Essays on incentive contracts, M&As, and firm risk

An, Suwei

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SUWEI AN

TILBURG UNIVERSITY

Essays on incentive contracts, M&As, and firm risk

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Suwei An

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Promotores:	prof. dr. L.T.M. Baele (Tilburg University) prof. dr. X. Tan (CUFE)
Copromotor:	dr. K. Wu (CUFE)
leden promotiecommissie:	prof. dr. F.A. de Roon (Tilburg University) prof. dr. R. Pownall (Maastricht University) prof. dr. M. Deloof (Universiteit Antwerpen) dr. P.C. de Goeij (Tilburg University)

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Suwei An
Beijing, November 2022

Contents

Chapter 1

Introduction

1.1 Agency Costs

A large and growing literature has discussions on the issue of the agency problem, which studies the conflicting interests between shareholders and managers (Fama & Jensen, 1983a, 1983b; Grossman & Hart, 1986; Holmstrom, 1979, 1982; Jensen, 1993; Jensen & Meckling, 1976; Ross, 1973; Shleifer & Vishny, 1997). Specifically, interest conflicts derive from the separation of firm ownership and firm control (Shleifer & Vishny, 1997). Jensen and Meckling (1976) define the agency relationship under which shareholders (the principals) engage managers (the agents) to perform firm management service and maximize the equity value of shareholders. Whereas, given self-utility maximizing incentive, managers do not always act in the best interests of shareholders (Hart, 1995). For instance, managers can have harmful actions of overexpansion (Jensen, 1986a), under- and over-investment (Stulz, 1990), and cash dissipation (Dittmar and Mahrt-Smith, 2007; Harford, 1999; Harford et al., 2008), etc. In particular, some researchers focus the agency costs on the investment activities of managers. (Jensen, 1986b), Lang, Stulz, & Walkling (1991), and Morck, Shleifer, & Vishny (1990) provide evidence that managers' acquisition choices are sometimes harmful to the interest of shareholders.

Agency problems are mostly based on the information asymmetry between

principals and agents. The asymmetrical information usually benefits the subjects with more information (Akerlof, 1970). Concerning firm operations, managers have more firm-specific information than shareholders and potential investors. Thus, managers are able to take advantage of information asymmetry and benefit themselves at the expense of shareholders and investors by manipulating the private information (Akerlof, 1970; Bartov & Bodnar, 1996; Jensen & Meckling, 1976; Krishnaswami & Subramaniam, 1999; Myers & Majluf, 1984; etc.). Moreover, the residual rights of firm control owned by managers, i.e., the management discretion, provides the feasibility for self-interested managerial behaviors (Shleifer & Vishny, 1997).

It is important to research the agency costs and find ways to control them. Numerous studies have found evidence of agency costs based on specific events (see, for instance, Fama, Fisher, Jensen, & Roll, 1969; McConnell & Muscarella, 1985). The basic idea is that agency costs are considered to exist when there are decreased stock returns ex-post, implying the interests of shareholders are not upheld.

One of the typical events is M&A. Literature demonstrates that managers undertake value-reducing investment activities (Lang & Stulz, 1994; Lang et al., 1991; Lewellen, Loderer, & Rosenfeld, 1985; Randall Morck et al., 1990; Roll, 1986). They claim the existence of agency costs, demonstrating that managers' acquisition choices are sometimes harmful to the interest of shareholders. Particularly, some studies focus on how takeovers are affected by behavioral factors of managers, such as the managerial over-confidence (Ferris, Jayaraman, & Sabherwal, 2013; Malmendier & Tate, 2008), managerial self-attribution bias (Billett & Qian, 2008), managerial envy

(Goel & Thakor, 2010), etc.

Chapter 2 of this thesis demonstrates that manager sentiment, a managerial trait proxy for managerial optimism, can incur agency costs. Specifically, this chapter examines how manager sentiment affects takeover characteristics and long-term performance using data from textual analysis based on 10-K and 10-Q filings. The findings demonstrate that manager sentiment has a strong positive predictive power for takeover activities, and high manager sentiment decreases the long-term performance of takeover deals. Moreover, high-sentiment managers tend to undertake large deals, decrease the all-stock payment, acquire hard-to-value targets, and offer high target valuation. The findings imply the over-investment channel for the underperformed high-sentiment deals.

1.2 Incentive Contracts

Fortunately, some protection mechanisms assure the interest of shareholders from being occupied by managers. For instance, laws can effectively protect the right of shareholders to vote on important corporate decisions (Easterbrook & Fischel, 1983; Mitchell & Lehn, 1990). Large investors and creditors can help improve the corporate governance and control the agency problems by providing additional monitoring (Grossman & Hart, 1986; Kang & Shivdasani, 1995; Kaplan & Minton, 1994).

One important way to align the interests of managers and shareholders and mitigate the agency costs relies on the incentive contracts (Holmstrom, 1979, 1982; Ross, 1973; Stiglitz, 1975). There are two major tasks of the board (or the

compensation committee responsible for the board) to avoid the deviation between managers' and shareholders' interests through designing the proper compensation contracts. One issue is constructing appropriate executive compensation strategies. Humphery-Jenner et al. (2016), Matolcsy & Wright (2011), and Mehran (1995) make efforts to recognize the pros and cons of the selection of cash and equity payments in the compensation strategies. The other issue is evaluating managers' performance and designing compensation contracts adequately.

In this dissertation, chapters 3 and 4 focus on the latter issue, the performance evaluation. There are typically two methods to evaluate managers' performance, i.e., the absolute performance evaluation (APE) versus the relative performance evaluation (RPE). APE usually sets absolute values of either accounting metrics or stock price as the benchmarks to evaluate managers' performance during the assessment periods. RPE selects a group of comparable companies as the relative benchmarks, such as market indices, industrial indices, and groups of peer firms. Holmstrom (1979, 1982) develops a moral hazard model to document optimal incentive contracts and derives RPE as a more informative way to evaluate managers' performance. Since the 1980s, studies conjecture RPE utilization to evaluate managers' performance and determine their compensation. The consensus is that RPE insulates managers' compensation from common shocks and removes unnecessary risk from the contracts, thus being more informative in evaluating the agent's performance and more beneficial for limiting agency costs (Antle & Smith, 1985, 1986; Gibbons & Murphy, 1990; Janakiraman, et al., 1992; etc.).

Previous papers demonstrate the existence of RPE in incentive contracts by finding the negative association between the executive compensation of a firm and the market (industry) index (Aggarwal and Samwick, 1999b; Antle and Smith, 1986; Barro and Barro, 1990; Garen, 1994; Gibbons and Murphy, 1990; Janakiraman et al., 1992). This negative association implies that firms remove the systematic component from incentive contracts, so-called implicit tests of RPE. A regulatory change in 2006 requires firms to disclose their executive compensation information in more detail, allowing us to observe the listed firms' utilization of RPE directly since then, so-called explicit tests of RPE.

Chapter 3 examines how incentive contract in the form of RPE affects stock price crash risk. Using a sample of 22,776 US listed firms from 2006 to 2017, this chapter finds that firms using RPE exhibit lower stock price crash risk. The decomposition of RPE identifies market-based performance metrics and self-selected peer groups as the driving forces. The decreased market pressure is the primary channel through which RPE affects crash risk. The RPE-crash risk relation mainly manifests in firms with higher managerial ability, systematic uncertainty, industry competition, and managerial myopia correctability. Additionally, RPE firms are associated with higher information disclosure quality and lower analyst optimism. The findings demonstrate the effectiveness of RPE for aligning the interests of managers and shareholders, and provide implications for managerial myopia and information disclosure.

Chapter 4 investigates how RPE relates to long-term acquisition performance.

Using a sample of 6,811 acquisition deals of U.S. firms from 2006 to 2017, this chapter finds that RPE increases the long-term acquisition performance. The decomposition of RPE identifies the performance benchmarks of self-selected peer groups as the driving forces. RPE and long-term acquisition performance mainly manifest in firms with higher market uncertainty, higher managerial myopia correctability, and lower external monitoring. Finally, RPE is associated with lower short-term abnormal returns and higher acquirer reference price ratios. The findings demonstrate the effectiveness of RPE for aligning the interests of managers and shareholders, which provides implications for corporate governance and managerial myopia.

1.3 Thesis Outline and Contributions

This dissertation consists of two parts of research chapters. The first part, Chapter 2, outlines that manager sentiment drives takeover activities and decreases the bidders' return, reflecting one type of agency problem. The second part consists of Chapters 3 and 4, demonstrating RPE as an effective way to suppress agency problems and reduce agency costs. Specifically, Chapter 3 demonstrates that firms using RPE exhibit lower stock price crash risk and Chapter 4 finds empirical evidence that RPE increases long-term acquisition performance.

Chapter 2 has two contributions. First, it contributes to the strand of behavioral corporate finance literature. This study is the first to demonstrate the effect of manager sentiment on firm policies in the M&A context. Literature has presented many managerial biases, including limited governance, bounded rationality,

over-optimism, overconfidence, and hubris (Baker and Wurgler, 2013). In particular, Malmendier & Tate (2008) and Goel & Thakor (2010) demonstrate that CEO overconfidence and CEO envy significantly impact takeovers, respectively. This study highlights the role of manager sentiment, which captures the managerial optimism (or pessimism in another way). It claims that the measure of manager sentiment is an important behavioral trait measured by the textual tone in financial statements. Second, this study contributes to the literature on the causes and consequences of M&A. Previous research documents the causes of M&As, such as regulatory changes (Slovin, 1991), technological innovations (Gort, 1969), liquidity constraints (Harford, 2005), policy uncertainties (Bonaime et al., 2018), stock market valuations (Dong et al., 2006), and acquirer reference prices (Ma, Whidbee, and Zhang, 2019). This chapter focuses on the managerial factors and demonstrates that manager sentiment is important in driving takeover activities and affecting deal performances. Managers make takeover deals because of not only their reactions to exogenous shocks but also their optimism. The findings explain how manager sentiment affects takeover performance by conducting detailed tests on various deal characteristics.

Chapters 3 and 4 both contribute to the literature on agency problems and optimal contracts. Previous studies postulate that RPE can effectively control agency costs and benefit shareholders (Holmstrom, 1979; Antle and Smith, 1985, 1986; Gibbons and Murphy, 1990; Janakiraman, Lambert, and Larcker, 1992). This part confirms the advantages of RPE in determining compensation contracts over non-RPE by inducing positive firm impacts. Chapter 3 demonstrates that RPE

decreases stock price crash risk. Chapter 4 provides evidence that RPE increases firms' acquisition performance. They both emphasize that RPE motivates favorable managerial factors, especially managerial long-termism.

In addition, Chapter 3 additionally contributes to the literature on stock price crash risk. Previous literature on stock price crash risk presents concerns on i) information disclosing (Hutton et al., 2009; Kim et al., 2016; Kim et al., 2019), ii) corporate operation (Kim, Li, & Zhang, 2011b; Kim et al., 2014; Kim & Zhang, 2016), and iii) manager characteristics (Kim et al., 2016; Callen and Fang, 2015). Several studies have addressed the connection between the labor market and crash risk, focusing on equity incentives (Kim, Li, & Zhang, 2011a) and industry tournament incentives (Chowdhury et al., 2020; Kubick & Lockhart, 2020). Chapter 4 proposes a new explanation of the causes of stock price crash risk and adds the connection between agency contract, disclosure quality, and crash risk. It highlights the RPE's utility of improving disclosure quality and mitigating information asymmetry.

Chapter 4 contributes to the literature on M&As. Previous efforts to document the causes of long-term acquisition performance focus on stock valuation (Fu et al., 2013; Raghavendra Rau and Vermaelen, 1998), acquirer reference prices (Ma et al., 2019), cash reserves (Harford, 1999b), etc. Moreover, Hasan et al. (2020) examine the association between labor and acquisition markets. Nevertheless, this study is very different from theirs. Chapter 3 proposes another labor market-based factor as the cause of long-term acquisition performance, illustrating that RPE is an essential positive driver. It demonstrates that shareholders can benefit from the well-performed

acquisitions of RPE managers.

Finally, Chapter 5 concludes the thesis and summarizes the main findings. Furthermore, it provides recommendations for further research.

Chapter 2

Manager sentiment, deal characteristics, and takeover performance

2.1 Introduction

The causes and consequences of takeover activities have attracted long-lasting attention from academia and professional investors. Several factors that drive takeover activities and affect deal characteristics have been documented, such as regulatory changes (Slovin, 1991), technological innovations (Gort, 1969), liquidity constraints (Harford, 2005), policy uncertainties (Bonaime et al., 2018), stock market valuations (Dong et al., 2006), and acquirer reference prices (Ma, Whidbee, and Zhang, 2019). Studies have also found the important role of firm managers' characteristics in M&A activities, typically, the CEO overconfidence. For instance, Malmendier and Tate (2008) examine the effect of CEOs' overconfidence on takeover frequency and deal quality as the overconfident CEOs overestimate their ability to create value. This topic is revisited in an international context (Ferris, Jayaraman, and Sabherwal, 2013). Another notable study is Billett and Qian (2008), who measure the CEOs' self-attribution bias as a common driver of overconfidence and illustrate its effect on CEOs' acquisition decisions. Besides, Goel and Thakor (2010) develop an envy-based model to address the overconfidence issue and discuss the difference between early acquisitions and late acquisitions in merger waves.

However, little research investigates the effect of manager sentiment on deal characteristics, despiting that investor sentiment (Danbolt, Siganos, & Vagenas-Nanos, 2015; Dong et al., 2006; Shleifer & Vishny, 2003) and media sentiment (Yang et al., 2019) have been studied in the field of merger and acquisition. Using the standard textual analysis method and the Loughran and Mcdonald (2011) financial and accounting dictionary, we measure manager sentiment based on 10-K and 10-Q filings. Specifically, the manager sentiment is calculated as the count difference between positive and negative words normalized by the total word count from the content, following Tetlock (2007), Loughran and Mcdonald (2011), García (2013), Jiang et al. (2019), and others. The Management's Discussion and Analysis (MD&A) section is the chapter where managers most likely disclose information through particular tone. As Loughran and Mcdonald (2011) demonstrated, the entire document and MD&A section usually use similar words. Thus, the measurement based on textual analysis on the filings is mainly derived from the tone variation of management. This measurement is supposed to be an effective proxy for managers' tone, i.e., the manager sentiment.

Manager sentiment reflects the managers' judgement over the past year and their expectations for the future economic outcomes to some extent, capturing the optimism for future economic growth and firm outcomes (Henry, 2008; Jiang et al., 2019; Li, 2008; 2010). The optimistic beliefs derive from two parts: 1) the rational part based on economic and firm fundamentals; 2) the irrational part based on imperfect information and behavioral traits. The behavioral traits may include various

driving factors. For instance, the ability and experience issue matters because managers who lack of ability and experience can fail to recognize potential threats thus being optimistic. There is also an overconfidence issue that managers overestimate their abilities to cope when risks are successfully identified[1].

Our study has three major differences from the existing literature. First, manager sentiment is constructed by analyzing entire financial statements. It reflects the subjective opinions about the firms' past and future performance of the whole management instead of a single manager or CEO. Second, we relate manager sentiment to long-term acquisition performance instead of short-run abnormal returns. As Ma, Whidbee, and Zhang (2019) point out, the bias of short-horizon returns can be eventually corrected in the long run. Thus, the long-term performance of acquirers warrants an in-depth examination. Finally, we construct a monthly aggregated sentiment index, which allows us to examine the association between the manager sentiment and takeover characteristics at the aggregate level.

This study offers novel evidence on how manager sentiment is associated with takeover activities, long-term acquisition performance, and deal characteristics. We measure a firm's manager sentiment (*MS*) by taking the difference between the

[1] Managerial optimism differs from the overconfidence (Ferris et al., 2013; Malmendier and Tate, 2008; Billett and Qian, 2008), even though they might be highly related. The distinguishments between managerial optimism and overconfidence are not only derived from the different measurements based on different data sources, but also because they reflect distinct features of managers. Overconfidence measures the overestimation of personal abilities and managerial skills (Malmendier & Tate, 2008) which performs as one of the driving factors of optimism. That is, managers can be overly optimistic for the future even though they hold the correct perception of their abilities. However, even though we can distinguish them conceptually, it's still a big challenge to separate them empirically. This paper tries to use customary measure of overconfidence following previous studies and construct manager sentiment to proxy for optimism. Because of the connections between optimism and overconfidence we explained, overconfidence drives manager sentiment to some extent. Our empirical findings in Column (1) Table 2.A.1 confirms this point of view.

number of positive words and the number of negative words normalized by the total number of words in its 10-K and 10-Q filings. The deal-level manager sentiment is constructed as the sentiment of the firm's nearest released 10-K or 10-Q filings over six months before the deal announcement. Additionally, previous research emphasizes the negative words and measures the text's tone by counting negative words only (Tetlock, 2007; Tetlock et al., 2008). Thus, we further decompose the *MS* by constructing positive *MS* and negative *MS* to find whether positive or negative words drive the results. We also conduct the aggregate-level manager sentiment index *MSI*, the monthly average manager sentiment using a four-month moving average weighted by filing numbers to mitigate the influence of seasonality and idiosyncratic jumps, as in Jiang et al. (2019).

We first conduct our major firm-level analyses to examine the extent to which manager sentiment drives takeover activities. We find that manager sentiment has a strong positive predictive power for takeover activities. The effect of manager sentiment on takeover probability is pronounced in firms with small board size, high board independence, and low pay-performance sensitivity. We further find that higher manager sentiment is associated with lower long-term performance of acquirers.

Next, we examine the role of deal characteristics and provide two possible channels for the underperformance of high-sentiment deals. Managers with high sentiment tend to be less conservative on target selection, transaction execution, and target valuation due to their optimism of future economy. They spend fewer days to complete the takeover deals. Specifically, high-sentiment managers tend to undertake

larger deals and decrease the all-stock payment, implying more serious cash exhaustion and a higher probability of financial distress. They are more likely to acquire hard-to-value targets and offer high target valuation, indicating the tendency of selecting risky and pricy investments. Consequently, the takeover deals made by high-sentiment acquirers will impair the long-term takeover performance.

Besides, we find that the deal-level results of payment method, target valuation, days of completion, and long-term performance are more inclined to be driven by acquisitions of private firms. We also decompose manager sentiment to determine whether positive or negative words drive the results. We construct positive (negative) manager sentiment by counting only the positive (negative) words scaled by total number of words. The results show that only negative manager sentiment is significantly associated with deal characteristics, illustrating that negative words mainly drive the empirical results.

Moreover, we conduct aggregate-level analyses to confirm the previous findings of takeover activities, payment methods, and preferences of target selection. The aggregate-level results provide additional evidence that bidders' manager sentiment can drive takeover rumors, even with marginal significance. Bidders with high manager sentiment also tend to undertake fewer hostile offers.

This study contributes to two strands of literature. First, it is closely related to behavioral corporate finance studies. To the best of our knowledge, this study is the first to demonstrate the effect of manager sentiment on firm policies in the M&A context. The existing literature has presented many managerial biases, including

limited governance, bounded rationality, overconfidence, and hubris (Baker and Wurgler, 2013). In particular, Malmendier & Tate (2008) and Goel & Thakor (2010) demonstrate that CEO overconfidence and CEO envy affect takeovers, respectively. This paper highlights the role of manager sentiment which captures the managerial optimism (or pessimism in another way). Second, this study contributes to the literature of the causes and consequences of M&A. Previous research documents the causes of M&As, such as regulatory changes (Slovin, 1991), technological innovations (Gort, 1969), liquidity constraints (Harford, 2005), policy uncertainties (Bonaime et al., 2018), stock market valuations (Dong et al., 2006), and acquirer reference prices (Ma, Whidbee, and Zhang, 2019). We focus on the managerial factors and demonstrate that manager sentiment is an important factor in driving takeover activities and affecting deal performances. Managers make takeover deals because of not only their reactions to exogenous shocks but also their own optimism. Our finding explains the channels of how manager sentiment affects takeover performance by carrying out detailed tests on various deal characteristics.

The remainder of this paper is organized as follows. Section 2 reviews the literature and proposes testable hypotheses. Section 3 describes the data and methodology, and Section 4 reports the empirical results. Section 5 conducts a series of robustness checks, and finally, Section 6 concludes the paper.

2.2 Hypothesis Development

Takeover activities are among managers' most important corporate decisions to pursue firm growth or other synergistic benefits. Under the theoretical framework of

neoclassical economics, takeover activities are driven by legal, regulatory, technological, and economic shocks (Betton, Eckbo, & Thorburn, 2008; Gort, 1969; Slovin, 1991)[2]. Literature typically assumes that market participants make fully rational decisions in M&A activities. However, ample empirical evidence has shown that behavioral biases are inconsistent with neoclassical economic theories. Two approaches have been developed to address the behavioral problems in mergers and acquisitions. The first approach focuses on irrational investors (Dong et al., 2006; Rhodes-Kropf and Viswanathan, 2004; Shleifer and Vishny, 2003), and the second approach focuses on irrational managers (Ben-David et al., 2013; Goel & Thakor, 2010; Greenwood & Shleifer, 2014; Heaton, 2002; Malmendier & Tate, 2005, 2008; Morck et al., 1990). Managers are exposed to all type of biases when taking decision. Baker and Wurgler (2013) systematically summarize managerial biases including limited governance, bounded rationality, overconfidence, and hubris in the field of behavioral corporate finance.

Managers from both the acquirer and target sides play decisive roles in takeover activities. Hypothetically, synergy gains result from the bidders' taking control of the targets. Well-run bidders' acquisitions of poorly managed targets can create value (Wang & Xie, 2009). Whereas the assumption that managers constantly make the right decisions is far from realistic. Focusing on managers' irrational behavior is critical to understanding the causes and consequences of takeovers and related to

[2] Furthermore, Harford (2005) shows that sufficient capital liquidity is the most important prerequisite for macro-level shocks as the driving force of takeover waves. Nguyen and Phan (2017) and Bonaime, Gulen, and Ion (2018) provide strong evidence that policy uncertainty is negatively associated with takeover activities.

M&A deal characteristics. Given massive evidence of managers' behavioral biases, they are reasonably assumed to make takeover deals not only because they intend to exploit the irrationality of investors[3] but also due to their own irrationality.

Manager sentiment captures the managerial optimism for future economic growth and firm outcomes. The textual sentiment derived from the qualitative description can reflect the managers' judgement over the past year and their expectations for the future economic outcomes to some extent (Henry, 2008; Jiang et al., 2019; Li, 2008; 2010). Certainly, being optimistic is correct at times. In a review of psychological literature of optimism, Carver et al. (2010) summarize the pros and cons of being optimistic. Even though optimism has been linked to emotional and physical benefits, there are some drawbacks that can be extended to economic behaviors. Carver et al. (2010) indicate three typical drawbacks of optimism. First, compared to pessimists, optimists are more likely to have more positive expectations for uncertainty opportunities (gambling) and less likely to reduce their bets after a poor outcome (see also, Gibson and Sanbonmatsu, 2004). Second, optimists have attentional bias towards positive over negative information (Isaacowitz, 2005; Segerstrom, 2001). Optimists tend to see only what they want to see, and ignore

[3] Shleifer and Vishny (2003) connect market mispricing with takeover activities. They postulate that stock market mispricing caused by investors' irrationality can drive takeovers. Management's motivation to make takeover deals could exploit the difference in mispricing degree between bidder and target to pursue other growth opportunities and better firm performance. When the bidder's valuation is high, the bidder's management tends to make stock payments for trading their high-valuation equity for relatively low-valuation target assets. This model is supported by Dong et al. (2006) who find that bidder and target mispricing can be widely related to the number of takeovers, payment method, takeover premium, successful rate, hostile rate, and announcement period cumulative abnormal return.

threats (Luo & Isaacowitz, 2007). Third, optimists stick to their decisions, which means they have a harder time realizing when to quit (Wrosch et al., 2003).

The first drawback of optimism implies that optimistic managers with high sentiment tend to have over-investment activities. This is aligned with the free cash flow theory of Jensen (1986) who documents managers' overgrowth incentives and the extrapolative expectation investment model of Gennaioli et al. (2016) and Jiang et al. (2019). Thus, we state that high sentiment leads managers to engage in more takeover deals[4]. Accordingly, our first hypothesis of the effect of manager sentiment on takeover activities is proposed as follows:

H1: Manager sentiment is positively associated with takeover activities.

The second drawback of optimism regarding to attention bias implies that optimistic managers tend to over-estimate the acquisition synergies, especially when the imperfect information cannot be well-corrected. Thus, high manager sentiment incurs value-reducing deals. Meanwhile, the third drawback of optimism which emphasizes the stubbornness of optimists brings a long-term effect of takeover decisions. In the long run, the true economic fundamentals gradually reveal and the quality of acquisition deals reflect on stock returns (Jiang et al., 2019; Baker and Wurgler, 2007). Thus, we predict that high manager sentiment leads to lower long-term acquisition performance[5]. Our second hypothesis is developed as follows:

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[4] From another perspective, since takeover is a kind of investment decision made by managers to pursue firm growth and synergistic benefits, managers of acquirer firms can also be regarded as target firms' investors. Managers may perform similar behavior patterns to stock investors. Kurov (2008) demonstrates that positive feedback trading appears to be more active when investor sentiment is high. Moreover, Liu (2015) finds that stock market liquidity increase when sentiment indices rise.

[5] Again, if we regard the acquisitions as investment behaviors of managers, from the investor sentiment

H2: Manager sentiment is negatively associated with acquirers' long-term performance.

2.3 Data and Methodology

2.3.1 Sample and Data Source

The data used in this study comes from several sources. We collected firm-level accounting information from Compustat, stock returns from CRSP, CEO characteristics from Compustat Excucomp, and macroeconomic indicators from the Federal Reserve. Our initial sample of manager sentiment starts with all the U.S. listed firms during 2003-2017 from the WRDS SEC Analytics Suite. Following Jiang et al. (2019), we exclude sentiment data before 2003 because of low disclosure quality. Also, firms with missing or negative total assets are excluded.

Our takeover sample data are from the Thomson Reuters SDC Merger and Acquisitions Database. Takeover data are subject to the following filtering criteria: 1) the form of deal is merger or acquisition of the majority interest; 2) acquirers are public firms; 3) deals of buyback, repurchase, spinoff, split-off, divestiture, restructuring, self-tender, recapitalization, acquirer, and target belonging to the same parent firm are excluded; and 4) the offer is announced between January 2003 and June 2018, with six months extended from manager sentiment data for deal-level pairing. After merging with the acquirer's manager sentiment, our final sample consists of 6,752 M&A observations.

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perspective, Baker and Wurgler (2006) and Huang et al. (2015) provide strong evidence of a negative correlation between high investor sentiment and low subsequent stock returns and illustrate that difficult to value stocks are more sensitive to sentiment.

The number of observations is decreased when manager sentiment on both acquirers and targets are considered for several reasons. First, the private target firms do not disclose 10-K and 10-Q filings. Thus, their values of manager sentiment are unavailable. Among all M&A deals with available manager sentiment of acquirers, only one-third of deals are associated with public target firms. Second, there is a 30% loss of observations while matching SDC with WRDS SEC Analytical Suite. Eventually, only one-fourth of deals with available manager sentiment of acquirers can be matched to target firms. Overall, there are 1,516 M&A deals with available manager sentiment on both acquirers and targets.

2.3.2 Measures of Manager Sentiment

The textual analysis and bag-of-words technology have developed rapidly over the last decade, leading to a precise capturing of manager sentiment. Dictionaries are set up to classify words into different categories: positive and negative, active and passive, and strong and weak. Many studies take the count difference between positive and negative words normalized by the total word count from the content as the proxy for the sentiment (Tetlock, 2007; Loughran and Mcdonald, 2011; García, 2013; Jiang et al., 2019). Henry (2008) build a dictionary to study manager sentiment. This dictionary is also used by Price, Doran, Peterson, and Bliss (2012), who state that textual tone is an efficient predictor for stock returns and trading volume. Subsequently, Loughran and Mcdonald (2011) construct the LM financial and accounting dictionary to mitigate the misclassification of standard dictionaries' financial and accounting words. Their dictionary is proven appropriate for analyzing financial content and is

utilized by Jiang, Lee, Martin, and Zhou (2019) and Loughran and Mcdonald (2016). Therefore, our research applies the LM financial and accounting dictionary to measure manager sentiment.

The Readability and Sentiment Analysis dataset in WRDS SEC Analytics Suite uses the LM financial and accounting dictionary. It provides the counting results of positive words (finterms_positive_count), negative words (finterms_negative_count), and total words (lm_master_dictionary_count) in the 10-K and 10-Q filings. Loughran and Mcdonald (2011) find that the entire document and Management's Discussion and Analysis (MD&A) section usually use similar words, and using the MD&A section only will incur an observation loss problem. Thus, we use the word counting results based on full documents offered by Readability and Sentiment Analysis dataset to compute our manager sentiment measures. This measurement is supposed to be an effective proxy for managers' tone or sentiment. We calculate firm-level manager sentiment as the difference between the proportion of positive words and negative words in firms' 10-K and 10-Q filings. Specifically, we calculate *MS* as

$$MS = \frac{finterms\_positive\_count - finterms\_negative\_count}{lm\_master\_dictionary\_count}. \quad (1)$$

Moreover, we calculate positive manager sentiment (*Pos. MS*) and negative manager sentiment (*Neg. MS*) as

$$Pos.MS = \frac{finterm\_positive\_count}{lm\_master\_dictionary\_count}, \quad (2)$$

$$Neg.MS = \frac{finterms\_negative\_count}{lm\_master\_dictionary\_count}, \quad (3)$$

respectively. Mathematically, *Pos. MS* and *MS* are positively correlated, and *Neg. MS* and *MS* are negatively correlated.

