile takeover. This provides plausible evidence for the governance mechanism through which social capital influences inefficient labor investment.

2.8. Conclusion

This paper analyses whether social capital in US counties where firms reside affects their labor investment inefficiency. We capture labor investment inefficiency using the firm's abnormal net hiring, and social capital using social norms and social networks. We argue that social capital can serve as a social monitoring and governing mechanism to constrain corporate manager's misbehavior in labor investment decision making. Consistent with our prediction, we find that social capital surrounding firm's headquarters is negatively associated with abnormal net hiring. The results are unchanged when investigating different forms of inefficiencies of labor investment, using alternative definitions of labor investment inefficiency. We also perform an additional test to highlight the governance mechanism through which social capital could affect labor investment inefficiency. We find that the effect of social capital on abnormal net hiring is more pronounced when firms have weak governance, as captured by the lower threats of hostile takeover.

We run several tests to deal with endogeneity concerns. We estimate our model using different fixed effects to control for unobserved time-invariant firm-level and state-level factors, and/or time-varying industry specific factors. We employ propensity score matching analysis to mitigate the impact of observable confounding characteristics on the results. We run instrumental variable regressions and difference-in-difference analysis. Further, we use alternative measures for social capital and abnormal hiring. We show that our results from these different tests are consistent with the main findings.

Our study sheds light on the impact of social capital in the region where firms are located on corporate labor investment. Consistent with the extant literature that shows social capital can add value to firms (e.g., Jha and Chen, 2015; Hasan et al., 2017a; Gupta et al., 2020; Bai et al., 2021), we show that social capital can reduce inefficiency of labor investment. This suggests that social capital can serve as a ’soft’ governing mechanism by disciplining corporate manager’s behaviors to alleviate agency problems. In particular, our results support Hoi et al. (2019)’s findings, who have documented that social capital can help mitigate agency conflicts in the corporate settings, such as CEO compensation.

Tables for Chapter 2

Table 2.1: Descriptive Statistics

This table reports descriptive statistics for variables specified in baseline model 2.4. The sample includes 52,268 firm-year observations, representing 5,957 unique firms from 1992 to 2015. *Abnormal Net Hiring* is the measure for inefficient investment in labor, calculated by taking the absolute values of the residuals estimated from Eq. (2.1). *Social Capital* is county-level social capital. It is constructed by implementing principal component analysis (PCA) based on four factors (PVOTE, RESPN, NCCS and ASSN). MTB is the market-to-book ratio. $Size$ is the natural logarithm of a firm's market value. $Quick$ is the ratio of cash and short-term investments plus receivables to current liabilities. $Leverage$ is the leverage ratio. $Dividend$ is an indicator variable set equal to one if a firm pays dividends, and zero otherwise. Std_cash is cash flow volatility. Std_sale is sales volatility. $Tangibility$ is the tangibility ratio. $Loss$ is a dummy variable set equal to one in years in which a firm has negative ROA. *Labor Intensity* is labor intensity, measured as the number of employees divided by total assets. *Ab. non-Labor Invest* is abnormal non-labor investment. $Income$ is the natural logarithm of per capital personal income in the county. $Education$ is the percentage of people aged 25 and over with a bachelor's degree or higher in the county.

Variables	N	Mean	Std. Dev. (Overall)	Std. Dev. (Between)	Std. Dev. (Within)	P25	Median	P75
$Abnormal\ Net\ Hiring$	52,268	0.147	0.197	0.149	0.167	0.038	0.084	0.169
$Social\ Capital$	52,268	-0.550	0.831	0.818	0.209	-1.186	-0.521	0.012
MTB	52,268	2.022	1.625	1.426	1.064	1.123	1.511	2.252
$Size$	52,268	5.581	2.141	1.994	0.744	3.991	5.552	7.079
$Quick$	52,268	2.041	2.491	2.231	1.537	0.805	1.284	2.251
$Leverage$	52,268	0.208	0.202	0.195	0.111	0.019	0.171	0.325
$Dividend$	52,268	0.324	0.468	0.381	0.221	0.000	0.000	1.000
$Std\ Cash$	52,268	2.580	1.748	1.588	0.622	1.317	2.494	3.759
$Std\ Sales$	52,268	3.791	2.011	1.875	0.696	2.365	3.790	5.178
$Tangibility$	52,268	0.263	0.221	0.220	0.069	0.091	0.197	0.372
$Loss$	52,268	0.326	0.469	0.377	0.349	0.000	0.000	1.000
$Labor\ Intensity$	52,268	0.008	0.011	0.011	0.004	0.002	0.005	0.010
$Ab.non-Labor\ Invest$	52,268	0.116	0.134	0.134	0.103	0.050	0.092	0.129
$Income$	52,268	10.563	0.369	0.356	0.185	10.297	10.551	10.798
$Education$	52,268	0.337	0.100	0.098	0.032	0.266	0.322	0.407

Table 2.2: The Effect of Social Capital on Labor Investment Inefficiency - Fixed Effects Models

This table reports estimates of the baseline model of equation (2.4). The different specifications show consistent results. The dependent variable is $Abnormal\ Net\ Hiring$ in absolute values. Column (1) excludes controls and column (2) includes all controls. Both columns include year and industry fixed effects (FE). Columns (3), (4) and (5) include all controls and use State FE, $Year \times Industry$ FE, and firm FE respectively. Variable definitions are provided in Table 2.1. We present t-statistics in parentheses and cluster standard errors at county level. ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels respectively.

	Abnormal Net Hiring				
	Industry & Year FE		State Fixed FE	$Year \times Industry$ FE	Firm FE
	(1)	(2)	(3)	(4)	(5)
$Social\ Capital$	-0.008***	-0.007***	-0.009***	-0.007***	-0.011**
	(-4.42)	(-5.00)	(-3.31)	(-4.47)	(-2.05)
MTB		0.006***	0.006***	0.006***	0.005***
		(6.25)	(6.23)	(5.59)	(4.23)
$Size$		-0.009***	-0.009***	-0.009***	-0.005***
		(-6.28)	(-6.31)	(-5.59)	(-2.48)
$Quick$		0.007***	0.007***	0.007***	0.006***
		(9.72)	(9.78)	(9.70)	(7.84)
$Leverage$		0.008	0.006	0.011	-0.011**
		(1.02)	(0.80)	(1.25)	(-1.07)
$Dividend$		-0.011***	-0.011***	-0.011***	0.008*
		(-4.64)	(-4.52)	(-4.30)	(1.98)
$Std\ Cash$		0.003*	0.004**	0.004**	-0.001
		(1.95)	(2.09)	(2.18)	(-0.31)
$Std\ Sales$		-0.002	-0.002	-0.002***	-0.015***
		(-0.78)	(-0.91)	(-0.091)	(-6.26)
$Tangibility$		-0.057***	-0.058***	-0.055***	-0.025
		(-7.05)	(-7.27)	(-6.59)	(-1.39)
$Loss$		0.030***	0.029***	0.031***	0.012***
		(14.68)	(14.67)	(15.24)	(4.50)
$Labor\ Intensity$		-0.716***	-0.716***	-0.726***	-2.116***
		(-4.52)	(-4.47)	(-4.29)	(-5.14)
$Ab.\ non-labor\ invest$		0.400***	0.399***	0.393***	0.394***
		(22.34)	(23.57)	(22.35)	(21.71)
$Income$		0.006	0.018**	0.003	0.063***
		(0.87)	(2.07)	(0.44)	(3.18)
$Education$		0.022	0.021	0.027	-0.226***
		(1.15)	(0.91)	(1.33)	(-2.71)
Constant	0.151***	0.083	-0.047	0.087	-0.410**
	(5.91)	(1.22)	(-0.54)	(1.16)	(-2.01)
Observations	52,268	52,268	52,268	52,268	52,268
Adjusted R^2	0.053	0.167	0.168	0.155	0.255
Year FE	Yes	Yes	Yes	No	Yes
Industry FE	Yes	Yes	Yes	No	No
State FE	No	No	Yes	No	No
Firm FE	No	No	No	Yes	Yes
Year*Industry	No	No	Yes	No	No
County Cluster	Yes	Yes	Yes	Yes	Yes

Table 2.3: The Effect of Social Capital on Labor Investment Inefficiency - Over and Under Labor Investing

This table reports estimates of the baseline model of equation (2.4) by splitting the sample according to the sign of Abnormal Net Hiring. Column (1) reports the effect of Social Capital on total labor over-investment which is the sample of firm/year observations where abnormal net hiring has a positive sign (*Abnormal Labor*$^+$). Columns (2) and (3) further decomposes *Abnormal Labor*$^+$ into labor over-investment resulting from over-hiring (*Over-hiring*$^+$) and labor over-investment resulting from under-firing (*Under-firing*$^+$). Column (4) reports the effect of Social Capital on total labor under-investment which is the sample of firm/year observations where abnormal net hiring has a negative sign (*Abnormal Labor*$^-$). Columns (5) and (6) further decomposes *Abnormal Labor*$^-$ into labor under-investment resulting from under-hiring (*Under-hiring*$^-$) and labor under-investment resulting from over-firing (*Over-firing*$^-$). Variable definitions are provided in Table 2.1. Estimations include year and industry fixed effects. We present t-statistics in parentheses and cluster standard errors at county level. ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels respectively.

	Labor over-investing			Labor under-investing		
	Abnormal Labor$^+$	*Over-hiring*$^+$	*Under-firing*$^+$	*Abnormal Labor*$^-$	*Under-hiring*$^-$	*Over-firing*$^-$
	(1)	(2)	(3)	(4)	(5)	(6)
Social Capital	-0.010***	-0.010***	-0.008***	-0.005***	-0.005***	-0.007***
	(-3.86)	(-3.34)	(-3.06)	(-4.57)	(-4.14)	(-2.76)
MTB	0.006***	0.008***	0.012***	0.006***	0.007***	-0.000
	(3.50)	(4.36)	(4.66)	(5.00)	(5.02)	(-0.18)
Size	-0.005**	-0.017***	-0.007***	-0.013***	-0.012***	-0.010***
	(-2.11)	(-4.55)	(-2.59)	(-9.69)	(-7.09)	(-4.54)
Quick	0.008***	0.008***	0.005***	0.006***	0.006***	0.004***
	(6.76)	(5.32)	(3.93)	(9.92)	(8.77)	(3.29)
Leverage	0.008	0.038**	-0.001	0.010	0.022**	-0.033***
	(0.64)	(2.10)	(-0.13)	(1.42)	(2.37)	(-4.10)
Dividend	-0.008*	-0.002	-0.013***	-0.007***	-0.008***	-0.004
	(-1.73)	(-0.34)	(-2.69)	(-3.54)	(-4.20)	(-0.80)
Std Cash	-0.014***	-0.012***	0.002	0.018***	0.020***	0.009***
	(-5.33)	(-3.30)	(0.60)	(9.19)	(8.55)	(3.51)
Std Sales	0.006**	0.012***	-0.005	-0.009***	-0.014***	0.003
	(2.29)	(3.10)	(-1.57)	(-4.15)	(-5.32)	(1.25)
Tangibility	-0.081***	-0.108***	-0.022	-0.044***	-0.040***	-0.057***
	(-5.16)	(-5.33)	(-1.41)	(-6.08)	(-5.07)	(-4.47)
Loss	0.022***	0.049***	0.005	0.040***	0.043***	0.016***
	(4.83)	(7.96)	(1.08)	(19.08)	(15.97)	(4.14)
Labor Intensity	-2.063***	-2.194***	-1.754***	0.378***	0.188	1.050***
	(-6.32)	(-5.32)	(-5.60)	(2.78)	(1.64)	(3.43)
$Ab.non-Labor\ Invest$	0.464***	0.493***	0.205***	0.184***	0.193***	0.116***
	(26.33)	(28.56)	(6.94)	(9.41)	(9.84)	(4.26)
Income	0.006	0.005	0.011	0.006	0.008	-0.001
	(0.56)	(0.30)	(1.06)	(0.85)	(1.10)	(-0.05)
Education	0.023	0.027	0.013	0.018	-0.001	0.083**
	(0.68)	(0.59)	(0.33)	(0.96)	(-0.04)	(2.57)
Constant	0.148	0.247	-0.009	0.077	0.054	0.165
	(1.24)	(1.53)	(-0.08)	(1.18)	(0.77)	(1.37)
Observations	21,217	14,982	6,235	31,051	23,700	7,351
Adjusted R^2	0.185	0.196	0.159	0.171	0.203	0.137
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
County Cluster	Yes	Yes	Yes	Yes	Yes	Yes

Table 2.4: The Effect of Social Capital on Labor Investment Inefficiency - Controlling for Additional Factors

This table reports estimates of the baseline model of equation (2.4) augmented with additional controls. The dependent variable is *Abnormal Net Hiring* in absolute values. Column (1), (2), (3) and (4) control for the labor union, financial constraints organization capital, and duality as well as independent directors respectively. Estimations control for industry & year fixed effects. Variable definitions are provided in Table 2.1. We present t-statistics in parentheses and cluster standard errors at county level. ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels respectively.

	Abnormal Net Hiring			
Additional controls	Labor union	Financial constraints	Organization capital	Independent director & Duality
	(1)	(2)	(3)	(4)
Social Capital	-0.007***	-0.007***	-0.007***	-0.005***
	(-4.32)	(-4.80)	(-4.46)	(-2.69)
MTB	0.006***	0.006***	0.007***	0.005***
	(6.21)	(5.24)	(5.87)	(3.53)
Size	-0.009***	-0.009***	-0.010***	-0.010***
	(-6.25)	(-5.36)	(-6.68)	(-3.58)
Quick	0.007***	0.007***	0.006***	0.006***
	(9.88)	(8.87)	(7.57)	(8.02)
Leverage	0.007	0.009	-0.001	0.020*
	(0.97)	(1.18)	(-0.19)	(1.81)
Dividend	-0.011***	-0.009***	-0.011***	-0.006**
	(-4.67)	(-3.68)	(-4.44)	(-2.18)
Std Cash	0.003*	0.004**	0.000	0.008***
	(1.88)	(1.98)	(0.22)	(3.01)
Std Sales	-0.002	-0.000	0.004**	-0.005
	(-0.79)	(-0.23)	(2.08)	(-1.46)
Tangibility	-0.057***	-0.057***	-0.045***	-0.051***
	(-7.12)	(-6.93)	(-5.70)	(-4.61)
Loss	0.030***	0.026***	0.029***	0.021***
	(14.77)	(11.76)	(11.48)	(6.89)
Labor Intensity	-0.715***	-0.589***	-0.409**	-0.644***
	(-4.52)	(-3.72)	(-2.46)	(-3.22)
$Ab.non-Labor\ Invest$	0.401***	0.410***	0.451***	0.388***
	(23.63)	(25.40)	(26.51)	(16.90)
Income	0.017**	0.004	0.008	0.006
	(2.17)	(0.63)	(1.15)	(0.68)
Education	0.001	0.020	0.007	0.010
	(0.03)	(1.04)	(0.38)	(0.40)
Union	-0.068***			
	(-3.12)			
Financial Constraints		0.009***		
		(4.65)		
Organization capital			-0.008***	
			(-2.61)	
Independent directors				-0.007
				(-0.63)
Duality				-0.002
				(-0.85)
Constant	-0.014	0.071	0.046	0.151
	(-0.19)	(1.12)	(0.66)	(1.45)
Observations	52,170	45,807	40,619	27,100
Adjusted R-squared	0.167	0.168	0.166	0.164
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
County cluster	Yes	Yes	Yes	Yes

Table 2.5: The Effect of Social Capital on Labor Investment Inefficiency - Alternative Proxies for Labor Investment inefficiency

This table reports estimates of the baseline model of equation (2.4) where we adopt different proxies for abnormal net hiring. Column (1) proxies our dependent variable *Abnormal net hiring* by the difference between a firm's actual hiring and its industry level. Column (2) and (3) proxy *Abnormal net hiring* by the absolute value of residuals estimated from equation 2.2 and residuals estimated from equation 2.3 respectively. First stage estimations are in Table 2.3. Variable definitions are provided in Table 2.1. We present t-statistics in parentheses and cluster standard errors at county level. ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels respectively.

	Abnormal Net Hiring		
Alternatives measures of Abnormal Net Hiring	Industry median	Sales growth Model	Additional factors Model
	(1)	(2)	(3)
Social Capital	-0.008***	-0.007***	-0.007***
	(-4.13)	(-4.88)	(-3.94)
MTB	0.009***	0.006***	0.005***
	(6.09)	(4.49)	(4.53)
Size	-0.011***	-0.012***	-0.008***
	(-6.14)	(-7.28)	(-4.50)
Quick	0.004***	0.004***	0.006***
	(5.05)	(5.11)	(7.85)
Leverage	-0.003	0.005	0.012
	(-0.35)	(0.60)	(1.55)
Dividend	-0.020***	-0.012***	-0.008***
	(-7.52)	(-4.87)	(-3.28)
Std Cash	-0.008***	-0.003**	0.003*
	(-4.61)	(-2.07)	(1.67)
Std sale	0.011***	0.009***	-0.001
	(6.36)	(5.38)	(-0.38)
Tangibility	-0.067***	-0.061***	-0.045***
	(-6.36)	(-6.37)	(-5.37)
Loss	0.033***	0.047***	0.028***
	(13.30)	(19.96)	(10.80)
Labor Intensity	-0.920***	-0.860***	-0.521***
	(-4.96)	(-4.87)	(-2.95)
$Abnormal\ non-Labor\ Invest$	0.471***	0.429***	0.390***
	(19.77)	(19.43)	(22.78)
Income	0.006	0.009	0.008
	(0.72)	(1.15)	(1.27)
Education	0.025	0.011	0.004
	(1.09)	(0.49)	(0.18)
Constant	0.062	0.073	0.017
	(0.71)	(0.94)	(0.26)
Observations	52,268	52,268	37,908
Adjusted R-squared	0.152	0.160	0.167
Year FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes

Table 2.6: Robustness-Alternative Proxies for Social Capital

This table reports estimates of the baseline model of equation (2.4) where we adopt different proxies for social capital. Column (1), (2), (3) and (4) proxy our main independent variable Social Capital by Vote, Social networks, Cooperative norms, Social capital (Back-fill), and SK respectively. The dependent variable is *Abnormal Net Hiring* in absolute values. Estimations control for industry & year fixed effects. Variable definitions are provided in Table 2.1. We present t-statistics in parentheses and cluster standard errors at county level. in all columns except column (1) where it is clustred at state level. ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels respectively.

	Abnormal Net Hiring				
Social Capital Proxies	Vote	Social networks	Cooperative norms	Back-filling	SK
	(1)	(2)	(3)	(4)	(5)
Social Capital	-0.062***	-0.005**	-0.006***	-0.007***	-0.006**
	(-3.59)	(-2.58)	(-4.77)	(-5.31)	(-2.08)
MTB	0.005***	0.006***	0.006***	0.006***	0.006***
	(3.46)	(6.22)	(6.30)	(6.25)	(2.77)
Size	-0.009***	-0.009***	-0.009***	-0.009***	-0.011***
	(-4.89)	(-6.23)	(-6.35)	(-6.30)	(-3.88)
Quick	0.007***	0.007***	0.007***	0.007***	0.006***
	(6.31)	(9.61)	(9.82)	(9.73)	(4.18)
Leverage	0.008	0.008	0.007	0.008	0.014
	(0.87)	(0.98)	(0.98)	(1.02)	(0.83)
Dividend	-0.009**	-0.012***	-0.012***	-0.011***	-0.005
	(-2.47)	(-4.89)	(-4.89)	(-4.63)	(-0.95)
Std Cash	0.006***	0.004**	0.004**	0.003*	0.009**
	(2.75)	(2.10)	(2.02)	(1.96)	(2.36)
Std Sales	-0.002	-0.002	-0.002	-0.002	-0.008**
	(-1.09)	(-0.78)	(-0.80)	(-0.78)	(-1.98)
Tangibility	-0.044***	-0.058***	-0.058***	-0.057***	-0.039**
	(-4.82)	(-7.16)	(-7.26)	(-7.06)	(-2.43)
Loss	0.029***	0.030***	0.030***	0.030***	0.023***
	(7.82)	(14.79)	(14.85)	(14.66)	(4.84)
Labor Intensity	-0.516***	-0.733***	-0.713***	-0.715***	-0.937***
	(-3.78)	(-4.60)	(-4.47)	(-4.52)	(-3.44)
$Ab.non-Labor\ Invest$	0.395***	0.400***	0.400***	0.400***	0.387***
	(13.17)	(23.35)	(23.30)	(23.35)	(14.21)
Income	-0.007	0.009	-0.001	0.006	0.004
	(-0.72)	(1.19)	(-0.24)	(0.86)	(0.34)
Education	0.028	-0.000	0.033*	0.022	0.067*
	(0.92)	(-0.01)	(1.67)	(1.14)	(1.75)
Constant	0.208**	0.055	0.158**	0.084	0.082
	(2.36)	(0.71)	(2.54)	(1.23)	(0.72)
Observations	23,174	52,268	52,268	52,268	8,866
Adjusted R^2	0.160	0.166	0.167	0.167	0.167
Year FE	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes
County cluster	No	Yes	Yes	Yes	Yes
State cluster	Yes	No	No	No	No

Table 2.7: Propensity Score Matching (PSM) - Results from Probit Model

This table reports results from the Probit model to estimate the propensity scores. The dependent variable in all regressions is the dummy variable *High Social Capital*, which equals one for firm-years above 75^{th} percentile line (treatment group) and zero for those under 25^{th} percentile line (control group). The independent Variables are firm characteristics specified in the baseline model in equation (2.4). The propensity score matching procedure is based on nearest neighbour matching approach, with replacement. Variable definitions are provided in Table 2.1. z-statistics are presented in parentheses. Standard errors are clustered at the county level. ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels respectively.

	High Social Capital	
	Pre-match	Post-match
MTB	-0.007	-0.002
	(-1.00)	(-0.21)
$Size$	0.032***	-0.010
	(2.99)	(-0.64)
$Quick$	0.005	-0.000
	(1.30)	(-0.05)
$Leverage$	0.208***	-0.031
	(4.17)	(-0.45)
$Std\ Cash$	-0.083***	0.009
	(-6.53)	(0.50)
$Std\ Sales$	0.026**	-0.000
	(2.33)	(-0.01)
$Tangibility$	0.250***	0.039
	(3.90)	(0.44)
Labor Intensity	7.798***	-2.821*
	(6.72)	(-1.67)
$Ab.non-Labor\ Invest$	0.025	0.065
	(0.37)	(0.71)
$Dividend$	0.391***	0.008
	(17.62)	(0.25)
$Loss$	-0.068***	0.023
	(-3.39)	(0.81)
Constant	-0.792***	-0.065
	(-4.04)	(-0.26)
Observations	25,890	11,722
Pseudo R^2	0.139	0.006
Year FE	Yes	Yes
Industry FE	Yes	Yes

Table 2.8: Propensity Score Matching (PSM) Results

This table reports propensity score matching estimation. Panel A reports pre-match and post-match univariate results comparing the firm-specific observables across treatment and control. t-statistics are presented in parentheses. Panel B presents matched sample estimates. Variable definitions are provided in Table 2.1. We present t-statistics in parentheses and cluster standard errors at county level. ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels respectively.

Panel A. Univariate comparison selected covariates between treatment group and control group.

	Pre-match			Post-match		
	(1)	(2)	(3)	(4)	(5)	(6)
Variables	*High Social Capital* $=0$ (N=13,162)	*High Social Capital* $=1$ (N=12,728)	Difference	*High Social Capital* $=0$ (N=5,828)	*High Social Capital* $=1$ (N=5,905)	Difference
Social Capital	-1.560	0.478	-2.038*** (-393.782)	-1.547	0.469	-2.016*** (-262.190)
MTB	1.979	2.001	-0.022 (-1.128)	2.042	2.054	-0.011 (-0.372)
Size	5.555	5.693	-0.139*** (-5.294)	5.465	5.443	0.021 (0.547)
Quick	2.007	1.861	0.146*** (5.164)	1.992	2.019	-0.026 (-0.603)
Leverage	0.208	0.211	-0.003 (-1.281)	0.204	0.201	0.003 (0.717)
Std Cash	2.635	2.626	0.009 (0.430)	2.479	2.465	0.014 (0.449)
Std Sales	3.812	3.929	-0.117*** (-4.781***)	3.691	3.660	0.031 (0.837)
Tangibility	0.295	0.265	0.030*** (10.455)	0.264	0.262	0.002 (0.487)
Loss	0.344	0.286	0.058*** (10.241)	0.323	0.332	-0.009 (-1.078)
Labor Intensity	0.008	0.009	-0.002*** (-11.890)	0.009	0.009	0.000 (0.762)
Ab.non − Labor Invest	0.117	0.112	0.005*** (3.157)	0.116	0.118	-0.002 (-0.798)
Dividend	0.255	0.410	-0.155*** (-27.335)	0.296	0.293	0.003 (0.338)

Panel B. Matched sample estimates

Variables	***Abnormal Net Hiring***
High Social capital	-0.011** (-2.07)
MTB	0.007*** (2.92)
Size	-0.008** (-2.09)
Quick	0.007*** (4.57)
Leverage	0.010 (0.63)
Dividend	-0.018*** (-3.36)
Std Cash	0.004 (1.02)
Std Sales	-0.004 (-1.09)
Tangibility	-0.071*** (-3.66)
Loss	0.036*** (6.88)
Labor Intensity	-1.428*** (-3.08)
Ab.non − Labor Invest	0.446*** (11.92)
Income	0.033** (2.04)
Education	-0.068 (-1.51)
Constant	-0.171 (-1.08)
Observations	11,733
Adjusted R-squared	0.242
Year FE	Yes
Industry FE	Yes

Table 2.9: Instrumental Variable Analysis

This table reports instrumental variable regression results. Column (1) presents the first stage regression results where the instrument, *Distance*, is the natural logarithm of one plus the distance between the corporate headquarter county and the US-Canadian boarder. Column (2) presents the second stage regression results where *Social Capital* is the first stage fitted value of social capital. Variable definitions are provided in Table 2.1. We present t-statistics in parentheses and cluster standard errors at county level. ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels respectively.

	Abnormal Net Hiring	
	First stage	Second stage
	(1)	(2)
Distance	-0.182***	
	(-8.07)	
Social Capital		-0.010***
		(-3.06)
MTB	-0.003	0.006***
	(-0.62)	(6.26)
Size	0.007	-0.009***
	(0.87)	(-6.30)
Quick	-0.001	0.007***
	(-0.38)	(9.77)
Leverage	0.068	0.008
	(1.42)	(1.05)
Dividend	0.133***	-0.011***
	(5.04)	(-4.46)
StdCash	-0.033***	0.003*
	(-3.65)	(1.84)
Std Sales	-0.000	-0.002
	(-0.02)	(-0.78)
Tangibility	0.229***	-0.056***
	(3.31)	(-6.82)
Loss	-0.026**	0.029***
	(-2.24)	(14.45)
Labor Intensity	1.819*	-0.707***
	(1.65)	(-4.47)
Ab. non-Labor Invest	-0.009	0.400***
	(-0.26)	(23.46)
Income	-0.346*	0.006
	(-1.79)	(0.86)
Education	3.341***	0.032
	(5.58)	(1.47)
Constant	2.805	0.076
	(1.46)	(1.03)
Kleibergen-Paap Wald rk $F-statistic$	65.08	
Observations	52,268	52,268
Adjusted R^2	0.423	0.167
Year FE	Yes	Yes
Industry FE	Yes	Yes

Table 2.10: Firm's relocation analysis: Entropy-balancing estimates

This table reports entropy balancing estimation. Panel A reports comparison of mean, variance and skewness of the covariates between control and treatment groups before balancing. Panel B reports comparison of mean, variance and skewness of the covariates between control and treatment groups after balancing. The treatment group is the sample of firms that move to a county with higher social capital, and control group is the sample of firms that move to a county with lower social capital

Panel A: Before entropy-balancing

	Treat			Control		
	Mean	Variance	Skewness	Mean	Variance	Skewness
MTB	1.951	2.735	3.600	2.131	3.646	3.197
FirmSize	5.397	4.431	0.093	5.548	4.617	0.073
Quick	2.212	7.754	4.113	1.992	6.179	4.142
Leverage	0.211	0.045	1.315	0.237	0.048	0.974
Dividend	0.185	0.151	1.626	0.270	0.197	1.038
Std Cash	2.650	3.136	0.223	2.690	3.243	0.193
Std Sale	3.837	3.628	0.062	3.925	4.343	-0.015
Tangibility	0.203	0.036	1.742	0.274	0.059	1.106
Loss	0.431	0.245	0.278	0.411	0.242	0.362
Labor Intensity	0.008	0.000	3.609	0.008	0.000	4.087
Ab. non − Labor Invest	0.117	0.019	4.191	0.127	0.022	4.149
Income	10.630	0.127	0.684	10.610	0.134	0.561
Education	0.342	0.010	0.364	0.340	0.011	0.607

Panel B: After balancing

	Treat			Control		
	Mean	Variance	Skewness	Mean	Variance	Skewness
MTB	1.951	2.735	3.600	1.951	2.736	3.600
Firm Size	5.397	4.431	0.093	5.397	4.432	0.093
Quick	2.212	7.754	4.113	2.212	7.753	4.113
Leverage	0.211	0.045	1.315	0.211	0.045	1.315
Dividend	0.185	0.151	1.626	0.185	0.151	1.626
Std Cash	2.650	3.136	0.223	2.650	3.136	0.223
Std Sale	3.837	3.628	0.062	3.837	3.628	0.061
Tangibility	0.203	0.036	1.742	0.203	0.036	1.741
Loss	0.431	0.245	0.278	0.431	0.245	0.279
Labor Intensity	0.008	0.000	3.609	0.008	0.000	3.609
Ab. non − Labor Invest	0.117	0.019	4.191	0.117	0.019	4.191
Income	10.630	0.127	0.684	10.630	0.127	0.684
Education	0.342	0.010	0.364	0.342	0.010	0.364

Table 2.11: Firm's Relocation Analysis based on Entropy Balanced Sample

This table reports the results for relocation difference-in-difference analysis based on entropy-balanced sample. The dependent variables is *Abnormal Net Hiring*. The main independent variable is the interaction term of $Post * Treat$. $Treat$ equals one if the firm moves to a county with higher social capital, and zero if the firm moves to a county with lower social capital. $Post$ equals one if firm-year observations are from the post-relocation window, and zero otherwise. Other control variables are identical to those reported in the Table 2.2, and specified in the baseline model. Variable definitions are provided in Table 2.1. t-statistics are presented in parentheses. Standard errors are clustered at the county level. ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels respectively.

Variables	(1) **Abnormal Net Hiring**
$Post * Treat$	-0.086***
	(-2.75)
MTB	0.007
	(1.35)
$Firm\ Size$	-0.033***
	(-3.08)
$Quick$	0.012**
	(1.99)
$Leverage$	-0.093*
	(-1.67)
$Dividend$	0.034
	(1.16)
$Std\ Cash$	-0.002
	(-0.19)
$Std\ Sale$	0.004
	(0.31)
$Tangibility$	-0.013
	(-0.21)
$Loss$	0.028**
	(2.18)
$Labor\ Intensity$	-5.531**
	(-2.51)
$Ab.\ non-Labor\ Invest$	0.293***
	(4.26)
$Income$	0.014
	(0.09)
$Education$	-0.124
	(-0.31)
Constant	0.276
	(0.18)
Observations	1,518
Adjusted R-squared	0.256
Year FE	YES
Industry FE	YES
County FE	YES

Table 2.12: Evidence from Governance Mechanism

This table reports regression results to for the moderating effects of takeover and analyst coverage, as the proxies for external governance, on the association between social capital and labor investment inefficiency. The dependent variables across all regressions are $Abnormal\ Net\ Hiring$. The main independent variables are Social Capital. *Low Takeover Index* is a dummy variable that equals to one if firm-year observations are below the 25^{th} percentile of takeover index value, and zero otherwise. The takeover index is constructed by Cain et al. (2017). *Low Coverage* is a dummy variable that equals to one if firm-year observations are below the 25^{th} percentile of the number of financial analysts, and zero otherwise. Other control variables are identical to those reported in the Table 2.2, and specified in the baseline model. Variable definitions are provided in Table 2.1. We present t-statistics in parentheses and cluster standard errors at county level. ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels respectively.

	(1)	(2)
Variable	**Abnormal Net Hiring**	
$Social\ Capital$	-0.005***	-0.004***
	(-3.00)	(-3.00)
$Low\ Takeover$	0.005*	
	(1.79)	
$Low\ Takeover * Social\ Capital$	-0.006**	
	(-2.56)	
$Low\ Coverage$		0.004
		(1.35)
$Low\ Coverage * Social\ Capital$		-0.005**
		(-2.06)
MTB	0.006***	0.006***
	(5.62)	(5.22)
$FirmSize$	-0.009***	-0.009***
	(-6.07)	(-5.60)
$Quick$	0.007***	0.007***
	(9.75)	(9.38)
$Leverage$	0.009	0.012*
	(1.31)	(1.73)
$Dividend$	-0.011***	-0.011***
	(-4.33)	(-4.33)
$Std\ Cash$	0.004*	0.004**
	(1.91)	(2.04)
$Std\ Sale$	-0.001	0.000
	(-0.64)	(0.04)
$Tangibility$	-0.059***	-0.049***
	(-7.64)	(-6.65)
$Loss$	0.029***	0.029***
	(14.65)	(13.21)
$LaborIntensity$	-0.708***	-0.667***
	(-4.02)	(-3.90)
$Ab.non-LaborInvest$	0.392***	0.407***
	(22.40)	(25.36)
$Income$	0.006	0.004
	(0.77)	(0.57)
$Education$	0.014	0.015
	(0.70)	(0.77)
Constant	0.075	0.072
	(1.03)	(1.17)
Observations	48,339	45,856
Adjusted R-squared	0.164	0.168
Year FE	YES	YES
Industry FE	YES	YES

Chapter 3

CO-OPTED BOARD AND LABOR INVESTMENT

3.1. Introduction

The traditional theory in corporate governance contends that the board of directors is crucial in overseeing and advising the management of a firm (e.g., Mace et al., 1971; Fama and Jensen, 1983). However, this idea is challenged by existing literature [1]. The fact that not all directors take their monitoring task effectively. For example, the firm's corporate governance can be weak if directors serve on the boards of many other firms (i.e. busy directors) (Fich and Shivdasani, 2006), serve on a staggered board (Bebchuk and Cohen, 2005), and have appointment-based connections with the firm's incumbent CEO (Khanna et al., 2015).