A monthly manager sentiment index (*MSI*) is proposed to construct an aggregate-level analysis between manager sentiment and takeover activities. At the aggregate level, we add market mispricing, market liquidity, and economic policy uncertainty as additional control variables with superior explanatory power on takeover activities. The *MSI* is the monthly average manager sentiment extracted from 10-K and 10-Q filings using a four-month moving average weighted by filing numbers to mitigate the influence of seasonality and idiosyncratic jumps, as in Jiang et al. (2019).

Based on the different data sources, the manager sentiment measured by textual analysis of 10-K and 10-Q filings could reflect distinct information relative to the overconfidence constructed by option-based method (Hirshleifer, Low, and Teoh, 2012; Malmendier and Tate, 2008), description-based method (Malmendier and Tate, 2008), and survey-based method (Ben-David et al., 2013). Our study is closely related to Malmendier and Tate (2008), who examine the effect of manager overconfidence on takeover frequency and deal quality. Their measure of manager overconfidence is based on option-based and description-based proxies, which are also adopted by Ferris et al. (2013) and Hirshleifer et al. (2012). However, despite the data source and construction method variation, manager sentiment can capture the intensity while

overconfidence is a binary variable.

Malmendier and Tate (2008) find that the overconfidence of CEOs can affect takeover quality. They measure the manager overconfidence based on the pattern of the CEOs' private investment decisions to exercise their executive stock options and the CEOs' business press portrayal by counting the number of articles containing descriptions of "confident/confidence" or "optimistic/optimism" versus "reliable," "cautious," "conservative," "practical," "frugal," or "steady." They demonstrate that overconfident managers tend to make low-quality takeovers, especially when they can obtain internal financing, and the target is in a different industry. Ferris, Jayaraman, and Sabherwal (2013) revisit the CEO overconfidence study in an international context and obtain similar conclusions. To illustrate the incremental information from manager sentiment, we add the Malmendier and Tate (2008) overconfidence as an important deal-level control variable of our empirical tests.

2.3.3 Other Key Variables

To construct a deal-level analysis between manager sentiment and takeover characteristics, we match each takeover deal with its acquirer and target firm's manager sentiment according to the announcement date of each takeover deal and the release date of 10-K and 10-Q filings. Deal-level manager sentiment on the announcement date equals the firm's latest filings' sentiment. The ultimate parent firm sentiment is used to complement the acquirer and target firms, wherein sentiment data are not paired to the takeover record. Takeover deals with no available matched sentiment are excluded. The long-term performance of buy-and-hold abnormal return

is calculated following Ma, Whidbee, and Zhang (2019). Deal-level control variables include four major types. First, firm characteristics include *BTM, Size, Age, Leverage, CHR, ROA,* and *Past return*. M&A activity conditions refer to *CH, NWC*, and *HHI* index, commonly used in the takeover activity tests. We also include several CEO characteristics, such as *CEO* age*,* gender*,* tenure*,* compensation, and degree of overconfidence. Finally, *Rel. size, Dormant > 1 yr, Same industry, Toehold, Public, Cash, Stock,* and *Hostile* are included as deal characteristics.

We add three control variables of book-to-market, interest rate spreads, and economic policy uncertainty at the aggregate level. First, market mispricing catches the effect of managerial timing of investor irrationality. Betton et al. (2008) review the literature that explains the market book-to-market (*BTM*) ratio as a better proxy for market misvaluation than the market price, long-term abnormal returns, market-to-earnings ratio, or market-to-residual value ratio. Second, Harford (2005) illustrates that interest rate spreads (*IRS*) can be a good proxy for aggregate market liquidity that will support macro-level shocks as the cause of takeover waves. Therefore, aggregate *BTM* (*ABTM*) and *IRS* are jointly applied as control variables on the aggregate-level test of management sentiment influence on takeover activities. *BTM* is calculated as the book value of equity at the end of the prior fiscal year divided by the price of equity at the end of the month (Baker and Wurgler, 2006). The *BTM* of stocks with a negative book value of equity is highly evaluated after winsorizing at 1% and 99%. The *ABTM* is the average *BTM* ratio of sample stocks each month (Dong et al., 2006). *IRS* is the four-quarter moving average of the rate

spread between the average interest rate on commercial and industrial loans and the Federal Funds rate (Harford, 2005). Finally, Bonaime, Gulen, and Ion (2018) and Nguyen and Phan (2017) likewise present strong evidence that policy uncertainty is negatively associated with takeover activities. Therefore, we also add economic policy uncertainty (*EPU*) as a control variable.

2.3.4 Summary Statistics

Table 2.1 Panel A reports the descriptive statistics for the deal-level characteristics. The detailed definitions are presented in Appendix A. The merging of manager sentiment with takeover activities results in 6,752 M&A deals with available manager sentiment of acquirers, among which 1,516 deals have available manager sentiment on both acquirers and targets. In particular, the average *Acquirer MS* is shown to be much higher than the *Target MS*, which suggests that the managers from acquirers tend to have more optimistic sentiment than managers from target firms. Moreover, the average *Acquirer BTM* is lower than the *Target BTM*, suggesting that the acquirers are more overvalued than the targets. This finding is aligned with the evidence from Dong et al. (2006).

Table 2.1 Descriptive Statistics

This table reports the descriptive statistics of the key variables. Panel A reports the descriptive statistics for the deal-level variables, and Panel B reports the descriptive statistics for the aggregate-level variables. The detailed definitions of variables are presented in Appendix 2.A.

Panel A: Deal-Level Variables						
	N	Mean	SD	Min	Median	Max
Public	6,752	0.36	0.479	0.00	0.00	1.00
Stock	6,752	0.12	0.328	0.00	0.00	1.00
Dsize	2,512	5.43	1.997	-2.30	5.44	11.40
PE	2,559	-0.00	1.000	-1.39	0.69	5.16
PMW	1,925	39.40	40.435	-35.80	30.84	243.75
1-year BHAR	5,793	-0.04	0.337	-1.99	-0.03	5.57
2-year BHAR	5,505	-0.05	0.393	-3.31	-0.04	5.74
3-year BHAR	4,882	-0.06	0.449	-2.57	-0.06	7.56
Acquirer MS	6,752	-0.02	1.028	-3.04	0.11	1.93
Pos. MS	6,752	0.04	0.925	-2.99	-0.05	6.60
Neg. MS	6,752	0.03	1.008	-2.42	-0.10	4.94
Acquirer BTM	6,752	0.48	0.554	-4.57	0.42	4.53
Target MS	1,516	-0.24	1.027	-3.04	-0.14	1.93
Target BTM	1,516	0.59	0.748	-4.57	0.50	4.53
Size	6,752	7.03	2.447	-2.86	7.19	11.58
Age	6,752	5.69	8.297	-11.00	5.00	27.00
Leverage	6,752	0.67	0.968	0.03	0.57	12.39
CHR	6,752	0.09	0.145	0.00	0.03	0.88
ROA	6,752	-0.04	0.353	-3.55	0.01	0.23
Rel. size	6,752	0.35	3.142	0.00	0.05	210.18
Dormant > 1 yr	6,752	0.19	0.390	0.00	0.00	1.00
Same industry	6,752	0.60	0.491	0.00	1.00	1.00
Toehold	6,752	0.05	0.221	0.00	0.00	1.00
Past return	6,752	0.19	0.448	-2.09	0.13	6.06
CEO Age	6,752	4.01	0.094	3.40	4.01	4.50
CEO Male	6,752	0.51	0.500	0.00	1.00	1.00
CEO Tenure	6,752	0.80	1.055	0.00	0.00	3.95
CEO Comp	6,752	4.37	4.313	-6.91	6.40	13.23
CEO OC	6,752	0.12	0.323	0.00	0.00	1.00

Panel B: Aggregate-Level Variables						
	N	Mean	SD	Min	Median	Max
MSI	174	-0.00	0.101	-0.32	0.02	0.19
MSI (low-BTM)	174	0.04	0.107	-0.32	0.06	0.23
MSI (high-BTM)	174	-0.14	0.125	-0.48	-0.15	0.08
ABTM	174	0.55	0.133	0.41	0.50	1.08
ABTM (low-BTM)	174	-0.15	0.086	-0.33	-0.16	0.05
ABTM (high-BTM)	174	1.33	0.360	0.87	1.28	2.59
IRS	174	0.00	0.060	-0.13	-0.00	0.16
EPU	174	4.71	0.382	3.80	4.68	5.65
Takeover	174	0.12	0.021	0.06	0.12	0.18
Rumor	174	0.00	0.002	0.00	0.00	0.01
Cash	174	0.17	0.054	0.04	0.18	0.27
Stock	174	0.14	0.036	0.04	0.14	0.21
Hostile	174	0.04	0.023	0.00	0.03	0.10
Public	174	0.16	0.037	0.08	0.16	0.28

Table 2.1 Panel B reports the descriptive statistics for the aggregate-level variables, including manager sentiment, control variables, and aggregate-level takeover characteristics. It shows that the *MSI* of *low-BTM* firms is much higher than that of *high-BTM* firms. According to Baker, Pan, and Wurgler (2012), Dong et al. (2006), and Shleifer and Vishny (2003), firms in the *low-BTM* group are potential acquirers, whereas firms in the *high-BTM* group are potential targets. Thus, the result is consistent with the results at the deal level. *MSI (low-BTM)* and *MSI (high-BTM)* have higher standard deviations than *MSI*. This result indicates that the *MSI* of both overvalued and undervalued firms tend to overreact to the stock market movements, possibly because they hold different beliefs concerning the cause of stock mispricing.

Figure 2.1 plots the time-series trends of *MSI* and monthly aggregate-level

takeover activities normalized by NYSE firm numbers (*Takeover*). *MSI (low-BTM)* and *MSI (high-BTM)* are constructed based on the firms' book-to-market ratios, and *low-BTM (high-BTM)* is defined as the bottom (top) 30%. Figure 2.1 shows a strong and positive correlation between *MSI* and takeover activities, and the *MSI* of *low-BTM* firms is relatively higher than that of *high-BTM* firms.

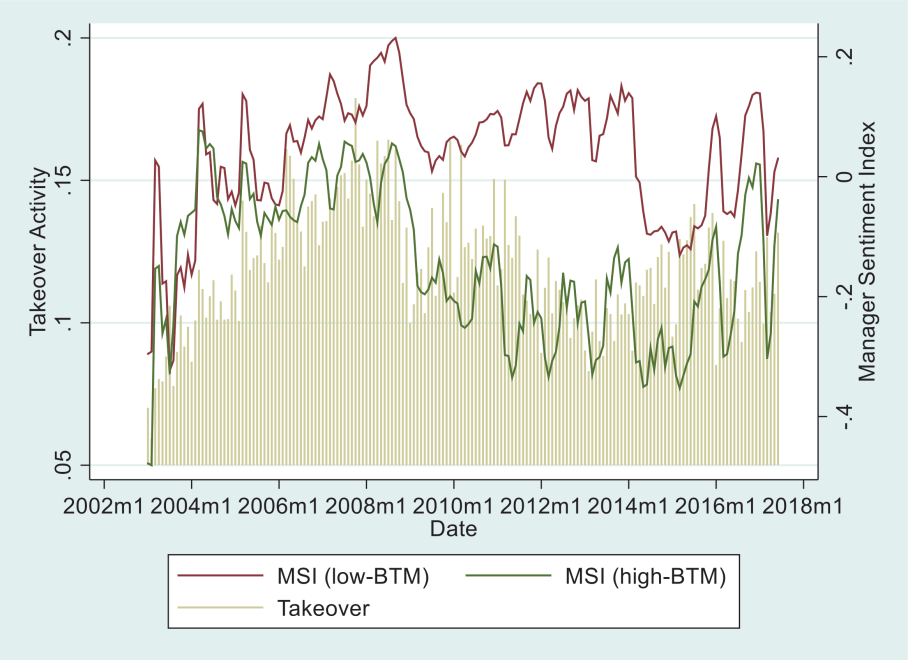

Figure 2.1 Aggregate Manager Sentiment and Takeover Activities

The figure presents the trends of monthly manager sentiment (MSI) and aggregate-level takeover activities normalized by the number of NYSE firms (Takeover). MSI (low-BTM) and MSI (high-BTM) are constructed based on firms' book-to-market ratios, where low-BTM and high-BTM firms have the bottom and top 30% of the book-to-market ratio, respectively.

2.4 Empirical Results

2.4.1 Manager Sentiment and Takeover Decisions

2.4.1.1 Baseline Regression

We begin our analyses by examining the association between the *MS* and takeover activities at the deal level. The following linear probability model with time and firm fixed effects regression is estimated to examine the association between manager sentiment and takeover probability:

$$TAKEOVER_{i,t} = \alpha + \beta MS_{i,t} + \sigma X_{i,t} + \theta_t + \mu_i + \varepsilon_m, \quad (4)$$

where $TAKEOVER_{i,t}$ is a dummy variable that equals one if the acquirer firm *i* makes a takeover deal in the subsequent six months following the latest 10-K and 10-Q filing and zero otherwise. $MS_{i,t}$ denotes the manager sentiment of firm *i* in year *t*, and $X_{i,t}$ includes a set of firm and deal characteristics. θ_t and μ_i denote time and firm fixed effects, respectively.

Table 2.2 presents the relevant results. Column (1) shows that higher valuation (lower *BTM*) of a firm will increase the probability of undertaking takeover deals, which is aligned with the results of Dong et al. (2006) and Rhodes-Kropf and Viswanathan (2004). In terms of economic magnitude, one standard deviation of firm's MS leads to a 0.007 (almost 6% from the overall average) increase in takeover activities. Also, high cash reserves increase the takeover probability, consistent with Harford (1999). Column (2) presents that manager sentiment is positively associated with takeover activities after controlling firm fundamentals. We further add M&A

liquidity, Herfindahl-Hirschman Index, and the past return in the regression, and column (3) shows that the explanatory power of *BTM* is subsumed by the past return before M&A deals.

Meanwhile, the association between *MS* and *Takeover* is still significant. Finally, we include CEO characteristics in the regression, including CEO age, gender, tenure, compensation, and CEO overconfidence. Column (4) shows that manager sentiment is still positively associated with takeover activities[6]. The finding supports our hypothesis H1 that high manager sentiment drives takeover activities. High-sentiment managers can be less risk-averse, be more eager for investment opportunities, and seek higher performance volatilities.

We admit that the sentiment contains multiple reasons for optimism including factors driven by economic and firm fundamentals. Therefore, we construct the adjusted manager sentiment in a robustness check by eliminating the fundamental-driven components.

2.4.1.2 Sub-sample Analyses

We conduct sub-sample analyses to determine whether the association between manager sentiment and takeover activities varies across board size, board independence, and CEO pay-performance sensitivity measured by option delta.

[6] Column (1) in Table 2.A.2 shows that all CEO characteristics are significantly associated with manager sentiment, especially for CEO OC with a *t*-statistic of 17.54.

Table 2.2 Predictive Regression of Takeover Activities

This table reports the estimation result of the linear probability model as follows:

$$Takeover_{i,t} = \alpha + \beta MS_{i,t} + \sigma X_{i,t} + \theta_t + \mu_i + \varepsilon_i$$

where $Takeover_{i,t}$ is a dummy variable that equals one if the acquirer makes a takeover deal in the subsequent six months of the latest 10-K filings and zero otherwise. $MS_{i,t}$ denotes the manager sentiment of firm *i* in year *t*, and $X_{i,t}$ denotes a set of control variables. θ_t and μ_i denote time and firm fixed effects, respectively. The detailed definitions of variables are presented in Appendix 2.A. The robust *t*-statistics clustered by the firm are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)
	Takeover	Takeover	Takeover	Takeover
MS		0.007***	0.007***	0.007***
		(3.28)	(2.97)	(2.90)
BTM	-0.004***	-0.004***	-0.002	-0.002
	(-4.17)	(-3.98)	(-1.56)	(-1.59)
Size	-0.005***	-0.005***	-0.005**	-0.006***
	(-2.89)	(-2.92)	(-2.36)	(-2.85)
Age	-0.000	0.000	-0.001	-0.001
	(-0.03)	(0.02)	(-0.31)	(-0.34)
Leverage	-0.003***	-0.003***	-0.002**	-0.002***
	(-3.57)	(-3.41)	(-2.40)	(-2.60)
CHR	0.041***	0.041***	0.042***	0.041***
	(5.66)	(5.61)	(5.54)	(5.40)
ROA	-0.003	-0.003	-0.002	-0.002
	(-0.89)	(-0.85)	(-0.77)	(-0.68)
CH			0.000	0.000
			(0.63)	(0.70)
NWC			-0.000	-0.000
			(-0.68)	(-0.71)
Past return			0.006***	0.006***
			(3.05)	(3.05)
HHI Index			-0.021	-0.022
			(-1.12)	(-1.16)
CEO Age				-0.036
				(-1.50)
CEO Male				0.016
				(1.46)
CEO Tenure				0.002
				(0.69)
CEO Comp				0.001
				(0.72)
CEO OC				-0.003
				(-0.47)
Firm FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Observations	76828	76828	60577	60577
Adjusted R^2	0.09	0.09	0.09	0.09

First, we examine the heterogeneous effect of manager sentiment on takeover activities by dividing the sample based on board size. A larger number of directors can produce more diversified information and suppress the probability of omitted important information, leading to a less impulsive board and less biased decisions. Cheng (2008) offers evidence that firms with larger boards have lower variability of firm performance. Thus, the association between *MS* and *Takeover* should be stronger in firms with small board sizes.

Second, we conduct sub-sample analyses to determine whether the manager sentiment effect varies across board independence. Harris and Raviv (2008) claim that an insider-controlled board can be more beneficial to shareholders especially when insiders can produce relatively more important information. Thus, outside board control can be costly and value-reducing due to a loss of information. Kumar and Sivaramakrishnan (2008) also indicate that a board composed of more independent directors could perform worse. Thus, we expect to find a larger *MS* effect in firms with high board independence.

Finally, we estimate the association between *MS* and *Takeover* in two sub-sample of executive option delta. The option delta measures managers' pay-performance sensitivity as defined in Coles, Daniel, and Naveen (2006). They find that riskier policy choices are positively associated with compensation structures with higher pay-stock volatility sensitivity (vega) and lower pay-performance sensitivity (delta). If managers lack performance incentives, they will need to undertake more deals to expand the firm size and increase their compensation to expected levels. Thus,

managers who lack incentives are more eager to acquire and invest to seek firm growth when they are optimistic. As a result, we expect to find a stronger association in the low delta firms.

Table 2.3 presents the results of the sub-sample analyses. Columns (1) and (2) show that manager sentiment has a significant and positive association with takeover probability in firms with small board sizes, which is as expected. Columns (3) and (4) show that manager sentiment has a significant and positive association with takeover probability in firms with high board independence. The results meet our expectations and additionally illustrate that the manager sentiment effect is different from agency problem theory because high board independence should mitigate agency problems (Lu and Wang, 2015). Sentiment-driven takeovers could be caused by less firm-specific information produced and herd mentality within the industry by independent directors, which lead firms to be follower acquirers. Columns (5) and (6) show that manager sentiment has a significant and negative association with takeover probability in firms with low executive delta. The result is consistent with our conjecture that executives who lack incentives are more eager to acquire and invest to expand their firm size and achieve satisfying compensation when they are optimistic.

Table 2.3 Firm Heterogeneity

This table reports the linear model of the takeover probability for subsamples based on board size, board independence, and executive option delta:

$$Takeover_{i,t} = \alpha + \beta MS_{i,t} + \sigma X_{i,t} + \theta_t + \mu_i + \varepsilon_i$$

where $Takeover_{i,t}$ is a dummy variable that equals one if the acquirer makes a takeover deal in the subsequent six months of the latest 10-K filings and zero otherwise. $MS_{i,t}$ denotes the manager sentiment of firm i in year t, and $X_{i,t}$ denotes a set of control variables. θ_t and μ_i denote time and firm fixed effects, respectively. Board size is the firm's number of board members, board independence is calculated as the proportion of independent board members, and option delta measures managers' pay-performance sensitivity is defined in Coles, Daniel, and Naveen (2006). The detailed definitions of variables are presented in Appendix 2.A. The robust *t*-statistics clustered by the firm are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	Board Size		Board Independence		Executive Option Delta	
	(1)	(2)	(3)	(4)	(5)	(6)
	Small	Big	Low	High	Low	High
MS	0.009**	0.004	0.006	0.010**	0.010*	-0.004
	(2.48)	(0.72)	(1.37)	(2.04)	(1.82)	(-0.50)
BTM	-0.002	-0.006*	-0.001	-0.008**	-0.005	-0.040***
	(-1.21)	(-1.66)	(-0.36)	(-2.51)	(-1.08)	(-2.91)
Size	-0.004	-0.023***	-0.010***	-0.006	-0.013	-0.020*
	(-1.21)	(-2.59)	(-2.66)	(-1.13)	(-1.62)	(-1.83)
Age	-0.001	-0.002	0.010**	0.004	0.004	-0.006
	(-0.09)	(-0.25)	(2.15)	(0.53)	(0.78)	(-0.80)
Leverage	-0.001	-0.033***	-0.003**	-0.009**	-0.048**	-0.138***
	(-1.19)	(-2.75)	(-2.18)	(-2.11)	(-1.98)	(-4.42)
CHR	0.034***	0.095***	0.038***	0.055***	0.067**	0.036
	(3.21)	(2.79)	(3.07)	(3.31)	(1.99)	(0.80)
ROA	-0.001	-0.025	0.000	-0.003	0.158**	0.423***
	(-0.18)	(-0.66)	(0.09)	(-0.20)	(2.30)	(2.66)
CH	-0.000	0.000	-0.000	0.000	0.000	0.000
	(-1.53)	(0.99)	(-0.04)	(1.22)	(1.58)	(0.69)
NWC	0.000*	-0.000	-0.000	-0.000	0.000	-0.000
	(1.76)	(-0.93)	(-1.03)	(-0.75)	(0.56)	(-0.85)
Past return	0.003	0.006	0.005	0.003	0.001	0.017*
	(1.21)	(1.06)	(1.56)	(0.90)	(0.13)	(1.83)
HHI Index	-0.014	-0.048	0.009	-0.044	0.004	0.012
	(-0.44)	(-0.95)	(0.25)	(-1.05)	(0.08)	(0.22)
CEO Age	-0.074*	0.018	0.008	-0.061*	0.009	-0.063
	(-1.74)	(0.48)	(0.20)	(-1.67)	(0.25)	(-1.26)
CEO Male	0.031	-0.007	0.023	0.019	-0.002	0.019
	(1.55)	(-0.40)	(0.97)	(1.13)	(-0.14)	(0.74)
CEO Tenure	0.011**	-0.002	0.011**	0.000	-0.003	0.005
	(2.53)	(-0.44)	(2.40)	(0.04)	(-0.68)	(0.99)
CEO Comp	-0.001	0.003	0.000	0.001	0.001	-0.005*
	(-0.47)	(1.23)	(0.02)	(0.22)	(0.38)	(-1.77)
CEO OC	-0.008	-0.003	-0.017	-0.008	-0.013	-0.003
	(-0.65)	(-0.32)	(-1.51)	(-0.82)	(-1.05)	(-0.30)
Firm FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Observations	27007	15383	21535	20780	10483	10623
Adjusted R^2	0.09	0.11	0.12	0.09	0.10	0.09

2.4.2 Long-term Performance

Next, we calculate acquirers' buy-and-hold abnormal returns by following Ma et al. (2019) to measure long-term deal performance. We choose three nodes of 1-year, 2-year, and 3-year. Specifically, we estimate the following regressions with time and industry fixed effects to examine the association between manager sentiment and *BHAR* of acquirers:

$$BHAR_{i,t} = \alpha + \beta AcquirerMS_i + \gamma TargetMS_i + \sigma X_i + \theta_t + \mu_j + \varepsilon_i, \qquad (5)$$

where $BHAR_{i,t}$ denotes the acquirers' buy-and-hold abnormal return of deal i; $AcquirerMS_i$ and $TargetMS_i$ denote the manager sentiment of acquirers and targets, respectively; and X_i includes a set of control variables. The regression also includes time and industry fixed effects. We focus on the coefficients β and γ, which suggest whether the acquirers' long-term performance is associated with manager sentiment.

Table 2.4 reports the regression results illustrating that high manager sentiment of acquirers associates with lower *BHAR*, with the first two columns presenting the regression results of 1-year *BHAR*. Columns (3) and (4) present the results of 2-year *BHAR*, and the final two columns present that of 3-year *BHAR*. Based on the total 6,752 M&A deals that are successfully matched with acquirers' manager sentiment, the samples of *BHAR* gradually decline over time. The negative association between *Acquirer MS* and *BHAR* is statistically significant for whole samples, with the *t*-statistics of coefficients being -2.00, -2.14, -2.64, respectively. The empirical results suggest that acquirers with high manager sentiment perform worse in the subsequent

years after takeover announcements. Moreover, the sentiment-performance effect increases over time, with the coefficients being -0.009, -0.012, -0.017. The economic magnitudes of the coefficients are also nontrivial, given the mean values of 1-year, 2-year, and 3-year *BHAR* being -0.04, -0.05, and -0.06 for the whole samples. One standard deviation increase of acquirer's MS leads to 0.9%-1.7% additional reduction of its long-term returns (about 20% to the overall average).

The effect of long-term performance decreases is not pronounced when public targets are selected. We document that acquirers will perform relatively more rationally while avoiding selecting private targets that are harder to value.

These findings support our hypothesis H2 that manager sentiment and acquirers' long-term performance are negatively related. In the long run, the true economic fundamentals gradually reveal, and the quality of acquisition deals reflect on stock returns. Since high-sentiment managers undertake deals based on their over-optimistic expectation on future economic growth and their over-investment incentives, the deals tend to be value-reducing in the long run.

Figure 2.2 presents the 1-month to 36-month *BHAR* of acquirers. Acquirers are ranked into five quintiles according to manager sentiment. The average *BHAR* of the lowest-sentiment quintile beats the average *BHAR* of the highest-sentiment quintile for the subsequent 36 months after takeover announcement for most of the time.