In this study, we focus on one specific aspect of the board failure, the board co-option. Board co-option arises when directors of a firm are appointed to the board after the CEO assumed the office (Coles et al., 2014). Given the timing of their appointment to the board, it is possible that these co-opted directors hold similar values with and

[1] Boivie, Bednar, Aguilera and Andrus (2016) provide a thorough review for multiple barriers to the board monitoring.

exhibit loyalty towards the CEO who may have played a role in their appointment and nomination. Such a CEO-director connection indicates that co-opted directors may not be able to fulfill their duties in monitoring. Moreover, the oversight function of the board is typically weakened by an increased number of co-opted directors. In line this argument, Coles et al. (2014) finds that companies with higher CEO pay levels and over-investing practices are also those with larger proportions of co-opted directors on board.

Recent empirical work investigates the effects of co-option on different corporate policies. For example, increased board co-option has been found to be associated with less dividend payment (Jiraporn and Lee, 2018), higher likelihood of covenant violations in loan contract (Lim et al., 2020), and more corporate misconduct (Zaman et al., 2021). However, the relation between board co-option and corporate labor investment remains unclear. Our study is based on the argument that board co-option reduces monitoring quality, and extend existing literature by investigating whether greater board co-option leads to inefficient labor investment.

Previous literature suggests that sub-optimal investment in human capital arises from agency conflicts, and takes two forms: 1) over-investment, and 2) under-investment. Over-investment occurs when managers over-hire labor for empire-building purpose. As stated in Williamson (1993), managers can obtain power, security, reputation, professional achievement and status within the firm through expansion of the size of employees. Moreover, the management can over-invest in labor by protecting poorly performed employees from dismissal (i.e. under-fire), which in turn leads to employees' allegiance to the management and reinforces the management status (Atanassov and Kim, 2009). On the other hand, under-investment arises when management are concerned with firm's short-term performance due to the pressure from investors (Porter, 1992). The management may also under-invest in labor if they prefer to enjoy a 'quiet life' and avoids to make effort in expanding profitable business, leading to under-hire of labor (Stein, 2003). If inefficient labor investment arises from agency problems, we posit that co-option tends to weaken the board monitoring and exacerbate conflicts between principals and agents, leading to greater labor investment inefficiency.

In order to examine this prediction, we use a sample of 2,040 unique US public listed firm from 1996 to 2014, representing 16,536 firm-year observations. We follow the approach by Pinnuck and Lillis (2007) and employ an indirect mesure for labor investment inefficiency. Specifically, we regress the firm's percentage change in the number of employees on several firm-level fundamentals, including sales growth, leverage, liquidity and profitability. We then obtain absolute value of residuals from this regression, and define it as firm's abnormal net hiring. Abnormal net hiring captures the extend to which a firm's actual hiring deviates from its expected level. Therefore, a greater absolute deviation from firms predicted hiring indicates high level of labor investment inefficiency. To measure board co-option, we follow Coles et al. (2014) and use the ratio of directors appointed after the CEO assumed office to the total board size. The higher co-option value indicates greater board capture.

Consistent with our prediction, the main result shows a positive association between co-option ratio and firm's abnormal net hiring. The effect is economically significant: a one standard deviation increase in co-option leads to approximately 3.1% (4.9%) increase in abnormal net hiring relative to the mean (median) in our sample. This finding supports the view that co-opted directors weaken the board monitoring and exacerbate agency conflicts, leading to corporate greater labor investment inefficiency. However, one concern with our main result is omitted heterogeneity. For robustness, we control for state, year-industry and year-state fixed effects. Our results remain unchanged.

To better identify the causal effect of co-option on labor investment inefficiency, we employ a modified difference-in-difference empirical design by Coles et al. (2014) based on the passage of Sarbanes–Oxley Act of 2002 (SOX). In response to corporate scandals in early 2000s, such as Enron and WorldCom, the SOX was introduced, and adopted by the Congress in a very shot time (Romano, 2004). One of the major governance provisions mandated by SOX is that all firms listed on NYSE and NASDAQ are required to maintain a board of directors consisting majority of independent members (Linck, Netter and Yang, 2009). Non-compliant firms prior to SOX must hire more independent directors after implementation of this new rule. The newly appointed independent directors are considered to be co-opted because they join the board after the CEO took the office. Therefore, the SOX is viewed as a quasi-natural experiment that causes an exogenous change in board co-option for non-compliant firms. The results from SOX are consistent with our baseline findings. To further reduce potential endogeneity concerns, such as omitted variables, we employ 2SLS instrumental variable regression analysis. The IV is the average value of co-option based on firm's industry. The IV is similar to Baghdadi et al. (2020). The results from 2SLS IV regression further confirm our baseline findings.

To test the potential mechanisms through which board co-option leads to inefficient labor investment, we first focus on the role played by the product market competition. Previous literature show that the product market competition plays an important role in providing external oversight to mitigate agency conflicts (e.g., Giroud and Mueller, 2010; Giroud and Mueller, 2011; Chhaochharia, Grinstein, Grullon and Michaely, 2017). Our results show that the positive relation between co-option and abnormal net hiring holds for firm facing low market competition, while it becomes insignificant for firms facing high market competition. This is consistent with the idea that competitive pressure is considered as external governance mechanism.

We next test the effect of co-option on labor investment inefficiency for highly regulated firms. We show that the effect of co-option on abnormal net hiring in regulated firms (financials and utilities) is not significant. This result supports the argument that firms belonging to regulated industries present less agency conflicts as a result of additional external regulations Jiraporn and Lee (2018).

In subsequent tests, we examine whether our main findings are more pronounced among the firms where over 50% board members are captured (i.e. over 50% co-opted directors). The results show that firms with co-option level above the median tend to have greater inefficient investment in labor, compared those with co-option below the median. We then investigate the role of non co-opted directors. As suggested by Coles et al. (2014), co-opted directors, irrespective of their independence, are weak monitors, while non co-opted directors perform more effectively in their monitoring responsibilities. This may have implication for our study as the presence of a higher proportion of non-co-opted directors in firms may reduce labor investment inefficiency. Consistent with this prediction, we find that abnormal labor investment is reduced when more non co-opted directors are appointed on the board, supporting Coles et al. (2014)'s argument that non co-opted directors are better monitors. Finally, we explore the relation between co-option and different sources of labor investment inefficiency. We classify abnormal hiring into two types: over-investing and under-investing. We find that our results are concentrated in over-investment, implying that higher co-option may cause over-investing activities.

Our research makes a contribution to the literature in two aspects. First, we make contribution to the literature studying labor investment inefficiency. Recent empirical studies view on sub-optimal labor investment as a result of agency conflicts. Jung et al. (2014) investigate the role played by reporting quality of financial statement in mitigating information asymmetry and moral hazard problem. Ghaly et al. (2020) find that long-term institutional investors act as external monitoring mechanism to reduce labor investment inefficiency. Moreover, Ee et al. (2022) show that stock liquidity can benefits corporate labor investment. Our results suggest that greater board co-option exacerbates agency conflicts, leading to inefficient labor investment.

Second, our study is related to existing literature investigating the effect of co-option on corporate outcomes. There has been considerable debate over the board effectiveness (e.g., Adams, Hermalin and Weisbach, 2010; Boivie et al., 2016). Coles et al. (2014) take the initiative in studying the consequences of board co-option, and find that co-option leads to weak board monitoring and adversely affects decision-making functions of the board. Subsequent empirical studies employ the view that co-option leads to board capture, and find that greater co-option leads to weak corporate payout policy (Jiraporn and Lee, 2018), lower financial reporting quality (Cassell et al., 2018), higher default risk (Baghdadi et al., 2020), lower credit ratings (Sandvik, 2020) and more corporate misconduct (Zaman et al., 2021). Our empirical research extends existing co-option literature by focusing on inefficient corporate labor investment, and supports the dark side view of the co-option.

The remainder of this paper is organised as follows. Next section discusses related literature on labor investment and board of directors, and hypothesis development. In Section 3, we present the research methods. Section 4 reports empirical results, including baseline analysis and further robustness. Section 5 and Section 6 present difference-in-difference and instrumental variable analysis to reduce endogeneity concerns respectively. In Section 7, we show results for additional analysis. Section 8 concludes this paper.

3.2. Related Literature

3.2.1. Board Oversight Function and Co-Opted Directors

Agency problems can arise from the separation of ownership and control due to the conflicts between principals and agents who pursue self-interest and utilize corporate resources for their own advantage (e.g., Jensen and Meckling, 1976; Eisenhardt, 1989). The corporate board of directors is widely recognized as an internal control system that aims to mitigate agency concerns through providing oversight and monitoring to the firm's management (e.g., Fama and Jensen, 1983; Hermalin and Weisbach, 2001). Prior literature suggests that directors, particularly those who are independent, have a critical influence on advising and monitoring top executives to maximize shareholder's wealth, such as encouraging them to invest in positive NPV projects (Coles, Daniel and Naveen, 2006) and dismissing those who destroy shareholder value (Jenter and Kanaan, 2015).

However, the previous research suggests that internal control may be difficult because of attribution problems and managerial entrenchment practices (Walsh and Seward, 1990). Moreover, in practice, the board offers very little monitoring because the corporate board could be captured by the CEO, and hence weakening the effectiveness of board's oversight function. For example, top executives (i.e., CEO) are likely to exert significant impact on the process through which directors are selected (Withers, Hillman and Cannella Jr, 2012). This process involves identifying, screening, approving, nominating and electing directors to the board. Hermalin and Weisbach (2001) state that CEOs usually participate in the initial director nominations. Generally, those nominated directors face no opposition and can be elected with a single affirmative vote under some director selection systems (Cai, Garner and Walkling, 2009). Moreover, Shivdasani and Yermack (1999) argue that CEOs can exert their own influence on the selection of new directors through serving on the nominating committee, and hence leading to fewer appointment of independent outside directors and more appointment grey directors (such as those are relatives of CEOs, are retired employees, or have business connections to the firm). In particular, Tosi, Shen and Gentry (2003) state that firm's CEO can have direct impact on the selection of board members through controlling which directors are nominated. In addition, Zajac and Westphal (1996) find that powerful CEOs tend to select board members for maintaining their control.

After the Sarbanes Oxley Act of 2002 (SOX) was passed, NYSE and NASDAQ adopted new regulations, stipulating that public listed firms must have a nominating committee composed entirely of independent directors. This new rule prohibits the CEO from serving on the nominating committee, hence significantly reducing the CEO's impact on the director's nominating procedure. However, CEOs may continue to influence the board nomination process. Clune, Hermanson, Tompkins and Ye (2014) interview 20 US public company nominating committee members for providing better insight into the nominating process, and they find the CEO may continue to influence the director nomination process although the nominating committees become fully independent in the post-SOX period. Moreover, in the 2020 US Spencer Stuart Board Index report, about 17% of new directors in Standard & Poor 500 companies comes from CEOs or other corporate insiders (SpencerStuart, 2020). Therefore, the board is captured or co-opted when CEOs have influence on the selection of board members in practice. According to Coles et al. (2014), co-opted directors refer to those who are appointed to the corporate board after the CEO assuming their position. Overall, previous studies suggest that the CEOs may capture the board by imposing substantial influence over the director selection. This study follows the idea of director co-option of Coles et al. (2014) to investigate the effectiveness of board monitoring.

3.2.2. Agency Problems and Determinants of Efficient Labor Investment

In the presence of agency problems, inefficiency in corporate labor investment can manifest in two aspects:, 1) over-investment, and 2) under-investment. On the one hand, over-investment arises when there is weak monitoring and higher free cash flows, because the management with excess cash has incentive to build their own empire (Jensen, 1986), such as over-hiring employees. Over-investment can also occur when managers exhibit a preference for maintaining a 'quiet life', thereby avoiding making tough decisions, such as firing staff, and investing profitable projects (e.g., Atanassov and Kim, 2009; Bertrand and Mullainathan, 2003; Pagano and Volpin, 2005). On the other hand, under-investment in labor can occur when managers prioritise short-term performance of the firm (e.g., Graham et al., 2005; Stein, 1989). Moreover, 'quiet life' managers may also underinvest in labor because they are unwilling to hire employees to avoid making efforts to expand firm's businesses (Stein, 2003).

From the perspective of agency conflicts, existing studies on labor investment inefficiency suggest that inefficient investment in labor can be non-value enhancing. Khedmati et al. (2020) state that shareholders may not be able to get expected return from their investments if the management overinvests or underinvests in labor. In the light of the potential negative impact of sub-optimal labor investment on corporate value, recent empirical research has focused on the factors that can mitigate or exacerbate agency conflicts in labor investment. For example, Ben-Nasr and Alshwer (2016) investigate the impact of stock price informativeness on labor investment inefficiency. Their findings indicate that the more informative the stock prices, which can enhance external monitoring mechanisms, the less sub-optimal labor decisions the managers involve. Ghaly et al. (2020) state that long-term institutional investors tend to mitigate agency problems associated with employment decisions. In line with this argument, they find that monitoring by long-term investor helps reduce under-hiring, under-firing and over-hiring labor investments. Khedmati et al. (2020) find that strong CEO-director ties, such as education, employment and friendship networks, enhance managerial entrenchment, leading to more actions in inefficient labor investment by CEOs. From the empirical work of Khedmati et al. (2020), one particular CEO-director connection (i.e. board co-option) is overlooked. Co-option represents board failure in monitoring, which is likely to affect firm's labor investment decisions, given that directors who have been co-opted are likely to present loyalty to the CEO and reduce their oversight responsibilities. (Coles et al., 2014).

3.2.3. Hypothesis Development: Director Co-Option and Labor Investment Inefficiency

Broadly speaking, the idea of board co-option considers the CEO-director connections through appointment decisions. Such appointment-based connections measure the proportion of directors appointed while the current CEO has been in office. Hwang and Kim (2009) state that, after the arrival of the new CEOs, they appear to seek the directors who share similar social connections. Khanna et al. (2015) also argue that the directors are more likely to have common beliefs and values to the CEO who played a role in their appointment. Moreover, the appointment of new directors is likely to be affected either directly or indirectly by the CEOs, such as consultation with nominating committee (Coles et al., 2014). Accordingly, the directors who are nominated during the current CEO's tenure are more likely to demonstrate loyalty towards to the CEO (e.g., Coles et al., 2014; Khanna et al., 2015).

To better understand the impact of board co-option, prior literature argues that the presence of co-opted directors tends to weaken the effectiveness of board monitoring and can be value-destroying from shareholder's perspective. For example, Coles et al. (2014) find that CEOs who has co-opted more directors have higher pay, and are less likely to face dismissal following poor performance. Khanna et al. (2015) find that appointment-based CEO-director connectedness increases the likelihood of corporate fraud and decreases the likelihood of detecting such fraud. More recent empirical studies find that the increase in co-opted directors can lead to greater likelihood of financial statement of misstatement (Cassell et al., 2018), more covenant restriction in the loan contracts (Lim et al., 2020), lower credit ratings and larger credit spreads (Sandvik, 2020), higher default risk (Baghdadi et al., 2020), and more corporate misconduct (Zaman et al., 2021). Overall, these empirical studies have documented the dark side of board co-option, and suggest that it tends to weaken the effectiveness of monitoring.

For the corporate investment policy, CEOs are more likely to make inefficient investment to satisfy their own interests when the directors are co-opted and not effective at monitoring. This is because such inappropriate investment decisions are caused by agency problems, leading to decreasing investment quality when CEOs obtain significant influence over the board (Pan, Wang and Weisbach, 2016). Coles et al. (2014) also argue that CEOs are more likely to permitted to have additional behavioral latitude and managerial discretion, such as over-investment and empire building activities, when the board is captured by the CEOs. Moreover, Fracassi and Tate (2012) state that weak board monitoring can result in opportunistic behaviours of the management, and hence leading to suboptimal investments. Based on these arguments, we can expect that the co-option may also affect firm's labor investment. Khedmati et al. (2020) state that labor investment decisions can be also made by the CEO. The presence of a greater number of co-opted directors on a firm's board may lead to less efficient hiring decisions because co-option reduces the effectiveness of board monitoring and exacerbate the agency problems. We state the main hypothesis as follow:

H1: *firms with higher fraction of co-opted directors on the board have higher level of inefficient labor investment.*

3.3. Data, Variables and Methods

3.3.1. Data Sources and Sample Selection

We obtain US data from several sources. We obtain financial data and stock return data for US public firms in Compustat/CRSP Merged (CCM). Information on firms' hiring is also obtained from CCM. As mentioned earlier, we collect the co-option data from Coles et al. (2014). Moreover, information on board of directors is obtained from the ISS (formerly RiskMetrics). To address outliers in our dataset, we employ winsorization on all continuous variables, limiting them at 1st and 99th percentiles within their distributions. We also remove financial firms (SIC 6000-6999) and utility firms (SIC 4900-4999). Our final sample used to test the main hypothesis consists of 16,536 firm-year observations, representing 2,040 unique US firms from 1996 to 2014, for which data are available from all sources. Our sample initiates in 1996 because it is period covered by co-option data.

3.3.2. Measuring Board Co-Option

The percentage of directors who are co-opted by the CEO serves as the basis for measuring board co-option. According to Coles et al. (2014), directors who are appointed to the board after the CEO took office are referred to as co-opted directors. Coles et al. (2014) utilize the RiskMetrics database spanning from 1996 to 2014 in order to compute co-option measures. Hence, the primary indicator of board co-option is the proportion of directors in a specific year who are categorised as co-opted ($Co-op$).

$$Co\_op = \frac{Co\_opted\ directors}{Board\ size}, \tag{3.1}$$

where the variable Co_op ranges between 0 and 1. The higher value of Co_op indicates greater co-option. We collect co-option data from Lalitha Naveen's webpage [2]. In addition to the main co-option variable, Coles et al. (2014) construct alternative proxies based on the director's tenure and the number of independent directors on a board. We discuss these alternative co-option measures in later section for robustness checks.

3.3.3. Measuring Labor Investment Inefficiency

To capture corporate labor investment inefficiency, we follow the idea of Pinnuck and Lillis (2007) and Jung et al. (2014), and use the absolute deviation of firms' actual net hiring from their expected net hiring. Obtaining this measure involves three steps. First, we calculate a firm's actual net hiring, defined as the percentage change in the number of employees (e.g., Pinnuck and Lillis, 2007; Jung et al., 2014; Khedmati et al., 2020). We then employ the empirical model suggested by Pinnuck and Lillis (2007) and regress the firm's actual net hiring based on a number of firm-level fundamentals. Formally, the model takes the following form:

$$\begin{aligned} Actual\_net\_hire_{it} = {} & \beta_0 + \beta_1 Sale\ growth_{it-1} + \beta_2 Sale\ growth_{it} + \beta_3 Ch\_ROA_{it-1} + \beta_4 Ch\_ROA_{it} \\ & + \beta_5 ROA_{it} + \beta_6 Return_it + \beta_7 Size_{it-1} + \beta_8 Quick_{it-1} + \beta_9 Ch\_quick_{it-1} \\ & + \beta_{10} Ch_quick_{it} + \beta_{11} Leverage_{it-1} + \beta_{12} LossBin1_{it-1} + \beta_{13} LossBin2_{it-1} \\ & + \beta_{14} LossBin3_{it-1} + \beta_{15} LossBin4_{it-1} + \beta_{16} LossBin5_{it-1} + \delta_j + \gamma_t + \varepsilon_{it}, \end{aligned} \tag{3.2}$$

where the subscripts i and t refer to firm i and year t respectively, $Actual\_net\_hire$ is the percentage change in a firm's staff number, $Sale\ growth$ is the percentage change in

[2] Data can be obtained from: https://sites.temple.edu/lnaveen/data/

sales. As in Pinnuck and Lillis (2007) we also include prior year sales growth to account for the potential time lag in the adjustment for labor demand.

Ch_ROA is the change in return on assets to capture the hiring activities due to the change in earnings. Prior year change in ROA is also included, to account for the time for labor demand to adjust. ROA is return on asset capture the profitability (Pinnuck and Lillis, 2007). $Return$ is the 12-month stock return to capture future expected growth (Pinnuck and Lillis, 2007). $Size$ is prior firm's market value in log. $Quick$ is short-term investment and cash divided by current debt. It captures short-term liquidity that may affect changes in employment (Jung et al., 2014). Ch_Quick is the percentage change in the quick ratio, as a further control for liquidity. Prior year change in the quick ratio is also included. $Leverage$ is the leverage ratio, which Leverage controls for financing needs that may affect the hiring decisions (Pinnuck and Lillis, 2007). Leverage controls for financing needs that may affect the hiring decisions (Pinnuck and Lillis, 2007). $LossBin$ are five dummy variables controlling for the occurrence of losses as firms making losses are more likely to reduce labor force. Each $LossBin$ dummy variable takes on the value of one if ROA in previous year is in a certain interval width. Following previous studies, we consider 0.005 as the interval of ROA (e.g., Jung et al., 2014; Ben-Nasr and Alshwer, 2016; Khedmati et al., 2020). For example, LossBin1 takes the value of one if ROA in previous year is between -0.005 and 0 and zero otherwise, LossBin2 takes the value of one if ROA in previous year is between -0.010 and -0.005 and zero otherwise, LossBin3 takes the value of one if ROA in previous year is between -0.015 and -0.010 and zero otherwise, and so on for the other LossBins. Pinnuck and Lillis (2007) state that firms are likely to cut down their labor force when making losses. Following Pinnuck and Lillis (2007) and Jung et al. (2014), I expect that net hiring is positively related to sales growth, profitability, stock return, firm size and liquidity, and negatively related to leverage and loss bins. The model also controls for industry and year fixed effects. Descriptive statistics of these variables are presented in Appendix.

We run the regression (3.2) and obtain the fitted value of $Actual\_net\_hire$ as the firm's expected hiring, see the Appendix for the regression results. Finally, we take the absolute value of the residual from regression (3.2) as abnormal net hiring, $Abnormal\_net\_hire$, which becomes our main proxy for the inefficient labor investment. More specifically, it can be defined as:

$$|Abnormal\_net\_hire| = |Actual\_net\_hire - Expected\_net\_hire|, \tag{3.3}$$

Following the idea of Jung et al. (2014), the measure for corporate inefficient labor investment, $|Abnormal\_net\_hire|$, captures the portion unexplained by those fundamentals specified in the model (3.2).

3.3.4. Empirical model

To investigate the relationship between corporate labor investment inefficiency and board co-option, we estimate the following baseline model:

$$\begin{aligned} |Abnormal\_net\_hire_{it}| = {} & \beta_0 + \beta_1 Co\_op_{it} + \beta_2 MBT_{it-1} + \beta_3 Size_{it-1} \\ & + \beta_4 Leverage_{it-1} + \beta_5 Dividend_{it-1} + \beta_6 Std\_cash_{it-1} + \beta_7 Std\_sale_{it-1} \\ & + \beta_8 Tangibility_{it-1} + \beta_9 Loss_{it-1} + \beta_{10} Labor\_intense_{it-1} \\ & + \beta_{11} Ab\_invest_{it-1} + \beta_{12} Board\_size_{it} + \beta_{13} Ind\_dir_{it} + \delta_j + \gamma_t + \varepsilon_{it}, \end{aligned} \tag{3.4}$$

where the subscripts i and t refer to firm i and year t respectively. The dependent variable $|Abnormal\_net\_hire|$ is our measure for labor investment inefficiency, estimated as the absolute residuals from Eq. (3.2). Our main independent variable Co_op is the measure for co-option. Following previous studies on labor investment (e.g., Jung et al., 2014; Biddle et al., 2009; Ghaly et al., 2020), we control for a number of firm-level characteristics. Specifically, we control for market-to-book ratio, firm size and age, leverage, payout, cash flow volatility, sales volatility, tangibility, losses, net hiring volatility and labor intensity. To isolate the effects of omitted time-invariant industry heterogeneity and time trend, we include industry fixed effects and year fixed effects (δ_j, γ_t) [3]. Detailed variable definitions are presented in Table 3.1 of the Appendix.

[3]We note that including firm fixed effects is a common practice in empirical research to control for

3.3.5. Summary Statistics

Table 3.1 shows summary statistics for all variables employed in the model Eq. (3.4). The mean and standard deviation of abnormal net hiring are 0.104 and 0.137 respectively, implying that on average firm's hiring practices deviate from the optimal level by 10.4%, inline with Jung et al. (2014). Board co-option variable has the mean of 0.468 and the standard deviation of 0.316, indicating that sample firms, on average, have about 46.8% co-opted directors. This is in line with Coles et al. (2014). All other firm characteristics are comparable with those in prior research (e.g., Jung et al., 2014; Ben-Nasr and Alshwer, 2016; Khedmati et al., 2020).

Table 3.2 reports the correlations for abnormal net hiring, board co-option and other firm characteristics. The correlation between abnormal net hiring and co-option is positive (0.042) and significant, consistent with higher fraction of co-opted directors on the board being associated more inefficient labor investment. The correlations for the control variables are generally consistent with prior research (e.g., Ben-Nasr and Alshwer, 2016; Zaman et al., 2021; Sualihu, Yawson and Yusoff, 2021). For example, firms with higher abnormal non-labor investments and losses are likely to have higher levels of abnormal net hiring. In contrast, firms with larger size, paying dividend, higher levels of tangibility and more independent directors tend to have reduced levels of abnormal net hiring.

---

unobservable across firms. However, there is a lack of within firm variation for our co-option variable, so inclusion of firm fixed effects in the model is not suitable. Hence, We refrain from controlling for firm fixed effects. This modelling choice is also common in existing empirical research on co-option (e.g., Cassell et al., 2018; Jiraporn and Lee, 2018; Lim et al., 2020; Sandvik, 2020; Dikolli, Heater, Mayew and Sethuraman, 2021). As further robustness, we include state fixed effects, year and industry interactive fixed effects, and year and state interactive fixed effects to control for unobserved heterogeneity.

3.4. Empirical Strategy and Results

3.4.1. Baseline Results

Table 3.3 reports the regression results of empirical model (3.4). We cluster the standard errors at the firm level. In column (1), we only regress abnormal net hiring on the boar co-option. The coefficient on Co_op is positive and significant at 1% level. This indicate that firms with more proportion of co-opted directors on the board present more inefficient labor investment. The result is also economically significant: a one-standard-deviation of increase in the fraction of co-opted directors is associated with 4.9% (7.8%) increase in abnormal net hiring relative to the mean (median) in the sample [4].

However, one concern with the estimate reported in column (1) is that the positive relationship between abnormal net hiring and board co-option is due to omitted variables. Therefore, we try to mitigate this possibility by including the firm-level characteristics specified in the model (3.4). Column (2) reports the estimation. The coefficient estimate on board co-option is positive and significant at 1% level. Turning to the economical significance, a one-standard-deviation increase in board co-option leads to a increase in abnormal net hiring by approximately 3.1% relative to the mean, and 4.9% relative to the median. For further robustness, in column (3), we control state fixed effects to take into account unobserved factors across state, such as state-level labor laws that affect firm's hiring decision. In column (4), we include industry-year and state-year fixed effects to control for time-varying unobserved heterogeneity across industries and across states (Gormley and Matsa, 2014). Across the columns (3) and (4), the estimates on

[4] The mean and median of $|Abnormal\_net\_hire|$ are 0.104 and 0.065 respectively. The coefficient on Co_op is 0.016, and its standard deviation is 0.318. Therefore, a one-standard-deviation increase of Co_op is associated with increase in $|Abnormal\_net\_hire|$ about 7.8% relative to the median (0.016*0.318/0.065=0.078=7.8%), and about 4.9% relative to the mean (0.016*0.318/0.104=0.049=4.9%).

board co-option remain positive and significant. This further confirms our main hypothesis that firms with higher fraction of co-opted directors on the board have higher level of inefficient labor investment.

Turning to control variables, the results are consistent with previous empirical studies (e.g., Ben-Nasr and Alshwer, 2016; Ghaly et al., 2020; Khedmati et al., 2020). For example, abnormal net hiring is negatively associated with firm size, dividend and labor intensity. Moreover, firms with more abnormal non-labor investment and losses present higher abnormal net hiring.

3.4.2. Robustness Tests

Alternative Measures for Co-Option

We check the robustness of our baseline findings by considering multiple alternative measures for board co-option. Specifically, we follow Coles et al. (2014) and employ three alternative measures for co-option: co-option (independence), co-option (tenure weight) and co-option (tenure weight independence). First, co-option (independence) is defined as fraction of co-opted independent directors to the board size. The traditional literature states that independent directors are more effective in serving as monitors of a firm (Fama and Jensen, 1983). However, Coles et al. (2014) question the robustness of the board independence as a traditional measure for effectiveness of internal monitoring. They find that not all independent directors can provide effective oversight. For example, they show that co-opted independent directors can lead to higher CEO pay and overinvestment. Therefore, once directors are co-opted, they weaken the effectiveness of monitoring regardless of whether they are independent or non-independent. The variable for co-option (independence) is given by:

$$Co\_op\_ind = \frac{Co - opted\ independent\ directors}{Board\ size}, \tag{3.5}$$

Next alternative measure is co-option (tenure weight), known as tenure-weighted co-option, which is defined as the sum of tenure of co-opted directors divided by the sum of the tenure of all directors:

$$TwCo\_op = \frac{\Sigma_{i=1}^{board\_size} Tenure_i * Coop\_dummy_i}{\Sigma_{i=1}^{board\_size} Tenure_i}, \tag{3.6}$$

where $Coop\_dummy_i$ is a dummy that equals one if the director i is a co-opted director, and zero otherwise. $Tenure_i$ is the tenure of the director i on the board. Coles et al. (2014) state that tenure-weighted co-option takes into account the change in influence of co-opted directors with their tenure. This measure assumes that the influence of co-opted directors on board decisions increases through time working with the CEO who appointed them. Therefore, the greater value of $TwCo\_op$ indicates the greater board capture. Smilar to $TwCo\_op$, we also allow for co-option (tenure weight independence), defined as the sum of tenure of co-opted independent directors divided by the sum of the tenure of all directors:

$$TwCo\_op\_ind = \frac{\Sigma_{i=1}^{board\_size} Tenure_i * Coop\_ind\_dummy_i}{\Sigma_{i=1}^{board\_size} Tenure_i}, \tag{3.7}$$

where $Coop\_ind\_dummy_i$ is a dummy that equals one if the director i is a co-opted independent director, and zero otherwise.

Therefore, we estimate our main specification by replacing the main independent variable with three alternative measures of co-option as discussed above. Table 3.4 reports the results. Across all regressions, the estimate coefficients on three measures remain positive and significant, suggesting that the relation between co-option and labor investment inefficiency holds when alternative proxies of co-option are employed.

Alternative Measures for Labor Investment Inefficiency

Following Ghaly et al. (2020) and Ee et al. (2022), we allow for several alternative proxies for abnormal hiring for further robustness check. First, following Harvey et al. (2004), we consider the difference between a firm's actual hiring and its industry median of hiring in a given year as alternative the measure for inefficient labor investment. This follows the idea that managers of a firm tend to mimic the hiring decisions of their peers in the same industry (Scharfstein and Stein, 1990). Therefore, the more a firm's actual hiring deviates from its industry median, the greater abnormal hiring practices.

Second, we follow Jung et al. (2014) to re-estimate the model (3.2) by only including sales growth, $Sale\_growth_{it-1}$, as the independent variable, then obtain the absolute value of residual as alternative measure for labor investment inefficiency. This specification is similar to Biddle et al. (2009), who state that sales growth is a key measure for strong growth opportunities. Following this idea, sales growth may affect a firm's hiring decisions, because firms with higher sales growth tend to hire more employees to increase productivity (Sualihu, Rankin and Haman, 2021).

Third, Ben-Nasr and Alshwer (2016) argue that a number of additional factors could influence a firm's hiring decision, such as union coverage, R&D expenditures, capital expenditures, GDP and acquisition expenditure. Therefore, we follow Ben-Nasr and Alshwer (2016) to re-estimate the model (3.2) by including additional variables: unionization, R&D expenditures, capital expenditures, natural logarithm of state-level GDP and acquisition expenditures, then obtain the absolute value of residual as alternative measure for labor investment inefficiency.

Lastly, recall that we estimate model (3.2) with industry and year fixed effects, but the raw model from Pinnuck and Lillis (2007) does not include the year fixed effects. Therefore, we consider the same specification in Pinnuck and Lillis (2007) by only considering industry fixed effects, then obtain the absolute value of residual as alternative measure for inefficient investment in labor. Moreover, we follow Ghaly et al. (2020) to estimate abnormal hiring by by including firm and year fixed effects in the model (3.2) to control for unknown time-invariant firm-level factors (such as firm's business strategy), then obtain the absolute value of residual as alternative measure for inefficient investment in labor.

We report all results in Table (3.5). In all cases, the estimated coefficient on co-option remains positive and significant at 5% or 1% level. Therefore, our results are robust across different measures for labor investment inefficiency.

Propensity Score Matching and Entropy Balancing Analysis

One concern to our baseline results is that the positive relation between corporate labor investment inefficiency and co-option can be attributed to the systematic differences in observable heterogeneity. Therefore, we employ a propensity score matching, introduced in Rosenbaum and Rubin (1983), to reduce the impact of this potential endogeneity on our main results. To conduct our PSM analysis, we follow Zaman et al. (2021) and define firms as the treatment group if their fraction of co-option is above the top quartile. The firms are considered as the control group if their fraction of co-option is below the bottom quartile. The sample used for conducting PSM include 8,659 firm-year observations, representing 1,719 unique firms. To estimate the propensity score, we run a Logit regression by including the covariates specified in our baseline model. We then match treatment and control using one-to-one nearest neighbour matching, with replacement, within caliper of 0.1% in absolute value.

We report PSM estimation in Table 3.6. Panel A shows univariate comparison in all covariates between treatment group and control group. As expected, there is no significant differences in all covariates between treatment group and control group. In Panel B, we report the average treatment effect (ATT), which is significant at 1% level. We next re-estimate our baseline model based on post-match sample. The estimation is reported in Panel C. The coefficient on co-option is positive and significant at 1% level. This is consistent with our main finding that firms with more proportion of co-opted directors on the board present greater inefficient labor investment.