Table 2.4 Long-term Performance of Acquirers

This table reports the association between manager sentiment and the long-term performance of acquirers. The dependent variables are the t-year buy-and-hold abnormal returns of acquirers. $Acquirer\ MS$ and $Target\ MS$ denote the manager sentiment of acquirers and targets, respectively. The regression includes time and industry fixed effects. The detailed definitions of variables are presented in Appendix 2.A. Robust standard errors are reported in the parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	1-Year		2-Year		3-Year	
	(1) All	(2) Public	(3) All	(4) Public	(5) All	(6) Public
Acquirer MS	-0.009**	-0.012	-0.012**	-0.009	-0.017***	-0.011
	(-2.00)	(-1.50)	(-2.14)	(-1.09)	(-2.64)	(-1.11)
Acquirer BTM	0.035*	0.029	0.058**	0.038	0.078***	0.054
	(1.72)	(1.21)	(2.30)	(1.24)	(2.81)	(1.25)
Target MS		-0.007		-0.005		0.010
		(-0.87)		(-0.59)		(0.95)
Target BTM		-0.005		-0.004		0.019
		(-0.41)		(-0.28)		(1.26)
Public	-0.002		-0.012		-0.013	
	(-0.20)		(-1.12)		(-0.93)	
Cash	0.007	0.008	0.004	-0.006	-0.012	0.008
	(0.76)	(0.44)	(0.35)	(-0.28)	(-0.91)	(0.33)
Stock	-0.019	-0.016	0.007	0.008	0.006	0.038
	(-1.05)	(-0.75)	(0.33)	(0.30)	(0.20)	(1.32)
Hostile	0.032	0.102***	0.043	0.086***	0.031	0.078*
	(1.44)	(3.39)	(1.50)	(2.60)	(0.79)	(1.79)
Size	-0.005	0.002	-0.000	0.010	-0.004	0.011
	(-0.84)	(0.30)	(-0.03)	(1.30)	(-0.58)	(1.25)
Age	0.000	-0.000	-0.000	-0.000	-0.001	-0.002
	(0.75)	(-0.16)	(-0.26)	(-0.44)	(-1.19)	(-1.57)
Leverage	0.091**	0.056	0.126**	-0.039	0.166***	0.049
	(2.30)	(1.14)	(2.31)	(-0.70)	(3.30)	(0.71)
CHR	0.074	0.140	0.283***	0.250***	0.203**	0.340***
	(1.20)	(1.36)	(4.02)	(2.62)	(2.55)	(3.05)
ROA	-0.034	-0.247	0.076	-0.138	-0.149	-0.016
	(-0.40)	(-1.07)	(0.67)	(-1.03)	(-1.12)	(-0.09)
Rel. size	0.007*	0.006	-0.002	-0.000	0.015	0.004
	(1.76)	(1.38)	(-0.94)	(-0.16)	(0.95)	(0.74)
Dormant > 1 yr	0.015	0.031	0.009	-0.010	0.008	0.027
	(1.48)	(1.45)	(0.70)	(-0.39)	(0.49)	(0.86)
Same industry	0.009	0.002	-0.016	0.013	-0.014	-0.047**
	(0.93)	(0.12)	(-1.31)	(0.61)	(-0.96)	(-1.97)
Toehold	-0.000	-0.011	0.019	-0.066	0.003	-0.040
	(-0.01)	(-0.31)	(0.84)	(-1.31)	(0.14)	(-1.05)
Past return	-0.229***	-0.330***	-0.218***	-0.295***	-0.310***	-0.311***
	(-5.89)	(-11.58)	(-4.69)	(-9.63)	(-12.16)	(-7.82)
CEO Age	0.052	0.022	0.082*	0.040	0.050	-0.041
	(1.49)	(0.32)	(1.73)	(0.42)	(0.98)	(-0.42)
CEO Male	-0.003	-0.003	-0.003	0.000	0.015	0.071*
	(-0.16)	(-0.12)	(-0.14)	(0.00)	(0.57)	(1.89)
CEO Tenure	0.002	0.012	0.000	0.009	0.002	0.012
	(0.50)	(1.49)	(0.01)	(0.83)	(0.28)	(0.95)
CEO Comp	0.002	0.001	0.002	0.003	0.001	-0.005
	(1.04)	(0.40)	(0.60)	(0.78)	(0.21)	(-1.15)
CEO OC	0.006	-0.011	-0.008	-0.053**	-0.002	-0.033
	(0.54)	(-0.56)	(-0.60)	(-2.22)	(-0.11)	(-1.30)
Industry FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Observations	5791	1384	5503	1330	4881	1193
Adjusted R^2	0.11	0.20	0.08	0.13	0.11	0.14

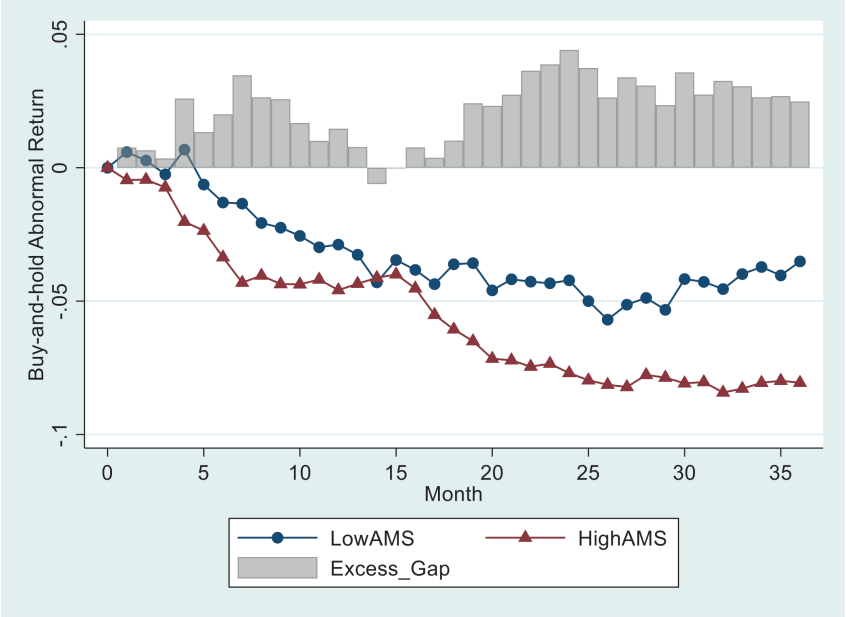

Figure 2.2: Long-term Buy-and-hold Abnormal Return of High and Low Acquirer Manager Sentiment Quintiles

The figure presents the long-term buy-and-hold abnormal returns (*BHAR*) of acquirers. Acquirers are ranked into five quintiles according to manager sentiment, with five being the highest acquirer manager sentiment quintile (*HighAMS*) and one being the lowest acquirer manager sentiment quintile (*LowAMS*). The red line denotes the average *BHAR* of the highest-sentiment quintile. The blue line denotes the average *BHAR* of the lowest-sentiment quintile in each month following the takeover announcement. Besides, we calculate the gap of *BHAR* between the lowest and highest acquirer manager sentiment quintiles and name it the all-sample gap. We also calculate the gap between two quintiles of private-target samples and name it the private gap. Finally, we subtract the all-sample gap from the private gap and plot the difference as *Excess_Gap*. The *Excess_Gap* is positive most of the time, illustrating that the effect of *MS* on *BHAR* is stronger among deals with private targets.

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2.4.3 Manager Sentiment and Deal Characteristics

To further address the possible channels that how high manager sentiment leads to the long-term takeover underperformance, we proceed to examine the association between manager sentiment and deal characteristics by using linear models with time and industry fixed effects regressions as follows:

$$DC_{i,t} = \alpha + \beta AcquirerMS_i + \gamma TargetMS_i + \sigma X_i + \theta_t + \mu_j + \varepsilon_i, \quad (6)$$

where $DC_{i,t}$ denotes the deal-level takeover characteristics for deal i. $Acquirer\ MS_i$ and $Target\ MS_i$ denote the manager sentiment of acquirer and target firms, respectively, and X_i denotes a set of control variables. θ_t and μ_j denote time and industry fixed effects, respectively. The coefficients of β and γ indicate the effect of acquirer manager sentiment and target manager sentiment on deal characteristics. Firstly, we consider the characteristics of the means of payment and transaction size, which may influence the cash reserve and incur a higher probability of financial distress. Second, we test the characteristics of public target selection and target valuation. We postulate that managerial over-optimism can lead to higher risk appetite and less conservatism, engaging in more hard-to-value targets and overpaying for the transactions to capture the expansion opportunities. Tables 2.5 and 2.6 present the relevant results[7].

2.4.3.1 Payment Method and Deal Size

We first address the deal characteristics of the payment method and deal size.

[7] We also provide the regression results using logit model results rather than OLS for dummy dependent variables. The logit regression results are reported in Table 2.A.8, which show similar findings as the OLS regression results.

The means of payment and transaction size will affect acquirers' cash reserves. In Table 2.5, a total of 6,752 M&A deals are successfully matched with acquirers' manager sentiment, among which 2,512 sample deals provide the available data of deal size as recorded in SDC.

High-sentiment acquirers tend to avoid all-stock payments. Column (1) of Table 2.5 reports the significantly negative association between acquirers' manager sentiment and the probability of all-stock payment deals[8]. In terms of economic magnitude, the coefficient of *Acquirer MS* on *Stock* for the whole sample test is -0.014, which is considerable given the mean value of *Stock* being 0.12 (about 12% reduction of *Stock* for one standard deviation increase of MS). Column (3) shows that the negative coefficient remains statistically significant for the public target samples.

According to Shleifer and Vishny (2003) and Dong et al. (2006), managers tend to make stock payments to trade their equities for target assets when they believe their equities are relatively over-valued. Managers with high sentiment are over-optimistic about the economic fundamentals. They will extrapolate to their firms' operating performance and stock returns, thus being more unlikely to exchange their firms' shares for the target firms' equities. However, stock-financed deals can create value, as Savor and Lu (2009) documented. From another perspective, avoiding all-stock payments implies more cash spending, which will impair the firms' free cash flow.

We further test the effect of *Acquirer MS* on the deal size[9]. Columns (2) shows a

[8] We also use the continuous variable of stock-payment proportion as recorded in SDC to redo the regressions. The results are reported in Table 2.A.9, showing similar findings.

[9] We get similar empirical results using the company size of target firms replacing for the deal size, that

significantly positive association in the whole sample. Column (4) shows that the association remains statistically significant in public targets' deals. The economic magnitudes of the coefficients are significant that one additional standard deviation of acquirer's MS leads to 1.3% increase of *Dsize*. Managers will undertake larger deals, especially when they hold optimistic expectations for the future economy. This finding is aligned with the managers' empire-building incentives (Jensen, 1986b).

The lower stock payment proportion and larger deal size will incur serious cash-consuming, leading to a higher probability of financial distress (see, for instance, Casey and Bartczak, 1985; Hill, Kelly, and Highfield, 2010). In the long run, the adverse influences on firm fundamentals reveal, thus decreasing the long-term takeover performance.

managers with high manager sentiment tend to select larger size of targets. The results are available upon request.

Table 2.5 Payment Method and Deal Size

This table reports the association between manager sentiment and deal characteristics of payment method and deal size. *Stock* denotes all-stock payment that equals one if the percentage of consideration paid in stock equals 100 in SDC and zero otherwise. *Dsize* is the natural logarithm of the deal size, which is transaction value excluding assumed liability, as reported in SDC. *Acquirer MS* and *Target MS* denote the manager sentiment of acquirers and targets, respectively. The regression includes time and industry fixed effects. The detailed definitions of variables are presented in Appendix 2.A. Robust standard errors are reported in the parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	All		Public Target	
	(1)	(2)	(3)	(4)
	Stock	Dsize	Stock	Dsize
Acquirer MS	-0.014***	0.073**	-0.018*	0.085**
	(-3.73)	(2.54)	(-1.70)	(2.10)
Acquirer BTM	0.010	-0.317***	0.015	-0.297**
	(1.03)	(-3.31)	(0.50)	(-2.25)
Target MS			-0.002	-0.003
			(-0.20)	(-0.07)
Target BTM			0.006	-0.192***
			(0.36)	(-2.62)
Size	-0.013***	0.598***	-0.045***	0.530***
	(-4.55)	(27.83)	(-5.19)	(16.34)
Age	0.000	0.006	0.000	0.008
	(0.75)	(1.58)	(0.32)	(1.56)
Leverage	-0.013*	0.020	-0.050	-0.432**
	(-1.73)	(0.17)	(-0.88)	(-2.09)
CHR	-0.074**	0.738***	-0.201*	0.301
	(-2.22)	(3.34)	(-1.80)	(0.90)
ROA	-0.041**	-0.009	-0.055	0.661*
	(-1.99)	(-0.05)	(-0.49)	(1.88)
Rel. size	0.004		0.004	
	(1.19)		(1.12)	
Dormant > 1 yr	-0.024**	0.128	-0.034	-0.001
	(-2.53)	(1.45)	(-1.14)	(-0.01)
Same industry	0.036***	0.298***	0.040*	0.229**
	(4.39)	(4.29)	(1.68)	(2.43)
Toehold	-0.017	-0.627***	0.074	-0.474*
	(-1.11)	(-3.45)	(1.21)	(-1.70)
Past return	0.014	0.085	0.021	0.100
	(1.22)	(1.19)	(0.61)	(0.92)
CEO Age	0.091**	0.403	0.274**	0.448
	(2.28)	(1.22)	(2.39)	(1.00)
CEO Male	0.035	0.202	0.016	0.135
	(1.58)	(1.18)	(0.34)	(0.70)
CEO Tenure	-0.014***	-0.052	-0.032**	-0.113**
	(-2.76)	(-1.21)	(-2.40)	(-2.20)
CEO Comp	-0.004	-0.008	0.001	0.010
	(-1.49)	(-0.33)	(0.21)	(0.40)
CEO OC	-0.012	-0.222**	-0.023	-0.173
	(-1.11)	(-2.21)	(-0.81)	(-1.42)
Industry FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Observations	6752	2512	1514	1406
Adjusted R^2	0.07	0.51	0.11	0.47

2.4.3.2 Target Selection and Valuation

This subsection tests the deal characteristics of public target selection and target valuation. We postulate that optimistic managers with high sentiment tend to be more risk-appetite and less conservative, engaging in more hard-to-value and pricy deals to capture the expansion opportunities. The takeover deals undertaken by high-sentiment managers resemble the lottery-type investments, which have greater valuation difficulty and higher return volatility (Kumar 2009). Consequently, the lottery-type deals provide negative expected abnormal returns.

Table 2.6 shows the empirical results that confirm our predictions. Column (1) of Table 2.6 illustrates the significant negative association between the acquirer's manager sentiment and the public target selection (*Public*). Column (2) shows that the offer price-to-target earnings ratio (*PE*) is positively associated with the acquirers' manager sentiment with the full sample, indicating that high-sentiment managers tend to offer higher target valuation. The effect weakens public firms' acquisition, as reflected in Column (3).

Meanwhile, Column (3) also presents that *PE* is strongly associated with the targets' manager sentiment. We attribute the positive association between *Target MS* and *PE* to the acquirers' analyzing and catering to target firms' high manager sentiment. The acquirers' managers tend to increase offer price to accelerate the deal completion once they perceive the high manager sentiment of targets through 10-K and 10-Q filings, conference calls, and in-person meetings.

Table 2.6 Target Selection and Valuation

This table reports the association between manager sentiment and deal characteristics of target selection and valuation. *Public* is a dummy variable that equals one if the target is a public firm and zero otherwise. *PE* is the offer price per share divided by target earnings per share, as recorded in the SDC. *Acquirer MS* and *Target MS* denote the manager sentiment of acquirers and targets, respectively. The regression includes time and industry fixed effects. The detailed definitions of variables are presented in Appendix 2.A. Robust standard errors are reported in the parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	All		Public Target
	(1)	(2)	(3)
	Public	PE	PE
Acquirer MS	-0.018***	0.087***	0.045*
	(-3.13)	(4.41)	(1.70)
Acquirer BTM	0.009	-0.031	-0.025
	(0.79)	(-0.56)	(-0.38)
Target MS			0.198***
			(7.76)
Target BTM			-0.082*
			(-1.95)
Size	0.053***	0.025*	0.057***
	(14.84)	(1.79)	(2.76)
Age	0.001	-0.006**	0.001
	(0.94)	(-2.41)	(0.38)
Leverage	0.007	0.068	-0.049
	(1.25)	(1.04)	(-0.37)
CHR	0.081*	-0.264	-0.211
	(1.91)	(-1.57)	(-0.89)
ROA	-0.041**	0.311***	0.862***
	(-2.42)	(2.79)	(3.05)
Rel. size	0.010	0.004**	0.014***
	(1.53)	(2.19)	(3.45)
Dormant > 1 yr	0.049***	0.031	-0.049
	(3.16)	(0.52)	(-0.62)
Same industry	0.095***	0.055	0.076
	(7.80)	(1.18)	(1.19)
Toehold	-0.115***	0.001	-0.205
	(-4.53)	(0.01)	(-1.09)
Past return	-0.017	0.143***	0.107
	(-1.42)	(2.75)	(1.40)
CEO Age	0.009	0.137	-0.234
	(0.14)	(0.63)	(-0.86)
CEO Male	-0.066*	0.066	0.160
	(-1.92)	(0.63)	(1.36)
CEO Tenure	-0.013	0.010	0.017
	(-1.51)	(0.36)	(0.51)
CEO Comp	0.008*	0.002	-0.005
	(1.93)	(0.16)	(-0.35)
CEO OC	0.029	-0.041	-0.057
	(1.43)	(-0.67)	(-0.74)
Industry FE	Y	Y	Y
Year FE	Y	Y	Y
Observations	6752	2556	1425
Adjusted R^2	0.12	0.12	0.20

Besides, following Betton, Eckbo, and Thorburn (2009), we use the bidding premium as the proxy for target valuation instead of *PE* to further address the over-pay issue in Table 2.A.5. We additionally consider the manager sentiment difference between acquirers and targets. For the public target samples with available market price and manager sentiment of target firms, we examine the association between manager sentiment and bidding premium. *PMW* denotes the offer price to target stock price premium one week before the announcement. The manager sentiment difference (*DMS*) is defined as the sentiment of bidder firms minus the sentiment of target firms. The acquirers' manager sentiment is shown to have no significant association with bidding premium. However, the difference in manager sentiment between acquirers and targets is positively associated with the bidding premium. The positive and significant coefficient of *DMS* suggests that when the manager sentiment of acquirers is higher relative to those of target firms, the acquirer tends to pay a high premium to increase the probability of successful takeovers. The results also indicate that acquirer managers who select public targets will analyze the targets' manager sentiment through information disclosures, conference calls, and in-person meetings, aligned with our previous findings.

Overall, the examination of deal characteristics suggests that managers with high sentiment tend to be less conservative on target selection, transaction execution, and target valuation due to their over-optimism of future economy. Specifically, high-sentiment managers tend to undertake larger deals and decrease the all-stock payment, implying more serious cash exhaustion and a higher probability of financial

distress. They are more likely to acquire hard-to-value targets and offer high target valuation, indicating the tendency of selecting risky and pricy investments. These findings of deal characteristics offer possible channels for the underperformance of high-sentiment takeover deals.

The manager sentiment effects on deal characteristics are less significant in public target samples since public target selection is associated with relatively low manager sentiment. Avoiding private target selection usually demonstrates that acquirers are more pessimistic and have less sub-optimal behaviours on deal characteristics. We rank the manager sentiment of acquirers into the high-, middle- and low-sentiment groups to support this postulation. The ranking reveals that *Acquirer MS'*s betas on takeover characteristics are insignificant in the low-sentiment group[10].

We provide additional evidence of lower conservatism with high manager sentiment by demonstrating the association between manager sentiment and days to completion (*Days*) in Table 2.A.6. We find that deals conducted by high-sentiment acquirers take short days to complete. Column (1) shows that *Days* has a strong and negative correlation with the *Acquirer MS,* with a *t*-statistics of -2.59, significant at the 1% level. Columns (2)-(4) show that the effect is only significant in the private target sample. We argue that high manager sentiment acquirers offer better deal terms such as a higher offer price to complete deals in a shorter time. Besides, deals involving acquirers and targets in the same industry take longer to complete, possibly

[10] The regression results are not presented but are available upon request.

due to antitrust regulations.

2.4.4 Decomposing Manager Sentiment

We decompose manager sentiment to determine whether positive or negative words drive the results. We construct positive manager sentiment *(Pos. MS)* and negative manager sentiment *(Neg. MS)* using positive word proportion and negative word proportion of 10-K and 10-Q filings. Managers can reflect their optimistic beliefs in disclosure filings by employing more positive words or fewer negative words. For example, let's consider the description "Next year's revenue continues to *enhance* with *contraction* on growth rate". Optimistic managers can document the information as "Next year's revenue continues to *enhance* to reach the *highest* level in the company's history accompanied with *contraction* on growth rate" (more positive words). Alternatively, they can declare "Next year's revenue continues to *enhance* with a controllable and acceptable growth rate" (fewer negative words)[11]. Following Loughran and Mcdonald (2011), we consider both positive and negative word lists, with the proportion of negative words being the primary focus. The idea is that previous studies find positive words provide less incremental information relative to negative words (Loughran and Mcdonald, 2011; Tetlock, 2007; Tetlock et al., 2008).

[11] According to Loughran and McDonald Dictionary, "enhance" and "highest" are classified as positive, "contraction" is classified as negative, "controllable" and "acceptable" are neither positive nor negative.

Table 2.7 Decomposing Manager Sentiment

This table reports the association between decomposing manager sentiment and dependent variables of deal characteristics and takeover performance. Positive manager sentiment and negative manager sentiment are constructed using positive word proportion and negative word proportion of 10-K and 10-Q filings. The regression includes time and industry fixed effects. The detailed definitions of variables are presented in Appendix 2.A. Robust standard errors are reported in the parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1) Stock	(2) Dsize	(3) Public	(4) PE	(5) BHAR 1Y
Pos. MS	-0.003	-0.056	0.003	0.001	-0.002
	(-0.64)	(-1.60)	(0.39)	(0.05)	(-0.35)
Neg. MS	0.015***	-0.096***	0.020***	-0.095***	0.010**
	(3.65)	(-3.19)	(3.35)	(-4.60)	(2.16)
Acquirer BTM	0.011	-0.321***	0.010	-0.032	0.035*
	(1.05)	(-3.36)	(0.84)	(-0.58)	(1.72)
Public					-0.002
					(-0.21)
Cash					0.007
					(0.76)
Stock					-0.019
					(-1.05)
Hostile					0.032
					(1.44)
Size	-0.013***	0.602***	0.052***	0.027*	-0.005
	(-4.55)	(27.96)	(14.65)	(1.89)	(-0.88)
Age	0.000	0.006	0.001	-0.006**	0.000
	(0.75)	(1.59)	(0.93)	(-2.39)	(0.74)
Leverage	-0.013*	0.020	0.007	0.068	0.091**
	(-1.72)	(0.17)	(1.24)	(1.04)	(2.31)
CHR	-0.074**	0.747***	0.078*	-0.261	0.073
	(-2.23)	(3.38)	(1.84)	(-1.56)	(1.19)
ROA	-0.041**	-0.033	-0.040**	0.301***	-0.033
	(-1.98)	(-0.19)	(-2.36)	(2.68)	(-0.39)
Rel. size	0.004		0.010	0.004**	0.007*
	(1.19)		(1.52)	(2.18)	(1.76)
Dormant > 1 yr	-0.024**	0.125	0.049***	0.030	0.015
	(-2.53)	(1.42)	(3.17)	(0.51)	(1.49)
Same industry	0.036***	0.294***	0.095***	0.054	0.009
	(4.38)	(4.22)	(7.78)	(1.16)	(0.92)
Toehold	-0.017	-0.630***	-0.115***	-0.001	-0.000
	(-1.11)	(-3.49)	(-4.53)	(-0.01)	(-0.01)
Past return	0.014	0.080	-0.017	0.141***	-0.229***
	(1.23)	(1.13)	(-1.40)	(2.72)	(-5.89)
CEO Age	0.092**	0.339	0.013	0.113	0.054
	(2.30)	(1.03)	(0.20)	(0.52)	(1.53)
CEO Male	0.035	0.219	-0.067*	0.071	-0.003
	(1.57)	(1.28)	(-1.94)	(0.68)	(-0.17)
CEO Tenure	-0.014***	-0.051	-0.013	0.010	0.002
	(-2.76)	(-1.20)	(-1.49)	(0.37)	(0.50)
CEO Comp	-0.004	-0.008	0.008*	0.002	0.002
	(-1.49)	(-0.35)	(1.92)	(0.14)	(1.04)
CEO OC	-0.012	-0.225**	0.030	-0.043	0.007
	(-1.10)	(-2.25)	(1.44)	(-0.69)	(0.56)
Industry FE	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y
Observations	6752	2512	6752	2556	5791
Adjusted R^2	0.07	0.51	0.12	0.12	0.11

Table 2.7 reports the results of decomposing manager sentiment that *Neg. MS* is significantly associated with deal characteristics including *Stock, Dsize, Public, PE,* and the one-year *BHAR* while *Pos. MS* is not. Moreover, the relationship between *Neg. MS* and deal characteristics are contrary to the relationship between *MS* and deal characteristics because *Neg. MS* and *MS* are negatively correlated. Our finding is aligned with the previous studies that illustrate that negative words can effectively measure text sentiment as reflected by significant correlations with financial variables. The results imply that increasing proportion of positive words incurs a simulated optimism. On the other hand, the decreasing proportion of negative words implies the true optimism and subsequent real activities of managers. That is, managers are just talking if there are more positive words. However, managers tend to take real actions and undertake optimistic decisions when fewer negative words are used.

2.4.5 Aggregate-level Results

We proceed to aggregate-level analyses by examining the association between the *MSI* and takeover characteristics at the aggregate level. The time-series regression model is formulated as follows:

$$AC_{t+1} = \alpha + \beta MSI_t + \mu X_{k,t} + \varepsilon_{t+1}, \quad (7)$$

where AC_{t+1} denotes the aggregate-level takeover characteristics in month t+1, MSI_t denotes the manager sentiment index, and $X_{k,t}$ includes the *ABTM* ratio, *IRS*, and *EPU*[12]. The coefficient of interest β indicates whether *MSI* drives takeover

[12] All the aggregate-level variables are stationary according to the Augmented Dickey-Fuller (ADF) tests

activities and takeover rumors and affects takeover characteristics. The regression results are presented in Table 2.8, with the decomposed *MSI* and *ABTM* based on the *BTM* ratio. High-BTM and low-BTM are defined as the top 30% and the bottom 30% of the BTM-ranked universe, following Baker et al. (2012), which show that low BTM firms are potential acquirers and high BTM firms are potential targets.

Column (1) of Table 2.8 shows that *low-BTM firms' MSI* is positively associated with the takeover activities, aligning with the deal-level results and supporting hypothesis H1. Note that the positive coefficient of *ABTM (low-BTM)* on *Takeover* is positive and marginally significant, which contrasts sharply with the earlier finding of Baker et al. (2012) at the aggregate level. We also find strong evidence that *EPU* predicts takeover activities negatively in the time-series setting, consistent with those of Nguyen and Phan (2017) and Bonaime et al. (2018).

Column (2) of Table 2.8 shows that *potential bidders' MSI* is positively associated with *Rumor*, even with marginal significance. One possible reason is that managers of potential acquirers with high sentiment will perform less conservatively on conference calls or public meetings, which will trigger investors' and media's associations with takeover activities. However, the high valuation of potential targets (high-BTM firms) will weaken this "Big News" conjecture of M&A activities because targets are too pricy to be worthy, which is indicated by the positive correlation between *ABTM (high-BTM)* and *Rumor*. Column (3) of Table 2.8 demonstrates that

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presented in Table 2.A.7. We apply two models of trend and drift to test the stationary of time-series variables, with results of p-value less than 0.1 for all variables and less than 0.01 for most variables.

the high *MSI* of potential acquirers increases the probability of all-cash payment, whereas the high MSI of potential targets decreases the probability. However, the probability of all-stock payment is affected by neither MSI of potential acquirers nor the MSI of potential targets, as shown in Columns (4). The finding is consistent with the results of the deal-level payment method. With cash and stock payment having opposite coefficients, the manager sentiment of (potential) acquirers is negatively associated with a stock payment in the deal-level results and positively associated with a cash payment in the aggregate-level results. Columns (5) and (6) of Panel B present that potential bidders' high manager sentiment decreases the probability of hostile deals and public targets. By contrast, potential targets' high manager sentiment increases the probability. The finding of target selection preference of private targets is consistent with the deal level results. Managers with high sentiment tend to be less risk-averse, leading to harder-to-value target selection. They are more eager for opportunities and performance volatilities, leading to better terms and behaving less hostile to accelerate the completion of deals. However, hostile offers can create value, as Bhagat et al. (2005) documented.

In sum, the aggregate-level analyses suggest that potential acquirers' manager sentiment promotes takeover activities and results in more rumor, more cash-payment, less hostility, and less public acquisition. Compared to *MS* of potential acquirers, *MS* of potential targets is associated with these variables in the opposite directions.

Table 2.8 Aggregate-level Relationship Between Manager Sentiment and Takeover Characteristics

This table reports the following time-series regressions of aggregate-level takeover characteristics with Newey–West standard errors (maximum lag of 6):

$$AC_{t+1}^{i} = \alpha^{i} + \beta^{i} MSI_{t} + \mu^{i} ABTM_{t} + \omega^{i} IRS_{t} + \gamma^{i} EPU_{t} + \varepsilon_{t+1}^{i},$$

where AC_{t+1}^{i} represents the one-month-ahead aggregate-level monthly takeover characteristics, including the takeover activities normalized by NYSE firms (*Takeover*), the rumour activity normalized by NYSE firms (*Rumor*), the proportion of deals that are all cash payment (*Cash*) or all stock payment (*Stock*), the proportion of deals that are hostile (*Hostile*), and proportion of public target deals (*Public*). MSI_t denotes the aggregate manager sentiment index, $ABTM_t$ denotes the aggregate-level average book-to-market ratio, IRS_t denotes the first difference on the four-quarter moving average of the rate spread between the average interest rate on commercial and industrial loans and the Federal Funds Rate, and EPU_t denotes the economic policy uncertainty. The detailed definitions of variables are presented in Appendix 2.A. *F*-statistics denote the test statistics for the joint significance of coefficients. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	Takeover	Rumor	Cash	Stock	Hostile	Public
MSI (low-BTM)	0.068**	0.004*	0.202***	-0.074	-0.134***	-0.180***
	(2.32)	(1.72)	(4.77)	(-1.63)	(-5.93)	(-4.57)
MSI (high-BTM)	-0.001	-0.000	-0.205***	0.001	0.102***	0.112***
	(-0.03)	(-0.22)	(-4.14)	(0.02)	(6.90)	(4.36)
ABTM (low-BTM)	0.061*	0.003	0.373***	0.273***	0.176***	0.233***
	(1.69)	(1.13)	(3.23)	(3.88)	(6.37)	(3.88)
ABTM (high-BTM)	0.004	0.002***	0.026	0.079***	0.042***	0.073***
	(0.58)	(3.56)	(1.10)	(5.27)	(4.98)	(6.64)
IRS	0.039*	0.005**	-0.061	-0.008	0.011	0.032
	(1.95)	(2.08)	(-0.88)	(-0.18)	(0.48)	(0.72)
EPU	-0.018***	-0.001	-0.018	-0.014	0.000	-0.002
	(-3.02)	(-1.19)	(-1.07)	(-1.30)	(0.10)	(-0.21)
Observations	173	173	173	173	173	173
F-statistics	7.98	6.53	7.66	4.88	20.79	15.07

2.5 Robustness Checks

2.5.1 Instrument Variable Regression

Our primary findings may raise potential endogeneity concerns for time reasons. Note that acquirers' internal research period exists before a takeover announcement. If the M&A motion is earlier than the drafting of 10-K and 10-Q filings, then manager sentiment may be affected by the expectation on upcoming takeovers. This situation may cause an endogenous problem. Therefore, an instrumental variable (IV) regression is estimated to address the endogeneity concerns.

We use the average manager sentiment of peer firms (*PMS)* as an instrumental variable. *PMS* is constructed by taking the average manager sentiment of other firms in the same life-cycle and 2-digit SIC industry but with different 4-digit SIC codes. We postulate that the peer managers will communicate and exchange their future judgments through public seminars, conferences, and informal discussions. Manager sentiment tends to transmit in a neighbour network, and a positive association exists between a firm's manager sentiment and its peer firms' manager sentiment. Meanwhile, confidential policies make it impossible that acquirers' takeover motions to affect other firms' manager sentiment. We emphasize that this instrument variable is closely related to manager sentiment because they probably share similar industry information and prospects. However, we hope the connections are not too strong so that peer firms' M&A activities will not determine managers' acquisition outcomes. Therefore, we exclude the same 4-digit SIC firms since they are close competitors. We follow the classification method in Dickinson (2011) for designating firms into

the growth, mature, and decline stage.