Although PSM technique is widely recognized in empirical studies, the issue about the quality of producing covariate balance may still exist. Therefore, we employ entropy balancing analysis proposed by Hainmueller (2012) to further reduce this concern. Entropy balancing not only produces a higher degree of covariate balance by adjusting differences in the first, second, and third moments of the covariate distribution, but also retains the information of the sample compared to the PSM where some observations are discard (Hainmueller, 2012). To conduct entropy balancing technique, we re-weight observations to satisfy first, second and third moment conditions and ensure that the covariates between control group and treatment group are highly balanced in terms of mean, variance and skewness. Table 3.7 shows that a high degree of covariate balance between treatment group and control group is achieved after entropy balance. We then re-estimate baseline regression using the entropy-balanced sample and present the result in Table 3.8. The estimate on co-option remains positive and significant.

3.4.3. Potential Endogeneity

Difference-in-Difference Design Based on Sarbanes–Oxley (SOX)

Although we allow for industry, year, state, year-industry and year-state fixed effects in the baseline model, it is very likely that our main results are still affected by unobserved factors, such as both firm-specific and non-firm specific. In addition, it is possible that both co-option and inefficient labor investment are determined in equilibrium simultaneously. To further mitigate these potential endogenous concerns, we follow Coles et al. (2014) and employ difference-in-difference analysis based on the passage of Sarbanes–Oxley Act (SOX) in 2002 and the regulatory changes to NYSE and NASDAQ listing requirements as a natural experiment.

We particularly focus on the rule enacted in 2002 by NYSE and NASDAQ, stipulating that all NYSE and NASDAQ listed firms must have a majority of independent directors on their board [5]. The firms compliant with this new requirement (i.e., have a majority of independent directors) before SOX were not affected. However, those who were noncompliant before SOX (i.e., do not have a majority of independent directors) were

[5] Chhaochharia and Grinstein (2007) present the detailed timeline of SOX and related regulatory changes

required to increase board independence after passage of the new rule, and hence they were required to appoint new independent directors to their board Linck et al. (2009). This leads to exogenous increase in co-option, as these new independent directors are appointed after the CEO took the office.

To investigate the impact of co-option, we exploit modified difference-in-difference specification:

$$\begin{aligned} |Abnormal\_net\_hire_{it}| = {} & \beta_0 + \beta_1 Cooption + \beta_2 Post * Cooption \\ & + \beta_3 Noncompliant * Cooption + \beta_4 Post * Noncompliant \\ & * Cooption + \beta_5 Noncompliant + \beta_6' \mathbf{Z}_{it-1} + \delta_j + \gamma_t + \varepsilon_{it}, \end{aligned} \tag{3.8}$$

where $Cooption$ is four co-option measures. Specifically, we allow for the main co-option proxy used in our baseline model, and other three alternative proxies employed in Coles et al. (2014). $Post$ is a dummy variable that equals one if year is 2002 and later, and zero otherwise. $Noncompliant$ is a dummy variable that equals one if firms were not compliant in 2001 (i.e., do not have more than 50% independent directors on the board), and zero otherwise. **Z** is the set of control variables used in our baseline model. Industry and year fixed effects are also included in the model (3.8). Note that we use the sample period from 1996 to 2010 for the DID analysis, the same as in Coles et al. (2014).

Model (3.8) is the modified DID setup by Coles et al. (2014). In the typical DID specification, the dependent variable is regressed on $Post$, $Noncompliant$ and their interaction $Post * Noncompliant$, and the focus is on the coefficient on interaction term. However, Coles et al. (2014) argue that the coefficient not only captures the effect of co-option, but also the effect of SOX through other channels. Examples of regulations from SOX can include complete independence of compensation, audit and monitoring committees, board meeting without management, and media scrutiny of all firms. Therefore, we assess the impact of co-option by estimating the modified model 3.8, which includes the interaction of $Post * Noncompliant * Cooption$. The regression results are reported in the Panel A of Table 3.9. Across all regressions, the estimates on co-option proxies are positive and significant at 1% or 5%, suggesting that more co-opted directors are associated with greater inefficient labor investment. However, the estimates on the interaction of $Post * Noncompliant * Cooption$ are insignificant, although the sign of estimates is positive. As explained in Coles et al. (2014), this interaction term is also biased due to endogeneity.

Specifically, we shows detailed implications of the coefficients based on four groups in Panel B of Table 3.9) compliant firms in the pre-SOX period, 2) compliant firms in the post-SOX period, 3) Noncompliant firms in the pre-SOX period, and 4) Noncompliant firms in the post-SOX period. Our interest is the noncompliant firms in the post-SOX period as this group of firms experienced exogenous increase in co-option. However, the impact for this group ($\beta_1 + \beta_2 + \beta_3 + \beta_4$) represents the combination of both co-option and SOX (i.e., contaminated by the direct effect of SOX through other channels). To obtain the clean effect of co-option arising from the exogenous increase in board independence, we follow Coles et al. (2014) and combine three coefficients: $Cooption$, $Noncompliant * Cooption$ and $Post * Noncompliant * Cooption$ (i.e., $\beta_1 + \beta_3 + \beta_4$). We report the clean estimates in Panel C of Table 3.9. The estimates are positive and significant at 5% in columns (1), (2) and (4), and 10% in column (3), indicating that noncompliant firms with increase in co-opted directors after the passage of SOX have more inefficient labor investment.

Instrumental Variable Analysis

So far, our results indicate that firms with more proportion co-opted directors on their board tend to have greater inefficient investment in labor. The results are robust when employing different fixed effects and difference-in-difference analysis. To further mitigate omitted heterogeneity and identify the causal effect of co-option on firm's abnormal net hiring, we employ instrumental variable estimation. We define the instrument as the average value of co-option in the industry that a firm belongs to. Note that the one firm itself in the industry for which the instrument variable is being calculated is excluded.

This instrumental variable is also employed by Baghdadi et al. (2020). The idea is that the co-option at industry level is considered to be more exogenous to firm's labor investment.

To implement the analysis, we run the first-stage estimation by regressing co-option on instrumental variable along with all control variables and fixed effects specified in our main model (3.4). Column (1) of Table (3.10) reports the corresponding results. The estimated coefficient on instrument are positive and significant at 1% level, which is consistent with Baghdadi et al. (2020). To check the strength of our IV, we show F-statistic for weak instrument is 24.59 and significant at 1% level, implying that our instruments are not weak.

To run the second-stage estimation, we continue to use our baseline model, except that the main independent variable is the predicted value of co-option, $Fitted\ co\_option$, based on the estimated coefficient on the instrument in our first-stage regression. We report this second-stage estimation in column (2). The coefficient on $Fitted\ co\_option$ remains positive and significant, providing the evidence that the relation between co-option and labor investment inefficiency is not affected by potential omitted factors [6].

3.4.4. Additional Analysis

Co-Option under Competitive Pressure

So far, we provide evidence in line with existing empirical literature on board co-option, indicating that co-opted directors tend to weaken the effectiveness of board monitoring and hence exacerbate agency conflicts (e.g., Baghdadi et al., 2020; Sandvik, 2020; Zaman et al., 2021). Previous literature finds that the market competition is considered as an external mechanism for corporate governance (e.g., Giroud and Mueller,

[6] We note that our instrument, industry-level co-option, is not perfect instrumental variables to address potential endogenous concerns. However, we obtain consistent results in our main fixed effects regressions and difference-in-difference analysis, we are confident on the causal effect of co-option on abnormal net hiring.

2011; Giroud and Mueller, 2010; Ammann, Oesch and Schmid, 2013; Knyazeva and Knyazeva, 2012; Chhaochharia et al., 2017). Specifically, the monitoring through product market competition helps discipline managers' behaviors and compels them to take their obligations more seriously. Following this view, if the product market competition deters manager's opportunistic behaviors and alleviates managerial agency problems, one could expect that the effect of co-option on abnormal hiring activities is more pronounced when firms face lower competitive pressure. To test this conjecture, we employ three measures for market competition, Herfindahl–Hirschman index (HHI), Learner index (LI) and $Fluidity$ by Hoberg, Phillips and Prabhala (2014). The higher value of HHI and LI indicates fewer product market competition. The higher value of $Fluidity$ suggests greater competitive pressures. We then classify firms into low (high) market competition subsample if HHI of the industry where the firm belongs is above (below) the sample median, if LI of the industry where the firm belongs is above (below) the sample median, and if $Fluidity$ of the industry where the firm belongs is below (above) the sample median.

Table 3.11 reports the results. As expected, the positive relation between co-option and abnormal net hiring is significant for firms facing low market competitive pressure, while becomes insignificant for firms facing high market competition due to firms in competitive industries may face greater external oversight. This is in line with the view that product market competitive threats reduces principal-agency conflict through providing external monitoring.

Monitoring by analysts and institutional investors

Given the monitoring role of financial analysts and institutional investors, we further investigate whether the association between co-option and abnormal net hiring vary when firms are followed by larger/lower number of financial analysts or have greater/less institutional holdings. We collect analysts earnings forecasts data from IBES and institutional ownership from 13F. The measure for analysts coverage, $Coverage$, is the

the natural logarithm of one plus the number of analysts earnings forecasts that a firm receives annually, and that for institutional holdings, $Institution$, is the percentage of shares held by institutions. We then split the full sample into different subsamples based on high/low analyst coverage and high/low institutional holdings. In particular, firms are assigned to low (high) analyst coverage group if $coverage$ is below (above) the sample median, and assigned to low (high) institutional holdings group if $Institution$ is below (above) the sample median.

Table 3.12 reports the results. The coefficients on Co_op in low analysts coverage and low institutional holdings groups are significant, but is muted in high analysts coverage and high institutional holdings groups. This is because firms with greater institutional holdings and analysts coverage have been well-governed, compared to those with less institutional holdings and analysts coverage.

Co-Option in Regulated Firms

Some industries are highly regulated, such as financial and utility. The firms within these industries tend to have less agency issues because greater monitoring via regulations can reduce managerial discretion. We could expect that managers are more difficult to take opportunistic behaviors at the cost of shareholder's interest. Empirical studies have documented that additional regulation can help reduce agency conflicts, hence may change the association between corporate governance and other corporate consequences. For example, Jiraporn and Gleason (2007) find that, in regulated firms, additional monitoring can remove the role of debt in mitigating agency issues where shareholder rights are suppressed. Following this idea, one could expect that the positive association between co-option and abnormal net hiring may not exist in regulated firms if the regulation helps alleviate agency conflicts. To explore the effect of co-option in highly regulated firms, we re-estimate the baseline model by including only financial firms or utility firms. Columns (1) and (2) of Table (3.13) present the estimations for financial firms and utility firms respectively. As expected, the coefficients across these subsamples are insignificant, implying that the effect of board co-option on labor investment inefficiency is muted in these regulated firms.

Co-Option Quartiles

Following the principle of majority rule, a CEO may exert significant influence over the board decisions when more than 50% directors have been co-opted. In this subsection, we explore whether the influence of co-option on labor investment decisions varies dependent on whether firms have a majority or a minority of co-opted directors on the board. Specifically, we expect that the positive association between co-option and abnormal net hiring is less likely to exist when firms have low proportion of co-opted directors (i.e., below 50%), and is more pronounced when firms have higher level of co-option (above 50%). To investigate this prediction, we re-estimate the baseline model, except that we replace our main explanatory variable, Co_op, with three dummy variables Co_op2, Co_op3 and Co_op4. Co_op2 takes the value of one if firm's co-option is in the second Co_op quartile (25%-50%), and zero otherwise, Co_op3 takes the value of one if firm's co-option is in the third Co_op quartile (50%-75%), and zero otherwise, and Co_op4 takes the value of one if firm's co-option is in the fourth Co_op quartile (above 75%), and zero otherwise [7].

We present the results in Table 3.14. In column (1), we omit all firm characteristics specified in the main model, and find that the coefficients on Co_op3 and Co_op4 are positive and significant, implying that the effect of co-option on labor investment is significant when co-option is greater than 50%. We then include all controls in column (2), and our result remains unchanged. In particular, across column (1) and (2), we find that the magnitude of the coefficient on Co_op4 is higher than that on Co_op3, suggesting that firms with co-option level above 75% tend to have greater inefficient investment in

[7] The classification of these co-option dummy variables is simililar to Lins, Servaes and Tamayo (2017), who investigate the effect of corporate social responsibility (CSR) on stock return by dividing firms into CSR quartiles.

labor, compared those with co-option between (50%-75%). Overall, our results indicate that increased co-option is viewed more detrimental to firm's investment in labor when co-option level is above 50%.

The Role of Non Co-Opted Directors

Another implication from Coles et al. (2014) is that not all independent directors necessarily perform their oversight duties seriously. Coles et al. (2014) show that once independent directors are co-opted, their effectiveness in monitoring weakens compared to independent directors who are not co-opted. These non co-opted directors are individuals who already served on the board before the CEO took office. Building on this insight, we test whether non co-opted directors have better monitoring capabilities. If non co-opted directors provide more effective oversight and monitoring, we could expect that firms with higher proportion of non co-opted directors may exhibit lower level of abnormal net hiring.

To examine this question, we follow Coles et al. (2014) and construct two non co-option measures, $Non\_co\_op\_ind$ and $Non\_co\_op\_non\_ind$. $Non\_co\_op\_ind$ is defined as the ratio of non co-opted independent directors to the board size, and $Non\_co\_op\_non\_ind$ is defined as The ratio of non co-opted non-independent directors to the board size. We then re-estimate our baseline model. The results are presented in Table 3.15. Columns (1) and (2) show the estimations for $Non\_co\_op\_ind$ and $Non\_co\_op\_non\_ind$ respectively. The coefficients on both non co-option measures are negative, implying that firms with higher fraction of non co-opted independent/non-independent directors exhibit less inefficient labor investment. Although the results are insignificant, this evidence can be consistent with the findings in Coles et al. (2014), showing that non co-opted directors act as more effective monitors.

Board Co-Option and Different Types of Inefficient Labor Investment

Labor investment inefficiency manifests in two forms: overinvestment and underinvestment in labor. Overinvestment can occur as a result of overhiring and/or underfiring of employees, while underinvestment may result from underhiring and/or overfiring of employees. In this subsection, we examine the relation board co-option and labor investment inefficiency based on four components. In particular, we follow Jung et al. (2014) and Ben-Nasr and Alshwer (2016) and divide our sample into overinvestment and underinvestment subsamples. These subgroups are further divided into overhiring, underfiring, underhiring, and overfiring:

1) Over-investing: contains observations with positive abnormal net hiring.

2) Over-hiring: contains observations with positive abnormal net hiring, and positive expected net hiring.

3) Under-firing: contains observations with positive abnormal net hiring, and negative expected net hiring.

4) Under-investing: contains observations with negative abnormal net hiring.

5) Under-hiring: contains observations with negative abnormal net hiring, and positive expected net hiring.

6) Over-firing: contains observations with negative abnormal net hiring, and negative expected net hiring

We then estimate our empirical model (3.4) for all these subsamples. Table 3.16 shows that our results are mainly driven by overinvestment activities. Specifically, the coefficient estimates for overinvesting subsample and overhiring subsample are positive and significant at 5% and 1% respectively. Thus, our results imply that more fraction of co-opted directors on the board can lead to firm's overinvestment in labor, particularly over-hiring practices.

3.5. Conclusion

In this study, we examine whether more proportion of co-opted directors on a firm's board exacerbate labor investment inefficiency. Using abnormal net hiring as the proxy for inefficient investment in labor, we find that board co-option is positively associated with abnormal net hiring, indicating that greater co-option exacerbate sub-optimal investment in labor. This effect is economically significant: a one standard deviation increase in co-option is associated with 4.7% increase in abnormal net hiring. Our results remain unchanged when employing different fixed effects, propensity score matching, entropy balancing, difference-in-difference empirical design based on Sarbanes–Oxley (SOX) Act of 2002, and instrumental variable analysis. We are more confident the causal effect of co-option on labor investment inefficiency.

In additional tests, we explore the effect of co-option on different types of labor investment inefficiency. We find that co-option particularly leads to over-investment in labor. We also investigate the role played by non co-opted directors. Our results show that non co-opted directors are more effective in monitoring than co-opted directors. Third, we test whether the effect of co-option on labor investment inefficiency is more pronounced when a majority of co-opted directors sit on the board. We find that firms with over 50% and 75% co-opted directors on the board have greater inefficient labor investment, compared to the firms with less than 50% co-option level. Finally, we examine the association between co-option and abnormal net hiring under competitive pressure. Our results reveal that the effect of co-option on labor investment inefficiency is muted for firms facing greater product market competition threats.

Our study highlights the effect of one specific board weakness (i.e. co-option) on corporate hiring decision making. We contribute to the existing literature on both board co-option and corporate labor investment by documenting that co-option is a key determinant of labor investment inefficiency. Our study can also make implications for rule makers within the firm, particularly for those who design corporate internal control and governance systems to protect shareholder’s interest and reduce agency conflicts.

Tables for Chapter 3

Table 3.1: Descriptive Statistics for Variables in Baseline Model

This table reports descriptive statistics for all variables specified in Eq. (3.4). The sample includes 16,536 firm-year observations, representing 2,040 US firms during the period from 1996 to 2014.$|Abnormal\_net\_hire|$ is the measure for inefficient investment in labor, calculated by taking the absolute values of the residuals estimated from Eq. (3.2). Co_op is board co-option measure, defined as the fraction of the number of directors elected after the CEO takes office to the board size. MTB is the market-to-book ratio. $Size$ is the natural logarithm of a firm's market value. $Leverage$ is the ratio of Long-term debt plus debt in current liabilities, divided by the book value of assets. $Dividend$ is a dummy variable set equal to one in years in which a firm pays common dividends, and zero otherwise. Std_cash is the standard deviation of the ratio of firm-level cash flow from operations to total assets for the previous five years. Std_sale is natural logarithm of the standard deviation of firm-level sales revenue for the previous five years. $Tangibility$ is the ratio of property, plant, and equipment to total assets. $Loss$ is a dummy variable set equal to one in years in which a firm has negative ROA. $labor\_intense$ is labor intensity, measured as the number of employees divided by total assets. Ab_invest is abnormal non-labor investment.

VARIABLES	(1) N	(2) Mean	(3) Std. Dev. (Overall)	(4) Std. Dev. (Between)	(5) Std. Dev. (Within)	(6) P25	(7) Median	(8) P75
$\|Abnormal\_net\_hire\|$	16,536	0.104	0.135	0.092	0.118	0.030	0.065	0.124
Co_op	16,536	0.473	0.318	0.268	0.215	0.200	0.444	0.750
MBT	16,536	2.984	2.009	1.654	1.267	1.560	2.378	3.772
$Size$	16,536	7.543	1.569	1.428	0.544	6.423	7.360	8.486
$Leverage$	16,536	0.205	0.169	0.163	0.088	0.051	0.196	0.314
$Dividend$	16,536	0.537	0.499	0.459	0.216	0.000	1.000	1.000
Std_cash	16,536	0.046	0.038	0.038	0.023	0.022	0.036	0.056
Std_sale	16,536	5.422	1.460	1.359	0.562	4.394	5.336	6.386
$Tangibility$	16,536	0.279	0.216	0.214	0.055	0.113	0.216	0.391
$Loss$	16,536	0.163	0.369	0.276	0.298	0.000	0.000	0.000
$Labor\_intense$	16,536	0.007	0.009	0.009	0.003	0.002	0.004	0.008
Ab_invest	16,536	0.089	0.131	0.082	0.116	0.034	0.065	0.099

Table 3.2: Correlation Matrix

VARIABLES	|*Abnormal_net_hire*|	*Co_op*	*MBT*	*Size*	*Leverage*	*Dividend*	*Std_cash*
|*Abnormal_net_hire*|	1						
Co_op	0.042***	1					
MBT	0.064***	0.0100	1				
Size	-0.154***	-0.052***	0.327***	1			
Leverage	-0.009*	-0.037***	-0.090***	0.027***	1		
Dividend	-0.148***	-0.112***	0.014***	0.398***	0.021***	1	
Std_cash	0.075***	0.037***	0.042***	-0.098***	-0.022***	-0.074***	1
Std_sale	-0.184***	-0.064***	0.026***	0.807***	0.182***	0.369***	-0.104***
Tangibility	-0.054***	-0.035***	-0.121***	0.086***	0.318***	0.166***	-0.061***
Loss	0.169***	0.001	-0.040***	-0.316***	0.037***	-0.295***	0.098***
Labor_intense	-0.037***	0.000	-0.059***	-0.187***	-0.010**	-0.019***	0.008*
Ab_invest	0.271***	0.023***	0.120***	-0.066***	-0.00300	-0.086***	0.098***

	Std_sale	*Tangibility*	*Loss*	*Labor_intense*	*Ab_invest*
Std_sale	1				
Tangibility	0.130***	1			
Loss	-0.292***	-0.091***	1		
Labor_intense	-0.051***	0.114***	-0.058***	1	
Ab_invest	-0.133***	-0.011**	0.113***	-0.022***	1

Table 3.3: Baseline results

This table reports regression results on labor investment efficiency on board co-option. The dependent variables across all regressions are $|Abnormal\_net\_hire|$. The main independent variable is Co_op. Column (1) presents the result by regressing $|Abnormal\_net\_hire|$ on Co_op only. In column (2), the firm-level control variables specified in the model (3.4) are included. In column (3), we re-estimate the specification of column (2) and control variables for state fixed effects. In column (4) we controls for year-industry and year-state fixed effects, instead of including year, industry, state separately. Firm-level charateristics include market-to-book ratio, firm size, leverage, dividend, volatility in cash flow and sales, tangibility, losses, labor intensity, abnormal non-labor investment, boar size and ratio of independent directors on the board. All variables are defined in Table 3.1 of Appendix. We present t-statistics in parentheses and cluster standard errors at firm level.
1% Significance level *** 5% Significance level ** 10% Significance level *

	Industry FE and Year FE		State FE	Year*Industry and Year*State FE
	(1)	(2)	(3)	(4)
VARIABLES	$\|Abnormal\_net\_hire\|$	$\|Abnormal\_net\_hire\|$	$\|Abnormal\_net\_hire\|$	$\|Abnormal\_net\_hire\|$
Co_op	0.016***	0.010***	0.009**	0.010***
	(3.97)	(2.66)	(2.42)	(2.62)
MBT		-0.001	-0.000	-0.001
		(-0.71)	(-0.61)	(-0.89)
$Size$		-0.003*	-0.003	-0.003*
		(-1.67)	(-1.58)	(-1.72)
$Leverage$		0.013	0.013	0.013
		(1.51)	(1.53)	(1.51)
$Dividend$		-0.016***	-0.014***	-0.014***
		(-6.02)	(-5.39)	(-5.02)
Std_cash		0.227***	0.228***	0.231***
		(5.88)	(5.87)	(5.69)
Std_sale		0.003	0.002	0.003
		(1.51)	(1.29)	(1.47)
$Tangibility$		-0.022***	-0.028***	-0.028***
		(-3.09)	(-3.76)	(-3.63)
$Loss$		0.017***	0.017***	0.017***
		(4.59)	(4.65)	(4.33)
$Labor\_intense$		-0.291**	-0.300**	-0.303**
		(-2.22)	(-2.24)	(-2.24)
Ab_invest		0.331***	0.330***	0.330***
		(19.05)	(19.12)	(18.91)
Constant	0.097***	0.081***	0.083***	0.083***
	(43.95)	(9.58)	(9.78)	(9.53)
Observations	16,536	16,536	16,536	16,536
Adjusted R-squared	0.027	0.155	0.157	0.153
Year FE	YES	YES	YES	NO
Industry FE	YES	YES	YES	NO
State FE	NO	NO	YES	NO
Year*Industry FE	NO	NO	NO	YES
Year*State FE	NO	NO	NO	YES

Table 3.4: Alternative Co-Option Measures

This table reports regression results for robustness by employing three alternative measures for co-option. We consider three alternative measures from Coles et al. (2014): Co_op_ind, $TwCo\_op$ and $TwCo\_op\_ind$. Co_op_ind is defined as the fraction of co-opted independent directors to the board size: $Co\_op\_ind = \frac{Co-opted\ independent\ directors}{Board\ size}$. $TwCo\_op$ is defined as the sum of tenure of co-opted directors divided by the sum of the tenure of all directors: $TwCo\_op = \frac{\Sigma_{i=1}^{board\_size} Tenure_i * Coop\_dummy_i}{\Sigma_{i=1}^{board\_size} Tenure_i}$, where $Coop\_dummy_i$ is a dummy that equals one if the director i is a co-opted director, and zero otherwise. $Tenure_i$ is the tenure of the director i on the board. $TwCo\_op\_ind$ is defined as the sum of tenure of co-opted independent directors divided by the sum of the tenure of all directors: $TwCo\_op\_ind = \frac{\Sigma_{i=1}^{board\_size} Tenure_i * Coop\_ind\_dummy_i}{\Sigma_{i=1}^{board\_size} Tenure_i}$, where $Coop\_ind\_dummy_i$ is a dummy that equals one if the director i is a co-opted independent director, and zero otherwise. The dependent variables across all regressions are $|Abnormal\_net\_hire|$. Control variables are identical to those reported in the Table 3.3, and specified in the baseline model. All variables are defined in Table 3.1 of Appendix. Year and industry fixed effects are included in all regressions We present t-statistics in parentheses and cluster standard errors at firm level. 1% Significance level *** 5% Significance level ** 10% Significance level *

VARIABLES	(1) $\lvert Abnormal\_net\_hire\rvert$	(2) $\lvert Abnormal\_net\_hire\rvert$	(3) $\lvert Abnormal\_net\_hire\rvert$
Co_op_ind	0.008*		
	(1.90)		
$TwCo\_op$		0.011***	
		(2.64)	
$TwCo\_op\_ind$			0.014***
			(2.70)
MBT	-0.001	-0.001	-0.001
	(-0.70)	(-0.75)	(-0.75)
$Size$	-0.003*	-0.003	-0.003*
	(-1.68)	(-1.63)	(-1.67)
$Leverage$	0.013	0.013	0.013
	(1.50)	(1.52)	(1.49)
$Dividend$	-0.016***	-0.015***	-0.016***
	(-6.18)	(-5.94)	(-6.03)
Std_cash	0.227***	0.227***	0.227***
	(5.88)	(5.87)	(5.88)
Std_sale	0.002	0.003	0.002
	(1.49)	(1.52)	(1.51)
$Tangibility$	-0.023***	-0.022***	-0.022***
	(-3.08)	(-3.08)	(-3.08)
$Loss$	0.016***	0.017***	0.017***
	(4.57)	(4.59)	(4.58)
$Labor\_intense$	-0.291**	-0.295**	-0.292**
	(-2.21)	(-2.24)	(-2.22)
Ab_invest	0.331***	0.331***	0.331***
	(19.07)	(19.05)	(19.08)
Constant	0.083***	0.082***	0.083***
	(9.98)	(9.85)	(10.06)
Observations	16,536	16,536	16,536
Adjusted R-squared	0.155	0.155	0.155
Year FE	YES	YES	YES
Industry FE	YES	YES	YES

Table 3.5: Alternative Measure for Abnormal Hiring

This table reports regression results for robustness by employing alternative measures for inefficient labor investment. In column (1), we use difference between a firm's actual net hiring and its industry median level of net hiring as the measure for inefficient labor investment. In column (2), we obtain abnormal net hiring from model (3.2) by including sales growth only. In column (3), we obtain abnormal net hiring from model (3.2) by including additional factors, such as R&D expenses, acquisition expenditure, capital expenditure, labor union coverage and state-level GDP. In column (4), we obtain abnormal net hiring from model (3.2) by controlling for industry fixed effects only. In column (5), we obtain abnormal net hiring from model (3.2) by controlling for firm and year fixed effects. Our main independent variables across all regressions (1)-(6) is board co-option, Co_op. All control variables are identical to those reported in the Table 3.3, and specified in the baseline model. All variables are defined in Table 3.1 of Appendix. Year and industry fixed effects are included in all regressions We present t-statistics in parentheses and cluster standard errors at firm level. 1% Significance level *** 5% Significance level ** 10% Significance level *

VARIABLES	(1) Industry median $\lvert Abnormal\_net\_hire \rvert$	(2) Model with sales growth $\lvert Abnormal\_net\_hire \rvert$	(3) Model with additional factors $\lvert Abnormal\_net\_hire \rvert$	(4) Model with industry FE only $\lvert Abnormal\_net\_hire \rvert$	(5) Model with firm&year FE $\lvert Abnormal\_net\_hire \rvert$
Co_op	0.014***	0.011**	0.008**	0.010***	0.010**
	(2.94)	(2.40)	(1.97)	(2.71)	(2.54)
MBT	0.004***	0.001	-0.001	0.000	-0.000
	(3.43)	(1.28)	(-0.94)	(0.24)	(-0.14)
$Size$	-0.006***	-0.005**	-0.001	-0.004**	-0.005***
	(-2.61)	(-2.54)	(-0.84)	(-2.48)	(-2.85)
$Leverage$	-0.009	0.009	0.006	0.009	0.015*
	(-0.75)	(0.91)	(0.62)	(1.00)	(1.71)
$Dividend$	-0.027***	-0.021***	-0.015***	-0.013***	-0.016***
	(-8.22)	(-6.66)	(-5.72)	(-4.54)	(-5.32)
Std_cash	0.165***	0.179***	0.216***	0.220***	0.219***
	(3.08)	(3.52)	(5.81)	(5.73)	(5.98)
Std_sale	0.005**	0.005***	0.001	0.003*	0.004**
	(2.40)	(2.62)	(0.75)	(1.77)	(2.17)
$Tangibility$	-0.035***	-0.034***	-0.014*	-0.038***	-0.037***
	(-3.88)	(-4.01)	(-1.77)	(-4.56)	(-4.19)
$Loss$	0.024***	0.034***	0.018***	0.018***	0.015***
	(4.90)	(7.34)	(4.63)	(4.84)	(4.35)
$Labor\_intense$	-0.391**	-0.435***	-0.333**	-0.349**	-0.214
	(-2.35)	(-2.87)	(-2.54)	(-2.41)	(-1.24)
Ab_invest	0.472***	0.421***	0.326***	0.338***	0.291***
	(20.82)	(19.91)	(18.62)	(19.19)	(18.60)
Constant	0.092***	0.095***	0.076***	0.091***	0.093***
	(8.47)	(9.04)	(8.71)	(10.73)	(10.71)
Observations	16,536	16,536	14,114	16,536	16,536
Adjusted R-squared	0.175	0.169	0.158	0.159	0.152
Year FE	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES

Table 3.6: PSM Estimation

This table reports propensity score matching estimation. We define firms' board co-option above the top quartile as the treatment group, and those below the bottom quartile as control group. We employ one-to-one nearest neighbour matching based on covariates specified in the baseline model. Panel A reports pre-match and post-match univariate results comparing covariates across treatment and control. t-statistics are presented in parentheses. Panel B presents the average tretment effect. Panel C presents regression result based on matched sample. Detailed definitions of all variables are presented in the Table 3.1 of Appendix. Year and industry fixed effects are included in all regressions. We present t-statistics in parentheses and cluster standard errors at firm level. 1% Significance level *** 5% Significance level ** 10% Significance level *

Panel A: Comparison for covariates across treatment group and control group

	Pre-match			Post-match		
VARIABLES	(1) Control High=0	(2) Treatment High=1	(3) Difference	(4) Control High=0	(5) Treatment High=1	(6) Difference
Co_op	0.087	0.901	-0.813***	0.087	0.901	-0.814***
			(-430.552)			(-312.006)
MTB	2.940	2.991	-0.051	2.911	2.987	-0.076
			(-1.179)			(-1.274)
Size	7.530	7.347	0.183***	7.413	7.455	-0.042
			(5.549)			(-0.925)
Leverage	0.208	0.192	0.016***	0.199	0.201	-0.002
			(4.427)			(-0.338)
Dividend	0.580	0.437	0.143***	0.511	0.517	-0.006
			(13.458)			(-0.395)
Std_cash	0.046	0.049	-0.004***	0.048	0.047	0.001
			(-4.043)			(0.483)
Std_sale	5.451	5.234	0.217***	5.309	5.339	-0.030
			(7.022)			(-0.709)
Tangibility	0.285	0.263	0.021***	0.277	0.277	0.000
			(4.649)			(-0.015)
Loss	0.167	0.168	-0.001	0.169	0.164	0.005
			(-0.085)			(0.466)
labor_intense w	0.007	0.007	0.000	0.007	0.007	0.000
			(0.467)			(0.509)
Ab_invest	0.086	0.092	-0.006**	0.088	0.091	-0.003
			(-2.290)			(-0.635)
Observations	4,377	4,282		2,269	2,249	

Panel B: Average treatment effect

VARIABLES	(1) Treatment	(2) Control	(3) Difference	(4) T-stat	(5) Std.Err
$\|Abnormal\_net\_hire\|$	0.110	0.100	0.010***	2.76	0.003

Panel C: Relation between labor investment inefficiency and co-option for the propensity-score matched sample

VARIABLES	(1) $\|Abnormal\_net\_hire\|$
Co_op	0.011**
	(2.03)
MTB	-0.000
	(-0.30)
Size	-0.004
	(-1.07)
Leverage	0.005
	(0.35)
Dividend	-0.012**
	(-2.50)
Std_cash	0.130**
	(2.03)
Std_sale	0.004
	(1.28)
Tangibility	-0.014
	(-0.97)
Loss	0.013*
	(1.94)
labor_intense	-0.370
	(-1.37)
Ab_invest	0.247***
	(7.01)
Constant	0.084***
	(5.95)
Observations	4,518
Adjusted R-squared	0.118
Year FE	YES
Industry FE	YES

Table 3.7: Entropy Balance: Comparison of Covariates

This table reports comparison of mean, variance, and skewness of the covariates between treatment group and control group. The covariates used in entropy balancing analysis are specified in the baseline model. Detailed definitions of all variables are presented in the Table 3.1 of Appendix.

Panel A. Before balancing

	Treatment			Control		
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Mean	Variance	Skewness	Mean	Variance	Skewness
MBT	2.994	3.966	1.224	2.936	4.115	1.296
Size	7.349	2.152	0.638	7.530	2.570	0.501
Leverage	0.192	0.031	0.842	0.209	0.027	0.802
Dividend	0.435	0.246	0.261	0.581	0.244	-0.327
Std_cash	0.049	0.002	3.882	0.046	0.001	3.335
Std_sale	5.235	1.981	0.146	5.453	2.151	0.107
Tangibility	0.263	0.046	1.174	0.285	0.046	1.079
Loss	0.169	0.140	1.771	0.168	0.140	1.781
Labor_intense	0.007	0.000	4.407	0.007	0.000	3.858
Ab_invest	0.092	0.017	6.398	0.086	0.015	10.970

Panel B. After balancing

	Treatment			Control		
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Mean	Variance	Skewness	Mean	Variance	Skewness
MBT	2.994	3.966	1.224	2.994	3.966	1.224
Size	7.349	2.152	0.638	7.349	2.152	0.638
Leverage	0.192	0.031	0.842	0.192	0.031	0.842
Dividend	0.435	0.246	0.261	0.435	0.246	0.261
Std_cash	0.049	0.002	3.882	0.049	0.002	3.882
Std_sale	5.235	1.981	0.146	5.235	1.981	0.146
Tangibility	0.263	0.046	1.174	0.263	0.046	1.174
Loss	0.169	0.140	1.771	0.169	0.140	1.771
Labor_intense	0.007	0.000	4.407	0.007	0.000	4.407
Ab_invest	0.092	0.017	6.398	0.092	0.017	6.485

Table 3.8: Regressions for Entropy Balanced Sample

This table reports regression result for entropy-blanced sample. The dependent variable is $|Abnormal\_net\_{h}ire|$. The main independent variable is Co_op. Control variables are identical to those reported in the Table 3.3, and specified in the baseline model. All variables are defined in Table 3.1 of the Appendix. Year and industry fixed effects are included in all regressions. We present t-statistics in parentheses and cluster standard errors at firm level. 1% Significance level *** 5% Significance level ** 10% Significance level *

VARIABLES	(1) $\|Abnormal\_net\_hire\|$
Co_op	0.008**
	(2.21)
MBT	-0.001
	(-0.64)
$Size$	-0.003
	(-1.35)
$Leverage$	0.003
	(0.28)
$Dividend$	-0.015***
	(-5.09)
Std_cash	0.167***
	(3.71)
Std_sale	0.002
	(0.96)
$Tangibility$	-0.022***
	(-2.59)
$Loss$	0.015***
	(3.09)
$Labor\_intense$	-0.141
	(-0.64)
Ab_invest	0.305***
	(9.30)
Constant	0.090***
	(8.66)
Observations	8,612
Adjusted R-squared	0.131
Year FE	YES
Industry FE	YES

Table 3.9: Difference-in-Difference Analysis Based on SOX

This table reports the difference-in-difference analysis based on the passage of Sarbanes-Oxley Act of 2002. The sample period used in DID analysis ranges from 1996 to 2010. $|Abnormal\_net\_hire|$ is our dependent variable. For independent variables, $Cooption$ is four co-option measures: Co_op, Co_op_ind, $TwCo\_op$ and $TwCo\_op\_ind$. $Post$ is a dummy variable that equals one if year is 2002 and later, and zero otherwise. $Noncompliant$ is a dummy variable that equals one if firms did not have more than 50% independent directors on the board, and zero otherwise. Control variables are identical to those reported in the Table 3.3, and specified in the baseline model. All variables are defined in Table 3.1 of the Appendix. Panel A reports the results for model (3.8). Panel B outlines the explanation of the clean effect. Panel C provides the clean effect results for the four co-option proxies. Year and industry fixed effects are included in all regressions. We present t-statistics in parentheses and cluster standard errors at firm level. 1% Significance level *** 5% Significance level ** 10% Significance level *

Panel A: regression results for Eq.3.8

VARIABLES	(1) $Cooption$=Co_op $\|Abnormal\_net\_hire\|$	(2) $Cooption$=Co_op_ind $\|Abnormal\_net\_hire\|$	(3) $Cooption$=$TwCo\_op$ $\|Abnormal\_net\_hire\|$	(4) $Cooption$=$TwCo\_op\_ind$ $\|Abnormal\_net\_hire\|$
$Cooption$	0.024***	0.013	0.025***	0.029**
	(2.77)	(1.17)	(2.68)	(2.17)
$Post * Cooption$	-0.022**	-0.011	-0.022**	-0.024*
	(-2.33)	(-0.93)	(-2.21)	(-1.69)
$Noncompliant * Cooption$	-0.008	0.017	-0.020	0.005
	(-0.62)	(0.79)	(-1.53)	(0.17)
$Post * Noncompliant * Cooption$	0.019	0.010	0.032**	0.026
	(1.53)	(0.53)	(2.18)	(0.95)
$Noncompliant$	-0.001	-0.006	0.001	-0.002
	(-0.26)	(-1.12)	(0.17)	(-0.47)
MBT	-0.001	-0.001	-0.001	-0.001
	(-0.76)	(-0.72)	(-0.80)	(-0.76)
$Size$	-0.003	-0.003	-0.003	-0.003
	(-1.31)	(-1.31)	(-1.29)	(-1.31)
$Leverage$	0.019*	0.020*	0.019*	0.019*
	(1.82)	(1.87)	(1.83)	(1.87)
$Dividend$	-0.017***	-0.018***	-0.017***	-0.017***
	(-5.58)	(-5.78)	(-5.48)	(-5.60)
Std_cash	0.210***	0.209***	0.210***	0.210***
	(5.00)	(4.96)	(5.01)	(4.97)
Std_sale	0.002	0.002	0.002	0.002
	(1.08)	(1.07)	(1.09)	(1.08)
$Tangibility$	-0.025***	-0.025***	-0.025***	-0.025***
	(-3.00)	(-3.06)	(-3.00)	(-3.02)
$Loss$	0.017***	0.017***	0.017***	0.017***
	(4.22)	(4.26)	(4.21)	(4.26)
$Labor\_intense$	-0.274*	-0.262*	-0.279*	-0.269*
	(-1.84)	(-1.75)	(-1.87)	(-1.80)
Ab_invest	0.334***	0.334***	0.334***	0.334***
	(16.61)	(16.62)	(16.59)	(16.63)
Constant	0.087***	0.090***	0.088***	0.089***
	(8.82)	(9.17)	(9.03)	(9.21)
Observations	12,878	12,878	12,878	12,878
Adjusted R-squared	0.149	0.148	0.149	0.148
Year FE	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES

Panel B: Explanation of the coefficients Coles et al. (2014)

VARIABLES	Estimated coefficient=($\partial\ \|Abnormal\_net\_hire\|/\partial\ Cooption$) Pre-SOX period (1996-2001)	Post-SOX period (2002-2010)	Difference
Compliant	β_1	$\beta_1+\beta_2$	β_2
	(Clean+Bias_c)	(Clean+Bias_c+SOX)	(SOX)
Non-compliant	$\beta_1+\beta_3$	$\beta_1+\beta_2+\beta_3+\beta_4$	$\beta_2+\beta_4$
	(Clean+Bias_nc)	(Clean+SOX)	(SOX-Bias_nc)
Difference	β_3	$\beta_3+\beta_4$	β_4
	(Bias_nc-Bias_c)	(-Bias_c)	(-Bias_nc)
	Clean effect=Clean+SOX-SOX=$\beta_1+\beta_2+\beta_3+\beta_4-\beta_2=\beta_1+\beta_3+\beta_4$		

Panel C: Clean effect

	(1)	(2)	(3)	(4)
Clean estimate ($\beta_1+\beta_3+\beta_4$)	0.035***	0.040**	0.037**	0.060***
$t-statistics$	2.54	2.31	2.44	2.79
Std_err	0.014	0.017	0.015	0.022

Table 3.10: Instrumental Variable Estimation

This table reports instrumental variable regression results. Column (1) presents the first stage regression result where the instruments, *Industry mean co_option*, defined as the average co-option of the industry that the firm belongs to, and *Early co_option*, defined as the firm's earliest year co-option level. Column (2) reports regression result for the second stage. *Fitted co_option* is the predicted values of co-option obtained from the first stage regression. Detailed variable definitions are provided in Appendix of Table 3.1. We present t-statistics in parentheses and cluster standard errors at firm level. 1% Significance level *** 5% Significance level ** 10% Significance level *

	First stage	Second stage
	(1)	(2)
VARIABLES	*Co_op*	$\lvert Abnormal\_net\_hire \rvert$
Fitted co_option		0.055***
		(2.65)
Industry mean co_option	0.799***	
	(13.93)	
MBT	0.003	-0.001
	(1.10)	(-0.82)
Size	-0.003	-0.003
	(-0.45)	(-1.61)
Leverage	-0.021	0.015*
	(-0.67)	(1.68)
Dividend	-0.038***	-0.013***
	(-3.43)	(-4.41)
Std_cash	-0.005	0.224***
	(-0.04)	(5.80)
Std_sale	-0.006	0.003
	(-1.03)	(1.62)
Tangibility	-0.011	-0.022***
	(-0.35)	(-3.03)
Loss	-0.015	0.017***
	(-1.53)	(4.81)
Labor_intense	-0.176	-0.278**
	(-0.25)	(-2.21)
Ab_invest	0.019	0.330***
	(0.90)	(19.03)
Constant	0.169***	0.056***
	(3.99)	(4.01)
F-statistics (strength of instrument)	F-stat=24.59 (P-val=0.000)	
Observations	16,536	16,536
Adjusted R-squared	0.061	0.155
Year FE	YES	YES
Industry FE	YES	YES

Table 3.11: The effect of co-option under competitive pressure

This table reports the results for high/low product market competition subsamples. Firms are classified into low (high) market competition subsample based on the median of measures for market competition. Dependent variable is $|Abnormal\_net\_hire|$. The key independent variable is Co_op. Control variables are identical to those reported in the Table 3.3, and specified in the baseline model. All variables are defined in Table 3.1 of the Appendix. Year and industry fixed effects are included in all regressions. We present t-statistics in parentheses and cluster standard errors at firm level. 1% Significance level *** 5% Significance level ** 10% Significance level *

	Low market competition (high HHI)	High market competition (low HHI)	Low market competition (high LI)	High market competition (low LI)	Low market competition (low Fluidity)	High market competition (high Fluidity)
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	$\|Abnormal\_net\_hire\|$	$\|Abnormal\_net\_hire\|$	$\|Abnormal\_net\_hire\|$	$\|Abnormal\_net\_hire\|$	$\|Abnormal\_net\_hire\|$	$\|Abnormal\_net\_hire\|$
Co_op	0.014**	0.006	0.013**	0.008	0.012**	0.008
	(2.47)	(1.13)	(2.45)	(1.54)	(2.41)	(1.36)
	(2.38)	(1.29)	(2.26)	(1.45)	(2.30)	(1.24)
MBT	0.001	-0.001	-0.001	0.000	-0.001	-0.001
	(0.73)	(-1.38)	(-0.87)	(0.14)	(-0.56)	(-0.47)
$Size$	-0.007***	0.001	-0.006**	-0.001	-0.005**	-0.002
	(-2.76)	(0.42)	(-2.21)	(-0.52)	(-2.39)	(-0.71)
$Leverage$	0.011	0.008	0.013	0.011	0.023*	0.005
	(0.83)	(0.71)	(1.15)	(0.87)	(1.93)	(0.43)
$Dividend$	-0.011***	-0.020***	-0.013***	-0.018***	-0.012***	-0.016***
	(-2.88)	(-5.78)	(-3.48)	(-5.19)	(-3.59)	(-4.19)
Std_cash	0.224***	0.231***	0.237***	0.214***	0.243***	0.198***
	(3.06)	(5.15)	(4.10)	(4.24)	(4.41)	(3.82)
Std_sale	0.006**	-0.001	0.003	0.003	0.003*	0.002
	(2.31)	(-0.42)	(1.18)	(1.63)	(1.74)	(0.73)
$Tangibility$	-0.025**	-0.056***	-0.026***	-0.019*	-0.008	-0.036***
	(-2.46)	(-3.95)	(-2.65)	(-1.79)	(-0.95)	(-3.46)
$Loss$	0.014***	0.020***	0.018**	0.019***	0.012***	0.018***
	(2.71)	(3.77)	(2.07)	(4.95)	(2.81)	(3.43)
$Labor\_intense$	-0.385	-0.178	-0.466*	-0.182	-0.240	-0.243
	(-1.50)	(-1.36)	(-1.70)	(-1.23)	(-1.63)	(-1.10)
Ab_invest	0.333***	0.329***	0.306***	0.393***	0.349***	0.319***
	(13.44)	(13.98)	(15.77)	(12.15)	(12.65)	(14.69)
Constant	0.095***	0.078***	0.108***	0.056***	0.076***	0.089***
	(7.37)	(6.61)	(8.50)	(4.82)	(7.09)	(7.26)
Observations	7,851	8,685	8,710	7,826	8,169	8,367
Adjusted R-squared	0.134	0.182	0.173	0.140	0.130	0.166
Year FE	YES	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES	YES

Table 3.12: The role of financial analysts and institutional investors

This table reports for high/low analysts coverage and high/low institutional holdings. Firms are assigned to low (high) analyst coverage group if $coverage$ is below (above) the sample median, and assigned to low (high) institutional holdings group if $Institution$ is below (above) the sample median. Dependent variable is $|Abnormal\_net\_hire|$. The key independent variable is Co_op. Control variables are identical to those reported in the Table 3.3, and specified in the baseline model. All variables are defined in Table 3.1 of the Appendix. Year and industry fixed effects are included in all regressions. We present t-statistics in parentheses and cluster standard errors at firm level. 1% Significance level *** 5% Significance level ** 10% Significance level *

	Low Coverage	High Coverage	Low Institution	High Institution
	(1)	(2)	(3)	(4)
VARIABLES	$\lvert Abnormal\_net\_hire \rvert$	$\lvert Abnormal\_net\_hire \rvert$	$\lvert Abnormal\_net\_hire \rvert$	$\lvert Abnormal\_net\_hire \rvert$
Co_op	0.012**	0.008	0.011**	0.008
	(2.34)	(1.57)	(2.06)	(1.60)
MTB	-0.002*	0.000	0.001	-0.001
	(-1.83)	(0.26)	(0.89)	(-0.76)
$Size$	-0.002	-0.004	-0.005**	-0.003
	(-0.87)	(-1.49)	(-2.23)	(-1.25)
$Leverage$	0.013	0.013	0.020	-0.000
	(1.06)	(1.19)	(1.57)	(-0.03)
$Dividend$	-0.017***	-0.015***	-0.020***	-0.005
	(-4.50)	(-4.22)	(-5.21)	(-1.45)
Std_cash	0.218***	0.245***	0.227***	0.231***
	(3.98)	(4.76)	(4.51)	(4.43)
Std_sale	0.002	0.003	0.005**	0.002
	(1.02)	(1.31)	(2.08)	(0.95)
$Tangibility$	-0.021**	-0.024***	-0.037***	-0.014
	(-2.01)	(-2.60)	(-3.20)	(-1.36)
$Loss$	0.024***	0.006	0.020***	0.012**
	(4.89)	(1.21)	(4.13)	(2.32)
$Labor\_intense$	-0.333*	-0.252*	-0.451**	-0.439**
	(-1.69)	(-1.69)	(-2.36)	(-2.12)
$Ab\_invest)$	0.355***	0.307***	0.306***	0.349***
	(13.79)	(12.60)	(12.63)	(14.41)
Constant	0.084***	0.078***	0.094***	0.077***
	(6.21)	(6.23)	(8.58)	(6.24)
Observations	8,283	8,253	8,340	8,166
Adjusted R-squared	0.156	0.149	0.138	0.182
Year FE	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES

Table 3.13: Results from Regulated Firms

This table reports results for regulated firms. Column (1) includes only financial firms, while column (2) includes only utility firms. The dependent variable is $|Abnormal\_net\_{h}ire|$. The main independent variable is Co_op. Control variables are identical to those reported in the Table 3.3, and specified in the baseline model. All variables are defined in Table 3.1 of the Appendix. Year and industry fixed effects are included in all regressions. We present t-statistics in parentheses and cluster standard errors at firm level. 1% Significance level *** 5% Significance level ** 10% Significance level *

	Financial firms	Utility firms
	(1)	(2)
VARIABLES	$\lvert Abnormal\_net\_hire\rvert$	$\lvert Abnormal\_net\_hire\rvert$
Co_op	0.019	0.018
	(0.87)	(0.94)
MBT	-0.003	0.000
	(-0.88)	(0.08)
$Size$	-0.002	-0.012**
	(-0.16)	(-2.11)
$Leverage$	0.006	-0.002
	(0.12)	(-0.06)
$Dividend$	-0.030*	0.034*
	(-1.84)	(1.69)
Std_cash	-0.058	0.268
	(-0.38)	(0.87)
Std_sale	-0.009	0.008
	(-1.10)	(1.60)
$Tangibility$	-0.015	-0.036
	(-0.52)	(-1.00)
$Loss$	0.029	-0.000
	(1.12)	(-0.02)
$Labor\_intense$	-2.226	-12.691
	(-1.11)	(-1.36)
Ab_invest	0.513***	0.516***
	(6.45)	(8.54)
Constant	0.151***	0.102*
	(2.83)	(1.76)
Observations	570	1,486
Adjusted R-squared	0.206	0.184
Year FE	YES	YES
Industry FE	YES	YES

Table 3.14: Co-Option Quartiles and Labor Investment Inefficiency

This table reports the results on dummies of co-option quartiles. We estimate our baseline model by replacing Co_op with three dummy variables, Co_op2, Co_op3 and Co_op4. Co_op2 takes the value of one if firm's co-option is in the second Co_op quartile, and zero otherwise, Co_op3 takes the value of one if firm's co-option is in the third Co_op quartile, and zero otherwise, and Co_op4 takes the value of one if firm's co-option is in the fourth Co_op quartile, and zero otherwise. Dependent variable is $|Abnormal\_net\_hire|$. Control variables are identical to those reported in the Table 3.3, and specified in the baseline model. All variables are defined in Table 3.1 of the Appendix. Year and industry fixed effects are included in all regressions. We present t-statistics in parentheses and cluster standard errors at firm level. 1% Significance level *** 5% Significance level ** 10% Significance level *

VARIABLES	(1) $\lvert Abnormal\_net\_hire \rvert$	(2) $\lvert Abnormal\_net\_hire \rvert$
Co_op2	0.000	0.000
	(0.03)	(0.06)
Co_op3	0.010***	0.008***
	(3.17)	(2.85)
Co_op4	0.012***	0.008**
	(3.30)	(2.23)
MBT		-0.001
		(-0.68)
$Size$		-0.003*
		(-1.71)
$Leverage$		0.013
		(1.51)
$Dividend$		-0.016***
		(-6.07)
Std_cash		0.227***
		(5.88)
Std_sale		0.003
		(1.51)
$Tangibility$		-0.023***
		(-3.11)
$Loss$		0.017***
		(4.59)
$Labor\_intense$		-0.292**
		(-2.23)
Ab_invest		0.331***
		(19.05)
Constant	0.099***	0.082***
	(45.69)	(9.81)
Observations	16,536	16,536
Adjusted R-squared	0.027	0.155
Year FE	YES	YES
Industry FE	YES	YES

Table 3.15: Non Co-Opted Directors and Labor Investment Inefficiency

This table reports the results on non co-opted directors. In column (1), we presents the estimation by taking into account $Non\_co\_op\_ind$ as the main independent variable, which is defined as the ratio of non co-opted independent directors to the board size. In column (2), we consider $non\_co\_op\_non\_ind$ as the main independent variable, which is defined as the ratio of non co-opted non independent directors to the board size. Dependent variable across columns (1) and (2) is $|Abnormal\_net\_hire|$. Control variables are identical to those reported in the Table 3.3, and specified in the baseline model. All variables are defined in Table 3.1 of the Appendix. Year and industry fixed effects are included in all regressions. We present t-statistics in parentheses and cluster standard errors at firm level. 1% Significance level *** 5% Significance level ** 10% Significance level *

VARIABLES	(1) $\|Abnormal\_net\_hire\|$	(2) $\|Abnormal\_net\_hire\|$
$Non\_co\_op\_ind$	-0.006	
	(-1.29)	
$Non\_co\_op\_non\_ind$		-0.013
		(-1.45)
MBT	-0.001	-0.001
	(-0.45)	(-0.41)
$Size$	-0.003	-0.003
	(-1.49)	(-1.56)
$Leverage$	0.018*	0.017*
	(1.96)	(1.86)
$Dividend$	-0.017***	-0.017***
	(-6.40)	(-6.53)
Std_cash	0.247***	0.244***
	(5.67)	(5.63)
Std_sale	0.003	0.003
	(1.60)	(1.56)
$Tangibility$	-0.021***	-0.021***
	(-2.72)	(-2.68)
$Loss$	0.015***	0.015***
	(4.05)	(4.02)
$Labor\_intense$	-0.261*	-0.263*
	(-1.92)	(-1.95)
Ab_invest	0.339***	0.339***
	(19.65)	(19.65)
Constant	0.081***	0.083***
	(9.51)	(9.55)
Observations	14,875	14,875
Adjusted R-squared	0.161	0.162
Year FE	YES	YES
Industry FE	YES	YES

Table 3.16: Over-Investment and Under-Investment

This table reports regression results for the relation between board co-option and overinvestment/underinvestment. The dependent variable is $|Abnormal\_net\_hire|$. The main independent variable is Co_op. Control variables are identical to those reported in the Table 3.3, and specified in the baseline model. All variables are defined in Table 3.1 of the Appendix. Column (1) reports the results for over-investment subsample. Firms are considered to over-invest when they have positive positive abnormal net hiring.In columns (2) and (3), we further decompose over-inivesment into over-hiring subsample and under-firing subsample respectively. Firms are classified as over-hiring (under-firing) when they have both positive abnormal net hiring and positive (negative) expected net hiring. Column (4) reports results for the under-investment subsample. Firms are considered to under-invest when they have negative abnormal net hiring. In columns (5) and (6), we further decompose under-investment into under-hiring subsample and over-firing subsample respectively. Firms are classified as under-hiring (over-firing) when they have both negative abnormal net hiring and positive (negative) expected net hiring. Year and industry fixed effects are included in all regressions. We present t-statistics in parentheses and cluster standard errors at firm level. 1% Significance level *** 5% Significance level ** 10% Significance level *

	Over-investment			Under-investment		
	(1) Over-investing	(2) Over-hiring	(3) Under-firing	(4) Under-investing	(5) Under-hiring	(6) Over-firing
VARIABLES	$\|Abnormal\_net\_hire\|$	$\|Abnormal\_net\_hire\|$	$\|Abnormal\_net\_hire\|$	$\|Abnormal\_net\_hire\|$	$\|Abnormal\_net\_hire\|$	$\|Abnormal\_net\_hire\|$
Co_op	0.020***	0.022**	0.001	0.003	0.005	0.003
	(2.76)	(2.49)	(0.14)	(0.80)	(1.52)	(0.41)
MBT	0.001	0.001	-0.000	-0.002***	-0.003***	0.002
	(0.64)	(0.56)	(-0.15)	(-3.38)	(-4.92)	(1.15)
$Size$	-0.008**	-0.011**	-0.007*	0.000	0.003**	-0.007*
	(-2.25)	(-2.45)	(-1.75)	(0.21)	(2.43)	(-1.72)
$Leverage$	0.014	0.045**	-0.008	0.019***	0.024***	-0.043***
	(0.83)	(2.00)	(-0.42)	(2.80)	(3.49)	(-2.60)
$Dividend$	-0.023***	-0.020***	-0.019***	-0.008***	-0.009***	-0.007
	(-4.79)	(-3.21)	(-3.30)	(-3.68)	(-4.25)	(-1.20)
Std_cash	0.165**	0.160*	0.229***	0.328***	0.358***	0.161**
	(2.36)	(1.79)	(2.68)	(8.35)	(8.28)	(2.09)
Std_sale	0.005	0.007*	0.003	0.000	-0.003**	0.010***
	(1.49)	(1.66)	(0.77)	(0.27)	(-2.00)	(3.05)
$Tangibility$	-0.039***	-0.041**	-0.012	-0.014**	-0.011*	-0.027*
	(-2.88)	(-2.33)	(-0.80)	(-2.35)	(-1.85)	(-1.78)
$Loss$	0.007	0.034***	-0.004	0.027***	0.024***	0.019***
	(0.93)	(2.63)	(-0.61)	(9.12)	(6.70)	(3.15)
$Labor\_intense$	-1.072***	-1.325***	-0.208	0.201	0.049	1.002***
	(-4.29)	(-4.47)	(-0.54)	(1.23)	(0.35)	(2.75)
Ab_invest	0.362***	0.355***	0.353***	0.076***	0.079***	0.076
	(16.81)	(16.17)	(4.48)	(4.15)	(3.87)	(1.07)
Constant	0.119***	0.135***	0.097***	0.070***	0.061***	0.090***
	(7.38)	(6.67)	(4.43)	(9.63)	(8.30)	(4.46)
Observations	6,379	4,843	1,536	10,157	8,202	1,955
Adjusted R-squared	0.188	0.189	0.136	0.095	0.096	0.146
Year FE	YES	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES	YES

Chapter 4

STOCK LIQUIDITY AND DIVIDEND SMOOTHING

4.1. Introduction

In the world of Miller and Modigliani (1961), a managed dividend policy is irrelevant under certain assumptions of perfect capital markets, and has no impact on firm value. In this case, given that firm's optimal investment plans hold constant, shareholders would be indifferent to whether firms decide to pay dividends or not, and how firms manage their dividend decisions, as their wealth does not decease or increase with one particular dividend policy. However, empirical evidence may not support well with theoretical explanations of M&M when relaxing one or more conditions related to perfect capital markets. In real capital markets characterized by frictions and uncertainty, managers believe that the practice of setting their dividend policies is important, and investors also seem to care about such behavior and react differently to dividend increase and decrease (e.g., Benartzi, Michaely and Thaler, 1997; Allen and Michaely, 2003; Brav, Graham, Harvey and Michaely, 2005).

In this study, we focus on one particular pattern of dividend policies, dividend smoothing: firm's dividend level does not change significantly over time, and hence exhibits a substantial degree of stability. This practice of dividend policy was first modeled in 1956 by Lintner (1956), who shows that the management develops a target payout rate, and manages to stabilize dividend payment through making gradual dividend changes toward the target year to year instead of significant changes and avoiding dividend cut at all possible. Although, dividend smoothing is widely discussed in the field of finance, there is little consensus on why managers decided to smooth the dividend payment. Brav et al. (2005) argue that dividend policy today has become less relevant to what Linter's model predicts. Recent empirical evidence indicates that dividend smoothing can be determined by economy-wide, firm-level characteristics and management attributes (e.g., Leary and Michaely, 2011; Michaely and Roberts, 2012; Javakhadze, Ferris and Sen, 2014; Garcia-Feijoo, Hossain and Javakhadze, 2021), but there is still limited understanding related to the mechanisms through which stock market affects such dividend behavior. We therefore aim to fill this void in the literature by taking into account stock liquidity.

To develop the link between stock liquidity and dividend smoothing, we rely on two strands of theoretical models associated with the dividend level (i.e., agency costs and information asymmetry). These well-established theories have also been viewed to explain why firms smooth their dividends, and can lead to competing predictions. Specifically, agency theories contend that dividends are considered as the means of reducing agency conflicts between corporate insiders and outside shareholders (e.g., Easterbrook, 1984; Jensen, 1986; Fluck, 1999; Myers, 2000). The key idea is that shareholders are more willing to receive dividends instead of keeping earnings inside firms, because a high and stable stream of dividends to shareholders reduces excess cash that can be used by insiders for private benefits. Among these theories, La Porta et al. (2000) propose two views on how managers are forced to disgorge cash, outcome view and substitute view. The outcome view implies that dividends are an outcome of strong governance because shareholders have greater rights and force insiders to disgorge cash by paying dividends, while the substitute view posits that dividends can act as a substitute for governance because among firms with weak governance managers must establish a reputation for good treatment of shareholders by paying dividends if firms need to raise external capital in the future.

From these agency theories, we can derive two competing predictions to explain the effect stock liquidity on dividend smoothing practices. Existing literature highlights the important role played by stock liquidity in facilitating governance through two channels. First, liquidity helps mitigate free-rider problems, and encourages shareholders to engage in costly intervention, known as voice, by allowing them to profit more from informed trading (e.g., Maug, 1998; Kahn and Winton, 1998). Second, liquidity allows blockholders to sell their shares more easily, known as exit, and such threat of exit is viewed as ex ante governance, disciplining managers and compelling them to engage in value-maximizing activities (e.g., Admati and Pfleiderer, 2009; Edmans, 2009; Edmans and Manso, 2011). Therefore, within the framework of agency problems, we could expect that stock liquidity can be good for governance through shareholder's voice and exit, forcing managers to disgorge cash through dividend smoothing (based on outcome view of dividends). Conversely, it could also reduce manager's need to use a steady stream of dividends to establish reputation, leading to less dividend smoothing efforts (based on substitute view of dividends) because free cash flow problems are already constrained by strong governance.

Prior literature also explains manager's practice to smooth dividends based on information asymmetry models. Theory of standard information asymmetry predicts that managers use dividends to convey firm's private information, as a signal, to the outside markets (e.g., Bhattacharya, 1979; John and Williams, 1985; Miller and Rock, 1985; Kumar, 1988). This model implies that signalling efforts through dividends smoothing should be more prevalent among the firms facing greater information asymmetry. In addition to signalling model, dividend smoothing can be more pronounced among firms with financial constraints due to precautionary savings motives (e.g., Almeida et al., 2004; Bates et al., 2009). In particular, firms, who expose the need for external financing but limited access to the capital markets, prefer to keep low level of dividends, and reluctant to increase dividends, leading to a smoothing pattern of dividends.

From the perspective of information asymmetry, we expect that stock liquidity leads to less dividend smoothing behaviors for two reasons. First, greater stock liquidity enables informed investors to earn higher trading gains based on their information, which strengthens the investor's incentives to acquire more information and to trade more actively, and hence enhancing share price informativeness (e.g., Holden and Subrahmanyam, 1992; Holmström and Tirole, 1993; Subrahmanyam and Titman, 2001). Managers can learn such information impounded in the share prices and use it as guidance for corporate decisions (e.g., Durnev et al., 2004; Luo, 2005; Bakke and Whited, 2010). If higher liquidity alleviates information asymmetry by improving the informativeness of share prices, we would predict that the benefits of signalling efforts is limited among firms with highly liquid stocks, leading to less dividend smoothing. Second, prior studies show that higher stock liquidity provides firms with better access to the capital markets by reducing transaction costs and cost of equity (e.g., Stoll and Whaley, 1983; Amihud and Mendelson, 1986; Brennan and Subrahmanyam, 1996; Butler, Grullon and Weston, 2005; Acharya and Pedersen, 2005). Therefore, based on precautionary savings view, if dividend smoothing is driven by external financing constraints, we would expect that stock liquidity reduces firm's incentive to smooth dividends.

We obtain a sample of 1,254 US public firms from period between 1993 and 2022 in the Compustat-CRSP universe. The measure for dividend smoothing employed in this study is modified speed of adjustment (SOA) proposed by Leary and Michaely (2011). This measure is estimated by regressing the changes in dividends per share on the deviation from the target payout ratio. The speed of adjustment is then captured by the coefficient on the deviation. To measure the stock liquidity, we employ closing percent quoted spread, calculated by dividing quoted bid-ask spread by the midpoint (Chung and Zhang, 2014).

To test our competing predictions, we estimate the speed of adjustment for each firm across whole sample period, and investigate the relation between stock liquidity and dividend smoothing in a cross-sectional setting. The results show that firms with more liquid stocks exhibit higher dividend smoothing. However, a possible concern is that firm's target payout rate may change over time, so is the speed of adjustment. Therefore, we follow Larkin, Leary and Michaely (2017) and Brockman, Hanousek, Tresl and Unlu (2022), and examine the effect of stock liquidity on dividend smoothing in a panel specification. Our baseline panel estimation shows that the higher liquidity leads to more dividend smoothing, consistent with our cross-sectional findings. The effect is economically significant. A one standard deviation increase in stock liquidity leads to 9.1% increase in dividend smoothing. To further check the robustness of our results, we employ alternative proxies for dividend smoothing and stock liquidity, and conduct propensity score matching analysis. We find the relation between stock liquidity and smoothing remains unchanged. Overall, our main empirical findings are supportive of the agency-based explanations, instead of infomation asymmetry models. This is broadly in line with Leary and Michaely (2011) and Javakhadze et al. (2014), who present the evidence that dividend smoothing is driven by agency considerations.

We rely on two approaches to control for potential endogeneity. First, as our primary interest is the causal effect of stock liquidity on dividend smoothing, we implement difference-in-difference (DID) analysis based on 2001 decimalization in US to reduce the potential for reverse causality. This event can be viewed as exogenous shock to stock liquidity, and has been widely discussed in prior literature (e.g., Fang, Noe and Tice, 2009; Edmans, Fang and Zur, 2013; Fang, Tian and Tice, 2014; Brogaard, Li and Xia, 2017; Chang, Chen and Zolotoy, 2017). In 2001, the Securities and Exchange Commission (SEC) mandated the transition of all US stock markets to the decimalization system. This alteration resulted in a reduction of the tick size from one-sixteenth to one cent, leading to significant improvement in market liquidity (Bessembinder, 2003). The results from DID estimation further confirm our baseline findings. Specifically, we find the effect is large: dividend smoothing increases by about 4.7% for the treatment firms after the decimalization compared with the control firms. Next, we employ instrumental variable analysis to mitigate the potential concern that both stock liquidity and dividend smoothing could be affected by unobserved omitted factors. The IV is calculated based on the median value of our liquidity measure in the industry. Our IV results indicate that the association between stock liquidity and dividend smoothing holds.

To test the potential mechanism through stock liquidity could drive smoothing behaviors, we focus on the role of financial constraints. According to Easterbrook (1984), firms with better access to external finance force management to rely on capital markets frequently by paying high and smooth dividends. Existing empirical evidence shows that stock liquidity may affect corporate policies through providing firms with lower costs of raising equity and reduce financial constraints (Shang, 2020). Therefore, we expect that stock liquidity could lead to more dividend smoothing by allowing firms to access equity market more easily. Using two measures of financial constraints, SA index Hadlock and Pierce (2010) and WW index Whited and Wu (2006), we show that stock liquidity leads to more dividend smoothing because it mitigates financial constraints.