Table 2.A.1 reports the results of the IV regression. The first-stage regression in Column (1) shows that *Acquirer MS* positively correlates with the instrument variable *PMS*, significant at the 1% level with a *t*-statistic of 17.23 and an *F*-statistic of 31.08. The large *F*-statistic suggests that the instrument variable strongly correlates with the endogenous variables. Thus, the weak instrument problem is trivial. The second-stage results are presented in Columns (2)-(5). Quantitatively similar results are obtained for the significant effect of manager sentiment on the deal characteristics.

2.5.2 Adjusted Manager Sentiment

The manager sentiment can be partially associated with the firm's fundamentals. Therefore, we construct the adjusted manager sentiment (*JMS*) to remove the composition that is associated with observable fundamental factors. *JMS* is calculated as the regression residuals of manager sentiment (*MS*) on factors including firm characteristics, M&A activity conditions, and CEO characteristics. First, firm characteristics include acquirer's *BTM, Size, Age, Leverage, CHR, ROA,* and *Past return*. We also consider M&A activity conditions, including *CH, NWC*, and *HHI Index* of acquirers. Finally, we control CEO characteristics, such as *CEO Age, CEO Male, CEO Tenure, CEO Comp*, and *CEO OC* of acquirers. The regression result in Column (1) of Table 2.A.2 shows that the firm's manager sentiment is strongly associated with most fundamental factors. Especially, there is a strong positive association between manager sentiment and *CEO OC* with a *t*-statistic of 17.54, implying that overconfidence performs as one of the most important drivers of

managerial optimism.

The adjusted manager sentiment is then used as the key explanatory variable to test the effect of manager sentiment on takeover activities. All three panels of Table 2.A.2 show that *JMS* has the same effects on takeover activities, long-term performance, and deal characteristics as those of the unadjusted manager sentiment.

2.5.3 Control for Market Sentiment

One concern about the manager sentiment is that the deal-level sentiment is just a reflection of market sentiment. Thus, we control for market sentiment by combining aggregate and individual sentiment in deal-level regressions. We use *MSI* of Section 4.5 as the measure of aggregate sentiment. The regression results are reported in Table 2.A.3, which shows that our primary findings are robust to controlling for market sentiment.

2.5.4 Alternative Matching Procedures

A concern with the supplement of ultimate parent firm's sentiment when the acquirer and target firms' manager sentiment is not available is that the ultimate parents' manager sentiment is not consistent with the acquirer and targets' manager sentiment. We address this concern by using alternative matching procedures to keep the deal sample that directly matches acquirers and targets' manager sentiment, excluding those matched by ultimate parent firms. Panel A of Table 2.A.4 reports the results and shows that our primary findings are robust to alternative matching procedures.

Another concern with the sample construction is the fixed 6-month window in matching M&A deals with manager sentiment. However, manager sentiment takes a period to be reflected in the 10-K and 10-Q filings. We use 3- and 12-month matching windows to conduct deal-level analyses to measure the manager sentiment effect on takeover activities in the robustness checks. Panels B and C of Table 2.A.4 present the relevant results. Column (1) reports the effect of manager sentiment on the takeover probability, and the result remains quantitatively similar. Columns (2)-(5) present robust and consistent evidence on the effect of manager sentiment on deal characteristics using alternative matching windows.

2.6 Conclusions

We examine the role of manager sentiment on takeover activities, long-term performance, and deal characteristics. We use advances in textual analysis and the Loughran and Mcdonald (2011) financial and accounting dictionary to construct sentiment measures at both the aggregate and firm level from 10-K and 10-Q filings. The manager sentiment we measured can reflect distinct and incremental information relative to the overconfidence and other managerial traits from different data sources. We first conduct our major deal-level analyses to examine the extent to which manager sentiment drives takeover activities and affects takeover characteristics. The findings are consistent with our hypotheses that manager sentiment can drive takeover activities and impair acquirers' long-term performance.

First, manager sentiment has a strong positive forecasting power for takeover activities at both deal and aggregate levels. The betas of manager sentiment on the

probability of undertaking takeovers are pronounced in firms with small board size, high board independence, and low pay-performance sensitivity. Second, acquirers with high manager sentiment consistently underperform acquirers with low manager sentiment after undertaking the takeover deals, which is reflected by the increasing difference of buy-and-hold abnormal returns between the high- and low-MS acquirers within 36 months.

Next, we examine the deal characteristics and provide two possible channels for the underperformance of high-sentiment deals. Managers with high sentiment tend to be less conservative on target selection, transaction execution, and target valuation due to their over-optimism of future economy. They spend fewer days to complete the takeover deals. Specifically, high-sentiment managers tend to undertake larger deals and decrease the all-stock payment, implying more serious cash exhaustion and a higher probability of financial distress. They are more likely to acquire hard-to-value targets and offer high target valuation, indicating the tendency of selecting risky and pricy investments. Consequently, the takeover deals made by high-sentiment acquirers will impair the long-term takeover performance. We also find that the deal-level results of payment method, target valuation, days of completion, and long-term performance are more likely to be driven by acquisitions of private firms.

We further decompose manager sentiment to determine whether positive or negative words drive the results. We construct positive (negative) manager sentiment by counting only the positive (negative) words scaled by total number of words. The results show that only negative manager sentiment is significantly associated with

deal characteristics, illustrating that negative words mainly drive the empirical results.

We also conduct additional robustness checks using adjusted manager sentiment and IV regressions, with average peer sentiment being an instrument. The effect on deal-level takeover characteristics remains quantitatively similar. Moreover, we conduct aggregate-level analyses to confirm the findings regarding takeover activities, payment methods, and preferences of target selection. Moreover, the aggregate-level results provide additional information that bidders' manager sentiment can drive takeover rumors, even with marginal significance. Bidders with high manager sentiment also tend to undertake less hostile offers.

This study helps us understand the causes and consequences of takeovers and how manager sentiment influences the takeover characteristics. In particular, managers make takeovers because of their reactions to economic fundamentals and investor sentiment and their sentiment. The findings of this study will help investors build accurate expectations on takeover activities. Investors and other stakeholders should have precise expectations on takeover activities by recognizing deals driven by managerial optimism. This study will also provide useful implications for regulatory agencies to establish appropriate supervisory procedures for M&A activities, highly relevant to firm value and financial market stability. Regulatory agencies should understand why takeover activities happen and avoid promptly overheated takeover activities that may damage firm value and economic growth. Firms should likewise encourage managers to be cautious and rational when evaluating investment opportunities.

Appendix

2.A Variable Definitions

ABTM is the monthly aggregate-level average *BTM* ratio of listed firms, with *ABTM (low-BTM*) being the *ABTM* of the bottom 30% *BTM*-ranked firms per month, and *ABTM (high-BTM*) being the *ABTM* of the top 30% *BTM*-ranked firms per month.

BHAR is the buy-and-hold abnormal return to the acquirer after takeover announcement using the reference portfolio approach, as in Ma, Whidbee, and Zhang (2019). Each month, all NYSE stocks are sorted into quintiles based on market capitalization, *BTM* ratio, and return over the past year in sequence. The average monthly return of each portfolio of the 125 portfolios is regarded as the benchmark for the stocks listed on NYSE, Amex, and Nasdaq, all of which correspond with the grouping standards. *BHAR 1Y, BHAR 2Y, and BHAR 3Y* are one-year, two-year, and three-year *BHAR* of acquirers.

BTM is the firm's *BTM* ratio, which is the book value divided by the market value.

CEO Age is the natural logarithm of the CEO's age, as recorded in the Compustat Execucomp.

CEO Comp is the natural logarithm of the executive's total compensation (Salary, Bonus, Other Annual, Total Value of Restricted Stock Granted, Net Value of Stock Options Exercised, Long-Term Incentive Payouts, and All Other Total) of the current CEO, as recorded in the Compustat Execucomp.

CEO Male is a dummy variable that equals one if the CEO is male and zero otherwise, as recorded in the Compustat Execucomp.

CEO OC is the variable of CEO overconfidence measured by whether the CEO is a long holder of options, as in Malmendier and Tate (2015). The binary variable of *CEO OC* (Longholder) is equal to one if the CEO exercised an option meeting the criteria that the exercise occurred within the same year of options expiration or the option was at least 40 percent in-the-money 12 months before expiration, with data recorded in Thomson Reuters data and the Compustat Executive Compensation data. Otherwise, CEOs are regarded as not overconfident and have *CEO OC* (Longholder) set equal to zero.

CEO Tenure is the natural logarithm of the CEO tenure.

CH is the acquirer's cash.

CHR is the acquirer's cash scaled by the total assets.

Days is the effective date minus the announcement date as reported in the SDC.

DMS is the manager sentiment of the acquirer minus the manager sentiment of the target.

Dormant > 1 yr is a dummy variable that equals one if the deal is at least one year from the

previous deal made by peers in the same four-digit SIC industry and zero otherwise. The definition follows Ma, Whidbee, and Zhang (2019).

Dsize is the natural logarithm of the deal size, which is transaction value excluding assumed liability, as reported in SDC.

EPU is the natural logarithm of the monthly U.S. economic policy uncertainty index developed by Baker, Bloom, and Davis (2016). The index is constructed from three components: the newspaper coverage of policy-related economic uncertainty, the number of federal tax code provisions set to expire in future years, and the disagreement among economic forecasters as a proxy for uncertainty.

HHI is the Herfindahl-Hirschman index, also known as the concentration index. Each year, all firms are grouped by 4-digit SIC, and the index is generated based on the sales revenue as recorded in Compustat Fundamentals.

Hostile is a dummy variable that equals one if the deal attitude is hostile or unsolicited in SDC and zero otherwise, with aggregate-level *Hostile* being the proportion of hostile deals per month.

IRS is the first difference on the four-quarter moving average of the rate spread between the average interest rate on commercial and industrial loans and the Federal Funds Rate, as listed on https://www.federalreserve.gov/releases/e2/e2chart.htm.

JMS is the adjusted manager sentiment defined as the OLS regression residuals of manager sentiment on firm fundamental factors, including *BTM* ratio, firm size, leverage, cash ratio, and return on assets.

Leverage is the acquirer's total debt divided by total asset, measured as the last financial statement before the takeover announcement.

MS is the difference between the number of positive words and the number of negative words normalized by the total number of words in 10-K and 10-Q filings, as recorded in the WRDS SEC Analytics Suite Readability and Sentiment Analysis Database. The deal-level MS is calculated as the sentiment of the firm's nearest released 10-K or 10-Q filings over the six months before the deal announcement.

MSI is the monthly average manager sentiment extracted from 10-K and 10-Q filings using a four-month moving average weighted by filing numbers to mitigate the influence of seasonality and idiosyncratic jumps, as in Jiang et al. (2019). *MSI* (*low-BTM*) is the MSI constructed by the bottom 30% BTM-ranked firms' manager sentiment per month, and *MSI* (*high-BTM*) is the MSI constructed by the manager sentiment of the top 30% *BTM* ranked firms per month.

Neg. MS is the negative manager sentiment, the number of negative words normalized by the

number of total words in 10-K and 10-Q filings, as recorded in the WRDS SEC Analytics Suite Readability and Sentiment Analysis Database.

Past return is the acquirer's raw stock return over the past year before the takeover announcement month, as defined in Ma, Whidbee, and Zhang (2019).

PE is the offer price per share divided by target earnings per share, as recorded in the SDC.

PMS is the firm's average peer sentiment by taking the average manager sentiment of other firms in the same life-cycle and 2-digit SIC industry but with different 4-digit SIC codes. Life-cycle is constructed using cash flow patterns following Dickinson (2011).

PMW is the offer price to target stock price premium with stock price one week before the takeover announcement, as recorded in the SDC.

Pos. MS is the positive manager sentiment, the number of positive words normalized by the number of total words in 10-K and 10-Q filings, as recorded in the WRDS SEC Analytics Suite Readability and Sentiment Analysis Database.

Public is a dummy variable that equals one if the target is a public firm and zero otherwise.

Rel. size is the deal value divided by the acquirer's market capitalization.

ROA is the acquirer's net income divided by the total asset.

Rumor is the number of takeover rumours divided by the number of NYSE listed firms per month.

Same industry is a dummy variable that equals one if the acquirer and target share the same two-digit SIC code and zero otherwise.

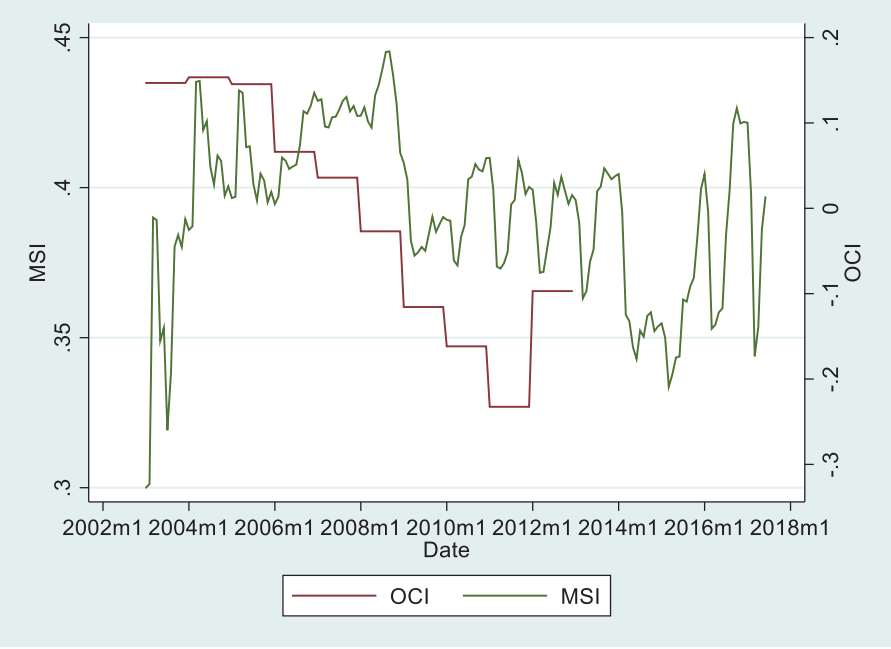
Size is the natural logarithm of the acquirer's total asset.

Stock is equal to one if the percentage of consideration paid in stock equals 100 in SDC and zero otherwise, with aggregate-level stock being the proportion of all-stock payment deals per month.

Takeover is a dummy variable that equals one if the firm makes a takeover in the subsequent six months after 10-K filing disclosures and zero otherwise. Aggregate-level *Takeover* is the monthly takeover numbers normalized by the number of NYSE listed firms per month.

Toehold is a dummy variable that equals one if the percentage of shares acquirer held at the announcement date is no less than 5% and zero otherwise.

2.B Aggregate Manager Sentiment and Overconfidence



The figure presents the trends of manager sentiment index (*MSI*) and overconfidence index (*OCI*). OCI is constructed based on the indicator variable of CEO overconfidence measured by whether the CEO is a long holder of options, as in Malmendier and Tate (2015). The firm-year overconfidence data is available until 2013.

Table 2.A.1 Instrumental Variable Regression

This table reports the association between manager sentiment and deal characteristics using instrumental variable regression. The average manager sentiment of peer firms with the same life-cycle and 2-digit SIC but different 4-digit SIC *PMS* is constructed as the instrumental variable. The detailed definitions of variables are presented in Appendix 2.A. Robust standard errors are reported in the parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	First Stage	Second Stage			
	(1)	(2)	(3)	(4)	(5)
	Acquirer MS	Stock	Dsize	Public	PE
PMS	0.751***				
	(17.23)				
Acquirer MS		-0.096***	0.405***	-0.063**	0.281***
		(-4.45)	(3.52)	(-2.30)	(3.70)
Acquirer BTM	-0.027	0.005	-0.287***	0.007	-0.027
	(-1.05)	(0.52)	(-3.03)	(0.58)	(-0.47)
Size	-0.090***	-0.020***	0.623***	0.049***	0.043***
	(-11.68)	(-5.82)	(26.69)	(11.56)	(2.81)
Age	-0.001	0.000	0.007*	0.000	-0.005*
	(-0.99)	(0.34)	(1.68)	(0.47)	(-1.81)
Leverage	-0.045**	-0.016**	0.042	0.005	0.098
	(-2.28)	(-2.10)	(0.38)	(0.90)	(1.44)
CHR	-0.562***	-0.110***	0.874***	0.061	-0.196
	(-5.49)	(-3.08)	(3.76)	(1.38)	(-1.12)
ROA	0.162***	-0.028	-0.093	-0.033*	0.298***
	(3.49)	(-1.31)	(-0.55)	(-1.88)	(2.71)
Rel. size	-0.010**	0.004		0.009	0.006**
	(-2.43)	(1.02)		(1.49)	(2.36)
Dormant > 1 yr	0.163***	-0.010	0.042	0.057***	-0.032
	(4.93)	(-0.95)	(0.45)	(3.51)	(-0.51)
Same industry	-0.048*	0.031***	0.300***	0.092***	0.056
	(-1.83)	(3.60)	(4.22)	(7.48)	(1.17)
Toehold	0.006	-0.018	-0.644***	-0.116***	-0.011
	(0.12)	(-1.09)	(-3.55)	(-4.55)	(-0.09)
Past return	-0.028	0.010	0.078	-0.019	0.130**
	(-0.98)	(0.86)	(1.08)	(-1.54)	(2.45)
CEO Age	0.418***	0.125***	0.095	0.027	-0.048
	(2.98)	(2.99)	(0.26)	(0.40)	(-0.20)
CEO Male	-0.080	0.025	0.320*	-0.072**	0.134
	(-1.20)	(1.10)	(1.78)	(-2.05)	(1.23)
CEO Tenure	0.011	-0.013**	-0.053	-0.011	0.003
	(0.63)	(-2.36)	(-1.21)	(-1.35)	(0.12)
CEO Comp	0.006	-0.004	-0.019	0.009**	-0.004
	(0.80)	(-1.26)	(-0.80)	(2.00)	(-0.30)
CEO OC	0.095**	-0.007	-0.239**	0.032	-0.055
	(2.15)	(-0.58)	(-2.34)	(1.54)	(-0.87)
Industry FE	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y
Observations	6749	6749	2512	6749	2512
Adjusted R^2	0.17	-0.05	0.37	0.05	-0.05
F-statistics	31.08	8.94	95.02	34.88	4.57

Table 2.A.2 Adjusted Manager Sentiment

This table reports the association between adjusted manager sentiment and takeover activities, deal characteristics, and acquirers' long-term performance. The adjusted manager sentiment (*JMS*) is calculated as the regression residuals of manager sentiment (*MS*) on factors including firm characteristics, M&A activity conditions, and CEO characteristics. Firm Characteristics include acquirer's *BTM, Size, Age, Leverage, CHR, ROA,* and *Past return*. M&A Activity Conditions include *CH, NWC*, and *HHI* index of acquirers. CEO Characteristics include *CEO Age, CEO Male, CEO Tenure, CEO Comp*, and *CEO OC* of acquirers. Deal characteristics include *Rel. size, Dormant > 1 yr, Same industry, Toehold.* The detailed definitions of variables are presented in Appendix 2.A. All specifications include year and industry fixed effects. Robust standard errors are reported in the parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Adjusted MS Generating and Takeover Activities				
	(1)	(2)	(3)	(4)
	MS	Takeover	Takeover	Takeover
JMS		0.004**	0.007***	0.007***
		(2.03)	(2.98)	(2.90)
BTM	0.010**	-0.001	-0.002	-0.002
	(2.56)	(-0.82)	(-1.55)	(-1.57)
Size	-0.030***	-0.005***	-0.005**	-0.006***
	(-19.25)	(-2.90)	(-2.35)	(-2.84)
Age	-0.006***	0.001	0.001	0.001
	(-18.05)	(0.39)	(0.19)	(0.17)
Leverage	-0.015***	-0.002***	-0.002**	-0.002***
	(-5.61)	(-2.79)	(-2.38)	(-2.58)
CHR	-0.426***	0.032***	0.042***	0.041***
	(-25.10)	(4.57)	(5.56)	(5.41)
ROA	-0.011	-0.002	-0.002	-0.002
	(-1.21)	(-0.83)	(-0.77)	(-0.68)
CH	-0.000***		0.000	0.000
	(-8.26)		(0.65)	(0.71)
NWC	-0.000		-0.000	-0.000
	(-0.22)		(-0.68)	(-0.71)
Past return	0.040***		0.006***	0.006***
	(6.80)		(3.03)	(3.03)
HHI Index	0.183***		-0.021	-0.022
	(11.78)		(-1.12)	(-1.16)
CEO Age	0.224***			-0.036
	(5.55)			(-1.50)
CEO Male	-0.123***			0.016
	(-5.75)			(1.47)
CEO Tenure	0.011**			0.002
	(2.03)			(0.66)
CEO Comp	0.007**			0.001
	(2.49)			(0.72)
CEO OC	0.221***			-0.003
	(17.54)			(-0.49)
Firm FE	N	Y	Y	Y
Year FE	N	Y	Y	Y
Observations	65733	76828	60577	60577
Adjusted R^2	0.04	0.10	0.09	0.09

Panel B: BHAR of Acquirers						
	1-Year		2-Year		3-Year	
	(1)	(2)	(3)	(4)	(5)	(6)
	All	Public	All	Public	All	Public
Acquirer JMS	-0.013**	-0.010	-0.015**	-0.003	-0.028***	-0.020*
	(-2.32)	(-1.10)	(-2.21)	(-0.34)	(-3.55)	(-1.65)
Target JMS		-0.007		-0.011		0.006
		(-0.73)		(-1.04)		(0.50)
Target BTM	Y	Y	Y	Y	Y	Y
Firm Characteristics	Y	Y	Y	Y	Y	Y
CEO Characteristics	Y	Y	Y	Y	Y	Y
Deal Characteristics	Y	Y	Y	Y	Y	Y
Industry FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Observations	4386	965	4145	927	3701	843
Adjusted R^2	0.10	0.23	0.08	0.17	0.13	0.19

Panel C: Takeover Characteristics				
	(1)	(2)	(3)	(4)
	Stock	Dsize	Public	PE
Acquirer JMS	-0.013***	0.066**	-0.015**	0.083***
	(-3.40)	(2.00)	(-2.36)	(3.82)
Firm Characteristics	Y	Y	Y	Y
CEO Characteristics	Y	Y	Y	Y
Deal Characteristics	Y	Y	Y	Y
Industry FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Observations	5255	1911	5255	1950
Adjusted R^2	0.06	0.49	0.11	0.10

Table 2.A.3 Control for Market Sentiment

This table reports the deal-level regression results with controlling for the aggregate sentiment (*MSI*). Firm Characteristics include acquirer's *BTM, Size, Age, Leverage, CHR, ROA,* and *Past return*. CEO Characteristics include *CEO Age, CEO Male, CEO Tenure, CEO Comp*, and *CEO OC* of acquirers. Deal characteristics include *Rel. size, Dormant > 1 yr, Same industry, Toehold.* The detailed definitions of variables are presented in Appendix 2.A. All specifications include year and industry fixed effects. Robust standard errors are reported in the parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Takeover Activities			
	(1)	(2)	(3)
	Takeover	Takeover	Takeover
MS	0.007***	0.007***	0.007***
	(3.29)	(2.99)	(2.91)
MSI	-0.003	-0.007	-0.006
	(-0.19)	(-0.35)	(-0.33)
BTM	-0.004***	-0.002	-0.002
	(-3.99)	(-1.57)	(-1.59)
SIZE	-0.005***	-0.005**	-0.006***
	(-2.91)	(-2.35)	(-2.84)
AGE	-0.001	-0.003	-0.003
	(-0.41)	(-0.81)	(-0.82)
LEV	-0.003***	-0.002**	-0.002***
	(-3.41)	(-2.40)	(-2.60)
CHR	0.040***	0.042***	0.041***
	(5.61)	(5.52)	(5.38)
ROA	-0.003	-0.002	-0.002
	(-0.86)	(-0.78)	(-0.69)
Cash		0.000	0.000
		(0.64)	(0.71)
NWC		-0.000	-0.000
		(-0.68)	(-0.71)
Past return		0.006***	0.006***
		(3.04)	(3.04)
HHI Index		-0.021	-0.022
		(-1.13)	(-1.17)
CEO Age			-0.036
			(-1.51)
CEO Male			0.016
			(1.46)
CEO Tenure			0.002
			(0.72)
CEO Comp			0.001
			(0.72)
CEO OC			-0.003
			(-0.47)
Firm FE	Y	Y	Y
Year FE	Y	Y	Y
Observations	76828	60577	60577
Adjusted R^2	0.09	0.09	0.09

Panel B: BHAR of Acquirers						
	1-Year		2-Year		3-Year	
	(1)	(2)	(3)	(4)	(5)	(6)
	All	Public	All	Public	All	Public
Acquirer MS	-0.010**	-0.011	-0.012**	-0.009	-0.017***	-0.011
	(-2.15)	(-1.38)	(-2.02)	(-1.02)	(-2.63)	(-1.07)
Target MS		-0.009		-0.006		0.010
		(-1.07)		(-0.59)		(0.92)
MSI	0.009	0.059	0.141	0.149	0.028	-0.049
	(0.11)	(0.52)	(1.54)	(1.25)	(0.26)	(-0.33)
Target BTM	Y	Y	Y	Y	Y	Y
Firm Characteristics	Y	Y	Y	Y	Y	Y
CEO Characteristics	Y	Y	Y	Y	Y	Y
Deal Characteristics	Y	Y	Y	Y	Y	Y
Industry FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Observations	5675	1355	5394	1301	4881	1193
Adjusted R^2	0.12	0.20	0.09	0.14	0.11	0.14

Panel C: Takeover Characteristics				
	(1)	(2)	(3)	(4)
	Stock	Dsize	Public	PE
Acquirer JMS	-0.016***	0.073**	-0.019***	0.087***
	(-4.03)	(2.49)	(-3.19)	(4.40)
MSI	-0.101	0.444	-0.086	-0.478
	(-1.47)	(0.91)	(-0.92)	(-1.51)
Firm Characteristics	Y	Y	Y	Y
CEO Characteristics	Y	Y	Y	Y
Deal Characteristics	Y	Y	Y	Y
Industry FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Observations	6625	2475	6625	2519
Adjusted R^2	0.07	0.50	0.12	0.12

Table 2.A.4 Alternative Matching Procedures

This table reports the association between manager sentiment and takeover activities and deal characteristics using alternative matching procedures. We either exclude the sample of ultimate parent firm sentiment in Panel A or modify the matching window from 6 months to 3 and 12 months in Panel B. *MS* denotes the manager sentiment of listed firms in Column (1) and the acquirers' manager sentiment in Column (2)-(7). Firm Characteristics include acquirer's *BTM, Size, Age, Leverage, CHR, ROA,* and *Past return*. M&A Activity Conditions include *CH, NWC*, and *HHI* index of acquirers. CEO Characteristics include *CEO Age, CEO Male, CEO Tenure, CEO Comp*, and *CEO OC* of acquirers. Deal Characteristics include *Rel. size, Dormant > 1 yr, Same industry, Toehold*. The detailed definitions of variables are presented in Appendix 2.A. The regression includes the year and industry fixed effects. Robust standard errors are reported in the parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Exclude Ultimate Parents

	(1) Takeover	(2) Stock	(3) Dsize	(4) Public	(5) PE
Acquirer MS	0.007***	-0.014***	0.075***	-0.019***	0.087***
	(3.00)	(-3.69)	(2.59)	(-3.20)	(4.42)
Firm Characteristics	Y	Y	Y	Y	Y
M&A Activity Conditions	Y	N	N	N	N
CEO Characteristics	Y	Y	Y	Y	Y
Deal Characteristics	N	Y	Y	Y	Y
Industry FE	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y
Observations	60577	6724	2504	6724	2548
Adjusted R^2	0.08	0.07	0.51	0.12	0.12

Panel B: 3-Month Matching Window

	(1) Takeover	(2) Stock	(3) Dsize	(4) Public	(5) PE
Acquirer MS	0.003**	-0.016***	0.067**	-0.015**	0.084***
	(1.98)	(-3.98)	(2.21)	(-2.51)	(4.12)
Firm Characteristics	Y	Y	Y	Y	Y
M&A Activity Conditions	Y	N	N	N	N
CEO Characteristics	Y	Y	Y	Y	Y
Deal Characteristics	N	Y	Y	Y	Y
Industry FE	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y
Observations	60577	6238	2352	6238	2396
Adjusted R^2	0.03	0.07	0.49	0.12	0.11

Panel C: 12-Month Matching Window

	(1) Takeover	(2) Stock	(3) Dsize	(4) Public	(5) PE
Acquirer MS	0.009***	-0.015***	0.069**	-0.018***	0.089***
	(2.79)	(-3.95)	(2.39)	(-3.08)	(4.53)
Firm Characteristics	Y	Y	Y	Y	Y
M&A Activity Conditions	Y	N	N	N	N
CEO Characteristics	Y	Y	Y	Y	Y
Deal Characteristics	N	Y	Y	Y	Y
Industry FE	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y
Observations	60577	6957	2579	6957	2623
Adjusted R^2	0.15	0.07	0.51	0.12	0.12

Table 2.A.5 Manager Sentiment and Bidding Premium

This table reports the association between manager sentiment and bidding premium. The dependent variables include the offer price to target stock price premium with one week before the announcement (*PMW*) in Columns (1)-(3) and the target market price-to-earnings ratio with target price one week before the deal announcement day (*TPE*) in Columns (4) and (5). $Acquirer\ MS_i$ and $Target\ MS_i$ denote the manager sentiment of acquirers and targets, respectively, and are replaced with the difference term (*DMS*) in Column (3). The regression includes time and industry fixed effects. The detailed definitions of variables are presented in Appendix 2.A. Robust standard errors are reported in the parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1) PMW	(2) PMW	(3) PMW
DMS			1.309**
			(2.03)
Acquirer MS	-0.446	0.034	
	(-0.54)	(0.04)	
Acquirer BTM	-1.761	-2.179	-2.248
	(-0.64)	(-0.82)	(-0.84)
Target MS		-2.508***	
		(-2.68)	
Target BTM		3.595	3.660
		(1.05)	(1.06)
Size	1.033	1.221	1.357
	(1.13)	(1.36)	(1.48)
Age	0.172	0.148	0.154
	(1.48)	(1.27)	(1.34)
Leverage	3.372	2.884	2.790
	(0.70)	(0.61)	(0.59)
CHR	-8.907	-6.167	-6.085
	(-1.09)	(-0.81)	(-0.76)
ROA	31.991	33.121	31.166
	(1.00)	(1.07)	(1.03)
Rel. size	-0.520**	-0.515**	-0.504**
	(-2.57)	(-2.31)	(-2.44)
Dormant > 1 yr	0.202	1.293	0.678
	(0.06)	(0.38)	(0.20)
Same industry	-1.096	-1.415	-1.550
	(-0.42)	(-0.54)	(-0.59)
Toehold	-14.908**	-15.261***	-15.519***
	(-2.61)	(-2.70)	(-2.72)
Past return	-4.399	-3.864	-3.843
	(-1.65)	(-1.48)	(-1.44)
CEO Age	-8.262	-7.514	-9.083
	(-0.63)	(-0.57)	(-0.68)
CEO Male	4.209	4.349	4.963
	(1.12)	(1.12)	(1.28)
CEO Tenure	-2.440	-2.430	-2.467
	(-1.31)	(-1.32)	(-1.33)
CEO Comp	-0.434	-0.398	-0.478
	(-0.85)	(-0.77)	(-0.93)
CEO OC	-2.390	-2.604	-2.543
	(-0.71)	(-0.78)	(-0.75)
Industry FE	Y	Y	Y
Year FE	Y	Y	Y
Observations	1239	1239	1239
Adjusted R^2	0.11	0.12	0.11

Table 2.A.6 Manager Sentiment and Days to Completion

This table reports the association between manager sentiment and days to complete. OLS regressions with time and industry fixed effects are formulated as follows:

$$Days_i = \alpha + \beta AcquirerMS_i + \gamma TargetMS_i + \sigma X_i + \theta_t + \mu_j + \varepsilon_i$$

where $Days_i$ denotes the days to completion of the deal i; $Acquirer\ MS_i$ and $Target\ MS_i$ denote manager sentiment of acquirers and targets, respectively; and X_i denotes a set of control variables. θ_t and μ_j are time and industry fixed effects, respectively. The detailed definitions of variables are presented in Appendix 2.A. Robust standard errors are reported in the parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)
	All	Private	Public	Public
Acquirer MS	-3.250***	-4.086**	0.609	-1.046
	(-2.59)	(-2.57)	(0.35)	(-0.53)
Acquirer BTM	1.971	1.777	-1.064	1.217
	(0.65)	(0.45)	(-0.23)	(0.21)
Target MS				-1.030
				(-0.56)
Target BTM				-1.372
				(-0.45)
Size	2.921***	0.012	-2.499*	-6.609***
	(3.33)	(0.01)	(-1.87)	(-4.13)
Age	0.000	0.160	-0.226	-0.024
	(0.00)	(0.93)	(-0.99)	(-0.08)
Leverage	2.671	-1.417	13.691**	21.383**
	(1.06)	(-0.49)	(2.01)	(2.23)
CHR	8.980	1.572	5.435	-3.969
	(1.04)	(0.16)	(0.37)	(-0.21)
ROA	-13.347*	-16.875**	11.369	29.079
	(-1.75)	(-2.04)	(0.54)	(1.22)
Rel. size	3.279**	9.598***	0.511	0.120
	(2.30)	(2.90)	(0.95)	(0.24)
Dormant > 1 yr	-3.298	-10.338**	7.737	20.341***
	(-0.92)	(-2.42)	(1.38)	(2.80)
Same industry	17.319***	11.771***	9.342**	12.567**
	(6.13)	(3.28)	(2.41)	(2.56)
Toehold	22.734*	40.496***	7.081	-0.463
	(1.91)	(2.65)	(0.56)	(-0.03)
Past return	-4.257	-1.234	-3.259	-11.467*
	(-1.48)	(-0.38)	(-0.65)	(-1.90)
CEO Age	18.982	7.545	30.206	56.897
	(1.24)	(0.43)	(1.06)	(1.38)
CEO Male	-13.477**	-8.593	-14.192	-13.757
	(-2.53)	(-1.33)	(-1.56)	(-1.19)
CEO Tenure	-4.356***	-3.306	-2.804	-5.114*
	(-2.61)	(-1.52)	(-1.21)	(-1.74)
CEO Comp	2.036***	1.298	2.335**	2.994**
	(2.84)	(1.35)	(2.13)	(2.23)
CEO OC	1.076	-5.939	2.760	1.483
	(0.24)	(-0.94)	(0.54)	(0.25)
Industry FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Observations	5385	3591	1790	1162
Adjusted R^2	0.16	0.12	0.16	0.20

Table 2.A.7 Stationarity of Aggregate-level Variables

This table reports the results of ADF tests for all the aggregate-level variables. The detailed definitions of variables are presented in Appendix 2.A. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	With Trend		With Drift	
	Test statistic	MacKinnon approximate p-value	Test statistic	MacKinnon approximate p-value
MSI	-4.766 ***	0.001	-4.192***	0.000
MSI (low-BTM)	-4.074***	0.007	-4.389***	0.002
MSI (high-BTM)	-5.074***	0.000	-5.192***	0.000
ABTM	-3.595**	0.030	-3.612***	0.000
ABTM (low-BTM)	-3.618**	0.028	-2.279**	0.012
ABTM (high-BTM)	-3.326*	0.062	-3.231***	0.001
IRS	-5.873***	0.000	-5.897***	0.000
EPU	-5.908***	0.000	-5.240***	0.000
Takeover	-6.003***	0.000	-5.978***	0.000
Rumor	-9.196***	0.000	-9.214***	0.000
Cash	-4.191***	0.005	-3.973***	0.000
Stock	-6.412***	0.000	-5.143***	0.000
Hostile	-10.885***	0.000	-5.320***	0.000
Public	-9.748***	0.000	-7.057***	0.000

Table 2.A.8 Logit Model Results

This table reports the regression results using logit model results rather than OLS for dummy dependent variables. *Public* is a dummy variable that equals one if the target is a public firm and zero otherwise. *Stock* denotes all-stock payment that equals one if the percentage of consideration paid in stock equals 100 in SDC and zero otherwise. The regression includes time and industry fixed effects. The detailed definitions of variables are presented in Appendix 2.A. Robust standard errors are reported in the parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	All		Public Target
	(1)	(2)	(3)
	Public	Stock	Stock
Acquirer MS	-0.081***	-0.152***	-0.130*
	(-2.75)	(-3.75)	(-1.76)
Acquirer BTM	0.003	0.110	0.063
	(0.04)	(1.27)	(0.42)
Target MS			-0.011
			(-0.14)
Target BTM			0.023
			(0.23)
Size	0.299***	-0.136***	-0.318***
	(9.85)	(-5.00)	(-5.70)
Age	0.003	0.006	0.003
	(0.96)	(1.14)	(0.37)
Leverage	-0.110	-0.110*	-0.385
	(-0.86)	(-1.94)	(-1.15)
CHR	0.506**	-0.593*	-1.071
	(2.07)	(-1.87)	(-1.57)
ROA	-0.190	-0.287**	-0.160
	(-1.01)	(-2.10)	(-0.32)
Rel. size	0.211	0.034	0.019
	(1.03)	(0.69)	(1.21)
Dormant > 1 yr	0.273***	-0.309**	-0.242
	(3.42)	(-2.29)	(-1.02)
Same industry	0.505***	0.371***	0.285*
	(7.93)	(3.94)	(1.69)
Toehold	-0.582***	-0.221	0.471
	(-4.20)	(-1.07)	(1.21)
Past return	-0.073	0.107	0.097
	(-0.94)	(1.17)	(0.48)
CEO Age	0.001	1.183**	1.945**
	(0.00)	(2.31)	(2.31)
CEO Male	-0.258*	0.665**	0.357
	(-1.65)	(2.45)	(1.02)
CEO Tenure	-0.048	-0.166**	-0.232**
	(-1.20)	(-2.57)	(-2.42)
CEO Comp	0.027	-0.077**	-0.009
	(1.38)	(-2.30)	(-0.22)
CEO OC	0.112	-0.254	-0.284
	(1.18)	(-1.43)	(-1.09)
Industry FE	Y	Y	Y
Year FE	Y	Y	Y
Observations	6752	6545	1431
Adjusted R^2	0.12	0.10	0.15

Table 2.A.9 Alternative Measure of Payment Method

This table reports the association between manager sentiment and payment method of acquisition deals. The dependent variable is the proportion of stock payment as recorded in SDC. Column (1) reports the regression result of all samples. Column (2) reports the regression result of public-target samples. The regression includes time and industry fixed effects. The detailed definitions of variables are presented in Appendix 2.A. Robust standard errors are reported in the parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1) All	(2) Public Target
Acquirer MS	-1.453***	-0.765
	(-3.42)	(-0.75)
Acquirer BTM	-1.361	-1.288
	(-1.30)	(-0.47)
Target MS		-1.302
		(-1.28)
Target BTM		-1.073
		(-0.72)
Size	-1.548***	-4.975***
	(-5.18)	(-6.20)
Age	0.092*	0.054
	(1.81)	(0.48)
Leverage	-2.776***	-3.320
	(-3.65)	(-0.52)
CHR	0.339	-19.684*
	(0.09)	(-1.86)
ROA	-5.708***	-8.707
	(-2.63)	(-0.62)
Rel. size	0.626	0.180
	(1.28)	(0.51)
Dormant > 1 yr	-2.448**	-4.428
	(-2.27)	(-1.46)
Same industry	6.445***	5.102**
	(7.18)	(2.19)
Toehold	-6.428***	2.170
	(-3.68)	(0.37)
Past return	2.369**	2.083
	(2.04)	(0.70)
CEO Age	5.042	13.855
	(1.14)	(1.31)
CEO Male	5.278**	6.352
	(2.17)	(1.39)
CEO Tenure	-0.937*	-2.559**
	(-1.67)	(-1.99)
CEO Comp	-0.963***	-0.658
	(-3.04)	(-1.13)
CEO OC	-3.179**	-5.306*
	(-2.56)	(-1.82)
Industry FE	6752	1514
Year FE	Y	Y
Observations	Y	Y
Adjusted R^2	0.18	0.27

Chapter 3

Informativeness of incentive contracts: Relative performance evaluation and stock price crash risk

3.1 Introduction

Relative performance evaluation (RPE) is a method to evaluate managers' performance relative to their peers' performance. Since the 1980s, studies conjecture that some companies use RPE instead of the absolute performance evaluation (APE) to evaluate managers' performance and determine their compensation (Holmstrom, 1979; Antle and Smith, 1985, 1986; Gibbons and Murphy, 1990; Janakiraman, Lambert, and Larcker, 1992). Such studies have found strong or weak evidence of RPE utilization. The consensus is that RPE can insulate managers' compensation from common shocks and remove unnecessary risk from the contract. Thus, it is informative for the agent's performance evaluation and more beneficial for limiting agency costs, having a positive firm impact.

Given that firms face market and firm-specific uncertainties, the simple idea is that managers' performance should be corrected for aggregate market uncertainty (Albuquerque et al., 2013; Gong et al., 2011; Jayaraman et al., 2020). Relative to APE (i.e., non-RPE), RPE can help insulate managers from market uncertainty

beyond managers' control and uncorrelated to their efforts. Thus, RPE eliminates managers' unnecessary common risk and provides a risk-sharing mechanism between shareholders and managers. The risk-sharing benefits reduce the agency cost of contracts. Such an idea is supported by Gibbons and Murphy (1990), illustrating that RPE can be a valuable tool to engage managers in making optimal decisions from the shareholders' viewpoint.

Several papers have documented RPE usage in compensation contracts (Aggarwal and Samwick, 1999b; Antle and Smith, 1986; Barro and Barro, 1990; Garen, 1994; Gibbons and Murphy, 1990; Janakiraman et al., 1992). These papers infer RPE use by finding evidence of the negative association between the executive compensation of a firm and the market (industry) index, implying the firm's subtraction of systematic component, so-called implicit tests of RPE. A regulatory change in 2006 that required firms to disclose their executive compensation information in more detail allows us to observe the listed firms' utilization of RPE directly since then, so-called explicit tests of RPE. In recent decades, the number of firms claiming usage of RPE has increased rapidly, which has attracted attention from academia. Bakke, Mahmudi, and Newton (2020) show that the number of S&P 500 firms using RPE approximately doubled from 17% in 2006 to 34% in 2012. Based on data of US-listed companies in 2006 – 2017, we find the proportion of RPE utilization to have increased from 15% in 2006 to 25% in 2012, but to slightly decrease to 22% by 2017.

A concern is that RPE disclosure in the firms' proxy statement does not necessarily tie to RPE use in practice. Black, Dikolli, and Hofmann (2012) dispel this worry by testing the real RPE usage of firms with or without claiming RPE usage in the proxy statements based on implicit tests. They show strong evidence of the actual utilization of RPE in RPE disclosure subsamples rather than non-RPE disclosure subsamples. Furthermore, Gong et al. (2011) offer evidence of implicit RPE use in firms disclosing explicit RPE details. Meanwhile, the implicit tests are not significant for firms without explicit RPE disclosure. The studies suggest that RPE disclosure in proxy statements is an effective and powerful proxy for firms' RPE use in practice.

Stock price crash risk is an important issue in both academia and industry. In this paper, we study whether RPE has an effect on stock price crash risk. Fundamentally, RPE affects stock price crash risk through the channel of information disclosure. That is, RPE encourages better information symmetry to mitigate the accumulation of crash risk possibility.

Based on theories of agency problem (Narayanan, 1985, 1987) and optimal contract (Holmstrom, 1979, 1982), RPE restrains the managerial incentives of bad news hoarding, thus decreasing the probability of crash risk. By removing the noisy signal of systematic risk that is out of managers' control, RPE is more informative to evaluate managers' productive inputs (Holmstrom, 1979, 1982). Hence, RPE managers rely less on short-term oriented results to convince the labor market about

their ability, and such diminished myopia motivation alleviates the managerial manipulation of private information (Narayanan, 1985, 1987). Therefore, RPE is negatively associated with bad news hoarding and the probability of crash risk[13]. We review the literature and develop our hypothesis in detail in the next section.

A distractive opinion is that RPE incurs higher firm-specific crash risk because of the selection of projects with higher idiosyncratic risk. Park and Vrettos (2015) demonstrate that RPE encourages managers to prefer firm-specific risk instead of systematic risk (see also Duan & Wei, 2005; Johnson & Tian, 2000). Thus, they may select projects bearing more firm-specific risk. Whereas, it is noteworthy that the stock price crash risk differs from firm-specific risk. The firm-specific risk focuses on the volatility of stock returns (Park & Vrettos, 2015), while crash risk emphasizes the skewness and left-tail risk. Specifically, RPE incurs managerial selection of projects with higher idiosyncratic risk, which does not mean RPE will aggravate the tail risk. In particular, theories about stock price crash risk emphasize the agency problem and indicates that the bad news hoarding activities of managers

[13] An opinion is that the role of measuring performance over longer periods can also incur a similar reduction on short-term orientation and crash risk. Different from common types of compensation based on the annual business results, long-term incentive plans (in the form of stock options and performance-contingent deferred units) are evaluated over longer periods (such as a three-year vesting schedule and a ten-year term). We generate a dummy variable LTIP that equals one if the firm has long-term incentive plans and zero otherwise. We find that RPE and LTIP are highly related with a 0.72 correlation coefficient. Thus, we do not add LTIP into the control variables. At the same time, we provide the LTIP regression results in Table 3.A.8 to show that LTIP has a reduction effect on crash risk, similar to RPE, possibly because of the homologous reduction effects on managerial myopia. Moreover, to further distinguish RPE and LTIP, we construct LTRPE/STRPE proxy for RPE firms with/without long term incentive plans. LTRPE and STRPE both significantly reduce crash risk, as shown in Column (4) of Table 3.A.8. In terms of economic magnitude, LTRPE (STRPE) shows 6.8% higher (12.1% lower) effect than RPE.

consequently accumulate the stock price crash risk (Andreou et al., 2017; Callen & Fang, 2015; Hutton et al., 2009; Kim et al., 2019; Kim et al., 2011a, 2011b; Kim, Wang, et al., 2016).

We use our sample of RPE and non-RPE firms to offer novel evidence of RPE associated with the stock price crash risk. Our empirical findings support the hypothesis that RPE is negatively associated with stock price crash risk. Our baseline finding is robust to using an endogenous treatment model estimation, the propensity score matching (PSM) regression technique, alternative crash risk measures, sampling criteria, and alternative model specifications. Next, we find that the coefficient on RPE is only statistically significant when market-based performance metrics are used, larger (by about 257%) in magnitude than the coefficient when accounting-based metrics are used. We also find the coefficient on RPE is only statistically significant when benchmarks of self-selected peer groups are used, larger (by about 48%) in magnitude than the coefficient when index benchmarks are used. We further study the heterogeneity and find that the decreasing effect of RPE on crash risk is more pronounced in firms with higher managerial ability, systematic uncertainty, industry competition, and managerial myopia correctability. We compare the industry tournament and market pressure channels to demonstrate that market pressure is the primary channel. Finally, we indicate that RPE firms are associated with higher information disclosure quality and lower analyst optimism.

Despite the growing importance of contract theory and executive incentives, the role of RPE utilization in stock price movement and financial market stability has gained limited interest. Yet efforts to document the relationship between labor market incentives and stock price crash risk have been recently taken based on industry tournament incentives (Chowdhury et al., 2020; Kubick and Lockhart, 2020). However, the effect of industry tournament incentives (ITI) on stock price crash risk is inconclusive. Kubick and Lockhart (2020) claim that ITI leads to managerial hoarding behavior, positively associated with crash risk. Thus, they document the negative externality of the executive labor market's incentive effects. Chowdhury et al. (2020) provide contrary evidence that ITI reduces future stock price crash risk. CEOs will undertake a long-term cost-benefit analysis of managerial hoarding and care more about their sustained long-term reputation.

The present study focuses on the effect of RPE utilization on stock price crash risk, which varies from ITI. ITI is measured by the compensation gap between the (second) highest-paid CEO and the target firm's current CEO. Based on different measurements and data sources, RPE captures the target firm's consideration of peer firms' performance to decide the compensation contract of the current executives. We connect RPE with ITI and claim that the compensation gap among managers measured by ITI is influenced by compensation contract design (i.e., the RPE). We find that RPE reduces crash risk by decreasing ITI. Our findings are aligned with Coles, Li, and Wang (2018) and Kubick and Lockhart (2020) that ITI is positively

associated with crash risk. We construct a channel through which RPE can help converge the compensation gap and thus reduce the firms' crash risk.

Our study contributes to two strands of literature. First, it is closely related to agency problems and optimal contracting studies. Studies conjecture RPE to effectively control agency cost (Holmstrom, 1979; Antle and Smith, 1985, 1986; Gibbons and Murphy, 1990; Janakiraman, Lambert, and Larcker, 1992). The present study provides empirical evidence that RPE induces positive firm impacts. This study connects the labor market and capital market and especially offers additional information about the controversial results of ITI on crash risk.

Second, we contribute to the literature on stock price crash risk. Previous literature on stock price crash risk presents concerns on i) information disclosing (Hutton et al., 2009; Kim et al., 2016; Kim et al., 2019), ii) corporate operation (Kim, Li, & Zhang, 2011b; Kim et al., 2014; Kim & Zhang, 2016), and iii) manager characteristics (Kim et al., 2016; Callen and Fang, 2015). More closely, several studies have addressed the connection between the labor market and crash risk, focusing on equity incentives (Kim, Li, & Zhang, 2011a) and industry tournament incentives (Chowdhury et al., 2020; Kubick & Lockhart, 2020). The present study proposes a new explanation of the causes of stock price crash risk and adds the connection between agency contract, disclosure quality, and crash risk. We highlight the RPE's utility of improving disclosure quality and mitigating information asymmetry.

The remainder of this paper is organized as follows. Section 2 reviews the literature and proposes the testable hypothesis. Section 3 describes the data sources and index measures. Section 4 reports the empirical results and a series of robustness checks. Section 5 develops further discussions. Section 6 concludes the paper.

3.2 Hypothesis Development

Agency theory in corporate finance studies the conflicting interests between shareholders and managers. Jensen and Meckling (1976) define an agency relationship as a contract under which shareholders (the principals) engage managers (the agents) to perform firm management service and maximize the equity value of shareholders. However, given self-utility maximizing incentive, managers do not always act in the best interests of shareholders (Hart, 1995). For instance, managers can have harmful actions of overexpansion (Jensen, 1986a), under- and over-investment (Stulz, 1990), and cash dissipation (Dittmar and Mahrt-Smith, 2007; Harford, 1999; Harford et al., 2008).

Several papers about agency problem emphasize the short-term orientation problem of agents (Flammer & Bansal, 2017; Laverty, 1996; Marginson & McAulay, 2008; Narayanan, 1985; Porter, 1992; Shleifer & Vishny, 1990; Stein, 1988, 1989). That is, agents tend to make decisions that yield short-term benefits at the expense of the long-term interests of principals. Narayanan (1985, 1987) indicates that agents are able to make such myopic decisions mainly because they have private

information[14]. He develops a model to document the essential drivers of myopia problem, stating that agents have incentives for short-term results because of their labor market consideration. The productive inputs of agents (e.g., managers' ability in the Narayanan model[15]) is unobservable to all. Quick and positive results make it easier for agents to relate the outperformance of firms to their decisions, thus being conducive to convince the labor market about their high ability. The early improvement of the market perception about agents' ability increase their total expected income and utility (see also Nagar, 1999). The Narayanan model documents that the myopia incentive problem is weakened when agents are able to show their ability through alternative ways, such as experience[16]. Campbell & Marino (1994) further develop the Narayanan model. They show higher competition of labor markets increase the probability of managerial myopia. Since in a competitive labor market, agents have more freedom to re-sign contracts with new principals, they will benefit more from early improving the perception of their ability and gain higher subsequent compensation.

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[14] Literature raises theories and finds evidence that managers take advantage of information asymmetry and benefit themselves at the expense of shareholders and investors by manipulating the private information (see, for example, Akerlof, 1970; Bartov & Bodnar, 1996; Jensen & Meckling, 1976; Krishnaswami & Subramaniam, 1999; Myers & Majluf, 1984; etc.).

[15] Narayanan (1985) defines the managers' ability and decision making as their inputs to the firms' output, when conventional models about agency problem such as Holmstrom (1979, 1982) define managers' efforts as the typical productive inputs. Narayanan indicates that principals concern more about agents' capability to make right decisions instead of their diligence. We simply regards managers' endogenetic productive inputs as a whole that can be controlled by managers, as opposed to the exogenous systematic factors.

[16] For example, studies provide empirical evidence that older CEOs are positively associated with higher quality of financial reporting (Huang et al., 2012) and lower stock price crash risk (Andreou et al., 2017),

To mitigate the conflict of interests and reduce agency costs, shareholders tend to utilize appropriate incentives for managers to limit the divergences from shareholders' interests[17]. Holmstrom (1979, 1982) develops an informativeness principle (also known as the moral hazard model) to solve the agency problem. The principle documents that signals carrying information about the agents' productive inputs ought to be included in the agents' compensation contracts. At the same time, to achieve informative compensation contracts with the Pareto optimality, noisy signals unrelated to the agents' control should not be put into the incentive contracts. This model derives RPE, the measurement relative to similar agents removing common noisy signals. The systematic risk isolated by RPE is a type of noisy signal in the contracts that fall out of managers' control, thus interfering with the precise measurement for their productive inputs. By filtering out the exogenous randomness in agents' contracts, a larger proportion of performance (compensation) fluctuation falls into the agents' control. Thus, agents are able to show their productive inputs more precisely and suppress their incentives to make myopic decisions (Narayanan, 1985). [18] Particularly, Nagar (1999) documents that managers care about

[17] There are two major tasks of the board (or the compensation committee responsible for the board) to avoid the deviation between managers' and shareholders' interests. One issue is constructing appropriate executive compensation strategies. Humphery-Jenner et al. (2016), Matolcsy and Wright (2011), and Mehran (1995) make efforts to recognize the pros and cons of the selection of cash and equity payments in the compensation strategies. The other issue is evaluating managers' performance and design compensation contract adequately.

[18] In particular, as Narayanan (1985, 1987) indicated, when managers have alternative ways to provide the labor market with precise perception about their productive inputs, they don't rely on information manipulation to convince the labor market. In this case, RPE motives managers become more willing to improve the disclosure transparency and information quality to protect their reputation (Kasznik & Lev, 1995; Kothari et al., 2009; Skinner, 1994).

performance evaluation and lower uncertainty of the market assessment on their human capital (productive inputs) motives higher managerial incentives of discretionary disclosure. Hence, RPE is more informative to evaluate agents, helping mitigate the managerial short-termism incentives and the private information manipulation behaviors. The alleviated accumulation of unfavorable information eventually reduces stock price crash risk (Andreou et al., 2017; Callen & Fang, 2015; Hutton et al., 2009; Kim et al., 2019; Kim et al., 2011a, 2011b; Kim et al., 2016). Thus, our testable hypothesis of the effect of RPE on stock price crash risk is as follows:

Relative performance evaluation is negatively associated with firms' stock price crash risk.

The empirical finding of Kim et al. (2016) also inspires our hypothesis development. They find that the financial statement comparability reduces the expected crash risk, which is more pronounced when managers are easier to hoard unfavorable information. Financial statements are used to reveal the operating results and performance of companies. As Kim et al. claimed, comparability is a special feature of financial statements to increase their usefulness, which helps readers to distinguish the similarities and differences between companies. Thus, the improvement of comparability implies a more precise perception of agents' productive inputs.

3.3 Data and Methodology

3.3.1 Data and Empirical Methodology

In the US, the Securities and Exchange Commission (SEC) has required companies to report executive compensation details in the proxy statements since 2006. Therefore, our samples include US-listed firms in 2006−2017. The proxy statements are available on SEC's website. Institutional Shareholder Services (ISS) collects RPE-relevant information and provides datasets. Thus, we can download RPE data directly from ISS.

Following the convention, we exclude financial firms with SIC from 6000 to 6999 and utility firms from 4000 to 4999. Finally, our sample consists of 22,776 firm-year observations.

Besides, we download the financial statement and executive data from Compustat. The analyst information data is downloaded from I\B\E\S, and data of stock returns is downloaded from CRSP.

3.3.2 Measurements of Stock Price Crash Risk

We follow the literature on firm-specific crash risk to construct our measures of stock price crash risk (for instance, Chen, Hong, and Stein, 2001; Chowdhury et al., 2020; Hutton et al., 2009; Jin and Myers, 2006; Kim et al., 2019; Kim et al., 2011a, 2011b; Kim and Zhang, 2016). First, we calculate firm-specific weekly returns using the expanded market model regression:

$$r_{it} = \alpha_i + \beta_{1i} r_{m,t-1} + \beta_{2i} r_{m,t} + \beta_{3i} r_{m,t+1} + \varepsilon_{it}, \quad (1)$$

where r_{it} denotes the return on stock *i* in week *t*, and $r_{m,t}$ denotes the return on the CRSP value-weighted market index in week *t*. Following Hutton et al. (2009) and Kim et al. (2011b), we exclude firms with fewer than 26 weeks of trading data over a fiscal year. The firm-specific weekly return W_{it} is defined as the natural logarithm of one plus the residual ε_{it} in Eq. (1), that is, $W_{it} = \ln(1 + \varepsilon_{it})$.

Our primary measure of stock price crash risk is the negative conditional return skewness (*NCSKEW*). The measure was proposed by Chen, Hong, and Stein (2001) and continuously used by much literature over the last two decades. Following Kim, Li, and Zhang (2011a, 2011b), we calculate *NCSKEW* by taking the negative of the third moment of firm-specific weekly returns scaled by the standard deviation of firm-specific weekly returns raised to the third power. As Chen, Hong, and Stein (2001) illustrate, the scaling procedure is a common way of statistical normalization for skewness. The minus sign in the front brings the convention that a high value of *NCSKEW* indicates a higher probability of crash risk. Thus, for each firm *i* in year *t*, we calculate *NCSKEW* as follows:

$$NCSKEW_{it} = -[n(n-1)\sum W_{it}^3] / [(n-1)(n-2)(\sum W_{it}^2)^{3/2}], \quad (2)$$

The alternative widely used measures of stock price crash risk are "down-to-up volatility" (*DUVOL*), stock price crash indicator *(CRASH)*, and the difference between crash (downside) and jump (upside) frequencies *(COUNT)*. *DUVOL* is also raised by Chen, Hong, and Stein (2001), which is calculated as the log of the ratio of the standard deviation on negative firm-specific return periods to the positive

periods. Thus, *DUVOL* captures asymmetric volatilities between down periods and up periods. Chen et al. demonstrate that this alternative measure of return asymmetry ignores the third moment and weigh less on extreme crash periods than *NCSKEW*. *CRASH* is a dummy variable that equals one if the firm experiences at least one crash week over the fiscal year and zero otherwise. A crash week is defined as the weekly return being k (usually 3.2 or 3.09 in previous studies) standard deviations below the average weekly returns over the fiscal year. This measure was put forward by Hutton et al. (2009) and was often used in conjunction with *NCSKEW* in the last decade. The final measure *COUNT* is the difference between crash (downside) and jump (upside) frequencies, as initially applied in Jin and Myers (2006). A crash (jump) week is defined as the weekly return being k standard deviations below (above) the average weekly returns over the fiscal year.