Our study makes a twofold contribution to the existing literature. First, our paper expands previous empirical studies related to the factors influencing the practice of dividend smoothing. For example, Leary and Michaely (2011) challenge established information asymmetry models and show that the phenomenon of dividend smoothing is pervasive among firms characterized by lower level of information asymmetry, less financially constrained, and greater susceptibility to agency problems. Michaely and Roberts (2012) find that public traded firms exhibit more pronounced dividend smoothing in comparison to their private counterparts, underscoring the role of capital market scrutiny in leading to this practice. Additionally, Javakhadze et al. (2014) provide international evidence in support of the phenomenon of dividend smoothing. Furthermore, Garcia-Feijoo et al. (2021) have documented that the influence of executive social connections on dividend smoothing. Our evidence reveals the impact of one specific factor in financial markets, stock liquidity, on firm's propensity for engaging in smoothing behaviors.

Second, our paper also makes a valuable contribution to the empirical research that investigates the impact of stock liquidity on corporate outcomes. Existing empirical studies have documented the role of stock liquidity in enhancing firm value (Fang et al., 2009), inhibiting corporate innovation (Fang et al., 2014), increasing price crash risk (Chang et al., 2017), mitigating firm's default risk (Brogaard et al., 2017), reducing tax avoidance activities (Chen, Ge, Louis and Zolotoy, 2019), extending more trade credit (Shang, 2020), and improving corporate investment and productivity (Amihud and Levi, 2023). Complementing these diverse perspectives on stock liquidity, we focus on firm's dividend smoothing practice, and supports the bright side perspective of stock liquidity.

Our study is related to existing work by Banerjee, Gatchev and Spindt (2007) and Jiang, Ma and Shi (2017), but is different from them. In Banerjee et al. (2007), their focus centers on the idea that, in capital markets with frictions, higher stock liquidity allows investors to sell a proportion of their investment holdings more easily to generate homemade dividends if they need some cash inflows (i.e., liquidity needs), because firms with highly liquid shares have less trading frictions. It implies that less liquid stocks are more inclined to pay dividends to compensate the liquidity needs of investors. The evidence in Banerjee et al. (2007) supports this prediction and shows that investors who hold less liquid shares are more likely to receive dividends relative to those holding more liquid shares, suggesting that stock liquidity and dividends are substitutes. However, Jiang et al. (2017) deviate from this perspective. Their starting point is that higher stock liquidity reduces information asymmetry between corporate insiders and outside shareholders, and a more transparent environment disciplines managerial behaviors concerning retaining excess cash inside the firm for private use, implying that stock liquidity could lead to higher dividends. Jiang et al. (2017) then find a positive link between stock liquidity and dividend level. The main difference between our paper and these studies is that we undertake a specific focus on the smoothing pattern of dividends, instead of the level of payout. It is not clear whether stock liquidity plays a role in shaping this behavior of dividend policy, and if so, through what mechanisms stock liquidity induces managers to smooth. We attempt to address these questions in our analysis by focusing on the firms who pay dividends regularly.

The remainder of this paper is organized as follows. Section 2 reviews dividend smoothing and stock liquidity theories, then establish our main hypothesis. Section3 describes the data and research methods. In section 4, we present the main empirical results and further robustness checks. We discuss potential endogeneity in section 5. Section 6 investigates the effect of financial constraints. Section 7 concludes.

4.2. Related Literature

4.2.1. Why Do Managers Smooth Dividends?

The pioneering study on dividend smoothing was implemented almost 60 years ago by Lintner (1956). After detailed interviews with managers in 28 US firms, who are usually involved in corporate dividend decision-making (such as presidents, financial vice-presidents, or treasurers), Lintner observed that, when considering what magnitude of the dividend change should be, managers tend to keep stable dividend payout streams and avoid the cut and the significant increase in dividends (i.e., smoothing). Although this pattern of dividend payout is based on the survey of a small sample of firms, subsequent studies show consistent results with Lintner's analysis (e.g., Baker, Farrelly and Edelman, 1985; Fama and Babiak, 1968). Firms do smooth their dividends over a couple of decades, and Lintner's research remains the best description of such dividend behavior (Benartzi et al., 1997). However, there is considerable debate over why firms smooth their dividend payout. In this subsection, we review the theoretical work of smooth dividends and provide an overview of what drives such a smooth pattern.

Existing theoretical literature on explaining dividend smoothing behavior can be classified into two strands, asymmetric information and agency costs. In terms of information asymmetry, a number of studies suggest that managers know more about their business than outside investors, hence utilize dividend payment for delivering inside information about firm's existing earnings and future prospects to the market (i.e., signaling model) (e.g., Miller and Rock, 1985; Kumar, 1988; Guttman, Kadan and Kandel, 2010). It implies that the market believe firms will choose to pay stable and larger dividends if the payment of dividends can proxy for favorable private information of the firms. If smooth dividends arise from the manager's signaling behavior, we can expect that such smoothing efforts should be prevalent among the firms facing greater asymmetric information, such as those small and younger firms, with fewer tangible assets and more growth opportunities (Javakhadze et al., 2014).

Another description to dividend smoothing is associated with financial constraints and cash holdings. For those financially constraint firms, the access to external capital market is more costly, hence the firms exhibit a greater propensity to retain cash out of cash flows in response to adverse shocks (i.e., precautionary motivation) (e.g., Almeida et al., 2004; Bates et al., 2009). In this case, managers are more reliant on internal financing, tend to save earnings inside the firm, and are reluctant to pay high dividends as a result of uncertainty of cash flows (Chay and Suh, 2009). Therefore, dividend smoothing is associated with a low level of dividend payment and should prevail particularly among the firms with financial constraints.

Moreover, smooth dividends can be associated with information asymmetry between the principal and the agent. In the theoretical work by Fudenberg and Tirole (1995), the principal perceives recent earnings and dividend reports more informative than older ones to learn about firm's future prospect. Managers then generate smoothing behaviors in two ways: 1) overstating earnings and dividends during poorly performed periods to reduce the risk of dismissal; and 2) understating earnings and dividends during well performed periods and save for the future bad time (Fudenberg and Tirole, 1995). Similarly, a theoretical model by DeMarzo and Sannikov (2016) show that both principal and agent can learn about firm's expected future profitability from current cash flows. The firm's perceived profitability increases when current earnings are high, the agent retains excess cash to increase financial slack, instead of paying higher dividends, in order to protect from liquidating the firm, and hence dividend smoothing arises (DeMarzo and Sannikov, 2016).

In addition to information asymmetry models, previous literature also explains dividend smoothing behaviors via agency-based models. Given that the management cannot be perfectly monitored, dividend payout is used as the means of reducing agency costs associated with the separation of ownership and control. Paying dividends forces management to rely on external capital market for financing more frequently (Easterbrook, 1984). Therefore, high and continuous dividend payment exposes managers to monitoring and discipline by the outsiders who directly or indirectly finance the firm, such as investment bankers and other intermediary. Managers then have less opportunities to behave in line with their private benefits when scrutinized by these outside professionals. Moreover, another explanation to payout based on agency problems is introduced by Jensen (1986). In particular, Jensen (1986) argues that cash can be easily misused by managers for inefficient investment. When firms have large balance of excess cash, defined as 'free cash' by Jensen, managers can use this money in the investment inconsistent with shareholder's interests. Therefore, Jensen's analysis suggests that paying dividends can reduce the amount of free cash from the management control.

Another view on dividend smoothing argues that dividend smoothing is considered as a consequence of higher agency costs. Lambrecht and Myers (2012) and Lambrecht and Myers (2017) show that self-interested managers pay dividends to extract rents, defined as benefits of over market salaries, job security and generous pensions. In their model, managers demand a smooth flow of rents as a result of their risk aversion and habit formation, leading to smooth dividend payout. Furthermore, Wu (2018) shows how manager's career concern can generate smooth dividends. In this model, self-interested managers avoid dividend cuts, if at all possible, in order to protect their tenure (i.e., managerial turnover risk) when firm's earnings decrease, and they are also reluctant to increase dividend payment when firm's profitability improves, because they deviate so far from the turnover threshold in this case (Wu, 2018) [1].

4.2.2. Stock Liquidity: Causative Theories

The stock liquidity has received considerable researcher's interests in the field of financial economics. This topic is also of particular interest to policy makers given that the liquidity can be affected by the financial market and securities rules. To understand how stock liquidity influences firm's decisions and leads to different financial outcomes, we aim to provide an overview on two representative causative theories widely discussed in previous literature (i.e., agency and feedback).

Agency-based view argues that a liquid stock market influences corporate governance through large shareholder (i.e., blockholder) voice and exit. Voice refers to the direct intervention by blockholder in corporate operations via either formal (e.g., voting) or informal (e.g., private letter to the management) mechanisms. Exit refers to the threats of directly selling company's shares by blockholder. Maug (1998) models the incentives of monitoring (i.e., value-enhancing intervention) decision by large shareholders. Large shareholders engage in costly monitoring to a firm with the purpose to benefit from capital gains on their shares. However, free-rider problem allows small shareholders to benefit from large shareholder's monitoring efforts. In liquid stock markets, large shareholders have greater incentives to monitor because liquidity allows them to gain higher informed trading profits to recoup monitoring costs, and helps overcome the free-rider problem, and therefore leading to more effective corporate governance (Maug, 1998). Similarly, in Kahn and Winton (1998), high liquidity encourages voice because blockholder can benefit from informed trading through acquiring shares at a lower price, leading to initial block formation. Consistent with the voice mechanism, Norli, Ostergaard and Schindele (2015) find that, on average, the stock liquidity increases the likelihood of intervention because it allows shareholders to earn higher

[1] Wu (2018) also embeds information asymmetry between managers and outside investors in the model, in which a regular dividend stream signals strong earnings.

profits created by trading through their private information.

Although prior research on stock liquidity focuses on shareholder's voice, more recent literature has documented the second mechanism (i.e., shareholder's exit) through which liquidity facilitates governance. Admati and Pfleiderer (2009) model large shareholder's engagement in exit based on fundamental agency problems. If large shareholders observe manager's behaviors inconsistent with shareholder's interests and cannot exert governance through voice, they may vote with their feet and sell their stocks (i.e., the Wall Street Walk), which drives down firm's stock prices. Stock liquidity, here, makes such exit threat more credible because higher liquidity lowers the transaction costs of informed selling. Therefore, the exit threat has disciplining effect on the management if managerial compensation is tied to stock prices. Similar to the work of Admati and Pfleiderer (2009), Edmans (2009) also analyzes the role of blockholder exit in enhancing governance, In his analysis, managers may avoid to engage in favorable long-term investment as a result of the concern of short-term stock performance (managerial myopia). However, blockholder can learn from firm's current earnings by acquiring private information about firm's intrinsic value. If weak earnings are driven by poor quality of management, the blockholder directly disposes her shares, resulting in decline in stock prices. If the blockholder observes that long-term investment depresses current earnings, she keeps her stakes of the target firms because the benefits of that investment can be reflected in future share prices. Therefore, such blockholder's behaviors based on her private information can drive stock prices closely towards firm's fundamental value, and encourage managers to pursue value-enhancing investment. The stock liquidity then plays a key role in determining the effectiveness of blockholder exit: higher the liquidity causes greater efforts of information gathering because of more profits from trading, the exit is then more effective. Subsequent empirical studies, for example Edmans et al. (2013), support the view that higher stock liquidity enhances corporate governance through blockholder exit threat.

Note that the main difference between Edmans (2009) and Admati and Pfleiderer

(2009) is Admati and Pfleiderer analyze the nature of two distinct agency problems (free cash flows and shirking), while Edmans focuses on managerial myopia. The blockholder exit threat reduces the abuse of free cash flows (Admati and Pfleiderer's analysis), and encourages managers to invest in long-term projects (Edmans's analysis). However, Admati and Pfleiderer (2009) argue that, in some case, blockholder can make shirking problem even worse. If all investors can observe whether the manager has taken an action to increase firm value, but blockholder can observe the consequence of the action by having private information, the blockholder may sell her shares if the increase in the amount of firm value is small. Therefore, the informed selling not only drives down stock prices, but also reduces the manager's incentive to make the value-maximizing efforts.

Another causative theory, known as the feedback, argues that liquidity can influence firm's decision and operating performance even in the absence of agency problems. The feedback-based theory implies that managers can acquire important information that they do not have from the changes in share prices, and such information indirectly provides them with the guidance of investments (Dow and Gorton, 1997). Subrahmanyam and Titman (2001) argue that the effect of feedback can be dependent on the costs of information acquiring and trading environment. If liquidity providers are risk neutral, the increase in liquidity then facilitates the entry of informed investors, so the share price movement is more informative to firm's stakeholders, which enhances the feedback effect. In the analysis of Khanna and Sonti (2004), informed traders not only take into account the effect of their trading patterns on firm's investment decisions, but also further price changes caused by such effect. If the informed traders realize that their trading behaviors can induce firms to accept the value-increasing investment, they choose to trade aggressively and push share prices high, and then enhancing the information efficiency of share prices. Managers therefore learn from the share prices and invest in the project that adds value to the firm.

4.2.3. Stock Liquidity and Dividend Smoothing

Stock liquidity can have opposing effects on dividend smoothing. In this subsection, we develop two competing hypotheses, based on agency and information asymmetry channels, to explain how stock liquidity could affect a firm's decision to engage in dividend smoothing.

Agency Problem Channel

In the context of dividend policy and agency conflicts, two agency-based models have emerged as competing frameworks: the outcome model and the substitute model (La Porta et al., 2000). The outcome model posits that effective governance practices help reduce agency costs by incentivizing corporate insiders to distribute excess cash through dividend payments. La Porta et al. (2000) show that in countries where minority shareholders are better protected by the legal system, firms are forced to pay higher dividends due to enhanced rights of these shareholders. Therefore, corporate dividend policy is an outcome of the effective governance. Supporting this perspective, Michaely and Roberts (2012) find that public firms in the United Kingdom exhibit greater dividend smoothing and higher dividend payouts compared to their private counterparts, primarily due to more scrutiny imposed on public firms by external capital markets.

By contrast, the substitute model proposes an alternative perspective, suggesting that dividends can function as a substitute for robust governance mechanisms. According to this view, firms must establish a good reputation if they intend to raise external capital through capital markets on favorable conditions. Building such a reputation involves a continuous commitment of paying dividends as a decent treatment for shareholders (La Porta et al., 2000). By doing so, firms can mitigate what is left for insider's expropriation, and this commitment is considered credible due to the negative market reactions that often follow dividend cuts (Brav et al., 2005). However, the need for reputation development through dividend payments may be less pronounced for firms with stronger governance practices. This is because free cash flow problems among these firms are already constrained by effective governance. Consequently, managers in well-governed firms are less inclined to keep a regular dividend payment. In other words, the substitute view predicts that a higher and stable dividend payment is associated with weaker governance. Consistent with this view, existing empirical research has demonstrated that firms with weaker shareholder rights (Leary and Michaely, 2011) and a lower proportion of independent directors (Javakhadze et al., 2014) tend to engage in more dividend smoothing practices.

Stock liquidity can play an important role in curbing the abuse of free cash through imposing effective governance. As we discussed earlier in Section 2.2, enhanced liquidity not only facilitates active monitoring and intervention (referred to as voice) by shareholders (Maug, 1998), but also strengthens the credibility of their exit threats (e.g., Admati and Pfleiderer, 2009; Edmans, 2009). This disciplining impact of liquidity through voice and/or exit on corporate outcomes has been documented in existing empirical literature. For instance, Brav, Jiang, Partnoy and Thomas (2008) find that hedge fund activists are more likely to intervene in firms facing free cash flow issues, and higher liquidity enables these activists to acquire stakes more quickly. Their results show that such shareholder activism by hedge funds leads to increased abnormal returns for target firms after the announcement of interventions. In addition to active intervention, large shareholders can exert governance on target firms through the threats of exit. Edmans et al. (2013) find that governance through exit threats leads to positive abnormal returns and improved operating performance, and this effect is particularly strong for highly liquid stocks. Overall, building on above discussion, stock liquidity can have contrasting effects on dividends smoothing. From the perspective of the outcome model, if stock liquidity can be good for governance, one might expect that it would lead managers to maintain high and stable dividends, leading to dividend smoothing as a means to mitigate free cash flow problems. For example, shareholders could vote for directors who advocate steady dividend payments (Voice), or sell their holdings to potential takeovers (Exit), if the target firm fails to disgorge cash. On the other hand, from the viewpoint of the substitute model, higher stock liquidity could result in lower dividend smoothing, as firms with greater stock liquidity are already governed effectively, such governance already mitigates problems of free cash flow, and substitutes for the need of using dividends to establish a reputation.

Information Asymmetry Channel

From the perspective of the dividend signalling model, managers utilize dividend payments as a means to convey private information on the firm's earnings persistence (e.g., Kumar, 1988; Guttman et al., 2010). This signalling model of dividends predict that dividend smoothing would be prevalent among firms with opaque information environment (i.e., high degree of information asymmetry). Previous research has documented that stock liquidity plays an important role in mitigating information asymmetry between firm management and outside investors. Greater liquidity enables informed investors to earn more profit through their trading, which would motivate investors to acquire more information and encourage trading through their information, hence enhancing the informativeness of stock prices (e.g., Holden and Subrahmanyam, 1992; Holmström and Tirole, 1993; Subrahmanyam and Titman, 2001). Consequently, managers can learn such information conveyed by changes in stock prices to make more informed and efficient corporate decisions (e.g., Durnev et al., 2004; Luo, 2005; Chen, Goldstein and Jiang, 2007; Bakke and Whited, 2010). If stock liquidity reduces information asymmetry by enhancing the informativeness of share prices, it follows that firms with highly liquid stocks would exhibit less dividend smoothing since the need for signalling efforts becomes less essential.

Another manifestation of asymmetric information between corporate insiders and outsiders is external financing constraints. Due to precautionary savings motivation, financially constrained firms are reluctant to increase dividend payouts, opting instead to retain cash within the firms and avoiding dividend cuts (e.g., Almeida et al., 2004; Bates et al., 2009). Therefore, dividend smoothing is expected to be prevalent among firms with constraint access to external finance. Stock liquidity may affect dividend smoothing through easing firm's access to external capital. Prior literature in market microstructure provides evidence that liquidity reduces a firm's cost of raising external capital. For example, Stoll and Whaley (1983) argue that small firms may have higher required rate of return, relative to large firms, because of infrequent trading activities and higher risks on these firms. Amihud and Mendelson (1986) investigate relation between bid-ask spread and asset returns, and their findings imply that stock illiquidity increases firm's cost of capital. Brennan and Subrahmanyam (1996) use intraday data and further show that liquid shares have lower required rate of return. Additionally, Butler et al. (2005) investigate the relation between stock market liquidity and cost of accessing external financing. Their findings show that liquid firms have significantly lower cost of issuing equity, captured by dollar gross fee. These evidence of the empirical studies imply that higher stock market liquidity lowers the cost of raising capital and improves firm's access to external financial markets. Therefore, if firms with liquid stocks have better access to external capital, we could conjecture that these firms would be less inclined to engage in dividend smoothing.

Based on the above discussion, we state our competing hypotheses as follows:

H1a. *Firms with highly liquid stock smooth their dividends more.*

H1b. *Firms with highly liquid stock smooth their dividends less.*

4.3. Research Methods

4.3.1. Sample Selection

To construct our sample, we start with collecting financial data from Compustat and stock data from CRSP from 1993 to 2022. The sample period initiates in 1993 is because closing ask price and closing bid price are available for all NYSE and NASDAQ securities since the end of 1992 in CRSP database. We follow Hasbrouck (2009) and focus on ordinary common shares (CRSP share code 10-11). To limit the sample to firms for which we are able to calculate dividend smoothing, we follow the procedure of Leary and Michaely (2011) and Larkin et al. (2017). First, we keep firms with at least 10 years of continuous non-missing data for dividend per share, earnings per share and adjustment factor. We then remove observations before each firm's first positive value for dividend per share and after each firm's last positive dividend per share. We also exclude financial firms (SIC 6000-6999). Our final sample includes 1,254 unique firms representing 22,535 firm-year observations from the period between 1993 and 2022.

A potential concern related to our sample construction is that we only keep dividend-paying firms in the final sample. We recognize that existing empirical research on payout level also takes into account the cases of non dividend-paying firms. However, our analysis focuses on dividend smoothing, including firms with zero dividend payment can plague our findings. Non dividend-paying firms have a steady dividend stream of zeros, this indicates that such firms are the smoothest in their dividend payment. This smoothing pattern of non dividend-paying firms is fundamentally different from the smoothing practice of dividend-paying firms. Therefore, we draw a sample of firms with a positive dividend stream to conduct the analysis with our best effort, and our findings are applicable only to the dividend-paying firms.

4.3.2. Measuring Dividend Smoothing

To measure dividend smoothing, we employ the augmented speed of adjustment (SOA) in Leary and Michaely (2011). Specifically, we estimate the SOA based on two-step procedure. First, we calculate the firm's payout ratio by dividing common dividends by income before extraordinary items, and estimate the median target payout ratio (TPR) for individual firm by using a 10-year rolling window (from period $t-9$ to period t). Then, for each period t, we use the following equation to calculate the deviation (DEV) from the target payout:

$$DEV_{it} = TPR_{it} * EPS_{it} - DPS_{it-1}, \tag{4.1}$$

Where TPR, is the target payout ratio; EPS is the earning per share; DPS is the dividend per share in the previous period. Note that both earning per share data and dividend per share data are adjusted for stock split.

For the second step, we estimate the regression of the firm's actual changes in dividends on deviations (DEV):

$$\Delta DPS_{it} = \alpha + \beta * DEV_{it} + \varepsilon_{it}, \tag{4.2}$$

This regression is also estimated by each firm for a 10-year rolling window. The coefficient (β) on the deviations is referred to the speed of adjustment (SOA). The higher level of SOA, the more the firm changes its dividend based on the changes in earnings, and the less smooth its dividends. Leary and Michaely (2011) suggest that SOA is conceptually limited between 0 and 1. Therefore, we restrict our SOA measure between 0 and 1.

4.3.3. Measuring Stock Liquidity

Following Amihud and Levi (2023) and Chung and Zhang (2014), we consider Closing Percent Quoted Spread, based on CRSP daily bid-ask data, as the main liquidity measure. As shown in Fong, Holden and Trzcinka (2017), daily Closing Percent Quoted Spread can be the best daily percent-cost proxy in US data. It is calculated by using the dollar quoted spread divided by the quote's midpoint, then calculate the yearly mean value of Closing Percent Quoted Spread:

$$Spread_{it} = \frac{ASK_{id} - BID_{id}}{Mid_{id}}, \tag{4.3}$$

Where ASK_{id} is the ask price of a stock i on day d, BID_{id} is the bid price of a stock i on day d, Mid_{id} is the mean of ASK_{id} and BID_{id}. To reduce the effect of data errors and outliers, we exclude $Spread_{id}$ that are greater than 50% of the quote midpoint. Lastly, we calculate the yearly average value for $Spread_{id}$ of each stock.

4.3.4. Control Variables

We follow prior literature and take into account a number of control variables to proxy for market frictions. We first control for several proxies for agency costs. Prior agency models suggest that a stable and high level of dividend payment is considered as the means of controlling for free cash flow problems (Jensen, 1986). Increase in firm's free cash flow is likely to exacerbate manager-shareholder agency costs, therefore leading to more dividend smoothing to reduce such agency costs. We follow Javakhadze et al. (2014) and consider three proxies for the degree of free cash flow problems: market-to-book ratio, firm's cash flow divided by total assets, and free cash ratio (operating income before depreciation minus interest expense, taxes, preferred dividends, and common dividends, scaled by total assets). Firms with low market-to-book ratio are likely to have excess cash relative to profitable investment opportunities (Fama and French, 2002), leading to greater conflicts of interests. We therefore expect firms with low market-to-book ratio, more cash scaled by total assets, and high free cash ratio smooth more dividends. In Allen, Bernardo and Welch (2000), high dividend-paying firms are considered to be more attractive to institutional investors, so managers are forced to keep high and stable dividend level demanded by these investors. We use payout ratio as the measure of dividend level.

We then control for a set of proxies for information asymmetry. From the perspective of asymmetric information models, smooth dividends are viewed as the signal of firm's private information about earnings and future cash flows (Kumar, 1988). Mature and large firms tend to face less information asymmetry as they are better known compared to small and younger firms (e.g., Frank and Goyal, 2003; Lemmon and Zender, 2010). We therefore control for firm size and firm age as proxies for maturity. We also control for tangibility since firm's tangible assets (net property, plant and equipment) can be easily valued by outside investors than intangible assets (Harris and Raviv, 1991). Furthermore, we use earnings volatility and stock return volatility as additional proxies for information asymmetry and risk (O'Hara, 2003), as the firms with high volatility are viewed to be less predictable than the less volatile firms. We finally control for stock turnover as dividend smoothing is likely to increase with the decrease in investment horizon of investors (Guttman et al., 2010).

4.3.5. Baseline Model

Our baseline empirical specification used to investigate the relation between stock liquidity and dividend smoothing is as follows:

$$SOA_{it} = \alpha + \beta_1 Ln(Spread_{it-1}) + \beta_2' \mathbf{X}_{it-1} + \gamma_t + \delta_j + \varepsilon_{it}, \tag{4.4}$$

Where the subscript i and t denote firm i in year t respectively. The dependent variable, SOA, is speed of adjustment. $Ln(Spread)$ is the independent variable of our primary interest, defined as the natural logarithm of Closing Percent Quoted Spread. **X** is a vector of control variables, including cash ratio, market-to-book ratio, stock turnover, firm size and age, volatility of return and earnings, tangibility and payout ratio.. To mitigate the influences of unknown omitted factors, we control for year fixed effects (γ_t) and industry fixed effects (δ_j). To address outliers in our dataset, we employ winsorization on all continuous variables, limiting them at 1st and 99th percentiles within their distributions.

4.4. Empirical Results

4.4.1. Cross-Sectional Analysis

We first examine the relation between stock liquidity and dividend smoothing in a cross-sectional setting. Specifically, we estimate SOA defined in Eq.(4.2) for each firm over the sample period from 1993 to 2022, then take median value for stock spreads and firm-level characteristics specified in Eq.(4.4) for each firm. Panel A of Table 4.1 reports descriptive statistics for all variables. The median and mean of SOA are 0.122

and 0.235 respectively. Our sample firms have both moderate volatility in earnings (mean of 0.056) and stock returns (mean of 0.089). The mean of market-to-book ratio is 1.766, indicating that sample firms have good growth opportunities.

Panel B of Table 4.1 shows the results for univariate analysis. In particular, we sort firms into SOA quartile, and for each quartile from columns (1) to (4) we report the mean value of stock liquidity and firm characteristics. In column (5), we show the difference in liquidity and firm characteristics between low SOA (first quartile) and high SOA (fourth quartile). We find that firms with highly liquid stocks smooth their dividends more. For control variables, high-dividend-smoothing-firms tend to be significantly large in size, and less volatile in earnings and returns, and pay higher dividends.

We further examine the relationship between stock liquidity and dividend smoothing using a multivariate regression analysis. We regress dividend smoothing (SOA) on stock liquidity ($Ln(Spread)$) and control variables. Table 4.3 reports the results. We control for industry fixed effects and use heteroscedasticity-robust standard errors. Column (1) presents the regression of SOA on $Ln(Spread)$ only. Across columns (2) through (11), we introduce one proxy for agency costs or the degree of information asymmetry in each column. In column (12), we include stock liquidity and all firm characteristics as independent variables simultaneously. However, the coefficient on $Ln(Spread)$ becomes insignificant in columns (6) and (12). One possible reason is that firms with larger size and lower volatility in return tend to be more predictable, and suffer from less information asymmetry, which can be also captured by higher stock liquidity. Therefore, both $Firm\ size$ and $Std(Return)$ could be highly correlated with $Ln(Spread)$. We then drop $Firm\ size$ and $Std(Return)$ in column (13). The coefficient sign and significance on $Ln(Spread)$ is consistent with previous columns, except columns (6) and (12).

Across all specifications, except column (5), the coefficient on $Ln(Spread)$ is positive and significant at 1% level, indicating that high liquid stocks tend to smooth dividends more. Turning to control variables, firms with large size, lower volatility of earnings and returns, and high dividend levels have more dividend smoothing. This results are generally in line with Leary and Michaely (2011) and Javakhadze et al. (2014).

4.4.2. Dividend Smoothing and Stock Liquidity: Results from Baseline Panel Regressions

In this subsection, we investigate the effect of stock liquidity on dividend smoothing by estimating our baseline panel specification Eq.(4.4) as the panel setting contains more information and variability than cross-sectional analysis. Both SOA and target payout ratio are estimated using 10-year rolling window as described in Section 3.2. This can help reduce the concern that firm's target payout ratio may not hold constant over time. Therefore, in our panel analysis, we obtain a time series of SOA for each firm during the sample period between 1993-2022. We present descriptive statistics for all variables used in the regression in Table 4.4. Our stock liquidity measure, $Ln(Spread)$, has mean value of -5.986 and standard deviation of 1.752, in line with Amihud and Levi (2023).

We present regression results in Tale 4.5. Standard errors are clustered at the firm level. All independent variables, including our liquidity measure, are lagged by one year. In column (1), we only regress dividend smoothing on the stock liquidity. The coefficient on $Ln(Spread)$ is positive and significant at 1% level, indicating that firms with high stock liquidity have more dividend smoothing. The effect is economically significant: a one standard deviation increase in $Ln(Spread)$ is associated with 9.1% increase in SOA [2]. In column (2), we add all firm characteristics specified in Eq.(4.4). The estimated coefficient on $Ln(Spread)$ remains positive and significant. Although the magnitude of the coefficient is attenuated, the effect is still economically significant. A one-standard-deviation increase in $Ln(Spread)$ is associated with 5.4% increase in SOA. To mitigate the effect of unobserved omitted factors across firms, we re-estimate our

[2] The coefficient on $Ln(Spread)$ is 0.052, and its standard deviation is 1.752. Therefore, a one-standard-deviation increase of $Ln(Spread)$ is associated with increase in SOA about 9.1% (0.052*1.752=0.091)

baseline specification and control for firm fixed effects. Results are presented in column (3), showing that the positive relation between $Ln(Spread)$ and SOA is unchanged. Overall, our results of panel regressions show that firms with greater stock liquidity smooth their dividends more. We conclude from cross-sectional and panel analysis that our evidence is supportive of agency-based models, as opposed to the dividend signalling and precautionary savings models.

For control variables, we show that firms that are large and mature, have lower volatility and low market-to-book ratio, and pay higher dividends tend to smooth more. This is consistent with the findings of Leary and Michaely (2011).

4.4.3. Further Robustness

Alternative Measures for Liquidity

The documented relation between stock liquidity and dividend smoothing could be driven by our choice of stock liquidity measures. To alleviate this concern, we consider the following three alternative measures of stock liquidity.

First, we employ Amihud (2002) illiquidity ratio, Amihud, defined as the absolute value of daily stock return divided by daily dollar trading volume:

$$Amihud_{it} = \frac{1}{D_{it}} \sum_{d=1}^{D} \frac{|Ret_{idt}|}{Volume_{idt}}, \tag{4.5}$$

Where Ret_{idt} and $Volume_{idt}$ are, respectively, the stock return and the trading volume in million dollars for firm i on trading day d in year t. D_{it} is the number of trading days for firm i in year t. A higher value of Amihud illiquidity ratio corresponds to lower liquidity.

Second alternative measure of liquidity is $Zeros$ of Lesmond, Ogden and Trzcinka (1999), defined as the proportion of days with zero returns:

$$Zeros_{it} = \frac{Zero\ Return\ Day_{it}}{Total\ Day_{it}}, \tag{4.6}$$

Where $Zero\ Return\ Day_{it}$ and $Total\ Day_{it}$ are the number of zero-return days and total number of trading days for firm i in year t. A higher value of Zeros represents lower liquidity.

Finally, we consider FHT, developed by Fong et al. (2017), as another alternative proxy for liquidity. The advantage of this measure is to combines two features of transaction costs: 1) return volatility; and 2) ratio of zero return. It can be computed as:

$$FHT_{it} = 2 * \sigma * N^{-1}(\frac{1 + Zeros}{2}), \tag{4.7}$$

Where σ is standard deviation of daily returns for firm i in year t. $Zeros$ is the proportion of days with zero returns. $N^{-1}()$ is the inverse function of the cumulative normal distribution. A higher value FHT indicates lower liquidity. As argued by Edmans et al. (2013), both $Amihud$ and FHT are highly skewed, we then take natural logarithm of these two measures respectively, $Ln(Amihud)$ and $Ln(FHT)$.

We re-examine the baseline specification, except replacing our main liquidity measure with $Ln(Amihud)$, $Zeros$ or $Ln(FHT)$. Table 4.6 reports the results from these regressions. Across all models, the coefficients on liquidity measures are positive and significant at 1% level, suggesting that our findings are not affected by the use of different liquidity measures.

Alternative Measures for Dividend Smoothing

We take into account a number of alternative proxies for dividend smoothing to further check the robustness of our findings. First, we follow Leary and Michaely (2011) and employ a non-parametric measure of dividend smoothing, referring to relative volatility. This measure capture volatility of dividends relative to volatility of earnings:

$$DPS_{it} = \alpha_1 + \beta_1 T + \beta_2 T^2 + \varepsilon_{it}, \tag{4.8}$$

$$TPR_i * EPS_{it} = \alpha_2 + \gamma_1 T + \gamma_2 T^2 + \delta_{it}, \tag{4.9}$$

$$RELVOL = \sigma(\varepsilon)/\sigma(\delta), \tag{4.10}$$

Where T and T^2 are time and quadratic time trends respectively. DPS, EPS and TPR are split adjusted dividends per share, earnings per share and target payout ratio as described in Section 3.2. Relative volatility ($RELVOL$) is then estimated by the ratio of root mean squared errors from above two regressions ($\sigma(\varepsilon)/\sigma(\delta)$). The higher value the relative volatility, the more smooth the firms dividends. Consistent with the procedure of estimating SOA, we also use 10-year rolling window to estimate relative volatility ($RELVOL10$). However, one potential concern is length of the rolling window used to estimate our dividend smoothing measure. To further confirm that our baseline results are not plagued by the choice of rolling windows. We re-estimate both $RELVOL$ and SOA using 7-year and 5-year rolling windows.