We provide some comparisons among these measures of crash risk. *DUVOL* and *COUNT* put more weights on the right tails. However, when we focus on the firm-specific crash risk, we are more concerned with the left-tail risk (the right-tail overweighting concern). Thus, Chen, Hong, and Stein (2001) and Jin & Myers (2006) use *NCSKEW* as the primary measure of crash risk while proposing alternative measures. *CRASH* is a competitive indicator to *NCSKEW* with emphasizing the left-tail events. Whereas, Kim and Zhang (2016) demonstrate another related concern that independent variables may lead to longer tails at both sides, which causes more downside crashes and more upside jumps. Overall,

NCSKEW can simultaneously mitigate the right-tail overweight and the bilateral long-tail concerns, thus being a valid measure of crash risk.

We employ three alternative measures to re-check our baseline findings of the association between RPE and crash risk. Table 3.A.2 shows similar findings to our previous results with *NCSKEW*.

3.3.3 Empirical Model

We conduct our baseline regression which examines the association between RPE and stock price crash risk with an OLS linear model with year and industry fixed effects:

$$NCSKEW_{i,t+1} = \alpha + \beta RPE_{i,t} + \gamma X_{i,t} + \theta_t + \mu_d + \varepsilon_{i,t+1}, \quad (3)$$

where $NCSKEW_{i,t+1}$ denotes our crash risk measure of firm *i* in year *t+1*. $RPE_{i,t}$ is a dummy variable that equals one if firm *i* claims the utilization of relative performance evaluation in its proxy statement in year *t*. In further analyses, we replace RPE with some variables of our interest. $X_{i,t}$ includes a set of control variables. First, following Kim et al. (2011a, 2011b), we add firm characteristics of firm size (*SIZE*), firm age (*FIRMAGE*), firm leverage (*LEV*), market-to-book ratio (*MTB*), return on assets (*ROA*), the change in turnover rate (*DTURN*), the average firm-specific weekly return (*RET*), and the standard deviation of firm-specific weekly return (*SIGMA*). Second, following Hutton et al. (2009), we include opaqueness (*OPAQUE*) as the control variable, measured as the moving sum of the previous three years' absolute value of discretionary accruals. To address executive

characteristics, we also control for CEO's age (*CEOAGE*), CEO's gender (*CEOFEMALE*), CEO's tenure (*TENURE*), the duality of CEO and Chair (*CHAIR*), size of the board (*BOARDSIZE*), and the independence of board (*BOARDINDEP*). Finally, we control for the first-order lag item of *NCSKEW*. All variables are defined in Table 3.A.1.

θ_t and μ_d denote time and industry fixed effects, respectively. Firms are not likely to frequently change their compensation policy between non-RPE and RPE. Moreover, 69% of firms keep using APE, and 7% of firms keep using RPE from the very beginning during our sample period. Using a firm fixed effect will absorb the main information of RPE. Hence, we induce industry fixed effect instead of firm fixed effect in the empirical regressions.

3.3.4 Summary Statistics

We obtain the data of all non-financial and non-utility firms in the United States from 2006 to 2017. Figure 3.1 reports the time trend of the number and proportion of RPE firms. RPE utilization increased from 15% in 2006 to 25% in 2012 and gradually down to 22% in 2017. An increasing number of listed firms adopted RPE to evaluate executive performance.

Table 3.1 Panel A reports the descriptive statistics of the firm and executive characteristics. The detailed definitions are presented in Table 3.A.1. RPE and non-RPE firms have some interesting differences. First, the firm size of RPE companies is much larger than non-RPE companies. Second, the profitability (*ROA*)

is higher for RPE firms. Third, *OPAQUE* representing the firms' lack of transparency is lower for RPE companies. Finally, the level of board governance is higher for RPE firms, which is reflected by the larger board size and the higher proportion of independent directors. These findings align with our conjecture that mature, transparent, and well-governance companies are more likely to limit the agency cost and use RPE. We provide detailed discussions in the following empirical analyses.

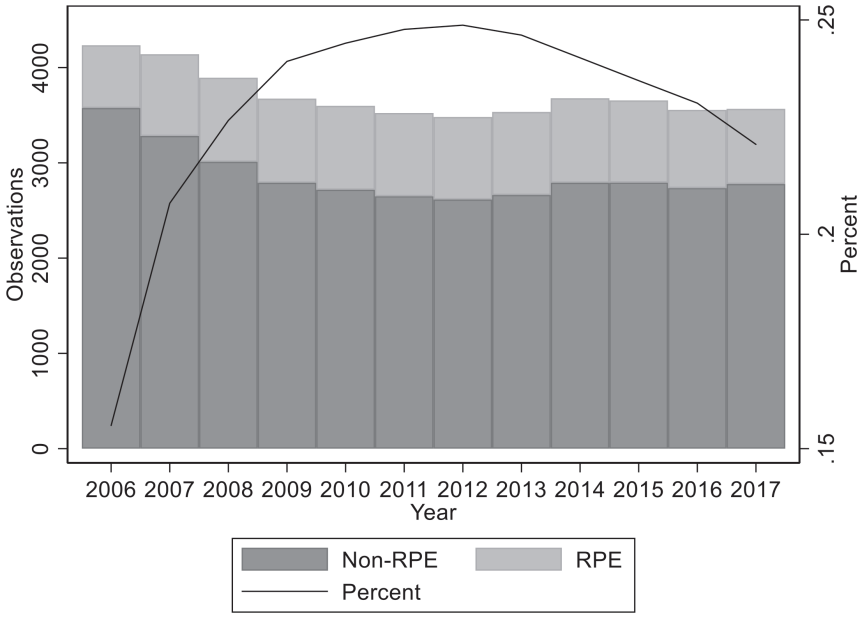

Figure 3.1: Time-Series Pattern of RPE

This figure presents the time-series pattern of RPE disclosing firms. The sample consists of U.S. listed firms from 2006–2017, with regulation forcing listed firms to disclose detailed executive compensation information in the proxy statement from 2006. Firms claim that relative performance evaluation in the proxy statement is labeled as RPE and Non-RPE otherwise. Percent is the number of RPE firms scaled by the total number of firms each year. There is a rapid uptrend of the percentage of RPE firms during the beginning three years.

Table 3.1 Descriptive Statistics

This table presents the descriptive statistics and Spearman correlation matrix for a sample of listed U.S. firms from 2006–2017. Panel A shows the mean and observations of the variables and reports the difference between the two parts based on RPE. Panel B provides Pearson pair-wise correlation coefficients for the selected variables of interest. The detailed definitions of variables are presented in Table 3.A.1.

Panel A: Firm Characteristics

	Non-RPE		RPE							
	Mean	N1	Mean	N2	Difference	N	Mean	SD	Min	Max
SIZE	5.37	15,969	8.40	6,807	-3.03***	22,776	6.28	2.062	0.34	13.59
FIRMAGE	7.62	15,969	7.97	6,807	-0.35**	22,776	7.73	8.003	-1.00	48.00
LEV	0.43	15,969	0.55	6,807	-0.12***	22,776	0.47	0.236	0.00	4.88
MTB	6.12	15,969	4.49	6,807	1.63	22,776	5.63	142.701	0.02	19,424.53
ROA	-0.09	15,969	0.04	6,807	-0.13***	22,776	-0.05	0.316	-9.20	2.55
OPAQUE	0.47	15,969	0.38	6,807	0.09***	22,776	0.44	0.522	0.00	17.98
DTURN	0.01	15,969	0.01	6,807	0.00	22,776	0.01	0.220	-13.74	6.65
RET	-0.00	15,969	0.00	6,807	-0.00	22,776	-0.00	0.126	-0.87	7.12
SIGMA	0.07	15,969	0.05	6,807	0.02***	22,776	0.07	0.069	0.01	2.03
CEOAGE	55.85	6,258	55.92	6,088	-0.07	12,346	55.89	7.402	29.00	96.00
CEOFEMALE	0.04	6,259	0.04	6,088	0.00	12,347	0.04	0.186	0.00	1.00
TENURE	7.96	6,181	6.51	6,064	1.44***	12,245	7.24	7.459	-12.00	61.00
CHAIR	0.09	6,259	0.13	6,088	-0.03***	12,347	0.11	0.312	0.00	1.00
BOARDSIZE	7.42	15,120	9.74	6,656	-2.32***	21,776	8.13	2.187	1.00	18.00
BOARDINDEP	0.74	15,120	0.81	6,656	-0.07***	21,776	0.76	0.127	0.00	1.00

Panel B: Spearman Correlation Matrix

	RPE	SIZE	FIRMAGE	LEV	MTB	ROA	OPAQUE
RPE	1.00						
SIZE	0.67***	1.00					
FIRMAGE	0.02***	-0.01**	1.00				
LEV	0.23***	0.36***	-0.04***	1.00			
MTB	-0.01	-0.01	-0.00	0.03***	1.00		
ROA	0.19***	0.38***	0.03***	-0.08***	-0.02***	1.00	
OPAQUE	-0.08***	-0.17***	0.02**	-0.04***	0.01	-0.19***	1.00

Panel B of Table 3.1 provides the Spearman correlations among RPE and control variables of firm characteristics. The correlations among these explanatory variables are modest, with almost all correlation coefficients less than 0.25, demonstrating less severe multicollinearity problems.

3.4 Empirical Results

3.4.1 RPE and Stock Price Crash Risk

We begin our analyses by examining the association between the RPE and stock price crash risk. Table 3.2 presents the relevant results illustrating that RPE use can significantly reduce the subsequent stock price crash risk. The *NCSKEW* measures of crash risk are negatively associated with RPE, as shown in Columns (1)–(3). Column (3) shows that *NCSKEW* decreases by 0.132 for RPE equal to 1 in economic significance. Given that the mean value of *NCSKEW* is 0.067 and the standard deviation of *NCSKEW* is 0.877, the economic magnitude of RPE is significant. The results support our hypothesis that RPE decreases the stock price crash risk. RPE is more informative for the agent's performance evaluation than APE and incurs a positive firm impact (Holmstrom, 1979, 1982).

The relationships between crash risk and control variables are consistent with previous studies. First, we find the change in turnover rate (*DTURN*) is positively associated with *NCSKEW*, which is consistent with the main finding of Chen et al. (2001). Second, we find positive coefficients for firm size, market-to-book ratio, and past *NCSKEW*, consistent with the findings of Chen et al. (2001) and Kim et al.

(2011a, 2011b). Third, we find a negative association between firm leverage and crash risk, consistent with Kim et al. (2011a, 2011b). We also find a positive coefficient for ROA, consistent with Kim & Zhang (2016) and Kim et al. (2014). Finally, we find CEO age decreases crash risk, consistent with the main finding of Andreou et al. (2017). In addition, we find that board independence increases crash risk, which may be counterintuitive. Kumar & Sivaramakrishnan (2008) explain why firms with higher board independence perform worse by emphasizing another agency problem of low-monitoring efficiency independent directors.

Besides, we test the results by constructing an alternative continuous measure of RPE to replace the baseline dummy measure. Companies provide multiple grants to executives with different award types and various benchmarks each year. APE firms set absolute benchmarks for all grants. RPE firms set relative benchmarks for some grants, and may also set absolute benchmarks for the other grants. Thus, we conduct the variable of *RPEPROP* by calculating the proportion of relative grants to total grants of each firm every year. This measure researches the firm's propensity of using RPE. Specifically, we calculate *RPEPROP* as the number of grants using RPE divided by the total number of grants. The results are presented in Table 3.A.3, supporting our baseline findings that RPE decreases the crash risk.

Table 3.2 RPE and Stock Price Crash Risk

This table presents the association between *RPE* and stock price crash risk for a sample of U.S. listed firms from 2006–2017. The dependent variable is *NCSKEW* in year *t*+1. *NCSKEW* is the negative conditional skewness of firm-specific weekly returns. The main explanatory variable *RPE* is a dummy variable that equals one if the firm claims utilization of relative performance evaluation in the proxy statement and zero otherwise. The detailed definitions of other variables are presented in Table 3.A.1. All regressions include the lagged *NCSKEW*, industry and year fixed effects. The robust *t*-statistics clustered by the firm are reported in parentheses. ***, **, and * denote the significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)
	NCSKEW	NCSKEW	NCSKEW
RPE	-0.134***	-0.133***	-0.132***
	(-6.65)	(-6.86)	(-6.80)
SIZE	0.067***	0.056***	0.063***
	(12.26)	(7.69)	(8.45)
FIRMAGE	-0.001	-0.001	-0.001
	(-0.61)	(-0.60)	(-0.73)
LEV	-0.140***	-0.108***	-0.118***
	(-4.11)	(-2.92)	(-3.21)
MTB	0.004**	0.004**	0.004**
	(2.36)	(2.28)	(2.31)
ROA		0.077**	0.082**
		(2.10)	(2.25)
OPAQUE		-0.002	-0.002
		(-0.09)	(-0.08)
DTURN		0.214***	0.222***
		(3.51)	(3.63)
RET		-13.674	-13.979
		(-1.14)	(-1.16)
SIGMA		-1.782	-1.793
		(-1.36)	(-1.35)
CEOAGE			-0.001**
			(-2.54)
CEOFEMALE			0.054
			(1.25)
TENURE			0.001
			(0.74)
CHAIR			-0.037
			(-1.55)
BOARDSIZE			-0.003
			(-0.87)
BOARDINDEP			0.134***
			(3.25)
NCSKEW	0.031***	0.034***	0.033***
	(3.85)	(3.89)	(3.80)
Industry FE	Y	Y	Y
Year FE	Y	Y	Y
Observations	22,776	22,776	22,776
Number of Firms	3880	3880	3880
Adjusted R^2	0.04	0.04	0.04

3.4.2 Identification Issues

3.4.2.1 Endogenous Treatment

RPE is not randomly assigned to firms. The RPE issue is usually decided by the board or compensation committee responsible to the board. Bakke, Mahmudi, and Newton (2020) document that firm managers can influence the choice of peer firms while utilizing RPE, and they tend to choose underperforming peers. Managers may influence the choice of whether use RPE. Therefore, RPE may be related to other covariates that we measure. We conduct an endogenous treatment robustness test to address this endogeneity problem.

Chowdhury et al. (2020) and Huang, Jain, and Kini (2019) argued that non-competition agreement (NCA) enforceability could be an influential exogenous factor that significantly affects the labor market. Although the NCAs are widely enforceable across the US, some states limit the enforceability during our sample period. We construct three measures to proxy for lower NCA enforceability. First, as Starr (2019) demonstrated, North Dakota is the state where NCAs are virtually unenforceable[19]. The first measure *UNENFORCED* is a dummy variable with the value of one if firms are headquartered in North Dakota, otherwise zero. Second, the NCA enforceability decreased in Montana in 2011 (Huang et al., 2019). *NEG.SHOCK* is a dummy variable with the value of one if firms are headquartered in

[19] North Dakota and California are the only two states where NCAs are not unenforceable. The coefficient of the indicator of whether the firm is headquartered in California is negative and statistically insignificant. We omit the California result for brevity, which is available upon request.

Montana from 2012 to 2017, otherwise zero[20]. Third, *NCA.INDEX* is the opposite value of the NCA enforceability index as in Starr (2019), with the minus sign bringing the convention that a high value of *NCA.INDEX* indicates a lower NCA enforceability. Thus, all three measures indicate lower NCA enforceability.

The expectation is that lower NCA enforceability implies higher executive mobility (Balasubramanian et al., 2022; Rubin & Shedd, 1981), under which managers are less concerned about firms' reform of compensation design. With a looser restriction of turnover, managers can choose to move to another company instead of strongly promoting the reform of the compensation system. Thus, we expect less RPE use in states with lower NCA enforceability, that is, RPE is positively related to NCA enforceability. On the other hand, the firm-specific crash risk is not likely to affect states' policymaking of NCA enforceability.

Table 3.3 presents the endogenous treatment model estimation results. The negative coefficients on *UNENFORCED*, *NEG.SHOCK*, and *NCA.INDEX* are all statistically significant, confirming our prediction that RPE is negatively associated with the lower NCA enforceability. Furthermore, the results of primary regressions provide evidence of negative association between RPE and crash risk. The endogenous treatment model estimation results support our previous main finding.

[20] As Huang et al. (2019) show, there were three decreasing shocks of NCA enforceability after 2006. We exclude the Illinois shock because the NCA enforceability increased in 2011 and decreased in 2013. The changes are too close and induce mixed effects. The NCA enforceability also decreased in South Carolina in 2010. The coefficient of the indicator of whether the firm is headquartered in South Carolina is negative and statistically insignificant. We omit the South Carolina result for brevity, available upon request.

Table 3.3 Endogenous Treatment Model Estimation

This table presents the effect of *RPE* on *NCSKEW* measure of crash risk, with endogenous treatment model estimation being applied. *UNENFORCED* is a dummy variable with the value of one if firms are headquartered in North Dakota, otherwise zero. *NEG.SHOCK* is a dummy variable with the value of one if firms are headquartered in Montana from 2012-2017, otherwise zero. *NCA.INDEX* is the opposite value of the 2009 NCA enforceability index as in Starr (2019), with the minus sign brings the convention that a high value of *NCA.INDEX* indicates a lower enforceability of NCA similar to the previous two measurements. The detailed definitions of other variables are presented in Table 3.A.1. All regressions include the lagged *NCSKEW*, industry and year fixed effects. The robust *t*-statistics clustered by the firm are reported in parentheses. ***, **, and * denote the significance at the 1%, 5%, and 10% levels, respectively.

	(1) NCSKEW	(2) NCSKEW	(3) NCSKEW
RPE=1	-0.428***	-0.429***	-0.418***
	(-9.32)	(-9.35)	(-9.07)
SIZE	0.103***	0.104***	0.101***
	(12.52)	(12.54)	(12.21)
FIRMAGE	0.001	0.001	0.001
	(0.76)	(0.76)	(0.93)
LEV	-0.173***	-0.173***	-0.166***
	(-5.13)	(-5.14)	(-4.91)
MTB	0.006***	0.006***	0.006***
	(3.86)	(3.86)	(3.64)
ROA	-0.014	-0.015	-0.006
	(-0.40)	(-0.41)	(-0.17)
OPAQUE	0.036**	0.036**	0.037**
	(2.03)	(2.04)	(2.03)
DTURN	0.272***	0.272***	0.283***
	(4.49)	(4.48)	(4.64)
RET	-12.251	-12.257	-13.093
	(-1.02)	(-1.03)	(-1.09)
SIGMA	-1.689	-1.689	-1.802
	(-1.31)	(-1.31)	(-1.39)
CEOAGE	-0.001*	-0.001*	-0.001*
	(-1.66)	(-1.67)	(-1.68)
CEOFEMALE	0.059	0.060	0.062
	(1.37)	(1.38)	(1.42)
TENURE	0.001	0.001	0.001
	(0.42)	(0.42)	(0.51)
CHAIR	-0.059***	-0.059***	-0.062***
	(-2.89)	(-2.88)	(-2.98)
BOARDSIZE	-0.002	-0.002	-0.002
	(-0.49)	(-0.48)	(-0.50)
BOARDINDEP	0.128***	0.127***	0.124***
	(3.22)	(3.22)	(3.07)
NCSKEW	0.047***	0.047***	0.049***
	(5.39)	(5.39)	(5.51)
Year FE	Y	Y	Y
Industry FE	Y	Y	Y
RPE			
SIZE	0.807***	0.808***	0.807***
	(23.62)	(23.64)	(23.82)
FIRMAGE	0.015***	0.015***	0.014***
	(3.94)	(3.93)	(3.71)
UNENFORCED	-4.789***		
	(-25.37)		
NEG.SHOCK		-1.052***	
		(-4.35)	
NCA.INDEX			-0.115*
			(-1.75)
Observations	22776	22776	22470
Number of Firms	3,880	3,880	3,813
Log Likelihood	-36374.52	-36378.32	-35865.37

3.4.2.2 Propensity Score Matching

To address further the endogenous concern that the systematic differences among firms led by executives with RPE and non-RPE utilization could drive baseline regression results, we provide additional evidence to demonstrate the negative association between RPE and crash risk using the PSM technique following Shipman et al. (2017). Thus, we make RPE firms as similar as possible to those in the control group. We use all firm variables and executive characteristics to generate the propensity score. Specifically, firm characteristics include *SIZE, FIRMAGE, LEV, MTB, ROA, OPAQUE, DTURN, RET,* and *SIGMA*. Executive characteristics include *CEOAGE, CEOFEMALE, TENURE, CHAIR, BOARDSIZE,* and *BOARDINDEP*.

After taking the nearest one-to-one matching with 0.02 maximum distance of controls, the observations are reduced by one-third. Panel A of Table 3.4 reports the covariate balance, with the *t*-statistics of the difference between control and treatment groups generally decreasing to insignificant levels for covariates in the matched group. The narrowing of the averages illustrates the effectiveness of sample matching using propensity scores.

We run OLS regressions based on the results of propensity scores matching, where the dependent variable is the *NCSKEW* measure of crash risk in Columns (1)–(3). Panel B of Table 3.4 presents the matched samples' regression results, illustrating that our baseline finding of the negative association between RPE and crash risk remains.

Table 3.4 Propensity Score Matching

This table presents regression estimates of the baseline model using the propensity score matching (PSM) regression technique. We use all variables of the firm and executive characteristics to generate the propensity score. We take the nearest one-to-one matching with 0.02 maximum distance of controls. Panel A reports the sample means for different variables from the whole sample and those from the matched sample. Panel B shows the baseline regression of RPE on crash risk based on the matched sample. *NCSKEW* in year t+1 is the proxy for stock price crash risk. The detailed definitions of other variables are presented in Table 3.A.1. All regressions include the lagged *NCSKEW*, industry and year fixed effects. The robust *t*-statistics clustered by the firm are reported in parentheses. ***, **, and * denote the significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Covariate balance

	Sample	Control	Treatment	Diff	T-stats
SIZE	Full	5.37	8.40	-3.03	-141.83
	Matched	7.53	7.50	0.03	0.96
FIRMAGE	Full	7.62	7.97	-0.35	-2.88
	Matched	8.37	8.06	0.30	1.53
LEV	Full	0.43	0.55	-0.12	-37.60
	Matched	0.56	0.55	0.00	0.33
MTB	Full	6.12	4.49	1.63	1.20
	Matched	3.21	3.26	-0.05	-0.44
ROA	Full	-0.09	0.04	-0.13	-39.77
	Matched	0.02	0.02	-0.01	-1.54
OPAQUE	Full	0.47	0.38	0.09	14.75
	Matched	0.32	0.31	0.01	1.24
DTURN	Full	0.01	0.01	0.00	0.71
	Matched	0.01	0.01	-0.00	-0.26
RET	Full	-0.00	0.00	-0.00	-1.65
	Matched	-0.00	-0.00	-0.00	-0.45
SIGMA	Full	0.07	0.05	0.02	18.70
	Matched	0.05	0.05	0.00	0.15
CEOAGE	Full	55.85	55.92	-0.07	-0.55
	Matched	44.65	43.35	1.30	2.23
CEOFEMALE	Full	0.04	0.04	0.00	0.38
	Matched	0.03	0.02	0.00	0.86
TENURE	Full	7.96	6.51	1.44	10.78
	Matched	5.67	5.68	-0.01	-0.04
CHAIR	Full	0.09	0.13	-0.03	-5.84
	Matched	0.09	0.09	-0.00	-0.39
BOARDSIZE	Full	7.42	9.74	-2.32	-77.85
	Matched	8.82	8.77	0.04	0.69
BOARDINDEP	Full	0.74	0.81	-0.07	-40.03
	Matched	0.77	0.77	0.00	0.53

Panel B: RPE and crash risk based on matched samples			
	(1)	(2)	(3)
	NCSKEW	NCSKEW	NCSKEW
RPE	-0.066***	-0.066***	-0.068***
	(-2.58)	(-2.60)	(-2.66)
SIZE	0.011	0.010	0.023
	(0.69)	(0.58)	(1.31)
FIRMAGE	0.002	0.002	0.002
	(1.21)	(1.19)	(1.20)
LEV	-0.024	-0.018	-0.034
	(-0.29)	(-0.21)	(-0.39)
MTB	0.001	0.002	0.002
	(0.37)	(0.56)	(0.62)
ROA		0.185*	0.198*
		(1.69)	(1.79)
OPAQUE		-0.001	0.001
		(-0.02)	(0.02)
DTURN		-0.168	-0.170
		(-1.49)	(-1.51)
RET		-25.371	-25.848
		(-1.28)	(-1.31)
SIGMA		-1.037	-1.101
		(-0.53)	(-0.56)
CEOAGE			-0.001
			(-1.29)
CEOFEMALE			0.031
			(0.45)
TENURE			-0.000
			(-0.23)
CHAIR			0.004
			(0.10)
BOARDSIZE			-0.010*
			(-1.67)
BOARDINDEP			0.163**
			(2.02)
NCSKEW	0.029*	0.029*	0.030*
	(1.96)	(1.90)	(1.93)
Industry FE	Y	Y	Y
Year FE	Y	Y	Y
Observations	6,576	6,576	6,576
Number of Firms	1982	1982	1982
Adjusted R^2	0.04	0.04	0.04

With the *t*-statistics remaining significant at the 0.01 significance level, the probability of crash risk coefficient's economic magnitude is relatively lower than the baseline results. The coefficient on RPE for *NCSKEW* in Column (3) is −0.068 in PSM results, which is −0.132 in baseline results. The coefficient reduction illustrates that the PSM technique helps facilitate the over-estimation of the average treatment effect on crash risk through limiting sample bias[21].

3.4.3 Performance Metrics and Benchmark Selection

3.4.3.1 Performance Metrics

All methods of performance evaluation need first to set up performance metrics. Typically, firms use two major types of metrics: accounting-based and market-based. Accounting-based metrics are profit-related ratios that include EBITDA, ROA, ROE, EPS, ROIC, and profit margin. Meanwhile, the market-based method relies on stock price or stock returns in another form.

We predict a significantly higher impact of market-based performance metrics on decreasing stock price crash risk than accounting-based metrics. Metrics based on stock price are forward-looking and hard to be manipulated (Dutta and Reichelstein, 2005). Especially in strong-form efficient capital markets, stock prices should reflect all available information, including non-public information (Fama, 1970). On the contrary, accounting-based measures are possibly manipulated. When managers face performance pressure, they can manage earnings to adjust accounting-based metrics

[21] We get similar results with alternative measures of crash risk. The results are available upon request.

(Irani and Oesch, 2016; Yu, 2008). As a result, market-based performance measures are relatively harder to manipulate and more effective in reflecting real managers' inputs. We expect that RPE disclosing firms adopting market-based measures can capture a more significant benefit in reducing crash risk.

Specifically, we divide RPE disclosing firms into two groups and conduct two variables of *ACCOUNTING* and *STOCKPRICE*. *ACCOUNTING* is a dummy variable that equals one if the firm utilizes accounting-based performance metrics and zero otherwise. *STOCKPRICE* is a dummy variable that equals one if the firm utilizes market-based performance metrics and zero otherwise. The metric type information for each RPE disclosing firm is available in the proxy statement. We repeat the baseline OLS regressions among RPE disclosing firms with the key variable of *RPE* replaced by *ACCOUNTING* and *STOCKPRICE*. Table 3.5 reports the results.

The dependent variable is *NCSKEW* in Columns (1)–(3). We add the variable of *ACCOUNTING* in Column (1), *STOCKPRICE* in Column (2), and both of them in Column (3). The coefficients on *STOCKPRICE* are statistically significant, while the coefficients on *ACCOUNTING* are not. In Column (3), the coefficient on *STOCKPRICE* is larger (by about 257%) in economic magnitude than the coefficient on *ACCOUNTING*. The results confirm our prediction that market-based performance metrics are more significant in decreasing stock price crash risk than accounting-based performance metrics.

Table 3.5 Performance Metrics and Crash Risk

This table presents the association between metric types and stock price crash risk. The dependent variable is *NCSKEW* in year *t*+1. *ACCOUNTING* is a dummy variable that equals one if the firm utilizes an accounting-based metric and zero otherwise. *STOCKPRICE* is a dummy variable that equals one if the firm utilizes a metric type of stock price, and zero otherwise. The detailed definitions of other variables are presented in Table 3.A.1. All regressions include the lagged *NCSKEW*, industry and year fixed effects. The robust *t*-statistics clustered by the firm are reported in parentheses. ***, **, and * denote the significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)
	NCSKEW	NCSKEW	NCSKEW
ACCOUNTING	0.024		0.023
	(0.62)		(0.60)
STOCKPRICE		-0.083***	-0.082***
		(-3.56)	(-3.55)
SIZE	0.043***	0.046***	0.046***
	(6.43)	(6.87)	(6.76)
FIRMAGE	-0.001	-0.001	-0.001
	(-1.02)	(-1.09)	(-1.07)
LEV	-0.109***	-0.109***	-0.108***
	(-2.96)	(-2.96)	(-2.95)
MTB	0.003	0.003	0.003
	(1.55)	(1.59)	(1.59)
ROA	0.098***	0.094***	0.094***
	(2.68)	(2.58)	(2.59)
OPAQUE	-0.003	-0.002	-0.002
	(-0.14)	(-0.09)	(-0.09)
DTURN	0.225***	0.222***	0.223***
	(3.68)	(3.64)	(3.65)
RET	-10.498	-11.456	-11.379
	(-0.87)	(-0.95)	(-0.94)
SIGMA	-1.440	-1.536	-1.528
	(-1.08)	(-1.15)	(-1.14)
CEOAGE	-0.001***	-0.001***	-0.001***
	(-2.92)	(-2.77)	(-2.77)
CEOFEMALE	0.058	0.056	0.057
	(1.32)	(1.30)	(1.30)
TENURE	0.002	0.001	0.001
	(1.12)	(0.92)	(0.93)
CHAIR	-0.043*	-0.044*	-0.044*
	(-1.78)	(-1.84)	(-1.85)
BOARDSIZE	-0.004	-0.003	-0.003
	(-1.05)	(-0.92)	(-0.92)
BOARDINDEP	0.130***	0.135***	0.134***
	(3.13)	(3.24)	(3.23)
NCSKEW	0.035***	0.034***	0.034***
	(3.97)	(3.93)	(3.93)
Industry FE	Y	Y	Y
Year FE	Y	Y	Y
Observations	22,776	22,776	22,776
Number of Firms	3880	3880	3880
Adjusted R^2	0.04	0.04	0.04

3.4.3.2 Relative Benchmark Selection

RPE disclosing firms have divergence on the choice of specific relative benchmarks. Usually, RPE firms use benchmarking methods of self-selected peer groups, traditional methods (market and industry indices), or hybrid methods. Each year, firms offer executives multiple grants, of which the award type includes cash, options, reload options, restricted stock unit, performance shares, and phantom stock. A firm disclosing RPE can still adopt a performance type of absolute benchmark or time for several grants. Thus, to research the impact on the crash risk of different relative benchmark selections, we divide RPE disclosing firms into two groups and conduct the relevant variables of *PEER* and *INDEX*. *PEER* is a dummy variable that equals one if the firm utilizes a relative benchmark of self-selected peers for at least one grant and zero otherwise. *INDEX* is a dummy variable that equals one if the firm uses relative benchmarks of traditional market or industry indices for all RPE grants and zero otherwise.

Albuquerque (2009) and Jayaraman et al. (2020) indicate that the traditional benchmarks of the market and industry indices can be inappropriate, arguing that traditional approaches fail in capturing the main RPE features and provide deficient support for RPE tests. They develop new grouping methods based on industry size and product similarity. Furthermore, Gong et al. (2011) find that self-selected peer groups are more efficient than relative benchmarks based on Albuquerque's industry-size grouping method, given that self-selected methods can be more powerful in seizing systematic and exogenous factors. Thus, self-selected peer group

benchmarks tend to be more beneficial than traditional indices. Accordingly, we predict a significantly higher impact of *PEER* on decreasing stock price crash risk relative to *INDEX*.

We repeat the baseline OLS regressions among RPE disclosing firms with the key variable of RPE replaced by *PEER* and *INDEX*. Table 3.6 reports the results. The dependent variable is *NCSKEW* in Columns (1)–(3). We add the variable of *PEER* in Column (1), *INDEX* in Column (2), and both of them in Column (3). The coefficients on *PEER* are statistically significant, while the coefficients on *INDEX* are not. In Column (3), the coefficient on *PEER* is larger (by about 48%) in economic magnitude than the coefficient on *INDEX*. The results confirm our prediction that the self-selected peer group benchmark method is more significant in decreasing stock price crash risk than the traditional index benchmark method.

To research the firm's propensity of using the benchmark of self-selected peers, we conduct the variable of *PEERPROP*. It measures the firms' trade-off between peer group benchmarks and index benchmarks. We calculate *PEERPROP* as the number of grants based on self-selected peers divided by the total number of grants based on all types of relative benchmarks. The results are presented in Table 3.A.7, supporting our findings in the previous subsection of relative benchmark selection.

Table 3.6 Benchmark Selection and Crash Risk

This table presents the association between relative benchmark types and stock price crash risk. The dependent variable is *NCSKEW* in year *t*+1. *PEER* is a dummy variable that equals one if the firm utilizes a relative benchmark of self-selected peers, and zero otherwise. *INDEX* is a dummy variable that equals one if the firm utilizes a relative benchmark of traditional market or industry indices, and zero otherwise. The detailed definitions of other variables are presented in Table 3.A.1. All regressions include the lagged *NCSKEW*, industry and year fixed effects. The robust *t*-statistics clustered by the firm are reported in parentheses. ***, **, and * denote the significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)
	NCSKEW	NCSKEW	NCSKEW
PEER	-0.062***		-0.065***
	(-2.63)		(-2.73)
INDEX		-0.036	-0.044
		(-1.09)	(-1.29)
SIZE	0.045***	0.044***	0.046***
	(6.71)	(6.56)	(6.76)
FIRMAGE	-0.001	-0.001	-0.001
	(-1.12)	(-1.02)	(-1.11)
LEV	-0.109***	-0.109***	-0.109***
	(-2.98)	(-2.96)	(-2.98)
MTB	0.003	0.003	0.003
	(1.56)	(1.57)	(1.59)
ROA	0.094***	0.097***	0.094**
	(2.58)	(2.66)	(2.57)
OPAQUE	-0.003	-0.003	-0.002
	(-0.13)	(-0.12)	(-0.11)
DTURN	0.223***	0.224***	0.223***
	(3.66)	(3.67)	(3.64)
RET	-11.064	-10.785	-11.340
	(-0.92)	(-0.89)	(-0.94)
SIGMA	-1.504	-1.466	-1.528
	(-1.13)	(-1.10)	(-1.14)
CEOAGE	-0.001***	-0.001***	-0.001***
	(-2.83)	(-2.90)	(-2.80)
CEOFEMALE	0.058	0.056	0.057
	(1.34)	(1.29)	(1.31)
TENURE	0.001	0.002	0.001
	(1.00)	(1.10)	(0.98)
CHAIR	-0.042*	-0.043*	-0.043*
	(-1.75)	(-1.79)	(-1.78)
BOARDSIZE	-0.004	-0.004	-0.003
	(-1.01)	(-1.01)	(-0.96)
BOARDINDEP	0.134***	0.131***	0.134***
	(3.22)	(3.15)	(3.23)
NCSKEW	0.034***	0.035***	0.034***
	(3.94)	(3.97)	(3.94)
Industry FE	Y	Y	Y
Year FE	Y	Y	Y
Observations	22,776	22,776	22,776
Number of Firms	3880	3880	3880
Adjusted R^2	0.04	0.04	0.04

3.4.4 Cross-Sectional Analyses

In this subsection, we study the heterogeneity in RPE across the different groups with various managerial ability, systematic uncertainty, industry competition, and managerial myopia correctability.[22]

3.4.4.1 Managerial Ability

The myopia problem is weakened when agents are able to show their ability through alternative ways (Narayanan, 1985). RPE provides such alternative way to show managers' productive inputs (more precisely than traditional APE) and suppress their incentives to make myopic decisions (Holmstrom, 1979, 1982). Whereas, the truly talented managers are easier to alleviate their incentives of private information manipulation relative to low-ability managers (Nagar, 1999). Therefore, we predict the RPE-crash risk reduction effect is stronger for high-ability managers. Moreover, the information manipulation incentives are possibly more serious for high-ability managers due to career concerns (for example, the discussion of a positive association between managerial ability and earnings smoothing in Baik et al., 2020) also contributes to a higher reduction of crash risk. Managers are reluctant to be dismissed because of market factors out of their control, however, which is actually happening (Jenter & Kanaan, 2015). We argue that, relative to

[22] We also construct sub-samples based on the degree of external monitoring. Following Kim et al. (2011b) and Yu (2008), we use institutional holding as the proxy for external monitoring. We find no statistical difference in the RPE effect between high- and low-institutional holding firms. The result indicates that RPE does not mitigate bad news hoarding and crash risk by inducing additional external monitoring. The results are available upon request.

low-ability managers, high-ability managers are harder to accept that they are fired because of exogenous economic shocks. Specifically, given that talent managers can generate higher-quality earnings and hold a higher reputation (Demerjian et al., 2013), they are more confident about their future performance recovery and more likely to temporarily withhold bad news and manage earnings. Thus, we expect the RPE to have an additional reducing impact on crash risk for high-ability managers. The interactive term of RPE and managerial ability should have a negative sign on crash risk. We use two measures to proxy for managerial ability. The regression results are present in Table 3.7 Panel A.

The first measure is the managerial ability score *(MAScore)* generated by Demerjian et al. (2012). They use the data envelopment analysis methodology to measure firm efficiency in converting company inputs (labor and capital) into revenue as the proxy for managerial ability. A high value of *MAScore* implies high managerial ability. Column (1) confirms our prediction that high managerial ability can lead to a higher probability of stock price crash risk. Column (2) presents the additional and marginal reduction effect of RPE on crash risk for high-ability managers, with the coefficient of the interactive term being −0.171. The economic magnitude is significant, given that coefficient on RPE is only −0.13. At the same time, the statistical significance is relatively weak, with *t*-statistics being −1.82. With RPE eliminating the common risk of volatile compensation, high-ability executives are more likely to disclose adequately. RPE mitigates the managerial hoarding

behavior of high-ability executives to a greater extent than low-ability executives.

The second measure is based on the conventional ratio of ROA (Demerjian et al., 2012). Scholars take adjustments on the ROA measure, such as industry-adjusted ROA (Rajgopal et al., 2006). We construct the peer-adjusted ROA as the alternative measure of managerial ability. The variable of *PeerAdjROA* denotes the difference between a firm's ROA and the average ROA of its relative peer firms. A high value of *PeerAdjROA* implies a relatively high managerial ability. Columns (3) and (4) present the results, which support our previous findings. Since the results are similar to those of *MAScore*, we don't repeat the explanations for terseness.

Our findings can reconcile with Rajgopal et al. (2006). They state that keeping market-wide effects and offering high-ability managers rewards for systematic shocks are optimal because managerial talent is scarce and oligopolistic. With our findings, the optimal contract could be asymmetric in that principals offer upside rewards and remove downside punishments because of systematic shocks for high-ability agents.

Table 3.7 Cross-Sectional Analyses

This table presents the heterogeneity among U.S. listed firms from 2006–2017. Panel A reports the moderating effect of managerial ability on the association between *RPE* and stock price crash risk. We use two measures of *MAScore* and *PeerAdjROA* as the proxy for managerial ability. *MAScore* is the managerial ability score generated by Demerjian et al. (2012) using a data envelopment analysis. *PeerAdjROA* is the difference between a firm's ROA and the average ROA of its relative peer firms. *ABILITY* equals to *MAScore* in Columns (1) and (2) and equals to *PeerAdjROA* in Columns (3) and (4). *RPE*×*ABILITY* is the interaction term between *RPE* and *ABILITY*. Panel B reports the sub-sample analysis results with samples being divided into two parts based on the systematic uncertainty (*EPU*), industry competition (*Industry HHI*), and managerial myopia correctability (*Career Horizon*). *EPU* is the economic policy uncertainty. *Industry HHI* is the Herfindahl-Hirschman index, also known as the concentration index. *Career Horizon* is the expected career horizon that proxies for the expected correctability of the managerial short-termism problem. The dependent variable is *NCSKEW* in year *t*+1 for all regressions. The detailed definitions of other variables are presented in Table 3.A.1. All regressions include the lagged *NCSKEW*, industry and year fixed effects. The robust *t*-statistics clustered by the firm are reported in parentheses. ***, **, and * denote the significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Managerial Ability

	(1) MAScore	(2) MAScore	(3) PeerAdjROA	(4) PeerAdjROA
RPE		-0.130***		-0.159***
		(-6.84)		(-6.83)
ABILITY	0.112**	0.230***	0.177**	-0.049
	(2.20)	(3.11)	(2.03)	(-0.40)
RPE×ABILITY		-0.171*		-0.222*
		(-1.82)		(-1.76)
SIZE	0.040***	0.061***	0.046***	0.063***
	(7.21)	(9.68)	(6.86)	(8.49)
FIRMAGE	-0.001	-0.001	-0.001	-0.001
	(-1.00)	(-0.75)	(-0.97)	(-0.78)
LEV	-0.126***	-0.139***	-0.112***	-0.121***
	(-3.54)	(-3.92)	(-3.05)	(-3.27)
MTB	0.002	0.004**	0.003*	0.004**
	(1.39)	(2.21)	(1.78)	(2.22)
ROA	0.094**	0.072*	-0.076	0.136
	(2.57)	(1.95)	(-0.81)	(1.11)
OPAQUE	-0.018	-0.018	-0.002	-0.003
	(-0.84)	(-0.84)	(-0.07)	(-0.13)
DTURN	0.220***	0.214***	0.223***	0.221***
	(3.63)	(3.54)	(3.65)	(3.62)
RET	2.181	-1.243	-12.084	-13.724
	(0.25)	(-0.14)	(-1.00)	(-1.12)
SIGMA	-0.087	-0.427	-1.614	-1.744
	(-0.10)	(-0.49)	(-1.21)	(-1.30)
CEOAGE	-0.001**	-0.001*	-0.001***	-0.001***
	(-2.04)	(-1.75)	(-2.79)	(-2.67)
CEOFEMALE	0.058	0.054	0.057	0.055
	(1.34)	(1.25)	(1.31)	(1.27)
TENURE	0.002	0.001	0.002	0.001
	(1.37)	(0.97)	(1.04)	(0.80)
CHAIR	-0.048**	-0.042*	-0.040*	-0.038
	(-2.03)	(-1.79)	(-1.67)	(-1.59)
BOARDSIZE	-0.003	-0.002	-0.004	-0.003
	(-0.84)	(-0.63)	(-1.01)	(-0.84)
BOARDINDEP	0.134***	0.140***	0.129***	0.135***
	(3.30)	(3.44)	(3.11)	(3.27)
NCSKEW	0.038***	0.037***	0.035***	0.033***
	(4.83)	(4.66)	(3.98)	(3.78)
Industry FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Observations	22,534	22,534	22,776	22,776
Number of Firms	3833	3833	3880	3880
Adjusted R^2	0.04	0.04	0.04	0.04

Panel B: Sub-sample Analyses

	EPU		Industry HHI		Career Horizon	
	(1)	(2)	(3)	(4)	(5)	(6)
	Low	High	Low	High	Low	High
RPE	-0.074***	-0.148***	-0.175***	-0.095***	-0.094***	-0.184***
	(-3.56)	(-5.67)	(-6.21)	(-3.62)	(-4.13)	(-4.05)
SIZE	0.054***	0.066***	0.081***	0.046***	0.029***	0.100***
	(7.38)	(7.59)	(8.07)	(4.14)	(2.58)	(10.16)
FIRMAGE	-0.000	-0.000	-0.003**	0.002	-0.000	-0.001
	(-0.42)	(-0.01)	(-2.17)	(1.46)	(-0.49)	(-0.34)
LEV	-0.104**	-0.155***	-0.109**	-0.114**	-0.086	-0.137***
	(-2.51)	(-2.89)	(-2.18)	(-2.02)	(-1.58)	(-2.64)
MTB	0.004*	0.004	0.003	0.004*	-0.000	0.008***
	(1.79)	(1.52)	(1.29)	(1.84)	(-0.13)	(3.13)
ROA	0.090**	0.097	0.032	0.199***	0.130**	0.041
	(2.34)	(1.57)	(0.68)	(3.30)	(2.35)	(0.83)
OPAQUE	0.040	0.006	0.014	-0.018	-0.006	0.028
	(1.52)	(0.17)	(0.43)	(-0.57)	(-0.20)	(0.90)
DTURN	0.217***	0.216**	0.155*	0.305***	0.136*	0.346***
	(3.14)	(2.35)	(1.77)	(3.67)	(1.68)	(3.78)
RET	9.091	-32.985**	2.169	-32.329*	-46.661***	3.219
	(0.75)	(-2.57)	(0.16)	(-1.73)	(-2.73)	(0.25)
SIGMA	0.792	-3.482***	-0.659	-3.051	-4.333**	-0.625
	(0.59)	(-2.87)	(-0.45)	(-1.45)	(-2.37)	(-0.43)
CEOAGE	-0.001**	0.000	-0.002***	-0.000	-0.000	-0.001
	(-2.57)	(0.60)	(-2.90)	(-0.35)	(-0.52)	(-0.31)
CEOFEMALE	0.069	0.020	0.118	0.018	0.052	-0.483***
	(1.41)	(0.32)	(1.42)	(0.38)	(1.19)	(-7.30)
TENURE	0.002	-0.002	0.001	0.001	-0.000	0.022
	(1.21)	(-0.96)	(0.42)	(0.51)	(-0.10)	(0.32)
CHAIR	-0.020	-0.229	-0.047	-0.040	0.003	-0.427
	(-0.86)	(-0.96)	(-1.24)	(-1.28)	(0.10)	(-1.24)
BOARDSIZE	-0.008**	0.002	-0.009*	0.000	-0.005	0.003
	(-2.50)	(0.42)	(-1.65)	(0.08)	(-1.17)	(0.53)
BOARDINDEP	0.088**	0.084	0.206***	0.077	0.114*	0.143**
	(2.08)	(1.53)	(3.27)	(1.47)	(1.83)	(2.44)
NCSKEW	0.025**	0.036***	0.014	0.054***	0.019*	0.027**
	(2.47)	(3.32)	(1.22)	(4.29)	(1.71)	(2.18)
Industry FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Observations	16,837	13,435	10,729	12,048	13,743	9,027
Number of Funds	4,908	3,844	2,264	2,100	2,065	1,875
Adjusted R^2	0.07	0.03	0.04	0.05	0.03	0.07
Coefficient Equality						
(1) vs. (2)	0.02					
(3) vs. (4)	0.04					
(5) vs. (6)	0.06					

3.4.4.2 Systematic Uncertainty

RPE differs from APE mainly by removing the common uncertainty from incentive contracts (Holmstrom, 1982). Thus, we predict a stronger effect of RPE when the systematic uncertainty is higher. As customary, we use the economic policy uncertainty (EPU) to measure systematic uncertainty. We adopt the method of Baker et al. (2016) to calculate the EPU and a higher EPU implies more systematic uncertainty.

Columns (1) and (2) in Table 3.7 Panel B indicate that firms with higher systematic uncertainty are associated with stock price crash risk to a great extent, which confirms our prediction. The coefficient on RPE of the high-EPU group is 100% larger in economic magnitude than that of the low-EPU group. The coefficient equality shows that the coefficient difference is statistically significant, with a significance level of 0.02.

3.4.4.3 Industry Competition

Campbell & Marino (1994) indicate that higher industry competition increases the probability of managerial myopia. If RPE decreases crash risk by mitigating the myopia incentives of managers, the crash risk reduction effect of RPE should be more pronounced for firms in competitive industries. Moreover, Aggarwal and Samwick (1999) state that companies in more competitive industries give more weight on peer firm performance than their firm performance. Thus, we expect the decreasing effect of RPE on crash risk to be more pronounced in firms with high competition. We conduct sub-sample analyses to determine whether the association

between RPE use and stock price crash risk varies across the degree of industry competition. We use the Herfindahl-Hirschman index (*Industry HHI*) to measure industry competition, also known as the concentration index.

Columns (3) and (4) in Table 3.7 Panel B indicate that firms operating in the low HHI industry are associated with stock price crash risk to a great extent. The coefficient on RPE of high-competitive industry (low HHI) group is 84% larger in economic magnitude than that of low-competitive industry (high HHI) group, which difference is statistically significant (significance level of 0.04). The result is aligned with our prediction. We raise the possible reason that a stronger tournament incentive effect on firm risk in highly competitive industries provides a basis for the higher impact of RPE on crash risk. According to Coles et al. (2018), the increasing effect of ITI on firm risk is stronger when there is higher mobility in the industry. Given the low concentration associated with high executive mobility, we predict ITI as an important channel through which the RPE associates with crash risk. In the following subsection, we conduct further tests and explanations on how ITI behaves as the mediation factor about possible mechanisms.

3.4.4.4 Managerial Myopia Correctability

Finally, we conduct sub-sample analyses based on the expected tenure of CEOs, which indicates the expected correctability of the managerial short-termism problem. Moral hazard models state that agents tend to pursue short-term targets that satisfy their interests. A shorter expected tenure means more rigid short-termism of

managers and lower correctability of managerial myopia problem because they are expected to leave soon. Executives with short expected tenure gain less benefit from overcoming their short-termism and resetting the long-term targets. Antia et al. (2010) find empirical evidence that shorter expected tenure is associated with higher agency costs and higher information risk.

Suppose RPE reduces the agency costs through dispersing the short-termism of managers. Following Antia et al. (2010) and Lee, Park, & Folta (2018), we conduct a measure of expected tenure of CEOs (*Career Horizon*). This measure is calculated as the distance from managers' current tenure to the industrial average tenure plus the distance from managers' current age to the industrial average age. A higher value of *Career Horizon* implies a higher probability of amendable short-termism and additional benefits through controlling managerial myopia incentives. Thus, if RPE can reduce agency costs by dispersing managers' short-termism, the coefficient should be more pronounced for firms with high *Career Horizon*. That is, we expect the decreasing effect of RPE on crash risk to be significantly stronger in firms with higher potential benefits from amending managerial myopia.

In Columns (5) and (6), we find that the impact of RPE on stock price crash risk is more pronounced for firms with higher *Career Horizon*. The coefficient on RPE of the high *Career Horizon* group is 96% larger in economic magnitude than that of the low *Career Horizon* group, the difference of which is statistically significant. The results confirm our prediction that RPE reduces agency cost via

mitigating managers' short-termism.

3.4.5 Possible Mechanisms

This subsection conducts mediating effect analyses to identify possible mechanisms. We test the industry tournament and market pressure channels with ITI and analyst coverage (ANA), respectively, as a mediator in the association between RPE and stock price crash risk.

We test the mediating effect of ITI to check the direct effect of RPE on managers' incentives. A new methodology of performance evaluation undoubtedly changes the compensation level of the person being evaluated. This will affect the incentives and extend to crash risk, given the association between ITI and crash risk has been exploited. Next, we test the mediating effect of ANA to emphasize the information asymmetry problem incurred by managerial myopia (our major hypothesis). The market pressure derived from analysts' target price (especially over-optimistic forecasts) aggravates this problem. If RPE disperse excessive market pressure and adjust forecasting bias, RPE can effectively improve the information symmetry and mitigate crash risk.

As Mackinnon and Dwyer (1993) explained, the mediating effect is statistically significant when i) the independent variable of RPE significantly affects the mediating variable, ii) the independent variable significantly affects the dependent variable without the appearance of the mediating variable, iii) the mediating variable significantly affects the dependent variable, and iv) the effect of the independent

variable on the dependent variable shrinks with the mediator being added to the model. Specifically, we apply a standard two-step mediating analysis formulated as follows:

$$M_{i,t} = \alpha + \beta RPE_{i,t} + \sigma X_{i,t} + \theta_t + \mu_i + \varepsilon_{i,t}, \quad (4)$$

$$NCSKEW_{i,t+1} = \alpha + \beta RPE_{i,t} + \mu M_{i,t} + \sigma X_{i,t} + \theta_t + \mu_i + \varepsilon_{i,t+1}, \quad (5)$$

where $NCSKEW_{i,t+1}$ denotes the stock price crash risk of firm *i* in year *t+1*, and $M_{i,t}$ denotes the mediating variables of ITI and ANA.

3.4.5.1 Industry Tournament Channel

First, we use the industry tournament incentive (ITI) as our mediating variable. Dye (1992) indicates that RPE enables managers with absolute disadvantages of ability to select projects in which they can play their comparative advantages, thus narrowing their performance and compensation gap to managers with absolute advantages of ability. Moreover, the firms' performance tends to diverge under APE, given that winners are usually more pro-cyclical. RPE can remove the composition of systematic risk deriving from the economic cycle and other market factors, thus converging the performance gap and decreasing ITI. Hence, RPE can reduce the crash risk by mitigating the ITI if the tournament incentive positively affects crash risk.

We notice the inconclusive effect of ITI on stock price crash risk. Kubick and Lockhart (2020) claim that higher ITI is associated with a higher risk of a stock

price crash. They provide a channel where high ITI will lead to managerial hoarding behavior, positively associated with large crash risk. Thus, they document the negative externality of the managerial labor market's incentive effects. Alternatively, Chowdhury et al. (2020) provide contrary evidence that the CEO's ITI can reduce the probability of future stock price crash risk. CEOs will undertake a long-term cost-benefit analysis of managerial hoarding and care about their sustained long-term reputation. The two studies use similar databases and periods but have different sample selection treatments. Specifically, Chowdhury et al. (2020) exclude a larger proportion of observations based on CEO and industry-related filters. Eventually, the sample size of Chowdhury et al. (2020) is approximately 40% less than Kubick and Lockhart (2020). However, CEO and industry-related filters are likely to affect the probability of RPE use, as demonstrated in Gong et al. (2011). For example, evidence illustrates that not all executives rely on firms' RPE strategy to insulate them from common risk. Younger and less wealthy managers are determinately concerned about RPE incentives (Garvey and Milbourn, 2003). Following Kubick and Lockhart (2020), we expect ITI and crash risk to be positively related because of bad news hoarding behavior. As a result, we expect RPE to decrease ITI and sequentially lessen the crash risk.

We infer that the prerequisite RPE as an omitted variable could affect the function channel of ITI on crash risk. Given that ITI measures the objective performance gap, using RPE or not will determine how firms value the performance

gap. Specifically, executives of RPE firms tend to have lower ITI, and the ITI effect on crash risk tends to be less pronounced for RPE firms[23].

3.4.5.2 Market Pressure Channel

Another mediating variable is analyst coverage (ANA) proxy for market pressure. Narayanan (1985) states that managers have incentives to show short-term good results to deal with the pressure from the capital markets. Gigler et al. (2014) document that the price pressure from frequent financial reporting increases managerial short-termism. Hence, RPE can increase the information symmetry and reduce crash risk by mitigating the short-orientation pressures.

ANA increases crash risk mainly because of analyst pressure[24]. Analyst coverage creates excessive pressure on managers because the stock price usually declines if the firm cannot reach analyst predictions (Yu, 2008). Analysts' forecast on earnings generates pressure on managers, leading them to focus more on short-term targets (He and Tian, 2013). As a result, managers will undertake real earnings management behaviors to meet short-term goals, accumulating bad news and stock price crash risk (Irani and Oesch, 2016). Furthermore, the conflicts of interest, analyst optimism, and forecast dispersion aggravate the increase of analyst

[23] We test the association between ITI and crash risk based on subsamples of RPE and non-RPE firms. The results indicate a significantly stronger increasing effect of ITI on crash risk for non-RPE firms. The results are available upon request.

[24] A naive belief is that effective analyst research can enhance the information symmetry between managers and investors by publishing their research results, thus making firms more transparent and mitigating firms' crash risk. Financial analysts are regarded as external monitors that offer incremental information. However, empirical evidence does not support the belief. Typically, Chan and Hameed (2006) demonstrate that analyst coverage increases stock return synchronicity, representing less specific information being acquired.

coverage on crash risk (Xu et al., 2013; Jin and Myers, 2006). Xu et al. (2013) show that conflicts of interest among sell-side analysts can bias their research upward and aggravate stock price crash risk. They provide evidence that analyst coverage can increase firm-specific crash risk, emphasizing the role of analyst optimism raised by Mola and Guidolin (2009). Jin and Myers (2006) demonstrate the dispersion of analysts' forecasts can reflect large opacity and incur a high probability of crash risk. To sum up, we predict an empirically positive association between analyst coverage and firm-specific crash risk in stock returns.

To connect RPE and ANA, we raise the hypothesis that the use of RPE leads to a low level of analyst coverage because of the following reasons. For RPE firms, executives have less incentive to hold bad news because of improving corporate governance and agency contract design. External analysts are less likely to contribute additional and valuable information. Thus, analysts gain more incentive in following firms with APE based on the cost-benefit consideration between research efforts and outcomes. Namely, analysts are more willing to follow a firm when they believe it contains more private information (Lobo et al., 2012). Hence, we predict that RPE firms' higher level of endogenous transparency will incur less analyst coverage because less marginal research contribution can be generated. We offer further discussions on the increasing effect of RPE utilization on information symmetry and disclosure quality in Section 5.

Table 3.8 Possible Mechanisms

This table presents the mediating role of industry tournament incentives and analyst coverage in the association between *RPE* and stock price crash risk. *ITI* is the industry tournament incentives calculated as the logarithm of the difference between the total compensation (TDC1) of the second-highest-paid CEO in the same size-adjusted three-digit industry group and the total compensation of a firm's CEO. *ANA* is the logarithm of the number of analysts following the firm during each fiscal year, as in He and Tian (2013). The detailed definitions of other variables are presented in Table 3.A.1. All regressions include the lagged *NCSKEW*, industry and year fixed effects. The robust *t*-statistics clustered by the firm are reported in parentheses. ***, **, and * denote the significance at the 1%, 5%, and 10% levels, respectively.