Table 4.7 reports regression results. In columns (1)-(3), we return to our baseline specification Eq.(4.4), except replacing the dependent variable with the relative volatility estimated using 10-year ($RELVOL10$), 7-year ($RELVOL7$) and 5-year ($RELVOL5$) rolling windows. In columns (4) and (5), we continue to use speed of adjustment as dependent variable, but employ 7-year ($SOA7$) and 5-year ($SOA5$) rolling windows. Across all these models, the estimated coefficients are positive and significant at either 1% or 5% levels, implying that our main findings are not affected by using alternative measures of dividend smoothing.

Propensity Score Matching Analysis

As another robustness check, we employ propensity score matching approach to reduce the effect of potential confounding factors. To conduct PSM analysis, we first rank $Ln(Spread)$ for each year, and classify firm-years in the top quartile into treatment group and those in the bottom quartile into control group. The sample used for conducting PSM includes 11,292 firm-year observations, representing 1,176 unique firms. To produce propensity score, we then run a Probit regression using $Treat$ as dependent variable. $Treat$ is a dummy variable that equals to one for firm-years in treatment group and zero for those in control group. The covariatea used in PSM analysis are specified in our main model Eq.(4.4). We next match treatment group and control group using one-to-one nearest neighbour matching with replacement and require that the difference in propensity scores between treatment group and control group does not exceed 0.1% in absolute value. This procedure generates a matched sample consisting of 803 firm-years.

We report our PSM estimates in Table 4.8. Panel A shows univariate comparison of covariates between treatment and control groups. As expected, there is no significant difference in firm characteristics across two groups after matching. In Panel B, we report average treatment effect on the treated. The coefficient is positive and significant at 1% level, indicating that firms in the treatment group have higher SOA compared to those in the control group. Finally, we re-estimate our baseline specification based on matched sample. The estimate on $Ln(Spread)$ remains positive and significant at 5% level. This is consistent with our main results.

4.5. Controlling Endogeneity

4.5.1. Decimalization in US

Although we use one-year lag for all independent variables in the baseline model to make a better causal inference, the potential for reverse causality regarding the relation between stock liquidity and dividend smoothing remains. This issue is particularly important because it cannot be mitigated by simply using lagged independent variables. Specifically, firms that adopt dividend smoothing policies may attract investors with a preference of receiving regular dividends. Such investors prefer to trade and invest in the stocks of these firms, resulting in higher stock liquidity. In order to mitigate this possibility, we employ a difference-in-difference (DID) design based on 2001 decimalization.

In 2001, Securities and Exchange Commission (SEC) ordered all stock markets within US to convert to decimalization system, where securities are quoted using the decimal format. Decimal pricing fully adopted on 29 January 2001 for NYSE-AMEX listed stocks and on 9 April 2001 for NASDAQ listed stocks. Before this implementation, the minimum price movement in a security price quote was one-sixteenth $(1/16), or$ 0.0625. With decimalization, the smallest price change has now become one cent ($0.01). Previous studies find that liquidity increases due to decimalization. For example, Bessembinder (2003) shows that quoted bid-ask spreads declined substantially in both NYSE and NASDAQ after decimalization, particularly for those heavily traded stocks.

Many studies employ decimalization as exogenous positive shock to stock liquidity (e.g., Bharath, Jayaraman and Nagar, 2013; Edmans et al., 2013; Fang et al., 2014; Brogaard et al., 2017). In this study, we also consider decimalization as a good candidate for exogenous shock to liquidity to mitigate the concern of reverse causality. The implementation of decimalization by SEC is to lower trading cost and encourage investors to place their trades, and hence it directly influences stock liquidity, instead of dividend smoothing. If more liquid stocks are associated with dividend smoothing, one could expect that a greater increase in liquidity after decimalization leads to more smoothing pattern. To test this conjecture, we employ the following difference-in-difference specification:

$$SOA_{it} = \alpha + \beta_1 Post + \beta_2 Treat + \beta_3 Post * Treat + \beta_4' \mathbf{X}_{it-1} + \delta_J + \varepsilon_{it}, \tag{4.11}$$

We follow Fang et al. (2014) and Brogaard et al. (2017) and define treatment (control) group based on the change in firm's liquidity. Specifically, we first calculate liquidity change by using $Ln(Spread_{2002})$ minus $Ln(Spread_{2000})$ for each firm, and then sort all firms into terciles based on their liquidity change. We define firms in the treatment group if they belong to first tercile ($Treat$=1), and in the control group if they belong to third tercile ($Treat$=0). Treatment group includes 136 firms, while control group includes 134 firms. Our DID analysis is based on pre-decimalization window (1999-2000) and post-decimalization window (2002-2003), here excluding decimalization year (2001). $Post$ is a dummy variable that equals one for post-decimalization window, and zero for pre-decimalization window. Our DID specification also includes all firm characteristics in the baseline model. The primary interest is the coefficient on the interaction term, $Treat * Post$. Firms in the treatment (control) group experienced the greatest (smallest) increase in liquidity after decimalization. Therefore, we expect that β_3 is positive.

Before estimating the DID regression, we employ entropy balance to re-weight mean, variance and skewness of the covariates, measured in 2000 (one year before decimalization), between treatment and control. This approach generates treatment group and control group with firms having not significant difference in characteristics before decimalization. Panel A of Table 4.9 reports comparison of covariates between treatment and control pre and post balancing in pre-decimalization year. The mean, variance and skewness of covariates present no observable difference between treatment and control after balancing. We next implement DID analysis. Results are presented in Panel B of Table 4.9. Consistent with our prediction, the coefficient on the interaction term is positive and significant at the 5% level. The interpretation is that, treatment firms, whose stocks experienced greater liquidity increase following decimalization, have more dividend smoothing, compared with control firms. The results further confirm our baseline finding. Note that we skip decimalization year 2001 in our DID analysis. However, our results remain unchanged when including decimalization year. These results are reported in Table 4.2 of Appendix.

4.5.2. Instrumental Variable Regression

Our previous results suggest causal effect of stock liquidity on dividend smoothing. However, the association between stock liquidity and dividend smoothing can be affected by omitted unknown heterogeneity. To reduce this potential concern, we employ instrumental variable analysis. Our IV is defined as the median value of our liquidity measure in the industry (based on two digit SIC) that a firm belongs to, $Industry\ median\ Ln(Spread)$. The idea is that firm's stock liquidity at the industry level tends to be more exogenous, and we expect stock liquidity is positively associated with the IV.

We report our instrumental variable estimations in Table 4.10. As the first-stage estimation, in column (1), we regress stock liquidity, $Ln(Spread)$, on the IV and firm characteristics. As expected, the coefficient on the IV is significant at 1% level, and positively associated with our liquidity measure. Moreover, Kleibergen-Paap rk Wald F statistic is 43.84, indicating that our instrument is not weak.

Column (2) shows results for the second-stage regression. We continue to use our baseline specification, except that the independent variable of our interest is replaced with fitted value of stock liquidity, $Fitted\ Ln(Spread)$, estimated from the first-stage regression. The coefficient on $Fitted\ Ln(Spread)$ is positive and significant at 5% level, indicating that the relation between stock liquidity and dividend smoothing is affected by omitted variable bias.

4.6. The Effect of Financial Constraints

In this section, we aim to examine how the relation between stock liquidity and dividend smoothing varies with financial constraints. From perspective of precautionary saving motives, dividend smoothing, as discussed previously in Section 2, arises because firms are reluctant to increase dividend payment. This smoothing behavior is therefore expected to be pronounced among financially constrained firms. However, Leary and Michaely (2011) challenge the arguments based on precautionary savings view, they find that dividend smoothing prevails among not financially constrained firms. This finding is supportive of the agency-based explanations: firms with low cost of external financing pay a high and smooth dividend, which forces managers to rely on external capital more frequently, and hence reducing agency costs by subjecting managers to frequent scrutiny of the financial markets (Easterbrook, 1984).

We propose that stock liquidity contributes to more dividend smoothing through lowering the cost of raising external capital and relaxing financial constraints. To test this mechanism, we two measures for financial constraints, SA index and WW index. SA index is calculated following Hadlock and Pierce (2010) as: $-0.737 * Firm\ size + 0.043 * Firm\ size^2 - 0.040 * Firm\ age$. When constructing SA index, $Firm\ size$ and $Firm\ age$ are capped at \$4.5 billion and 37 years respectively. WW index is calculated following Whited and Wu (2006) as: $-0.091 * Cash\ flow - 0.062 * Dividend + 0.021 * Long-term\ debt - 0.044 * Firm\ size + 0.102 * Industry\ sales\ growth - 0.035 * Sales\ growth$. Higher SA index and WW index imply greater financial constraints. We then use following two empirical specifications to examine how stock liquidity affects dividend smoothing through financial constraints:

$$Constraints_{it} = \alpha_0 + \alpha_1 Ln(Spread_{it-1}) + \beta_2' \mathbf{X}_{it-1} + \gamma_t + \delta_j + \varepsilon_{it}, \tag{4.12}$$

$$SOA_{it} = \beta_0 + \beta_1 Constraints_{it-1} + \beta_2' \mathbf{X}_{it-1} + \gamma_t + \delta_j + \mu_{it}, \tag{4.13}$$

Where $Constraints$ refers to our measures for financial constraints, SA index or WW index. Stock liquidity measure and control variables are defined in our baseline model Eq.(4.4). In Eq.(4.12), we estimate the association between stock liquidity and financial constraints. Eq.(4.13 estimates how financial constraints affect dividend smoothing. Our results are reported in Table 4.11. In columns (1) and (3), the coefficients on stock liquidity, $Ln(Spread)$, are negative and significant at 1% level, indicating that highly liquid stocks alleviate financial constraints. In columns (3) and (4), we find negative and significant coefficients on $Constraints$ (at 1% level), which supports the findings in Leary and Michaely (2011) and Garcia-Feijoo et al. (2021) that dividend smoothing is common among not financially constrained firms.

4.7. Conclusion

In this paper, we investigate the effect of stock liquidity on firm's dividend smoothing policies by testing two competing predictions derived from information asymmetry and agency theories. Firms suffering from asymmetric information have greater incentives to pay regular dividends for signalling purpose. From this perspective, we hypothesize that higher stock liquidity reduces the need to use dividend smoothing to signal because it mitigates information asymmetry. Conversely, based on the agency view, we predict that firms with liquid stocks smooth their dividends more. This is because stock liquidity enhances intervention and exit threats of outside shareholders, thereby forcing managers to disgorge excess cash by paying high and steady dividends.

Using a sample of US public firms during the period between 1993 and 2022, we find that firms with liquid stocks tend to smooth their dividends more. Our finding is robust to multiple measures for liquidity and dividend smoothing. To mitigate potential for reverse causality, we employ DID analysis and focus on the exogenous regulatory change regarding US decimalization in 2001. The results further confirm our baseline findings. In order to explore the potential mechanism through stock liquidity influences dividend smoothing, we find that higher stock liquidity improves firm's access to external capital, leading to more smoothing. Overall, our findings are more consistent with the agency-based explanations of dividend smoothing.

This study provides insight into the factors of determining firm's dividend smoothing practices. We show that one specific force within the capital market, stock liquidity, can shape such smoothing behavior.

Tables for Chapter 4

Table 4.1: Cross-sectional Univariate Analysis

The sample consists of 1,254 firms during the period between 1993 and 2022. SOA of each firm is estimated across the whole sample period. stock liquidity and firm-level characteristics are calculated based on the sample median for each firm. Panel A reports summary statistics for all variables specified in Section 3.4. Panel B reports univariate analysis for stock liquidity and firm characteristics across dividend smoothing quartiles. For each dividend smoothing quartile, the mean value of each variable is reported in columns (1)-(4). Column (5) reports the results of a t-test of the difference in means between the top and bottom quartiles. P-values are reported in the parentheses. All variables are defined in Table 4.1 of Appendix. 1% Significance level *** 5% Significance level ** 10% Significance level *

Panel A. Summary statistics

VARIABLES	(1) N	(2) Mean	(3) Std.Dev	(4) Min	(5) Max	(6) p25	(7) p50	(8) p75
SOA	1,254	-0.2352	0.2866	-1.0000	0.0000	-0.3227	-0.1220	-0.0222
$Spread$	1,254	0.0065	0.0112	0.0002	0.1069	0.0007	0.0015	0.0076
$Ln(Spread)$	1,254	6.0948	1.4414	2.2354	8.7690	4.8782	6.4798	7.2225
$Market\_to\_Book$	1,254	1.7006	0.6801	1.0230	3.5341	1.2166	1.4565	1.9517
$Cash$	1,254	0.1023	0.1183	0.0013	0.6211	0.0226	0.0592	0.1360
$Free\ cash$	1,254	0.0782	0.0366	0.0020	0.1837	0.0534	0.0771	0.1002
$Turnover$	1,254	0.1235	0.0882	0.0071	0.4713	0.0623	0.1046	0.1604
$Firm\ size$	1,254	7.2447	1.8358	-0.8867	12.8357	6.0813	7.3569	8.4898
$Firm\ age$	1,254	2.5346	0.3732	1.7006	3.2385	2.2499	2.7081	2.7403
$Std(Return)$	1,254	0.0890	0.0277	0.0364	0.2684	0.0692	0.0859	0.1047
$Std(EBITDA)$	1,254	0.0564	0.0391	0.0108	0.2292	0.0303	0.0457	0.0713
$Tangibility$	1,254	0.3254	0.2318	0.0013	0.9397	0.1378	0.2566	0.4834
$Payout$	1,254	0.3108	0.2312	0.0000	1.0805	0.1357	0.2685	0.4456

Panel B. Univariate comparison

	SOA quartiles				
VARIABLES	(1) Q1	(2) Q2	(3) Q3	(4) Q4	(5) (Q4-Q1)
$Ln(Spread)$	5.8410	6.0814	6.0655	6.3912	0.5501***
					(0.000)
$Market\_to\_Book$	1.8332	1.5789	1.6295	1.7603	-0.0728
					(0.199)
$Cash$	0.1492	0.0899	0.0796	0.0905	-0.0586***
					(0.000)
$Free\ cash$	0.0806	0.0745	0.0738	0.0839	0.0033
					(0.279)
$Turnover$	0.1204	0.1364	0.1188	0.1183	-0.0021
					(0.763)
$Firm\ size$	6.5277	7.2683	7.4298	7.7538	1.2260***
					(0.000)
$Firm\ age$	2.5768	2.5176	2.5194	2.5242	-0.0526*
					(0.086)
$Std(Return)$	0.1001	0.0920	0.0837	0.0801	-0.0199***
					(0.000)
$Std(EBITDA)$	0.0693	0.0602	0.0486	0.0473	-0.0220***
					(0.000)
$Tangibility$	0.3066	0.3377	0.3414	0.3149	0.0083
					(0.646)
$Payout$	0.2733	0.3186	0.3478	0.3036	0.0303*
					(0.088)
N	314	313	313	314	628

Table 4.2: Correlation Matrix

VARIABLES	*SOA*	*Ln(Spread)*	*Market_to_Book*	*Cash*	*Free cash*	*Turnover*	*Firm size*
SOA	1						
Ln(Spread)	0.119***	1					
Market_to_Book	-0.082***	0.324***	1				
Cash	-0.216***	-0.046	0.355***	1			
Free cash w	-0.029	0.181***	0.489***	-0.003	1		
Turnover	0.018	0.564***	0.087***	0.041	0.176***	1	
Firm size	0.233***	0.671***	0.090***	-0.295***	0.149***	0.387***	1
Firm age	-0.044	0.489***	0.157***	0.101***	0.057**	0.237***	0.161***
Std(Return)	-0.275***	-0.272***	-0.165***	0.197***	0.023	0.243***	-0.303***
Std(EBITDA)	-0.207***	-0.082***	0.253***	0.389***	0.201***	0.202***	-0.255***
Tangibility	0.037	-0.016	-0.259***	-0.401***	0.015	0.036	0.060**
Payout	0.110***	0.078***	0.126***	0.002	-0.286***	-0.181***	0.0120

VARIABLES	*Firm age*	*Std(Return)*	*Std(EBITDA)*	*Tangibility*	*Payout*
Firm age	1				
Std(Return)	-0.109***	1			
Std(EBITDA)	0.070**	0.393***	1		
Tangibility	-0.116***	-0.165***	-0.127***	1	
Payout	-0.017	-0.461***	-0.172***	0.220***	1

Table 4.3: Dividend Smoothing and Stock Liquidity: Cross-Sectional Results

This table reports cross-sectional regression results of dividend smoothing on stock liquidity. The dependent variables across all regressions are SOA. The main independent variable is $Ln(Spread)$. Firm-level characteristics include cash, market-to-book ratio, stock turnover, firm size, firm age, standard deviation of stock returns, standard deviation of EBITDA, dividend payout ratio and tangibility. SOA is estimated over the sample period. Independent variables are medians over the sample period. All variables are defined in Table 4.1 of Appendix. t-statistics are presented in parentheses. Standard errors are adjusted for heteroscedasticity. 1% Significance level *** 5% Significance level ** 10% Significance level *

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	((13)
VARIABLES	SOA	SOA	SOA	SOA	SOA	SOA	SOA	SOA	SOA	SOA	SOA	SOA	SOA
$Ln(Spread)$	0.036***	0.044***	0.033***	0.036***	0.035***	-0.011	0.046***	0.020***	0.032***	0.037***	0.035***	-0.018	0.028***
	(5.35)	(6.07)	(5.02)	(5.34)	(4.34)	(-1.19)	(5.86)	(2.78)	(4.81)	(5.30)	(5.20)	(-1.48)	(2.69)
$Market\_to\_Book$		-0.048***										-0.036*	-0.032
		(-2.67)										(-1.66)	(-1.38)
$Cash$			-0.576***									-0.356***	-0.494***
			(-5.64)									(-3.15)	(-4.26)
$Free\ cash$				0.038								0.086	0.476
				(0.12)								(0.22)	(1.20)
$Turnover$					0.054							0.508***	0.230
					(0.37)							(3.18)	(1.52)
$Firm\ size$						0.055***						0.031***	
						(7.88)						(4.17)	
$Firm\ age$							-0.073**					-0.027	-0.040
							(-2.55)					(-0.95)	(-1.42)
$Std(Return)$								-2.675***				-2.542***	
								(-5.67)				(-4.40)	
$Std(EBITDA)$									-1.338***			-0.178	-0.776**
									(-4.42)			(-0.55)	(-2.37)
$Tangibility$										0.021		-0.134*	-0.147*
										(0.26)		(-1.82)	(-1.83)
$Payout$											0.073	0.068	0.154***
											(1.49)	(1.31)	(2.88)
Constant	-0.405***	-0.352***	-0.344***	-0.406***	-0.400***	-0.536***	-0.298***	-0.077	-0.337***	-0.415***	-0.419***	0.051	-0.172
	(-3.97)	(-3.11)	(-3.24)	(-3.96)	(-3.90)	(-4.36)	(-2.84)	(-0.69)	(-3.11)	(-3.76)	(-4.22)	(0.34)	(-1.45)
Observations	1,254	1,254	1,254	1,254	1,254	1,254	1,254	1,254	1,254	1,254	1,254	1,254	1,254
Adjusted R-squared	0.096	0.103	0.136	0.095	0.095	0.150	0.101	0.138	0.120	0.095	0.097	0.200	0.153
Industry FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES

Table 4.4: Descriptive Statistics-Panel Sample

This table reports descriptive statistics for all variables specified in baseline model (4.4). The sample consists of 22,535 observations, representing 1,254 unique firms, during the period between 1993 and 2022. All variables are defined in Table 4.1 of Appendix.

VARIABLES	(1) N	(2) Mean	(3) Std. Dev. (Overall)	(4) Std. Dev. (Between)	(5) Std. Dev. (Within)	(6) P25	(7) Median	(8) P75
SOA	22,535	-0.2172	0.2955	0.2401	0.2076	-0.2916	-0.0847	-0.0033
$Ln(Spread)$	22,535	5.9861	1.7519	1.3401	1.2906	4.4236	6.2068	7.4744
$Cash$	22,535	0.0988	0.1186	0.1120	0.0655	0.0169	0.0542	0.1372
$Free\ cash$	22,535	0.0798	0.0470	0.0350	0.0331	0.0452	0.0752	0.1067
$Market\_to\_Book$	22,535	1.8088	1.0213	0.9275	0.5915	1.1845	1.4795	2.0522
$Turnover$	22,535	0.1305	0.1163	0.0954	0.0781	0.0500	0.1002	0.1702
$Firm\ size$	22,535	7.3874	1.8349	1.7718	0.5166	6.2075	7.4378	8.6526
$Firm\ age$	22,535	3.3034	0.6333	0.6025	0.2960	2.9444	3.4340	3.7842
$Std(Return)$	22,535	0.0920	0.0492	0.0294	0.0404	0.0579	0.0805	0.1121
$Std(EBITDA)$	22,535	0.0395	0.0313	0.0287	0.0172	0.0190	0.0305	0.0493
$Tangibility$	22,535	0.3431	0.2375	0.2253	0.0712	0.1512	0.2792	0.5109
$Payout$	22,535	0.4504	0.6783	0.3696	0.6035	0.1151	0.2955	0.5403

Table 4.5: Dividend Smoothing and Stock Liquidity: Baseline Panel Setting

This table reports panel regression results of dividend smoothing on stock liquidity and control variables. The dependent variables and main independent variables across all regressions are SOA and $Ln(Spread)$ respectively. SOA is estimated using 10-year rolling window. Column (1) reports the results of SOA on $Ln(Spread)$, excluding firm characteristics. In column (2), all the firm characteristics are specified in the model (4.4) are included. Column (3) re-estimates the model (4.4) and controls for firm fixed effects. Firm-level characteristics include cash, market-to-book ratio, stock turnover, firm size, firm age, standard deviation of stock returns, standard deviation of EBITDA, dividend payout ratio and tangibility. All variables are defined in Table 4.1 of Appendix. We present t-statistics in parentheses and cluster standard errors at firm level. 1% Significance level *** 5% Significance level ** 10% Significance level *

	Excluding controls	Industry and Year FE	Firm FE
	(1)	(2)	(3)
VARIABLES	SOA	SOA	SOA
$Ln(Spread)$	0.053***	0.032***	0.016**
	(9.65)	(4.57)	(2.26)
$Cash$		-0.194***	-0.109**
		(-3.71)	(-1.99)
$Free\ cash$		0.118	0.021
		(1.16)	(0.23)
$Market\_to\_Book$		-0.042***	-0.033***
		(-6.30)	(-4.53)
$Turnover$		0.081*	0.004
		(1.71)	(0.09)
$Firm\ size$		0.013***	0.021*
		(2.82)	(1.95)
$Firm\ age$		0.045***	0.121***
		(4.71)	(4.22)
$Std(Return)$		-0.117	-0.087
		(-1.35)	(-1.26)
$Std(EBITDA)$		-0.671***	-0.586***
		(-3.49)	(-2.61)
$Tangibility$		-0.015	-0.015
		(-0.40)	(-0.29)
$Payout$		-0.008**	-0.009***
		(-2.14)	(-3.13)
Constant	-0.461***	-0.447***	-0.652***
	(-4.54)	(-4.00)	(-6.09)
Observations	22,535	22,535	22,535
Adjusted R-squared	0.169	0.215	0.034
Year FE	YES	YES	YES
Industry FE	YES	YES	NO
Firm FE	NO	NO	YES

Table 4.6: Alternative Measures for Liquidity

This table reports regressions results when employing alternative proxies for liquidity. $Ln(Amihud)$ (in logarithm) is defined as the absolute value of daily stock return divided by daily dollar trading volume: $Amihud_{it} = \frac{1}{D_{it}} \sum_{d=1}^{D} \frac{|Ret_{idt}|}{Volume_{idt}}$. $Zeros$ is defined as the proportion of days with zero returns: $Zeros_{it} = \frac{Zero\ Return\ Day_{it}}{Total\ Day_{it}}$. $Ln(FHT)$ (in logarithm) is calculated as: $FHT_{it} = 2 * \sigma * N^{-1}(\frac{1+Zeros}{2})$. The dependent variables across all regressions are SOA. Firm characteristics are specified in Table 4.4. All variables are defined in Table 4.1 of Appendix. Year and industry fixed effects are included in all regressions We present t-statistics in parentheses and cluster standard errors at firm level. 1% Significance level *** 5% Significance level ** 10% Significance level *

VARIABLES	(1) SOA	(2) SOA	(3) SOA
$Ln(Amihud)$	0.012***		
	(3.10)		
$Zeros$		0.393***	
		(4.08)	
$Ln(FHT)$			0.023***
			(4.59)
$Cash$	-0.196***	-0.184***	-0.191***
	(-3.68)	(-3.50)	(-3.50)
$Free\ cash$	0.163	0.124	0.107
	(1.59)	(1.19)	(0.98)
$Market\_to\_Book$	-0.044***	-0.042***	-0.043***
	(-6.15)	(-6.09)	(-6.00)
$Turnover$	0.089*	0.145***	0.152***
	(1.78)	(3.04)	(3.14)
$Firm\ size$	0.011*	0.020***	0.017***
	(1.72)	(5.16)	(4.29)
$Firm\ age$	0.033***	0.034***	0.033***
	(3.34)	(3.39)	(3.23)
$Std(Return)$	-0.164*	-0.299***	-0.131
	(-1.80)	(-3.31)	(-1.41)
$Std(EBITDA)$	-0.755***	-0.717***	-0.712***
	(-3.77)	(-3.58)	(-3.44)
$Tangibility$	-0.023	-0.021	-0.019
	(-0.61)	(-0.54)	(-0.51)
$Payout$	-0.010**	-0.010**	-0.009**
	(-2.58)	(-2.53)	(-2.20)
Constant	-0.340***	-0.326***	-0.488***
	(-7.04)	(-6.94)	(-9.73)
Observations	20,686	20,686	18,435
Adjusted R-squared	0.215	0.217	0.210
Year FE	YES	YES	YES
Industry FE	YES	YES	YES

Table 4.7: Alternative Measures for Dividend Smoothing

This table reports regressions results when employing alternative proxies for dividend smoothing. $RELVOL10$, $RELVOL7$ and $RELVOL5$ are ratio of dividend volatility to earnings volatility estimated using 10-year, 7-year and 5-year rolling windows respectively. $SOA7$ and $SOA5$ are speed of adjustment estimated using 7-year and 5-year rolling windows respectively. Stock liquidity proxy is identical to that employed in baseline regressions. Firm characteristics are specified in Table 4.4. All variables are defined in Table 4.1 of Appendix. Year and industry fixed effects are included in all regressions We present t-statistics in parentheses and cluster standard errors at firm level. 1% Significance level *** 5% Significance level ** 10% Significance level *

VARIABLES	(1) $RELVOL10$	(2) $RELVOL7$	(3) $RELVOL5$	(4) $SOA7$	(5) $SOA5$
$Ln(Spread)$	0.074***	0.067***	0.061***	0.028***	0.022***
	(2.59)	(2.74)	(2.73)	(4.25)	(3.59)
$Cash$	-0.969***	-0.967***	-0.878***	-0.212***	-0.216***
	(-5.15)	(-5.37)	(-5.07)	(-4.37)	(-4.71)
$Free\ cash$	-0.689*	-0.830**	-1.016***	0.119	0.126
	(-1.84)	(-2.48)	(-3.12)	(1.22)	(1.30)
$Market\_to\_Book$	-0.120***	-0.128***	-0.129***	-0.040***	-0.040***
	(-4.51)	(-5.52)	(-5.82)	(-6.53)	(-6.93)
$Turnover$	0.192	0.201	0.318*	0.053	0.045
	(1.06)	(1.21)	(1.89)	(1.15)	(0.99)
$Firm\ size$	0.067***	0.058***	0.057***	0.013***	0.013***
	(4.36)	(4.23)	(4.11)	(3.17)	(3.29)
$Firm\ age$	0.074**	0.072***	0.058**	0.043***	0.040***
	(2.38)	(2.62)	(2.20)	(4.98)	(5.05)
$Std(Return)$	0.343	-0.034	-0.457	-0.066	-0.123
	(0.98)	(-0.11)	(-1.36)	(-0.77)	(-1.47)
$Std(EBITDA)$	-1.203*	-0.477	0.308	-0.512***	-0.459***
	(-1.75)	(-0.81)	(0.55)	(-2.88)	(-2.61)
$Tangibility$	0.095	-0.012	0.096	-0.005	0.017
	(0.67)	(-0.11)	(0.91)	(-0.13)	(0.53)
$Payout$	-0.041***	-0.042***	-0.046***	-0.011***	-0.012***
	(-2.82)	(-3.05)	(-3.15)	(-2.82)	(-3.17)
Constant	-1.578***	-1.301***	-1.224***	-0.514***	-0.472***
	(-8.73)	(-8.51)	(-8.66)	(-11.32)	(-11.11)
Observations	21,806	21,640	21,425	22,499	22,433
Adjusted R-squared	0.208	0.190	0.151	0.186	0.159
Year FE	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES

Table 4.8: Propensity Score Matching Analysis

This table reports propensity score matching estimates. $Ln(Spread)$ of firms above the top quartile is classified into treatment group, and below the bottom quartile into control group. The matching is based on Probit regressions with $Treat$ as dependent variable. $Treat$ is a dummy variable that equals to one for firm-years in treatment group, and zero for firm-years in control group. One-to-one nearest neighbour matching, with replacement, is employed. Panel A presents comparison of covariates across treatment and control groups. Panel B shows average treatment effect on the treated. Panel C reports regression results based on matched sample. All variables are specified in Eq.(4.4). Detailed definitions of variables are presented in the Table 4.1 of Appendix. We present t-statistics in parentheses and cluster standard errors at firm level. 1% Significance level *** 5% Significance level ** 10% Significance level.

Panel A. Differences in firm characteristics

	Pre-match			Post-match		
VARIABLES	(1) Control Treat=0	(2) Treatment Treat=1	(3) Difference	(4) Control Treat=0	(5) Treatment Treat=1	(6) Difference
$Ln(Spread)$	4.506	7.047	-2.541***	4.618	6.420	-1.802***
			(-93.546)			(-18.826)
$Cash$	0.124	0.088	0.036***	0.089	0.094	-0.005
			(15.508)			(-0.686)
$Free\ cash$	0.068	0.090	-0.022***	0.079	0.081	-0.002
			(-24.595)			(-0.780)
$Market\_to\_Book$	1.550	2.164	-0.614***	1.819	1.807	0.012
			(-31.106)			(0.172)
$Turnover$	0.073	0.148	-0.075***	0.134	0.137	-0.003
			(-40.589)			(-0.381)
$Firm\ size$	5.589	8.920	-3.330***	7.455	7.406	0.049
			(-123.521)			(0.604)
$Firm\ age$	3.118	3.509	-0.392***	3.240	3.239	0.002
			(-34.746)			(0.045)
$Std(Return)$	0.110	0.075	0.035***	0.101	0.102	-0.002
			(38.323)			(-0.495)
$Std(EBITDA)$	0.048	0.033	0.015***	0.038	0.039	-0.001
			(26.582)			(-0.389)
$Tangibility$	0.320	0.343	-0.023***	0.330	0.339	-0.009
			(-5.202)			(-0.587)
$Payout$	0.475	0.415	0.060***	0.434	0.383	0.051
			(4.805)			(1.163)
Observations	5,646	5,646		490	490	

Panel B. Regression results for the propensity-score matched sample

VARIABLES	(1) SOA
$Treat$	0.080**
	(2.58)
$Cash$	0.068
	(0.37)
$Free\ cash$	0.449
	(1.21)
$Market\_to\_Book$	-0.083***
	(-4.28)
$Turnover$	-0.264*
	(-1.66)
$Firm\ size$	0.043***
	(3.37)
$Firm\ age$	0.046
	(1.41)
$Std(Return)$	0.198
	(0.51)
$Std(EBITDA)$	0.799
	(1.53)
$Tangibility$	0.200*
	(1.86)
$Payout$	-0.051***
	(-2.71)
Constant	-0.672***
	(-4.00)
Observations	980
Adjusted R-squared	0.490
Year FE	YES
Industry FE	YES

Table 4.9: Difference-in-Difference Design Based on 2001 Decimalization

This table reports difference-in-difference analysis based on the decimalization in 2001. Panel A reports comparison of mean, variance, and skewness of the covariates between treatment group and control group for pre-decimalization year. The covariates used in entropy balancing analysis are specified in model (4.4). Panel B reports difference-in-difference estimates based on balanced sample. *Treat* is a dummy variable equal to one if stocks are in the treatment group, and zero if in the control group. *Post* is a dummy variable equal to one for the years of 2002 and 2003, and zero for the years 1999 and 2000. $Treat * Post$ is the interaction between the two dummy variables. *SOA* is dependent variable. Firm characteristics are specified in model (4.4). All variables are defined in Table 4.1 of Appendix. We present t-statistics in parentheses and cluster standard errors at firm level. 1% Significance level *** 5% Significance level ** 10% Significance level *

Panel A. Comparison of covariates between treatment and control

	Before balancing					
	Treatment (N=150)			Control (N=150)		
VARIABLES	Mean	Variance	Skewness	Mean	Variance	Skewness
Cash	0.102	0.020	2.111	0.075	0.012	2.955
Free cash	0.083	0.002	0.476	0.083	0.002	0.458
Market_to_Book	1.700	1.439	2.705	1.743	1.603	2.640
Turnover	0.081	0.002	1.189	0.080	0.002	1.803
Firm size	6.072	2.991	0.442	6.943	4.004	0.158
Firm age	2.992	0.431	-1.008	3.137	0.402	-0.897
Std(Return)	0.117	0.002	0.551	0.112	0.002	1.363
Std(EBITDA)	0.042	0.001	1.638	0.037	0.001	2.647
Tangibility	0.341	0.046	0.737	0.347	0.052	0.768
Payout	0.425	0.369	4.543	0.365	0.256	6.284

	After balancing					
	Treatment (N=150)			Control (N=150)		
VARIABLES	Mean	Variance	Skewness	Mean	Variance	Skewness
Cash	0.102	0.020	2.111	0.102	0.020	2.111
Free cash	0.083	0.002	0.476	0.083	0.002	0.476
Market_to_Book	1.700	1.439	2.705	1.700	1.439	2.705
Turnover	0.081	0.002	1.189	0.081	0.002	1.189
Firm size	6.072	2.991	0.442	6.072	2.991	0.442
Firm age	2.992	0.431	-1.008	2.992	0.431	-1.008
Std(Return)	0.117	0.002	0.551	0.117	0.002	0.553
Std(EBITDA)	0.042	0.001	1.638	0.042	0.001	1.638
Tangibility	0.341	0.046	0.737	0.341	0.046	0.737
Payout	0.425	0.369	4.543	0.425	0.369	4.543

Panel B. Difference-in-Difference regression

VARIABLES	(1) *SOA*
$Treat * Post$	0.078**
	(2.46)
Treat	-0.090**
	(-2.12)
Post	-0.046*
	(-1.79)
Cash	-0.042
	(-0.27)
Free cash	0.376
	(1.06)
Market_to_Book	-0.016
	(-0.75)
Turnover	0.556**
	(2.36)
Firm size	-0.004
	(-0.31)
Firm age	0.080**
	(2.10)
Std(Return)	-0.169
	(-0.76)
Std(EBITDA)	-0.806
	(-0.93)
Tangibility	0.228**
	(2.02)
Payout	-0.007
	(-0.54)
Constant	-0.438***
	(-3.27)
Observations	1,176
Adjusted R-squared	0.320
Industry FE	YES

Table 4.10: Instrumental Variable Regression

This table reports instrumental variable regression results. Column (1) presents the first stage regression result where the instruments, *Industry median Ln(Spread)*, defined as the median closing Percent Quoted Spread of the industry that the firm belongs to. Column (2) reports regression result for the second stage. *Fitted Ln(Spread)* is the predicted values of closing Percent Quoted Spread obtained from the first stage regression. Detailed variable definitions are provided in Appendix of Table 4.1. We present t-statistics in parentheses and cluster standard errors at firm level. 1% Significance level *** 5% Significance level ** 10% Significance level *

	First stage	Second stage
	(1)	(2)
VARIABLES	*Ln(Spread)*	*SOA*
Fitted Ln(Spread)		0.125**
		(2.39)
Industry median Ln(Spread)	0.135***	
	(7.79)	
Cash	0.037	-0.198***
	(0.68)	(-8.18)
Free cash	0.988***	0.022
	(7.57)	(0.29)
Market_to_Book	0.159***	-0.057***
	(22.94)	(-6.40)
Turnover	2.794***	-0.180
	(42.50)	(-1.21)
Firm size	0.377***	-0.022
	(93.52)	(-1.13)
Firm age	-0.078***	0.052***
	(-9.63)	(9.10)
Std(Return)	-4.327***	0.292
	(-34.45)	(1.24)
Std(EBITDA)	-2.368***	-0.435***
	(-12.65)	(-2.89)
Tangibility	-0.173***	-0.001
	(-4.67)	(-0.05)
Payout	-0.009	-0.007**
	(-1.23)	(-2.52)
Constant	2.440***	-0.835***
	(21.17)	(-4.81)
Kleibergen-Paap rk Wald F statistic	60.65	
Observations	22,523	22,523
Adjusted R-squared	0.871	0.211
Industry FE	YES	YES
Year FE	YES	YES

Table 4.11: The Role of Financial Constraints

This table shows the results for the effect of financial constraints. Measures for financial constraints are SA index and WW index. In columns (1) and (3), we estimate the relation between financial constraints and stock liquidity. In columns (2) and (4), we investigate the relation between dividend smoothing and financial constraints. All variables are defined in Table 4.1 of Appendix. Year and industry fixed effects are included in all regressions We present t-statistics in parentheses and cluster standard errors at firm level. 1% Significance level *** 5% Significance level ** 10% Significance level *

	SA Index		WW Index	
	(1)	(2)	(3)	(4)
VARIABLES	*Constraints*	*SOA*	*Constraints*	*SOA*
Constraints		-0.139***		-0.550***
		(-3.97)		(-2.79)
Ln(Spread)	-0.058***		-0.008***	
	(-12.29)		(-11.33)	
Cash	0.155***	-0.168***	-0.019***	-0.196***
	(4.07)	(-3.25)	(-4.17)	(-3.64)
Free cash	0.209***	0.179*	0.071***	0.157
	(3.04)	(1.74)	(6.47)	(1.49)
Market_to_Book	-0.002	-0.039***	-0.003***	-0.039***
	(-0.47)	(-5.72)	(-5.24)	(-5.52)
Turnover	-0.152***	0.116**	0.011**	0.146***
	(-4.90)	(2.40)	(2.19)	(3.03)
Firm size	-0.095***	0.009*	-0.041***	0.002
	(-22.41)	(1.81)	(-76.63)	(0.24)
Firm age	-0.015**	0.032***	-0.001	0.026**
	(-2.40)	(3.23)	(-1.08)	(2.41)
Std(Return)	-0.085	-0.244***	0.080***	-0.195**
	(-1.57)	(-2.67)	(7.97)	(-1.98)
Std(EBITDA)	0.915***	-0.610***	0.088***	-0.711***
	(6.63)	(-2.99)	(4.25)	(-3.37)
Tangibility	-0.035	-0.020	-0.015***	-0.019
	(-1.21)	(-0.54)	(-3.27)	(-0.50)
Payout	0.010***	-0.008**	-0.000	-0.012***
	(4.06)	(-2.18)	(-0.08)	(-3.00)
Constant	-2.041***	-0.709***	-0.041***	-0.414***
	(-52.18)	(-7.86)	(-7.26)	(-8.70)
Observations	22,535	20,686	20,608	18,892
Adjusted R-squared	0.758	0.218	0.915	0.220
Year FE	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES

Chapter 5

CONCLUSION

This thesis draws a large sample of US firms and investigates two critical corporate policies, labor investment and dividend smoothing. More specifically, we consider three factors, social capital, board co-option and stock liquidity, shaping firm's labor investment and dividend smoothing.

In Chapter 2, we examine whether community social capital affects firm's labor investment. Given that social capital has been documented to benefit firms in different settings (e.g., Jha and Chen, 2015; Hasan et al., 2017a; Hasan et al., 2017b; Hoi et al., 2019; Gupta et al., 2020; Hossain, Hossain, Jha and Mougoué, 2023), social capital is considered as an informal governance and monitoring mechanism to constraint corporate manager's opportunism. We hypothesize that firms residing in counties with higher level of social capital tend have less inefficient labor investment. To test this conjecture, we measure labor investment inefficiency using firm's abnormal hiring, and social capital using cooperative norms and social networks. Our main results show a negative relation between social capital and abnormal hiring, consistent with our prediction. This relation is robust to multiple sensitivity tests

To control for potential endogeneity, we employ two identification strategies. First, we use a difference-in-difference approach based on firm's relocation event to better identify the causal effect of social capital on labor investment. Second, we construct an instrumental variable using the distance between the county where firms are located and US-Canada border. The results from DID and IV remain unchanged.

In Chapter 3, we investigate another driver of corporate inefficient labor investment, board co-option. Given the timing of being appointed to the board, co-opted directors may show allegiance to the incumbent CEO who engage in their appointment. Therefore, greater co-option is considered to weaken the monitoring function of the board (e.g., Coles et al., 2014; Khanna et al., 2015). We conjecture that firms with higher board co-option present greater labor investment inefficiency. The measure of labor investment inefficiency follows that presented in Chapter 2. Board co-option is constructed by using the number of co-opted directors divided by board size. In line with our hypothesis, the baseline evidence shows that firms with more proportion of co-opted directors exhibit significantly higher abnormal hiring. This finding holds after employing various robustness tests.

To control for endogenous issue, we consider Sarbanes–Oxley (SOX) Act of 2002 as an exogenous shock to board co-option, then employ a difference-in-difference specification modified by Coles et al. (2014). The results from DID estimation further support our main finding.

In Chapter 4, we explore one specific dividend policy of firms, dividend smoothing. In particular, we test whether stock market liquidity induces managers to smooth their dividends. We argue that higher stock liquidity enhances shareholders' intervention and exit threats, forcing managers to smooth dividends to reduce excess cash flows within the firm. We use the speed of adjustment to measure dividend smoothing, and daily closing percent quoted spread to proxy for stock liquidity. We find that more liquid firms smooth more, in line with our prediction. The finding is unchanged after multiple robustness checks. To address potential reverse causality, we conduct a difference-in-difference empirical design and consider US decimalization of 2001 as exogenous shock to stock liquidity. The results continue to hold.

This thesis sheds light on the determinants of labor investment and dividend smoothing policies. Previous empirical evidence shows that labor investment is affected by financial reporting quality (Jung et al., 2014), stock price informativeness (Ben-Nasr and Alshwer, 2016), long-term investor horizion (Ghaly et al., 2020), equity compensation (Sualihu, Rankin and Haman, 2021). We document the role played by social capital in serving as the informal monitoring to constraint inefficient labor investment, while board co-option in weakening board monitoring to exacerbate inefficient labor investment. Prior studies on dividend smoothing find that this practice is prevalent among public firms, and firms with certain characteristics, such as less information asymmetry, fewer financial constraints and more executive networking (e.g., Leary and Michaely, 2011; Michaely and Roberts, 2012; Javakhadze et al., 2014; Garcia-Feijoo et al., 2021). We show that stock liquidity can shape firm's dividend smoothing policy.

Bibliography

Acharya, V. V. and Pedersen, L. H. (2005), 'Asset pricing with liquidity risk', *Journal of Financial Economics* **77**(2), 375–410.

Adams, R. B., Hermalin, B. E. and Weisbach, M. S. (2010), 'The role of boards of directors in corporate governance: A conceptual framework and survey', *Journal of Economic Literature* **48**(1), 58–107.

Admati, A. R. and Pfleiderer, P. (2009), 'The "wall street walk" and shareholder activism: Exit as a form of voice', *The Review of Financial Studies* **22**(7), 2645–2685.

Akerlof, G. A. (2007), 'The missing motivation in macroeconomics', *The American Economic Review* **97**(1), 5–36.

Allen, F., Bernardo, A. E. and Welch, I. (2000), 'A theory of dividends based on tax clienteles', *The Journal of Finance* **55**(6), 2499–2536.

Allen, F. and Michaely, R. (2003), 'Payout policy', *Handbook of the Economics of Finance* **1**, 337–429.

Almeida, H., Campello, M. and Weisbach, M. S. (2004), 'The cash flow sensitivity of cash', *The Journal of Finance* **59**(4), 1777–1804.

Amihud, Y. (2002), 'Illiquidity and stock returns: cross-section and time-series effects', *Journal of Financial markets* **5**(1), 31–56.

Amihud, Y. and Levi, S. (2023), 'The effect of stock liquidity on the firm's investment and production', *The Review of Financial Studies* **36**(3), 1094–1147.

Amihud, Y. and Mendelson, H. (1986), ‘Asset pricing and the bid-ask spread’, *Journal of Financial Economics* **17**(2), 223–249.

Ammann, M., Oesch, D. and Schmid, M. M. (2013), ‘Product market competition, corporate governance, and firm value: Evidence from the eu area’, *European Financial Management* **19**(3), 452–469.

Anheier, H. K., Gerhards, J. and Romo, F. P. (1995), ‘Forms of capital and social structure in cultural fields: Examining Bourdieu’s social topography’, *American Journal of Sociology* **100**(4), 859–903.

Atanassov, J. and Kim, E. H. (2009), ‘Labor and corporate governance: International evidence from restructuring decisions’, *The Journal of Finance* **64**(1), 341–374.

Atkeson, A. and Kehoe, P. J. (2005), ‘Modeling and measuring organization capital’, *Journal of Political Economy* **113**(5), 1026–1053.

Attig, N. and Cleary, S. (2014), ‘Organizational capital and investment□cash flow sensitivity: The effect of management quality practices’, *Financial Management* **43**(3), 473–504.

Baghdadi, G. A., Nguyen, L. H. and Podolski, E. J. (2020), ‘Board co-option and default risk’, *Journal of Corporate Finance* **64**, 101703.

Bai, J. J., Shang, C., Wan, C. and Zhao, Y. E. (2021), ‘Social Capital and Individual Ethics: Evidence from Financial Adviser Misconduct’, *Journal of Business Ethics* pp. 1–24.

Baker, H. K., Farrelly, G. E. and Edelman, R. B. (1985), ‘A survey of management views on dividend policy’, *Financial management* pp. 78–84.

Bakke, T.-E. and Whited, T. M. (2010), ‘Which firms follow the market? an analysis of corporate investment decisions’, *The Review of Financial Studies* **23**(5), 1941–1980.

Banerjee, S., Gatchev, V. A. and Spindt, P. A. (2007), ‘Stock market liquidity and firm dividend policy’, *Journal of Financial and Quantitative Analysis* **42**(2), 369–397.

Bates, T. W., Kahle, K. M. and Stulz, R. M. (2009), ‘Why do us firms hold so much more cash than they used to?’, *The Journal of Finance* **64**(5), 1985–2021.

Bebchuk, L. A. and Cohen, A. (2005), ‘The costs of entrenched boards’, *Journal of Financial Economics* **78**(2), 409–433.

Becker, G. S. (1964), *Human Capital*, New York: Columbia University Press.

Ben-Nasr, H. and Alshwer, A. A. (2016), ‘Does stock price informativeness affect labor investment efficiency?’, *Journal of Corporate Finance* **38**, 249–271.

Benartzi, S., Michaely, R. and Thaler, R. (1997), ‘Do changes in dividends signal the future or the past?’, *The Journal of Finance* **52**(3), 1007–1034.

Benmelech, E., Bergman, N. and Seru, A. (2021), ‘Financing labor’, *Review of Finance* **25**(5), 1365–1393.

Bertrand, M. and Mullainathan, S. (2003), ‘Enjoying the quiet life? Corporate governance and managerial preferences’, *Journal of Political Economy* **111**(5), 1043–1075.

Bessembinder, H. (2003), ‘Trade execution costs and market quality after decimalization’, *Journal of Financial and Quantitative Analysis* **38**(4), 747–777.

Bharath, S. T., Jayaraman, S. and Nagar, V. (2013), ‘Exit as governance: An empirical analysis’, *The Journal of Finance* **68**(6), 2515–2547.

Bhattacharya, S. (1979), ‘Imperfect information, dividend policy, and” the bird in the hand” fallacy’, *The Bell Journal of Economics* pp. 259–270.

Biddle, G. C., Hilary, G. and Verdi, R. S. (2009), 'How does financial reporting quality relate to investment efficiency?', *Journal of Accounting and Economics* **48**(2-3), 112–131.

Boivie, S., Bednar, M. K., Aguilera, R. V. and Andrus, J. L. (2016), 'Are boards designed to fail? the implausibility of effective board monitoring', *Academy of Management Annals* **10**(1), 319–407.

Boubaker, S., Dang, V. A. and Sassi, S. (2022), 'Competitive pressure and firm investment efficiency: Evidence from corporate employment decisions', *European Financial Management* **28**(1), 113–161.

Bourdieu, P. (1986), The forms of social capital, *in* J. G. Richardson, ed., 'Handbook of Theory and Research for the Sociology of Education', New York: Greenwood Press.

Boxman, E. A., De Graaf, P. M. and Flap, H. D. (1991), 'The impact of social and human capital on the income attainment of dutch managers', *Social Networks* **13**(1), 51–73.

Brav, A., Graham, J. R., Harvey, C. R. and Michaely, R. (2005), 'Payout policy in the 21st century', *Journal of Financial Economics* **77**(3), 483–527.

Brav, A., Jiang, W., Partnoy, F. and Thomas, R. (2008), 'Hedge fund activism, corporate governance, and firm performance', *The Journal of Finance* **63**(4), 1729–1775.

Brennan, M. J. and Subrahmanyam, A. (1996), 'Market microstructure and asset pricing: On the compensation for illiquidity in stock returns', *Journal of Financial Economics* **41**(3), 441–464.

Brockman, P., Hanousek, J., Tresl, J. and Unlu, E. (2022), 'Dividend smoothing and firm valuation', *Journal of Financial and Quantitative Analysis* **57**(4), 1621–1647.

Brogaard, J., Li, D. and Xia, Y. (2017), 'Stock liquidity and default risk', *Journal of Financial Economics* **124**(3), 486–502.

Bushee, B. J. (1998), 'The influence of institutional investors on myopic R&D investment behavior', *The Accounting Review* pp. 305–333.

Butler, A. W., Grullon, G. and Weston, J. P. (2005), 'Stock market liquidity and the cost of issuing equity', *Journal of Financial and Quantitative Analysis* **40**(2), 331–348.

Cai, J., Garner, J. L. and Walkling, R. A. (2009), 'Electing directors', *The Journal of Finance* **64**(5), 2389–2421.

Cain, M. D., McKeon, S. B. and Solomon, S. D. (2017), 'Do takeover laws matter? Evidence from five decades of hostile takeovers', *Journal of Financial Economics* **124**(3), 464–485.

Campello, M., Graham, J. R. and Harvey, C. R. (2010), 'The real effects of financial constraints: Evidence from a financial crisis', *Journal of Financial Economics* **97**(3), 470–487.

Cao, Z. and Rees, W. (2020), 'Do employee-friendly firms invest more efficiently? Evidence from labor investment efficiency', *Journal of Corporate Finance* **65**, 101744.

Cassell, C. A., Myers, L. A., Schmardebeck, R. and Zhou, J. (2018), 'The monitoring effectiveness of co-opted audit committees', *Contemporary Accounting Research* **35**(4), 1732–1765.

Chang, X., Chen, Y. and Zolotoy, L. (2017), 'Stock liquidity and stock price crash risk', *Journal of Financial and Quantitative Analysis* **52**(4), 1605–1637.

Chay, J.-B. and Suh, J. (2009), 'Payout policy and cash-flow uncertainty', *Journal of Financial Economics* **93**(1), 88–107.

Chen, H. J., Kacperczyk, M. and Ortiz-Molina, H. (2011), ‘Labor unions, operating flexibility, and the cost of equity’, *Journal of Financial and Quantitative Analysis* **46**(1), 25–58.

Chen, Q., Goldstein, I. and Jiang, W. (2007), ‘Price informativeness and investment sensitivity to stock price’, *The Review of Financial Studies* **20**(3), 619–650.

Chen, Y., Ge, R., Louis, H. and Zolotoy, L. (2019), ‘Stock liquidity and corporate tax avoidance’, *Review of Accounting Studies* **24**, 309–340.

Chhaochharia, V. and Grinstein, Y. (2007), ‘Corporate governance and firm value: The impact of the 2002 governance rules’, *The Journal of Finance* **62**(4), 1789–1825.

Chhaochharia, V., Grinstein, Y., Grullon, G. and Michaely, R. (2017), ‘Product market competition and internal governance: Evidence from the sarbanes–oxley act’, *Management Science* **63**(5), 1405–1424.

Chung, K. H. and Zhang, H. (2014), ‘A simple approximation of intraday spreads using daily data’, *Journal of Financial Markets* **17**, 94–120.

Clune, R., Hermanson, D. R., Tompkins, J. G. and Ye, Z. (2014), ‘The nominating committee process: A qualitative examination of board independence and formalization’, *Contemporary Accounting Research* **31**(3), 748–786.

Coleman, J. S. (1988), ‘Social capital in the creation of human capital’, *American Journal of Sociology* **94**, S95–120.

Coles, J. L., Daniel, N. D. and Naveen, L. (2006), ‘Managerial incentives and risk-taking’, *Journal of Financial Economics* **79**(2), 431–468.

Coles, J. L., Daniel, N. D. and Naveen, L. (2014), ‘Co-opted boards’, *The Review of Financial Studies* **27**(6), 1751–1796.

DeMarzo, P. M. and Sannikov, Y. (2016), ‘Learning, termination, and payout policy in dynamic incentive contracts’, *The Review of Economic Studies* **84**(1), 182–236.

Dikolli, S. S., Heater, J. C., Mayew, W. J. and Sethuraman, M. (2021), 'Chief financial officer co-option and chief executive officer compensation', *Management Science* **67**(3), 1939–1955.

Dixit, A. (1997), 'Investment and employment dynamics in the short run and the long run', *Oxford Economic Papers* **49**(1), 1–20.

Dow, J. and Gorton, G. (1997), 'Stock market efficiency and economic efficiency: Is there a connection?', *The Journal of Finance* **52**(3), 1087–1129.

Durnev, A., Morck, R. and Yeung, B. (2004), 'Value-enhancing capital budgeting and firm-specific stock return variation', *The Journal of Finance* **59**(1), 65–105.

Easterbrook, F. H. (1984), 'Two agency-cost explanations of dividends', *The American Economic Review* **74**(4), 650–659.

Edmans, A. (2009), 'Blockholder trading, market efficiency, and managerial myopia', *The Journal of Finance* **64**(6), 2481–2513.

Edmans, A., Fang, V. W. and Zur, E. (2013), 'The effect of liquidity on governance', *The Review of Financial Studies* **26**(6), 1443–1482.

Edmans, A. and Manso, G. (2011), 'Governance through trading and intervention: A theory of multiple blockholders', *The Review of Financial Studies* **24**(7), 2395–2428.

Ee, M. S., Hasan, I. and Huang, H. (2022), 'Stock liquidity and corporate labor investment', *Journal of Corporate Finance* **72**, 102142.

Eisenhardt, K. M. (1989), 'Agency theory: An assessment and review', *Academy of Management Review* **14**(1), 57–74.

Eisfeldt, A. L. and Papanikolaou, D. (2013), 'Organization capital and the cross□section of expected returns', *The Journal of Finance* **68**(4), 1365–1406.

Fama, E. F. and Babiak, H. (1968), 'Dividend policy: An empirical analysis', *Journal of The American Statistical Association* **63**(324), 1132–1161.

Fama, E. F. and French, K. R. (2002), 'Testing trade-off and pecking order predictions about dividends and debt', *Review of financial studies* pp. 1–33.

Fama, E. F. and Jensen, M. C. (1983), 'Separation of ownership and control', *The journal of Law and Economics* **26**(2), 301–325.

Fang, V. W., Noe, T. H. and Tice, S. (2009), 'Stock market liquidity and firm value', *Journal of Financial Economics* **94**(1), 150–169.

Fang, V. W., Tian, X. and Tice, S. (2014), 'Does stock liquidity enhance or impede firm innovation?', *The Journal of Finance* **69**(5), 2085–2125.

Fich, E. M. and Shivdasani, A. (2006), 'Are busy boards effective monitors?', *The Journal of Finance* **61**(2), 689–724.

Fluck, Z. (1999), 'The dynamics of the management-shareholder conflict', *The Review of Financial Studies* **12**(2), 379–404.

Fong, K. Y., Holden, C. W. and Trzcinka, C. A. (2017), 'What are the best liquidity proxies for global research?', *Review of Finance* **21**(4), 1355–1401.

Foucault, T. and Frésard, L. (2012), 'Cross-listing, investment sensitivity to stock price, and the learning hypothesis', *The Review of Financial Studies* **25**(11), 3305–3350.

Fracassi, C. and Tate, G. (2012), 'External networking and internal firm governance', *The Journal of Finance* **67**(1), 153–194.

Francois, P. and Zabojnik, J. (2005), 'Trust, social capital, and economic development', *Journal of the European Economic Association* **3**(1), 51–94.

Frank, M. Z. and Goyal, V. K. (2003), 'Testing the pecking order theory of capital structure', *Journal of Financial Economics* **67**(2), 217–248.

Fudenberg, D. and Tirole, J. (1995), ‘A theory of income and dividend smoothing based on incumbency rents’, *Journal of Political Economy* **103**(1), 75–93.

Fukuyama, F. (1995), *Trust: The social virtues and the creation of prosperity*, New York: Free Press.

Fukuyama, F. (1997), ‘Social capital and the modern capitalist economy: Creating a high trust workplace’, *Stern Business Magazine* **4**(1), 1–16.

Funk, P. (2010), ‘Social incentives and voter turnout: Evidence from the Swiss mail ballot system’, *Journal of the European Economic Association* **8**(5), 1077–1103.

Garcia-Feijoo, L., Hossain, M. M. and Javakhadze, D. (2021), ‘Managerial social capital and dividend smoothing’, *Journal of Corporate Finance* **66**, 101811.

Ghaly, M., Dang, V. A. and Stathopoulos, K. (2020), ‘Institutional investors’ horizons and corporate employment decisions’, *Journal of Corporate Finance* **64**, 101634.

Giroud, X. and Mueller, H. M. (2010), ‘Does corporate governance matter in competitive industries?’, *Journal of Financial Economics* **95**(3), 312–331.

Giroud, X. and Mueller, H. M. (2011), ‘Corporate governance, product market competition, and equity prices’, *The Journal of Finance* **66**(2), 563–600.

Gormley, T. A. and Matsa, D. A. (2014), ‘Common errors: How to (and not to) control for unobserved heterogeneity’, *The Review of Financial Studies* **27**(2), 617–661.

Graham, J. R., Harvey, C. R. and Rajgopal, S. (2005), ‘The economic implications of corporate financial reporting’, *Journal of Accounting and Economics* **40**(1-3), 3–73.

Guiso, L., Sapienza, P. and Zingales, L. (2004), ‘The role of social capital in financial development’, *The American Economic Review* **94**, 526–556.

Guiso, L., Sapienza, P. and Zingales, L. (2006), ‘Does culture affect economic outcomes?’, *Journal of Economic Perspectives* **20**(2), 23–48.

Guiso, L., Sapienza, P. and Zingales, L. (2011), Civic Capital as the Missing Link, Vol. 1 of *Handbook of Social Economics*, North-Holland, pp. 417–480.

Gupta, A., Raman, K. and Shang, C. (2018), 'Social capital and the cost of equity', *Journal of Banking and Finance* **87**, 102–117.

Gupta, A., Raman, K. and Shang, C. (2020), 'Do informal contracts matter for corporate innovation? Evidence from social capital', *Journal of Financial and Quantitative Analysis* **55**(5), 1657–1684.

Guttman, I., Kadan, O. and Kandel, E. (2010), 'Dividend stickiness and strategic pooling', *The Review of Financial Studies* **23**(12), 4455–4495.

Hadlock, C. J. and Pierce, J. R. (2010), 'New evidence on measuring financial constraints: Moving beyond the kz index', *The Review of Financial Studies* **23**(5), 1909–1940.

Hainmueller, J. (2012), 'Entropy balancing for causal effects: A multivariate reweighting method to produce balanced samples in observational studies', *Political Analysis* **20**(1), 25–46.

Halpern, D. (2005), *Social Capital*, Key concepts, Polity Press.
URL: *https://books.google.com/books?id=fAdR6ufr8NsC*

Hamermesh, D. S. (1996), *Labor demand*, Princeton University Press.

Hansson, B., Johanson, U. and Leitner, K.-H. (2004), 'The impact of human capital and human capital investments on company performance: Evidence from literature and European survey results', *Impact of Education and Training, Cedefop Reference Series* **54**, 262–319.

Harris, M. and Raviv, A. (1991), 'The theory of capital structure', *The Journal of Finance* **46**(1), 297–355.

Harvey, C. R., Lins, K. V. and Roper, A. H. (2004), 'The effect of capital structure when expected agency costs are extreme', *Journal of Financial Economics* **74**(1), 3–30.

Hasan, I., Hoi, C.-K. S., Wu, Q. and Zhang, H. (2020), 'Is social capital associated with corporate innovation? Evidence from publicly listed firms in the US', *Journal of Corporate Finance* **62**, 101623.

Hasan, I., Hoi, C. K., Wu, Q. and Zhang, H. (2017a), 'Does social capital matter in corporate decisions? Evidence from corporate tax avoidance', *Journal of Accounting Research* **55**, 629–668.

Hasan, I., Hoi, C. K., Wu, Q. and Zhang, H. (2017b), 'Social capital and debt contracting: Evidence from bank loans and public bonds', *Journal of Financial and Quantitative Analysis* **52**, 1017–1047.

Hasan, M. M. and Habib, A. (2019), 'Social capital and trade credit', *International Review of Financial Analysis* **61**, 158–174.

Hasbrouck, J. (2009), 'Trading costs and returns for us equities: Estimating effective costs from daily data', *The Journal of Finance* **64**(3), 1445–1477.

Hermalin, B. and Weisbach, M. S. (2001), 'Boards of directors as an endogenously determined institution: A survey of the economic literature'.

Hicks, J. R. (1935), 'Annual survey of economic theory: the theory of monopoly', *Econometrica* pp. 1–20.

Hoberg, G., Phillips, G. and Prabhala, N. (2014), 'Product market threats, payouts, and financial flexibility', *The Journal of Finance* **69**(1), 293–324.

Hoi, C. K., Wu, Q. and Zhang, H. (2018), 'Community social capital and corporate social responsibility', *Journal of Business Ethics* **152**, 647–665.

Hoi, C. K., Wu, Q. and Zhang, H. (2019), 'Does social capital mitigate agency problem? Evidence from chief executive officer (CEO) compensation', *Journal of Financial Economics* **133**, 498–519.

Holden, C. W. and Subrahmanyam, A. (1992), 'Long-lived private information and imperfect competition', *The Journal of Finance* **47**(1), 247–270.

Holmström, B. and Tirole, J. (1993), 'Market liquidity and performance monitoring', *Journal of Political Economy* **101**(4), 678–709.

Hossain, A., Hossain, T., Jha, A. and Mougoué, M. (2023), 'Credit ratings and social capital', *Journal of Corporate Finance* **78**, 102338.

Hubbard, R. G. (1997), 'Capital-market imperfections and investment'.

Hubbard, R. G. (1998), 'Capital-market imperfections and investment', *Journal of Economic Literature* **36**(1), 193–225.

Hwang, B.-H. and Kim, S. (2009), 'It pays to have friends', *Journal of Financial Economics* **93**(1), 138–158.

Javakhadze, D., Ferris, S. P. and Sen, N. (2014), 'An international analysis of dividend smoothing', *Journal of Corporate Finance* **29**, 200–220.

Jensen, M. C. (1986), 'Agency costs of free cash flow, corporate finance, and takeovers', *The American Economic Review* **76**(2), 323–329.

Jensen, M. C. and Meckling, W. H. (1976), 'Theory of the firm: Managerial behavior, agency costs and ownership structure', *Journal of Financial Economics* **3**(4), 305–360.

Jenter, D. and Kanaan, F. (2015), 'Ceo turnover and relative performance evaluation', *The Journal of Finance* **70**(5), 2155–2184.

Jha, A. (2019), 'Financial reports and social capital', *Journal of Business Ethics* **115**.

Jha, A. and Chen, Y. (2015), 'Audit fees and social capital', *The Accounting Review* **90**, 611–639.

Jiang, F., Ma, Y. and Shi, B. (2017), 'Stock liquidity and dividend payouts', *Journal of Corporate finance* **42**, 295–314.

Jiraporn, P. and Gleason, K. C. (2007), 'Capital structure, shareholder rights, and corporate governance', *Journal of Financial Research* **30**(1), 21–33.

Jiraporn, P. and Lee, S. M. (2018), 'Do co-opted directors influence dividend policy?', *Financial Management* **47**(2), 349–381.

John, K. and Williams, J. (1985), 'Dividends, dilution, and taxes: A signalling equilibrium', *The Journal of Finance* **40**(4), 1053–1070.

Jung, B., Lee, W. and Weber, D. P. (2014), 'Financial reporting quality and labor investment efficiency', *Contemporary Accounting Research* **31**(4), 1047–1076.

Kahn, C. and Winton, A. (1998), 'Ownership structure, speculation, and shareholder intervention', *The Journal of Finance* **53**(1), 99–129.

Khanna, N. and Sonti, R. (2004), 'Value creating stock manipulation: feedback effect of stock prices on firm value', *Journal of Financial markets* **7**(3), 237–270.

Khanna, V., Kim, E. H. and Lu, Y. (2015), 'Ceo connectedness and corporate fraud', *The Journal of Finance* **70**(3), 1203–1252.

Khedmati, M., Sualihu, M. A. and Yawson, A. (2020), 'Ceo-director ties and labor investment efficiency', *Journal of Corporate Finance* **65**, 101492.

Knack, S. (2002), 'Social Capital and the Quality of Government: Evidence from the States', *American Journal of Political Science* **46**(4), 772–785.

Knyazeva, A. and Knyazeva, D. (2012), 'Product market competition and shareholder rights: International evidence', *European Financial Management* **18**(4), 663–694.

Kumar, P. (1988), ‘Shareholder-manager conflict and the information content of dividends’, *The Review of Financial Studies* **1**(2), 111–136.

La Porta, R., Lopez-de Silanes, F., Shleifer, A. and Vishny, R. W. (2000), ‘Agency problems and dividend policies around the world’, *The Journal of Finance* **55**(1), 1–33.

Lambrecht, B. M. and Myers, S. C. (2012), ‘A lintner model of payout and managerial rents’, *The Journal of Finance* **67**(5), 1761–1810.

Lambrecht, B. M. and Myers, S. C. (2017), ‘The dynamics of investment, payout and debt’, *The Review of Financial Studies* **30**(11), 3759–3800.

Larkin, Y., Leary, M. T. and Michaely, R. (2017), ‘Do investors value dividend-smoothing stocks differently?’, *Management Science* **63**(12), 4114–4136.

Le, A.-T. and Tran, T. P. (2022), ‘Corporate governance and labor investment efficiency: International evidence from board reforms’, *Corporate Governance: An International Review* **30**(5), 555–583.

Leary, M. T. and Michaely, R. (2011), ‘Determinants of dividend smoothing: Empirical evidence’, *The Review of Financial Studies* **24**(10), 3197–3249.

Lemmon, M. L. and Zender, J. F. (2010), ‘Debt capacity and tests of capital structure theories’, *Journal of Financial and Quantitative Analysis* **45**(5), 1161–1187.

Lesmond, D. A., Ogden, J. P. and Trzcinka, C. A. (1999), ‘A new estimate of transaction costs’, *The Review of Financial Studies* **12**(5), 1113–1141.

Leung, W. S., Mazouz, K., Chen, J. and Wood, G. (2018), ‘Organization capital, labor market flexibility, and stock returns around the world’, *Journal of Banking and Finance* **89**, 150–168.

Lev, B., Radhakrishnan, S. and Zhang, W. (2009), ‘Organization capital’, *Abacus* **45**(3), 275–298.

Li, K., Qiu, B. and Shen, R. (2018), 'Organization capital and mergers and acquisitions', *Journal of Financial and Quantitative Analysis* **53**(4), 1871–1909.

Lim, J., Do, V. and Vu, T. (2020), 'Co-opted directors, covenant intensity, and covenant violations', *Journal of Corporate Finance* **64**, 101628.

Linck, J. S., Netter, J. M. and Yang, T. (2009), 'The effects and unintended consequences of the sarbanes-oxley act on the supply and demand for directors', *The Review of Financial Studies* **22**(8), 3287–3328.

Lins, K. V., Servaes, H. and Tamayo, A. (2017), 'Social capital, trust, and firm performance: The value of corporate social responsibility during the financial crisis', *The Journal of Finance* **72**, 1785–1824.

Lintner, J. (1956), 'Distribution of incomes of corporations among dividends, retained earnings, and taxes', *The American Economic Review* **46**(2), 97–113.

Luo, Y. (2005), 'Do insiders learn from outsiders? evidence from mergers and acquisitions', *The Journal of Finance* **60**(4), 1951–1982.

Mace, M. L. et al. (1971), 'Directors: Myth and reality'.

Maug, E. (1998), 'Large shareholders as monitors: Is there a trade-off between liquidity and control?', *The Journal of Finance* **53**(1), 65–98.

McDonald, M. P. (2014), 'Presidential voter turnout rates'.

Merz, M. and Yashiv, E. (2007), 'Labor and the market value of the firm', *The American Economic Review* **97**(4), 1419–1431.

Michaely, R. and Roberts, M. R. (2012), 'Corporate dividend policies: Lessons from private firms', *The Review of Financial Studies* **25**(3), 711–746.

Miller, M. H. and Modigliani, F. (1961), 'Dividend policy, growth, and the valuation of shares', *the Journal of Business* **34**(4), 411–433.

Miller, M. H. and Rock, K. (1985), ‘Dividend policy under asymmetric information’, *The Journal of Finance* **40**(4), 1031–1051.

Myers, S. C. (2000), ‘Outside equity’, *The Journal of Finance* **55**(3), 1005–1037.

Norli, Ø., Ostergaard, C. and Schindele, I. (2015), ‘Liquidity and shareholder activism’, *The Review of Financial Studies* **28**(2), 486–520.

O’Hara, M. (2003), ‘Presidential address: Liquidity and price discovery’, *The journal of Finance* **58**(4), 1335–1354.

Oi, W. Y. (1962), ‘Labor as a quasi-fixed factor’, *Journal of political economy* **70**(6), 538–555.

Pagano, M. and Volpin, P. F. (2005), ‘Managers, workers, and corporate control’, *The Journal of Finance* **60**(2), 841–868.

Pan, Y., Wang, T. Y. and Weisbach, M. S. (2016), ‘Ceo investment cycles’, *The Review of Financial Studies* **29**(11), 2955–2999.

Peters, R. H. and Taylor, L. A. (2017), ‘Intangible capital and the investment-q relation’, *Journal of Financial Economics* **123**(2), 251–272.

Pfeffer, J. (1994), ‘Competitive advantage through people’, *Boston/Mass* .

Pinnuck, M. and Lillis, A. M. (2007), ‘Profits versus losses: Does reporting an accounting loss act as a heuristic trigger to exercise the abandonment option and divest employees?’, *The Accounting Review* **82**(4), 1031–1053.

Porter, M. E. (1992), ‘Capital choices: Changing the way america invests in industry’, *Journal of Applied Corporate Finance* **5**(2), 4–16.

Portes, A. (1998), ‘Social capital: Its origins and applications in modern sociology’, *Annual Review of Sociology* **24**(1), 1–24.

Posner, E. A. (2000), *Law and social norms*, Harvard University Press, Canbridge, MA.

Posner, R. A. (1980), 'A theory of primitive society, with special reference to law', *The Journal of Law and Economics* **23**(1), 1–53.

Putnam, R. (1995), 'Tuning In, tuning out: The strange disappearance of social capital in America', *PS: Political Science and Politics* **28**, 664–683.

Putnam, R. (2001), 'Social capital: Measurement and consequences', *Canadian Journal of Policy Research* **2**(1), 41–51.

Putnam, R. D. (2000), *Bowling alone: The collapse and revival of American community*, Simon and schuster.

Putnam, R. D., Leonardi, R. and Nanetti, R. Y. (1993), *Making democracy work: Civic traditions in modern Italy*, Princeton University Press, Princeton, New Jersey.

Romano, R. (2004), 'The sarbanes-oxley act and the making of quack corporate governance', *Yale LJ* **114**, 1521.

Rosenbaum, P. R. and Rubin, D. B. (1983), 'The central role of the propensity score in observational studies for causal effects', *Biometrika* **70**(1), 41–55.

Rupasingha, A., Goetz, S. J. and Freshwater, D. (2006), 'The production of social capital in US counties', *The Journal of Socio-Economics* **35**(1), 83–101.

Sandvik, J. (2020), 'Board monitoring, director connections, and credit quality', *Journal of Corporate Finance* **65**, 101726.

Scharfstein, D. S. and Stein, J. C. (1990), 'Herd behavior and investment', *The American Economic Review* pp. 465–479.

Scrivens, K. and Smith, C. (2013), 'Four interpretations of social capital: An agenda for measurement', *OECD Statistics Working Papers* **No. 2013/06**.

Serfling, M. (2016), 'Firing costs and capital structure decisions', *The Journal of Finance* **71**(5), 2239–2286.

Shang, C. (2020), 'Trade credit and stock liquidity', *Journal of Corporate Finance* **62**, 101586.

Shivdasani, A. and Yermack, D. (1999), 'Ceo involvement in the selection of new board members: An empirical analysis', *The Journal of Finance* **54**(5), 1829–1853.

Shleifer, A. and Vishny, R. W. (1989), 'Management entrenchment: The case of manager-specific investments', *Journal of Financial Economics* **25**(1), 123–139.

SpencerStuart (2020), '2020 u.s. spencer stuart board index'.

Stein, J. C. (1989), 'Efficient capital markets, inefficient firms: A model of myopic corporate behavior', *The Quarterly Journal of Economics* **104**(4), 655–669.

Stein, J. C. (2003), 'Agency, information and corporate investment', *Handbook of the Economics of Finance* **1**, 111–165.

Stoll, H. R. and Whaley, R. E. (1983), 'Transaction costs and the small firm effect', *Journal of Financial Economics* **12**(1), 57–79.

Sualihu, M. A., Rankin, M. and Haman, J. (2021), 'The role of equity compensation in reducing inefficient investment in labor', *Journal of Corporate Finance* **66**, 101788.

Sualihu, M. A., Yawson, A. and Yusoff, I. (2021), 'Do analysts''forecast properties deter suboptimal labor investment decisions? evidence from regulation fair disclosure', *Journal of Corporate Finance* **69**, 101995.

Subrahmanyam, A. and Titman, S. (2001), 'Feedback from stock prices to cash flows', *The Journal of Finance* **56**(6), 2389–2413.

Tosi, H. L., Shen, W. and Gentry, R. J. (2003), 'Why outsiders on boards can't solve the corporate governance problem', *Organizational Dynamics* **32**(2), 180–192.

Uphoff, N. and Wijayaratna, C. M. (2000), 'Demonstrated benefits from social capital: The productivity of farmer organizations in Gal Oya, Sri Lanka', *World Development* **28**(11), 1875–1890.

Walsh, J. P. and Seward, J. K. (1990), 'On the efficiency of internal and external corporate control mechanisms', *Academy of Management Review* **15**(3), 421–458.

Whited, T. M. and Wu, G. (2006), 'Financial constraints risk', *The Review of Financial Studies* **19**(2), 531–559.

Williamson, O. E. (1963), 'Managerial discretion and business behavior', *The American Economic Review* **53**(5), 1032–1057.

Williamson, O. E. (1993), 'Calculativeness, trust, and economic organization', *The Journal of Law and Economics* **36**(1, Part 2), 453–486.

Withers, M. C., Hillman, A. J. and Cannella Jr, A. A. (2012), 'A multidisciplinary review of the director selection literature', *Journal of Management* **38**(1), 243–277.

Wu, W.-p. (2008), 'Dimensions of social capital and firm competitiveness improvement: The mediating role of information sharing.', *Journal of Management Studies* **45**, 122–147.

Wu, Y. (2018), 'What's behind smooth dividends? evidence from structural estimation', *The Review of Financial Studies* **31**(10), 3979–4016.

Zajac, E. J. and Westphal, J. D. (1996), 'Director reputation, ceo/board power, and the dynamics of board interlocks.', *Academy of Management Proceeding* **41**(3), 507–529.

Zaman, R., Atawnah, N., Baghdadi, G. A. and Liu, J. (2021), 'Fiduciary duty or loyalty? evidence from co-opted boards and corporate misconduct', *Journal of Corporate Finance* **70**, 102066.

Appendices

Appendix for Chapter 2

A. Variable Definition

Table 2.1: Variable Definition

Variables	Definition
Variables used in first-stage regression	
$Net\ Hiring_{it}$	The percentage change in the number of employees.
$Sales\ Growth$	The percentage change in sales.
ΔROA	The change in return on assets.
ROA	The return on assets.
$Return$	The annual total stock return.
$Size$	The natural logarithm of a firm's market value.
$Quick$	The ratio of cash and short-term investments plus receivables to current liabilities.
$\Delta Quick$	The percentage change in the quick ratio.
$Leverage$	The ratio of Long-term debt plus debt in current liabilities, divided by the book value of assets.
$LossBin$	Five dummy variables indicating each 0.005 interval of ROA from 0 to -0.025. For example, LossBin1 takes the value of one if ROA in previous year is between -0.005 and 0 and zero otherwise, LossBin2 takes the value of one if ROA in previous year is between -0.010 and -0.005 and zero otherwise, LossBin3 in previous year takes the value of one if ROA is between -0.015 and -0.010 and zero otherwise, and so on for the other LossBins.
$R\&D$	The ratio of research and development expenses to total asset
$CAPEX$	The ratio of capital expenditures to total asset
$Acquisitions$	Acquisition expenditures
$Union$	The percentage of state-level of union coverage.
GDP	The natural logarithm of state-level GDP.
Variables used in baseline regression	
Abnormal Net Hiring	Inefficient investment in labor measured as the absolute values of the residuals from equation (2.1).
Social Capital	County-level social capital measure constructed by implementing principal component analysis (PCA) based on four factors (PVOTE, RESPN, NCCS and ASSN), using data from Northeast Regional Centre for Rural Development (NR-CRD) (Rupasingha et al., 2006). PVOTE is the percentage of voters who voted in presidential elections. RESPN is the response rate to the Census Bureau's decennial census. NCCS is the total of nonprofit organizations divided by population per 10,000. ASSN is the total of social organizations divided by population per 100,000.
MTB	The market-to-book ratio.
$Dividend$	A dummy variable set equal to one in years in which a firm pays common dividends, and zero otherwise.
Std Cash	The standard deviation of the ratio of cash flow to assets for the previous five years.
Std Sales	The standard deviation of sales revenue for the previous five years.
$Tangibility$	The ratio of property, plant, and equipment to total assets.
$Loss$	A dummy variable set equal to one in years in which a firm has negative ROA.
Labor Intensity	Labor Intensity, measured as the number of employees divided by total assets.
Ab. non-Labor Invest.	Abnormal non-Labor Investments, defined as the absolute value of the residual from the equation: $Invest\_other_{it} = \beta_0 + \beta_1 Sales\_growth_{it} + \varepsilon_{it}$, where $Invest_other$ is the sum of capital expenditure, R&D expenditures, less cash receipts from the sale of property, plant, and equipment, all scaled by lagged total assets.
$Income$	County per capita personal income in natural logarithm.
$Education$	County percentage of people aged 25 and over with a bachelor's degree or higher.

(Continued on next page)

Variables	Definition
Signed Abnormal Net Hiring	
Labor Over-Investment	
Abnormal Labor^{+}	Positive *Abnormal Net Hiring*
Over-hiring^{+}	Positive *Abnormal Net Hiring* and positive expected net hiring.
Under-firing^{+}	Positive *Abnormal Net Hiring* and negative expected net hiring.
Labor Under-Investment	
Abnormal Labor^{-}	Negative *Abnormal Net Hiring*
Over-hiring^{-}	Negative *Abnormal Net Hiring* and positive expected net hiring.
Under-firing^{-}	Negative *Abnormal Net Hiring* and negative expected net hiring.
Additional controls	
$Union$	The percentage of state-level of union coverage available from www.unionstats.com.
Financial Constraints	A dummy variable that equals to one if firm's external financing dependence (EF) value is greater than its industry median, and zero otherwise. EF is measured as the industry median value of the difference between capital expenditures and cash flow from operations, divided by capital expenditures (Foucault and Frésard, 2012).
Organisation Capital	Firm-level organization capital, measured by firm's capitalized selling, general and administrative expenses. Details of the construction of this variables are in Appendix C.
Independent directors	The percentage of independent directors on the board. Data available from Boardex.
$Duality$	A dummy variable equals to one if a firm's CEO also takes the role of the board chair, and zero otherwise. Data available from Boardex.
Alternative proxies for abnormal net hiring	
Abnormal Net Hiring (MED)	The difference between a firm's actual hiring and the industry median for robustness
Abnormal Net Hiring (Sales)	Inefficient investment in labor measured as the absolute values of the residuals from equation (2.2).
Abnormal Net Hiring (Add. Factors)	Inefficient investment in labor measured as the absolute values of the residuals from equation (2.3).
Alternative proxies for social capital	
$Vote$	The percentage of voting-age population voted for the highest office in a state in a given election year. Data from: (www.electproject.org/home)
Social Networks	Measure for social networks, decomposed from social capital index, PCA.
Cooperative Norms	Measure for cooperative norms, decomposed from social capital index, PCA.
Social Capital (Backfill)	Social capital index based on back-filling approach to estimate the missing value, suggested by (Hoi et al., 2019).
SK	Raw social capital index constructed by Rupasingha et al. (2006).
IV and mechanism analysis	
$Distance$	The natural logarithm of one plus the distance between the county where the firm is located and US-Canada border.
Low Takeover Index	A dummy variable that equals to one if firm-year observations are below the 25th percentile of takeover index value, and zero otherwise. The takeover index is constructed by Cain et al. (2017), https://pages. uoregon. edu/smckeon/

B. First-Stage Regressions Results

Table 2.2: Descriptive Statistics

This table reports descriptive statistics for all variables in the first-stage regression.

Variables	N	Mean	Median	Std. Dev.
$Net\ Hiring_{it}$	52,268	0.065	0.024	0.311
$Sales\ Growth_{it}$	52,268	0.130	0.068	0.488
$Sales\ Growth_{it-1}$	52,268	0.149	0.075	0.502
ΔROA_{it}	52,268	-0.005	-0.000	0.171
ΔROA_{it-1}	52,268	-0.001	0.001	0.169
ROA_{it}	52,268	-0.013	0.038	0.220
$Return_{it}$	52,268	0.159	0.051	0.673
$Size_{it-1}$	52,268	5.581	5.552	2.141
$Quick_{it-1}$	52,268	2.041	1.284	2.491
$\Delta Quick_{it}$	52,268	0.111	-0.004	0.662
$\Delta Quick_{it-1}$	52,268	0.115	-0.002	0.668
$Leverage_{it-1}$	52,268	0.208	0.171	0.202
$LossBin1_{it-1}$	52,268	0.012	0.000	0.111
$LossBin2_{it-1}$	52,268	0.012	0.000	0.109
$LossBin3_{it-1}$	52,268	0.012	0.000	0.107
$LossBin4_{it-1}$	52,268	0.011	0.000	0.107
$LossBin5_{it-1}$	52,268	0.010	0.000	0.098
$R\&D_{it-1}$	37,908	0.053	0.006	0.102
$CAPEX_{it-1}$	37,908	0.052	0.034	0.056
$Acquisitions_{it-1}$	37,908	42.644	0.000	150.170
$Union_{it-1}$	52,170	0.153	0.168	0.062
GDP_{it-1}	37,908	13.079	13.021	0.896

Table 2.3: First-stage Regressions

Column (1) reports estimates of the baseline model of equation (2.1). Columns (2) and (3) report estimates of robustness models of equations (2.2) and (2.3) respectively. The dependent variable is $Net\ Hiring$. Definitions of the variables are provided in Panel A of Table 2.2. Year and industry fixed effects are included. *, ** and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

	Main model	Robustness	
Variables		Sales growth	Additional factors
	(1)	(2)	(3)
$Sales\ Growth_{it}$	0.239***		0.228***
	(24.50)		(13.03)
$Sales\ Growth_{it-1}$	0.041***	0.063***	0.041***
	(8.48)	(12.52)	(7.86)
ΔROA_{it}	-0.237***		-0.179***
	(-15.21)		(-9.50)
ΔROA_{it-1}	-0.046***		-0.045***
	(-3.55)		(-2.78)
ROA_{it}	0.112***		0.056**
	(9.22)		(2.45)
$Return_{it}$	0.055***		0.051***
	(19.53)		(15.60)
$Size_{it-1}$	0.006***		0.008***
	(7.99)		(7.01)
$Quick_{it-1}$	0.005***		0.005***
	(4.65)		(5.34)
$\Delta Quick_{it}$	0.032***		0.032***
	(10.45)		(9.73)
$\Delta Quick_{it-1}$	0.015***		0.012***
	(4.99)		(3.70)
$Leverage_{it-1}$	-0.060***		-0.062***
	(-7.22)		(-6.93)
$LossBin1_{it-1}$	-0.024***		-0.019**
	(-2.90)		(-2.10)
$LossBin2_{it-1}$	-0.020**		-0.021***
	(-2.09)		(-2.44)
$LossBin3_{it-1}$	-0.013		-0.014
	(-1.17)		(-0.98)
$LossBin4_{it-1}$	-0.002		0.003
	(-0.15)		(0.22)
$LossBin5_{it-1}$	-0.017		-0.023**
	(-1.52)		(-2.31)
			(-1.84)
$R\&D_{it-1}$			-0.235***
			(-6.21)
$CAPEX_{it-1}$			0.097***
			(2.83)
$Acquisitions_{it-1}$			-0.000***
			(-4.33)
$Union_{it-1}$			-0.051*
			(-1.84)
GDP_{it-1}			0.002
			(0.72)
Constant	-0.015***	0.056***	-0.038
	(-2.86)	(35.65)	(-1.35)
Observations	52,268	52,268	37,908
Adjusted R^2	0.200	0.032	0.193
Year FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes

C. Construction of Organization Capital Variable

Following Eisfeldt and Papanikolaou (2013), organization capital is measured based on firm's selling, general and administrative expenses (SGA) using the perpetual inventory method. Specifically, the stock of organization capital (OC) is computed by accumulating inflation-adjusted SGA expenses:

$$OC_{it} = (1-\delta)OC_{it-1} + \frac{SGA_{it}}{CPI_{it}}, \tag{1}$$

where δ is the depreciation rate of business R&D capital, which is 15% estimated by the Bureau of Economic Analysis, SGA is the general and administrative expenses, CPI is the annual average consumer price index. The initial organization capital is then computed as:

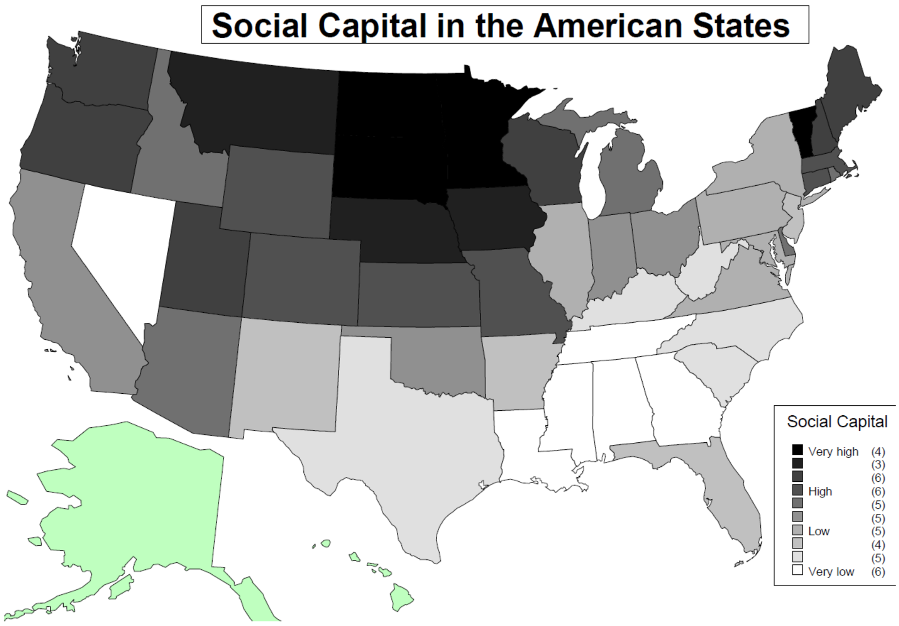
$$OC_{i0} = \frac{SGA_{i0}}{g+\delta}, \tag{2}$$

where g is the average growth of rate of firm's SGA expenses, which is set to 30% estimated by Peters and Taylor (2017). Finally, firm-level organization capital is divided by total assets:

$$\textit{Organization Capital} = \frac{OC}{TA}, \tag{3}$$

D. Social Capital Map

Figure 1: Canadian boarder as a predictor of social capital in US states. Figure from Putnam (2001).



Appendix for Chapter 3

A. Variable Definition

Table 3.1: Variable Definitions

VARIABLES	Definition
Variables used in first-stage regression	
Actual_net_hire	The percentage change in the number of employees.
Expected_net_hire	Expected percentage change in the number of employees estimated from model (3.2)
Sales_growth	The percentage change in sales.
Ch_ROA	The change in return on assets.
ROA	The return on assets.
Return	The annual total stock return.
Size	The natural logarithm of a firm's market value.
Quick	The ratio of cash and short-term investments plus receivables to current liabilities.
Ch_quick	The percentage change in the quick ratio.
Leverage	The ratio of Long-term debt plus debt in current liabilities, divided by the book value of assets.
LossBin	Five dummy variables indicating each 0.005 interval of ROA from 0 to -0.025. For example, LossBin1 takes the value of one if ROA in previous year is between -0.005 and 0 and zero otherwise, LossBin2 takes the value of one if ROA in previous year is between -0.010 and -0.005 and zero otherwise, LossBin3 in previous year takes the value of one if ROA is between -0.015 and -0.010 and zero otherwise, and so on for the other LossBins.
Variables used in baseline model	
$\|Abnormal\_net\_hire\|$	It is the absolute values of the residuals obtained from model (3.2)
Co_op	The ratio of the number of directors elected after the CEO takes office to the board size.
MTB	The market-to-book ratio.
Dividend	A dummy variable set equal to one in years in which a firm pays common dividends, and zero otherwise.
Std_cash	The standard deviation of the ratio of firm-level cash flow from operations to total assets for the previous five years.
Std_sale	Natural logarithm of the standard deviation of firm-level sales revenue for the previous five years.
Tangibility	The ratio of property, plant, and equipment to total assets.
Loss	A dummy variable set equal to one in years in which a firm has negative ROA.
Labour_intense	Labour intensity, measured as the number of employees divided by total assets.

continued on next page…

(continued)

VARIABLES	Definition
Ab_invest	Abnormal non-labor investments, defined as the absolute value of the residual from the following equation: $$\text{Invest\_Other}_{it} = \beta_0 + \beta_1 \text{Sales\_growth}_{it-1} + \varepsilon_{it},$$ where Invest_Other is the sum of capital expenditure, R&D expenditures, less cash receipts from the sale of property, plant, and equipment, all scaled by lagged total assets.
Variables used in robustness and additional analysis	
Co_op_ind	The ratio of the number of co-opted directors who are independent to total board size.
TwCo_op	Sum of tenure of co-opted directors divided by the sum of tenure of all directors.
TwCo_op_ind	Sum of tenure of co-opted independent directors divided by the sum of tenure of all directors.
Non_co_op_ind	The ratio of non co-opted independent directors to the board size. Non co-opted directors are those who are already on the board before the CEO takes office.
Non_co_op_non_ind	The ratio of non co-opted non independent directors to the board size. Non co-opted directors are those who are already on the board before the CEO takes office.
Industry mean co_option	The average co-option of the industry that the firm belongs to.
HHI	Herfindahl–Hirschman index, calculated as sum of the squared market share based on firm sales at two-digit SIC codes.
LI	Lerner Index, calculated as the price–cost margin scaled by sales.
Fluidity	Product market competitive threats constructed by Hoberg et al. (2014).

B. Regressions Results for First Stage

Table 3.2: Summary Statistics for variables used in First-Stage Regression

This table reports descriptive statistics for all variables in the first-stage regression.

VARIABLES	(1) N	(2) Mean	(3) Std.Dev	(4) Min	(5) Max	(6) P25	(7) Median	(8) P75
$Actual\_net\_hire_{it}$	62,713	0.061	0.289	-0.651	1.762	-0.052	0.021	0.120
$Sale\_growth_{it}$	62,713	0.124	0.422	-0.807	3.130	-0.036	0.068	0.195
$Sale\_growth_{it-1}$	62,713	0.146	0.439	-0.757	3.003	-0.028	0.078	0.214
Ch_ROA_{it}	62,713	-0.005	0.161	-0.647	0.672	-0.043	-0.001	0.034
Ch_ROA_{it-1}	62,713	-0.001	0.159	-0.598	0.640	-0.042	-0.000	0.035
ROA_{it-1}	62,713	-0.011	0.211	-1.143	0.379	-0.033	0.036	0.085
$Return_{it}$	62,713	0.156	0.651	-0.860	3.023	-0.235	0.059	0.374
$Size_{it-1}$	62,713	5.894	2.238	0.583	11.029	4.234	5.855	7.455
$Quick_{it-1}$	62,713	1.992	2.486	0.098	20.730	0.758	1.231	2.189
Ch_quick_{it}	62,713	0.112	0.670	-0.831	4.766	-0.198	-0.005	0.217
Ch_quick_{it-1}	62,713	0.108	0.667	-0.821	4.496	-0.205	-0.009	0.215
$Leverage_{it-1}$	62,713	0.217	0.204	0.000	0.919	0.023	0.185	0.341
$LossBin1_{it-1}$	62,713	0.013	0.112	0.000	1.000	0.000	0.000	0.000
$LossBin2_{it-1}$	62,713	0.012	0.109	0.000	1.000	0.000	0.000	0.000
$LossBin3_{it-1}$	62,713	0.011	0.106	0.000	1.000	0.000	0.000	0.000
$LossBin4_{it-1}$	62,713	0.011	0.104	0.000	1.000	0.000	0.000	0.000
$LossBin5_{it-1}$	62,713	0.010	0.098	0.000	1.000	0.000	0.000	0.000

Table 3.3: First-Stage Regression Output

This table reports regression results from model (3.2). The dependent variable is $Actural\_net\_hire$. The independent variables are $Sale\_growth$, Ch_ROA, ROA, $Return$, $Size$, $Quick$, Ch_quick, $Leverage$ and $LossBins$. Year and industry fixed effects are included. t-statistics are presented in parentheses. 1% Significance level *** 5% Significance level ** 10% Significance level *

VARIABLES	Predicted sign	(1) $Actual\_net\_hire_{it}$
$Sale\_growth_{it}$	+	0.274***
		(35.38)
$Sale\_growth_{it-1}$	+	0.041***
		(9.66)
Ch_ROA_{it}	-	-0.244***
		(-18.36)
Ch_ROA_{it-1}	+	-0.048***
		(-4.51)
ROA_{it-1}	+	0.112***
		(11.22)
$Return_{it}$	+	0.049***
		(19.74)
$Size_{it-1}$	+	0.006***
		(9.58)
$Quick_{it-1}$	+	0.004***
		(4.80)
Ch_quick_{it}	+	0.033***
		(12.86)
Ch_quick_{it-1}	+	0.011***
		(4.85)
$Leverage_{it-1}$	-	-0.047***
		(-7.02)
$LossBin1_{it-1}$	-	-0.027***
		(-3.75)
$LossBin2_{it-1}$	-	-0.026***
		(-3.41)
$LossBin3_{it-1}$	-	-0.025***
		(-2.77)
$LossBin4_{it-1}$	-	-0.008
		(-0.94)
$LossBin5_{it-1}$	-	-0.019*
		(-1.94)
Constant		-0.021***
		(-4.73)
Observations		62,713
Adjusted R-squared		0.223
Year FE		YES
Industry FE		YES

Appendix for Chapter 4

A. Variable Definition

Table 4.1: Variable Definitions

VARIABLES	Definition
Variables used in baseline regressions	
DPS	Dividends per share (adjusted to stock split).
EPS	Earnings per share (adjusted to stock split).
$Payout$	Payout ratio, calculated as dividends divided by income before extraordinary items.
TPR	Target payout ratio, calculated as the median of payout for individual firm by using a 10-year rolling window.
SOA	The speed of adjustment, estimated from the regression: $\Delta DPS_{it} = \alpha + \beta * DEV_{it} + \varepsilon_{it}$, where $DEV_{it} = TPR_{it} * EPS_{it} - DPS_{it}$. SOA is the β coefficient of the regression.
$Spread$	Closing Percent Quoted Spread, calculated by using the dollar quoted spread divided by the midpoint of quotes.
$Ln(Spread)$	Natrual logarithm of $Spread$.
$Firm\ size$	Natural logarithm of firm's sales.
$Firm\ age$	Natural logarithm of the number of years that firm appears in the Compustat database.
$Market\_to\_Book$	The Mmarket-to-book ratio.
$Turnover$	The 12-month average ratio of monthly trading volume to shares outstanding.
$Tangibility$	The ratio of net property, plant and equipment to total assets
$Cash$	Cash flow divided by total asset.
$Free\ cash$	Operating income before depreciation minus interests, taxes, preferred dividends and common dividends, all divided by total assets.
$Std(Return)$	Annual standard deviation of monthly returns.
$Std(EBITDA)$	Standard deviation of EBITDA to total asset, calculated using 10-year rolling window.
Variables used in robustness and additional tests	
$Ln(Amihud)$	Illiquidity ratio by Amihud (2002), calculated as $Amihud_{it} = \frac{1}{D_{it}} \sum_{d=1}^{D} \frac{\lvert Ret_{idt} \rvert}{Volume_{idt}}$. Where Ret_{idt} and $Volume_{idt}$ are, respectively, the stock return and the trading volume in million dollars for firm i on trading day d in year t. D_{it} is the number of trading days for firm i in year t. A higher value of Amihud illiquidity ratio corresponds to lower liquidity.
$Zeros$	Ratio of zero return days by Lesmond et al. (1999), calculated as: $Zeros_{it} = \frac{Zero\ Return\ Day_{it}}{Total\ Day_{it}}$. Where $Zero\ Return\ Day_{it}$ and $Total\ Day_{it}$ are the number of zero-return days and total number of trading days for firm i in year t. A higher value of Zeros represents lower liquidity.
$Ln(FHT)$	Proxy for liquidity by Fong et al. (2017), calculated as: $FHT_{it} = 2 * \sigma * N^{-1}(\frac{1+Zeros}{2})$. Where σ is standard deviation of daily returns for firm i in year t. $Zeros$ is the proportion of days with zero returns. $N^{-1}()$ is the inverse function of the cumulative normal distribution. A higher value FHT indicates lower liquidity.

continued on next page…

(continued)

$RELVOL10$	Relative volatility, estimated from following two regressions using 10-year rolling window: $DPS_{it} = \alpha_1 + \beta_1 T + \beta_2 T^2 + \varepsilon_{it}$, and $TPR_i * EPS_{it} = \alpha_2 + \gamma_1 T + \gamma_2 T^2 + \delta_{it}$. Where T and T^2 are time and quadratic time trends respectively. Relative volatility is then calculated by the ratio of root mean squared errors from above two regressions ($\sigma(\varepsilon)/\sigma(\delta)$).
$RELVOL7$	Relative volatility estimated using 7-year rolling window.
$RELVOL5$	Relative volatility estimated using 5-year rolling window.
$SOA7$	Speed of adjustment estimated using 7-year rolling window.
$SOA5$	Speed of adjustment estimated using 5-year rolling window.
SA	SA Index by Hadlock and Pierce (2010), calculated as $-0.737 * Firm\ size + 0.043 * Firm\ size^2 - 0.040 * Firm\ age$. $Firm\ size$ is capped at \$4.5 billion, $Firm\ age$ is capped at 37 years.
WW	WW Index by Whited and Wu (2006), calculated as $-0.091 * Cash\ flow - 0.062 * Dividend + 0.021 * Long-term\ debt - 0.044 * Firm\ size + 0.102 * Industry\ sales\ growth - 0.035 * Sales\ growth$. $Sales\ growth$ is the percentage change in sales. $Industry\ sales\ growth$ is estimated using the mean value of sales growth based on 3-digit SIC code.

B. Additional Robustness Checks

Table 4.2: Results When Including Decimalization Year as Robustness

This table reports difference-in-difference analysis based on the decimalization in 2001. $Treat$ is a dummy variable equal to one if stocks are in the treatment group, and zero if in the control group. $Post$ is a dummy variable equal to one for the years of 2001, 2002 and 2003, and zero for the years 1999 and 2000. $Treat * Post$ is the interaction between the two dummy variables. SOA is dependent variable. Firm characteristics are specified in model (4.4). All variables are defined in Table 4.1 of Appendix. t-statistics are presented in parentheses. Standard errors are clustered at the firm level. 1% Significance level *** 5% Significance level ** 10% Significance level *

VARIABLES	(1) SOA
$Treat * Post$	0.054***
	(3.00)
$Treat$	-0.048
	(-1.46)
$Post$	-0.032***
	(-2.77)
$Cash$	0.465**
	(2.00)
$Free\ cash$	0.221
	(0.66)
$Market\_to\_Book$	0.003
	(0.18)
$Turnover$	-0.056
	(-0.36)
$Firm\ size$	0.001
	(0.04)
$Firm\ age$	-0.033
	(-1.01)
$Std(Return)$	0.439***
	(3.14)
$Std(EBITDA)$	0.905
	(1.58)
$Tangibility$	-0.060
	(-0.85)
$Payout$	-0.002
	(-0.31)
Constant	0.174
	(1.29)
Observations	1,166
Adjusted R-squared	0.495
Industry FE	YES