	(1) NCSKEW	(2) ITI	(3) ANA	(4) NCSKEW	(5) NCSKEW	(6) NCSKEW
RPE	-0.132***	-0.165*	-0.127***	-0.131***	-0.118***	-0.117***
	(-6.80)	(-1.73)	(-11.41)	(-6.76)	(-6.03)	(-5.99)
ITI				0.006***		0.006***
				(2.81)		(2.84)
ANA					0.111***	0.111***
					(5.29)	(5.29)
SIZE	0.063***	-0.035	0.110***	0.063***	0.051***	0.051***
	(8.45)	(-1.29)	(22.34)	(8.42)	(6.40)	(6.38)
FIRMAGE	-0.001	-0.002	0.002***	-0.001	-0.001	-0.001
	(-0.73)	(-0.56)	(3.41)	(-0.72)	(-0.97)	(-0.96)
LEV	-0.118***	-0.078	0.019	-0.118***	-0.120***	-0.120***
	(-3.21)	(-0.70)	(0.88)	(-3.19)	(-3.28)	(-3.27)
MTB	0.004**	-0.004	0.006***	0.004**	0.003*	0.003*
	(2.31)	(-0.90)	(7.13)	(2.33)	(1.90)	(1.92)
ROA	0.082**	-0.025	0.256***	0.083**	0.054	0.054
	(2.25)	(-0.35)	(14.80)	(2.26)	(1.47)	(1.48)
OPAQUE	-0.002	-0.041	-0.026**	-0.001	0.001	0.001
	(-0.08)	(-0.64)	(-2.32)	(-0.07)	(0.05)	(0.06)
DTURN	0.222***	-0.146	0.050***	0.223***	0.216***	0.217***
	(3.63)	(-0.95)	(2.69)	(3.65)	(3.56)	(3.57)
RET	-13.979	53.225	22.473***	-14.286	-16.467	-16.779
	(-1.16)	(1.55)	(4.85)	(-1.17)	(-1.39)	(-1.40)
SIGMA	-1.793	6.923*	1.897***	-1.833	-2.003	-2.043
	(-1.35)	(1.73)	(3.54)	(-1.36)	(-1.54)	(-1.56)
CEOAGE	-0.001**	0.006***	0.002***	-0.001***	-0.001***	-0.001***
	(-2.54)	(3.51)	(8.83)	(-2.63)	(-3.15)	(-3.25)
CEOFEMALE	0.054	0.020	-0.041*	0.054	0.059	0.058
	(1.25)	(0.07)	(-1.81)	(1.26)	(1.36)	(1.37)
TENURE	0.001	0.008	0.001	0.001	0.001	0.001
	(0.74)	(1.04)	(0.80)	(0.70)	(0.70)	(0.67)
CHAIR	-0.037	-0.190	-0.015	-0.036	-0.035	-0.034
	(-1.55)	(-1.51)	(-1.64)	(-1.50)	(-1.48)	(-1.43)
BOARDSIZE	-0.003	-0.011	-0.006**	-0.003	-0.002	-0.002
	(-0.87)	(-0.75)	(-2.55)	(-0.85)	(-0.70)	(-0.68)
BOARDINDEP	0.134***	-0.082	0.196***	0.135***	0.113***	0.113***
	(3.25)	(-0.51)	(7.36)	(3.26)	(2.72)	(2.74)
NCSKEW	0.033***	0.012	0.020***	0.033***	0.031***	0.031***
	(3.80)	(0.49)	(6.84)	(3.78)	(3.61)	(3.58)
Industry FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Observations	22,776	22,776	22,776	22,776	22,776	22,776
Number of Firms	3,880	3,880	3,880	3,880	3,880	3,880
Adjusted R^2	0.04	0.00	0.46	0.04	0.05	0.05
Sig. of Total Mediated Effect						-0.78
Pct. of Mediated Effect: ITI						0.06
Sig. of Mediated Effect: ITI						-1.48
Pct. of Mediated Effect: ANA						0.94
Sig. of Mediated Effect: ANA						-4.80

Table 3.8 shows the results of mediating tests. Column (1) repeats the baseline results that RPE is negatively associated with stock price crash risk. Column (2) presents that negative association between ITI and RPE, confirming our prediction that RPE decreases ITI[25]. However, the effect is marginal with a *t*-statistic of −1.73. In Column (3), RPE has a strong negative association with ANA, indicating that the use of RPE will dispel analysts' coverage. Columns (4) and (5) examine the explanatory power of the two channels. Column (6) examines the explanatory power of the two channels in a single regression. The mediating effect of ITI and ANA are statistically significant. ITI and ANA increase the crash risk, whereas RPE utilization decreases both. The results suggest that RPE can affect stock price crash risk through the industry tournament and market pressure channels.

The coefficient decline of crash risk probability is stronger through the ANA channel than through the ITI channel in terms of economic magnitude. The coefficient of *RPE* on *NCSKEW* is −0.118 in Column (5), with a change of 11% compared with results in Column (1). At the same time, the coefficient of *RPE* on *NCSKEW* is −0.131 in Column (4), with a change of 1% compared with results in Column (1). Thus, putting the channel variable ITI into the basic regression equation leads to a more noticeable decline in the RPE coefficient. The results show that the mediation effect mainly comes from ANA with 94%, illustrating that market

[25] The results are aligned with previous literature and our findings of the exogenous variable of NCA enforceability. We find NCA enforceability increases RPE, and RPE decreases ITI. The relation is aligned with Chowdhury et al. (2020) and Huang et al. (2019) that NCA enforceability decreases ITI.

pressure is the primary channel. The results are all aligned with our findings in cross-sectional analyses.

3.4.6 Robustness Checks

3.4.6.1 Alternative Crash Risk Measures

In Table 3.A.2, we conduct three alternative crash risk measures based on Kim, Li, and Zhang (2011a, 2011b). Using the alternative measures of crash risk, we redo baseline regressions. Table 3.A.2 shows that RPE is negatively associated with all three alternative crash risk measures supporting our baseline findings using *NCSKEW*. We also redo the regressions of performance metrics, benchmark selection, cross-sectional, and mediating analyses using alternative measures. The results remain robust. They are available upon request.

3.4.6.2 Control for Overall Skewness

In baseline results, we control for the one-year lagged skewness of firms following the customary operation of crash risk literature. In Table 3.A.4, we control for the full-sample skewness and the backward-looking skewness rather than the one-year lagged skewness. *SKEWALL* is the full-sample skewness of firms over the entire sample. *SKEWROLL* is the backward-looking skewness of firms over the previous years. Panel A and B reports the regression results of *SKEWALL* and *SKEWROLL* respectively. The adjusted R-square increases substantially from 0.04 to 0.23 in Panel A and 0.42 in Panel B, demonstrating the strong explanatory power of the firm's overall skewness on its crash risk. Nevertheless, the negative association

between *RPE* and *NCSKEW* remains. In terms of economic magnitude, there is a 68% (75%) reduction on coefficients of RPE compared to the baseline results.

3.4.6.3 Sampling Criteria

We conduct extension tests based on our baseline results. In Table 3.A.5, we undertake an analysis that excludes 2006, 2007, and 2008. Given that 2006 is the first year when firms are forced to disclose RPE information in the proxy statement. The number of RPE disclosing firms rapidly increased in 2006−2008, as shown in Figure 3.1. The samples leading RPE disclosing firms may contain the most representative information. Thus, we exclude 2006−2008 and redo the baseline regressions in Table 3.A.5. The results support our previous findings.

3.4.6.4 Alternative Model Specifications

Table 3.A.6 reports the additional test results of alternative model specifications, replacing three-digit SIC with four-digit SIC, FF48, and industry-year fixed effect. FF48 denotes Fama-French 48 industries. Industry-Year FE denotes the fixed effect of interaction between year and FF48. The results support our main findings.

3.5 Further Discussions

3.5.1 Information Disclosure Quality

To confirm further the benefits of RPE on decreasing crash risk by mitigating bad news hoarding and controlling agency cost, we examine the association between RPE and information disclosure quality. Extensive literature agrees that firms' information opacity drives stock price crash risk (Hutton et al., 2009; Jin & Myers,

2006; Kim et al., 2019; Kim et al., 2016; Kim & Zhang, 2016). We consider RPE utilization as a clear signal of improved corporate governance that agencies will adequately disclose information to eliminate asymmetry between shareholders and managers. Jin and Myers (2006) postulate that information asymmetry is the primary foundation of crash risk. They develop a model with inadequate transparency to demonstrate that stock price crashes happen when accumulated negative firm-specific information suddenly becomes public.

We contend that RPE firms associate with better information disclosure quality. The improvement of information transparency can remove the ladder of the accumulation of unobservable bad news. Thus, the probability of sudden release of firm-specific bad news and stock price crashes will be less for RPE firms. We conduct three measures of information disclosure quality. Following Basu (1997), we construct the estimation of *CSocre,* which denotes accounting conservatism. The score is higher when the earnings reflect bad news faster than good news, indicating better information disclosure quality. The second measure is *EarnAgg*, which denotes earnings aggressiveness, following Bhattacharya et al. (2003). EarnAgg measures the earnings opacity that presents for negative information disclosure quality. The third measure of *Synch* is stock return synchronicity. Higher *Synch* indicates less firm-specific information and lower disclosure quality (Chan & Hameed, 2006; Morck et al., 2000). We expect better information disclosure quality for RPE firms, which decreases the probability of crash risk.

Table 3.9 Information Disclosure Quality

This table presents the association between *RPE* and measures of information disclosure quality for a sample of U.S. listed firms from 2006–2017. *CScore* is the accounting conservatism representing high information disclosure quality, following Basu (1997). *EarnAgg* is the earning aggressiveness representing low information disclosure quality, following Bhattacharya et al. (2003). *Synch* is the price synchronicity representing low information disclosure quality, following Chan & Hameed (2006) and Morck et al. (2000). The detailed definitions of other variables are presented in Table 3.A.1. All regressions include the industry and year fixed effects. The robust *t*-statistics clustered by the firm are reported in parentheses. ***, **, and * denote the significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)
	CScore	EarnAgg	Synch
RPE	0.725*	-0.020***	-0.151***
	(1.80)	(-5.90)	(-5.11)
SIZE	-0.167*	0.008***	0.296***
	(-1.76)	(7.38)	(22.08)
FIRMAGE	-0.008	0.000	-0.000
	(-0.56)	(0.14)	(-0.22)
LEV	1.271*	0.070***	-0.263***
	(1.89)	(10.05)	(-4.51)
MTB	-0.064***	0.001*	0.014***
	(-3.15)	(1.90)	(5.22)
ROA	-0.074	0.051***	-0.260***
	(-0.22)	(8.11)	(-5.28)
OPAQUE	-0.036	0.033***	0.013
	(-0.13)	(7.11)	(0.39)
DTURN	-5.455*	0.062***	-0.244***
	(-1.94)	(4.93)	(-3.17)
RET	364.178**	3.936***	69.392***
	(2.47)	(3.42)	(3.33)
SIGMA	45.995***	0.285**	1.864
	(2.61)	(2.40)	(0.79)
CEOAGE	0.011	-0.000***	0.005***
	(1.41)	(-2.63)	(8.81)
CEOFEMALE	-0.210	-0.004	-0.000
	(-1.35)	(-0.58)	(-0.00)
TENURE	-0.008	0.000	0.003
	(-0.24)	(1.16)	(1.25)
CHAIR	-0.961**	-0.013***	0.074**
	(-2.53)	(-2.88)	(2.19)
BOARDSIZE	0.076	-0.001**	-0.014**
	(1.13)	(-2.24)	(-2.30)
BOARDINDEP	-0.477	-0.011	0.241***
	(-0.68)	(-1.55)	(3.43)
NCSKEW	-0.298**	-0.000	0.011
	(-2.03)	(-0.21)	(0.95)
Industry FE	Y	Y	Y
Year FE	Y	Y	Y
Observations	22,776	22,776	22,776
Number of Firms	3880	3880	3880
Adjusted R^2	0.05	0.05	0.38

We test the association between RPE and the three measures of information disclosure quality and report the results in Table 3.9. Column (1) shows that RPE increases accounting conservatism. Columns (2) and (3) indicate that RPE decreases earnings aggressiveness and stock return synchronicity, respectively. These findings confirm our prediction that RPE is a signal of higher information disclosure quality.

3.5.2 Analyst Optimism

Another benefit of RPE we would like to emphasize is the adjustment effect of external expectations and forecasts, relieving the market pressure. Given improved information symmetry, external forecasting bias can be appropriately adjusted. The external expectations and forecasts that could counterproductively affect managers are typically from shareholders and analysts. Correction of these biases leads to less unnecessary pressure on managers. We focus on the pressure from analyst optimistic bias to connect managerial myopia, analyst coverage, and crash risk.

Literature illustrates that excessive pressure can distort managers' operations and lead them to focus more on short-run targets (He and Tian, 2013; Irani and Oesch, 2016). Especially, Xu et al. (2013) illustrate the increasing effect of analyst coverage on crash risk, emphasizing analyst optimism raised by Mola and Guidolin (2009). Thus, we find the pressure from analyst coverage as the primary channel to explain the negative association between RPE and crash risk in Subsection 4.5. We demonstrate that the RPE-crash risk relation mainly manifests in firms with higher managerial myopia correctability in Subsection 4.4. The evidence points to a

coherent explanation. Given that analyst forecasts can generate market pressure on managers, postulating that optimistic analyst forecasts with higher stock price or EPS targets lead to excessive pressure and a higher probability of bad news hoarding is reasonable. Thus, we refine our focus of attention from analyst coverage to analyst forecasting bias, that is, analyst optimism.

The strand of literature regarding analyst coverage finds that analysts can indeed offer optimistic recommendations and forecasts. Analyst optimism has several possible causes. Typically, Beyer, and Guttman (2011), Cowen et al. (2006), Hayes (1998), and Jackson (2005) document that optimistic analyst forecasts can generate excess trades and commissions for their brokerages. Meanwhile, Jackson (2005) shows that accurate analyst forecasts are associated with higher reputations. Therefore, analysts face a trade-off between trading commissions and reputations. They have incentives to give optimistic recommendations, especially when their inaccuracy is much harder to verify. We contend that improving information transparency can make subjective optimistic forecasts more easily identified, thus lessening analyst optimism. We examine the association between RPE and analyst optimism and expect to reduce analyst optimism for RPE firms.

Table 3.10 shows the test results. We find the negative association between RPE and analyst optimism to be statistically significant for all three measures, as reported in three columns. The results confirm our prediction that RPE decreases the analyst optimism.

Table 3.10 Analyst Optimism

This table presents the association between *RPE* and measures of analyst optimism for a sample of U.S. listed firms from 2006–2017. We follow Chang & Choi (2017), Gu & Wu (2003), and Xu et al. (2013) to conduct three measures of analyst optimism. *Bias* is the average analyst forecast error calculated as the consensus analyst's forecast EPS minus the actual EPS scaled by the firm's stock price each year. *OptNumber* is the logarithm of the number of optimistic analysts following the firm, with optimal analysts having positive forecast bias. *OptPercent* is the number of optimistic analysts divided by total analysts following the firm. The detailed definitions of other variables are presented in Table 3.A.1. All regressions include the industry and year fixed effects. The robust *t*-statistics clustered by the firm are reported in parentheses. ***, **, and * denote the significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)
	Bias	OptNumber	OptPercent
RPE	-0.022**	-0.191***	-0.085***
	(-1.99)	(-8.83)	(-8.81)
SIZE	0.001	0.052***	0.018***
	(0.32)	(7.75)	(6.00)
FIRMAGE	-0.000	0.000	0.000
	(-0.19)	(0.34)	(0.60)
LEV	0.039***	-0.082**	-0.030*
	(2.84)	(-2.38)	(-1.90)
MTB	-0.001	0.006***	0.003***
	(-0.93)	(4.15)	(3.60)
ROA	-0.039***	-0.021	-0.017
	(-4.29)	(-0.72)	(-1.22)
OPAQUE	-0.005	-0.048***	-0.022**
	(-0.80)	(-2.58)	(-2.47)
DTURN	-0.006	-0.058*	-0.038**
	(-0.36)	(-1.66)	(-2.20)
RET	4.638	24.105***	11.573***
	(1.59)	(5.12)	(5.25)
SIGMA	0.695*	2.047***	1.052***
	(1.94)	(3.83)	(4.16)
CEOAGE	-0.000	0.000	-0.000
	(-1.40)	(0.48)	(-1.09)
CEOFEMALE	0.017	-0.042	-0.020
	(0.59)	(-0.90)	(-0.95)
TENURE	-0.000	0.004**	0.001**
	(-1.23)	(2.48)	(2.26)
CHAIR	0.011	-0.046**	-0.016
	(1.37)	(-2.16)	(-1.57)
BOARDSIZE	0.002	0.006	0.002
	(0.96)	(1.62)	(1.36)
BOARDINDEP	-0.009	0.145***	0.058***
	(-0.70)	(3.37)	(2.90)
NCSKEW	0.011*	0.064***	0.028***
	(1.92)	(13.40)	(12.14)
Industry FE	Y	Y	Y
Year FE	Y	Y	Y
Observations	22,776	22,776	22,776
Number of Firms	3880	3880	3880
Adjusted R^2	0.00	0.08	0.06

3.6 Conclusions

This study examines the role of RPE on stock price crash risk. We use a sample of 22,776 US-listed firms from 2006 to 2017 and find that RPE firms exhibit lower levels of stock price crash risk. To address the endogeneity problem that the systematic differences among firms led by executives with RPE and non-RPE could drive baseline regression results, we provide additional evidence by conducting endogenous treatment model estimation and the PSM regression technique. Our baseline findings remain robust to using alternative crash risk measures, sampling criteria, and alternative model specifications.

Next, we find that the coefficient on RPE is only statistically significant when market-based performance metrics are used, larger (by about 257%) in magnitude than the coefficient when accounting-based metrics are used. We also find the coefficient on RPE is only statistically significant when benchmarks of self-selected peer groups are used, larger (by about 48%) in magnitude than the coefficient when index benchmarks are used. Furthermore, we study the heterogeneity and find a stronger decreasing effect of RPE on crash risk in firms with higher managerial ability, systematic uncertainty, industry competition, and managerial myopia correctability. We further compare the industry tournament and market pressure channels and demonstrate that the latter is primary. Finally, we find that RPE improves the information disclosure quality and lessens analysts' optimism.

Overall, the noisy signal of systematic factors impairs the optimality of compensation contracts (Holmstrom, 1979, 1982). The managerial myopia and private information manipulation derived from the preservation of systematic risk in compensation structure aggravate the stock price crash risk. RPE removes systematic factors and reduces agency costs by improving information symmetry between principals and agents. The findings have important implications for our understanding of optimal contracting, corporate disclosing, and asset pricing.

Appendix

Table 3.A.1 Variable Names and Definitions

ACCOUNTING	*A dummy variable that equals one if the firm utilizes an accounting-based metric, and zero otherwise, as recorded in ISS.*
ANA	*The analyst coverage which is calculated as the logarithm of the number of analysts following the firm during each fiscal year, as in He and Tian (2013).*
Bias	*The average analyst forecast error calculated as the consensus analyst's forecast EPS minus the actual EPS scaled by the firm's stock price each year.*
BOARDINDEP	*The board independence that calculated as the proportion of independent board members*
BOARDSIZE	*The firm's number of board members.*
Career Horizon	*The CEO's career horizon that proxy for managerial myopia correctability, which is calculated as the industry average CEO tenure and age minus the firm's current CEO tenure and age, following Antia, Pantzalis, & Park (2010) and Lee, Park, & Folta (2018). A higher value of Career Horizon indicates a longer expected career horizon and higher probability of managerial myopia correctability.*
CEOAGE	*The natural logarithm of the CEO's age, as recorded in the Compustat Execucomp.*
CEOFEMALE	*A dummy variable that equals one if the CEO is female and zero otherwise, as recorded in the Compustat Execucomp.*
CHAIR	*A dummy variable that equals one if the CEO is also the chairman of the board.*
COUNT	*The number of crashes minus the number of jumps over the fiscal year; a crash (jump) occurs when the firm-specific weekly return is 3.09 standard deviations below (above) its mean over the fiscal year, following Chowdhury et al. (2020) and Hutton et al. (2009).*
CRASH	*A dummy variable that is equal to one if there is at least one crash over the fiscal year and zero otherwise. A crash occurs when the firm-specific weekly return is 3.09 standard deviations below its mean over the fiscal year, following Chowdhury et al. (2020) and Hutton et al. (2009).*
CScore	*The accounting conservatism representing for high information disclosure quality, following Basu (1997).*
DTURN	*The change in turnover rate, where the turnover rate is calculated as the average ratio of the monthly turnover over the monthly trading volume over a fiscal year.*
DUVOL	*The down-to-up volatility that is calculated as the log of the ratio of the standard deviation on negative firm-specific return weeks to the positive weeks, following*

	Kim, Li, and Zhang (2011a, 2011b). DUVOL captures asymmetric volatilities between down weeks and up weeks.
EarnAgg	*The earning aggressiveness representing low information disclosure quality, following Bhattacharya et al. (2003).*
FIRMAGE	*The number of years after a firm' IPO date.*
ITI	*The industry tournament incentives calculated as the logarithm of the difference between the total compensation (TDC1) of the second-highest-paid CEO in the same size-adjusted three-digit industry group and the total compensation of a firm's CEO, following Chowdhury et al. (2020), Coles et al. (2018) and Kubick & Lockhart (2020).*
INDEX	*A dummy variable that equals one if the firm utilizes relative benchmark of traditional market or industry indices for all RPE grants, and zero otherwise.*
Industry HHI	*The Herfindahl-Hirschman index, which is also known as the concentration index.*
Institutional Shares	*The firms' proportion of shares held by institutions.*
LEV	*The book value of all liabilities scaled by total assets.*
LTIP	*A dummy variable that equals one if the firm has long-term incentive plans disclosed in the proxy statement and zero otherwise. The long-term incentive plans usually take forms of stock options, time-vested deferred units, performance-contingent deferred units, etc. They are evaluated over longer periods (such as a three-year vesting schedule and a ten-year term) relative to common types of compensation based on the annual business results (base salary, performance award and cash bonus plans, approved cash performance awards, etc.).*
MAScore	*The score to measure managerial ability using a data envelopment analysis, following Demerjian et al. (2012). They use the data envelopment analysis methodology to construct a measure of firm efficiency on converting company inputs (labor, capital, etc.) into revenue as the proxy for managerial ability.*
MTB	*The market capitalization over the book value of equity.*
NCA.INDEX	*The opposite value of the 2009 NCA enforceability index as in Starr (2019), with the minus sign brings the convention that a high value of NCA.INDEX indicates a lower enforceability of NCA similar to the previous two measurements.*
NCSKEW	*The negative conditional skewness of firm-specific weekly returns.*
NEG.SHOCK	*A dummy variable with the value of one if firms are headquartered in Montana from 2012-2017, otherwise zero.*
OPAQUE	*The moving sum of the previous three years' absolute value of discretionary accruals.*
OptNumber	*The logarithm of the number of optimistic analysts following the firm for each year. An analyst is defined as an optimistic analyst if the forecast bias is positive.*

OptPercent	*The number of optimistic analysts divided by total analysts following the firm. An analyst is defined as an optimistic analyst if the forecast bias is positive.*
PEER	*A dummy variable that equals one if the firm utilizes relative benchmark of self-selected peers for at least one RPE grant, and zero otherwise, as recorded in ISS.*
PeerAdjROA	*The conventional ROA measure of managerial ability adjusted by self-selected peers, which is calculated as the difference between a firm's ROA and the average ROA of its relative peer firms.*
PEERPROP	*The propensity of using self-selected peers as the relative benchmark. PEERPROP measures the firms' trade-off between peer group benchmark and index benchmark. For each year, a firm's PEERPROP is the number of grants of which the performance is evaluated based on self-selected peers divided by the total number of grants based on all types of relative benchmarks. The benchmark of relative performance evaluation for each grant is disclosed in the proxy statement, as recorded in the ISS.*
RET	*The average firm-specific weekly return over the fiscal year.*
ROA	*The firm's net income scaled by total assets.*
RPE	*A dummy variable that is equal to one if the firm claims utilization of relative performance evaluation in the proxy statement.*
SIGMA	*The standard deviation of the firm-specific weekly return over the fiscal year.*
SIZE	*The natural logarithm of the acquirer's total asset.*
STOCKPRICE	*A dummy variable that equals one if the firm utilizes a metric type of stock price, and zero otherwise, as recorded in ISS.*
Synch	*The stock return synchronicity. High synchronicity represents low firm-specific information and low information disclosure quality, following Chan & Hameed (2006) and Morck et al. (2000).*
TENURE	*The natural logarithm of the CEO's past tenure, which calculated as the number of years since she or he becomes CEO.*
UNENFORCED	*A dummy variable with the value of one if firms are headquartered in North Dakota, otherwise zero.*

Table 3.A.2 Alternative Crash Risk Measures

This table presents the association between *RPE* and alternative measures of crash risk for a sample of U.S. listed firms from 2006–2017. *DUVOL* is the down-to-up volatility calculated as the log of the ratio of the standard deviation of firm-specific weekly returns on down weeks to that on up weeks. *CRASH* is a dummy variable equal to one if there is at least one crash over the fiscal year and zero otherwise. *COUNT* is the number of crashes minus the number of jumps over the fiscal year. A crash (jump) occurs when the firm-specific weekly return is 3.09 standard deviations below (above) its mean over the fiscal year. The detailed definitions of other variables are presented in Table 3.A.1. All regressions include the lagged *NCSKEW*, industry and year fixed effects. The robust *t*-statistics clustered by the firm are reported in parentheses. ***, **, and * denote the significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)
	DUVOL	CRASH	COUNT
RPE	-0.079***	-0.035***	-0.068***
	(-6.66)	(-3.82)	(-4.70)
SIZE	0.040***	0.017***	0.040***
	(10.14)	(5.85)	(8.53)
FIRMAGE	-0.001	0.000	-0.000
	(-1.15)	(0.88)	(-0.04)
LEV	-0.065***	0.002	-0.073***
	(-3.01)	(0.10)	(-2.87)
MTB	0.003***	-0.001	0.002*
	(2.60)	(-1.33)	(1.84)
ROA	0.059***	-0.002	0.094***
	(2.74)	(-0.10)	(3.81)
OPAQUE	-0.001	0.002	-0.000
	(-0.05)	(0.18)	(-0.03)
DTURN	0.116***	0.069**	0.144***
	(3.11)	(2.49)	(3.24)
RET	-7.637	1.058	-0.100
	(-1.52)	(0.40)	(-0.02)
SIGMA	-0.528	-0.236	-0.660
	(-1.10)	(-0.83)	(-1.44)
CEOAGE	-0.001**	-0.000	-0.001**
	(-2.55)	(-1.53)	(-2.02)
CEOFEMALE	0.028	0.041**	0.044
	(1.07)	(2.13)	(1.46)
TENURE	0.001	0.000	0.001
	(0.78)	(0.21)	(0.79)
CHAIR	-0.034**	0.007	-0.003
	(-2.23)	(0.50)	(-0.12)
BOARDSIZE	-0.001	-0.006***	-0.002
	(-0.61)	(-3.37)	(-0.92)
BOARDINDEP	0.064**	0.070***	0.094***
	(2.56)	(3.63)	(3.03)
NCSKEW	0.018***	0.010***	0.010*
	(3.89)	(2.81)	(1.75)
Industry FE	Y	Y	Y
Year FE	Y	Y	Y
Observations	22,776	22,776	22,776
Number of Firms	3880	3880	3880
Adjusted R^2	0.05	0.03	0.03

Table 3.A.3 RPE Propensity and Crash Risk

This table presents the association between *RPEPROP* and stock price crash risk. The main explanatory variable *RPEPROP* measures firms' propensity of using RPE in grants. For each year, a firm's *RPEPROP* is the number of grants based on relative benchmarks scaled by the total number of grants. Thus, *RPEPROP* measures the firms' propensity of using RPE relative to APE. The benchmark of performance evaluation for each grant is disclosed in the proxy statement. The detailed definitions of other variables are presented in Table 3.A.1. All regressions include the industry and year fixed effects. The robust t-statistics clustered by the firm are reported in parentheses. ***, **, and * denote the significance at the 1%, 5%, and 10% levels, respectively

	(1)	(2)	(3)
	NCSKEW	NCSKEW	NCSKEW
RPEPROP	-0.138***	-0.139***	-0.137***
	(-6.06)	(-6.65)	(-6.50)
SIZE	0.065***	0.054***	0.060***
	(11.41)	(7.07)	(7.79)
FIRMAGE	-0.000	-0.000	-0.001
	(-0.47)	(-0.46)	(-0.61)
LEV	-0.145***	-0.112***	-0.121***
	(-4.23)	(-3.01)	(-3.27)
MTB	0.004**	0.004**	0.004**
	(2.55)	(2.48)	(2.49)
ROA		0.078**	0.084**
		(2.12)	(2.29)
OPAQUE		-0.000	0.000
		(-0.01)	(0.01)
DTURN		0.218***	0.226***
		(3.57)	(3.69)
RET		-14.085	-14.291
		(-1.16)	(-1.16)
SIGMA		-1.835	-1.833
		(-1.37)	(-1.35)
CEOAGE			-0.001***
			(-2.61)
CEOFEMALE			0.052
			(1.20)
TENURE			0.001
			(0.99)
CHAIR			-0.035
			(-1.49)
BOARDSIZE			-0.002
			(-0.69)
BOARDINDEP			0.129***
			(3.14)
SKEWALL	0.031***	0.034***	0.033***
	(3.79)	(3.83)	(3.74)
Industry FE	Y	Y	Y
Year FE	Y	Y	Y
Observations	22,776	22,776	22,776
Number of Firms	3880	3880	3880
Adjusted R^2	0.04	0.04	0.04

Table 3.A.4 Control for Overall Skewness

This table presents the association between *RPE* and stock price crash risk for a sample of U.S. listed firms from 2006–2017. The dependent variable is *NCSKEW* in year *t*+1. *NCSKEW* is the negative conditional skewness of firm-specific weekly returns. *SKEWALL* is the full-sample skewness of firms over the entire sample. *SKEWROLL* is the backward-looking skewness of firms over the previous years. The detailed definitions of other variables are presented in Table 3.A.1. All regressions include the industry and year fixed effects. The robust *t*-statistics clustered by the firm are reported in parentheses. ***, **, and * denote the significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Control for full sample skewness			
	(1)	(2)	(3)
	NCSKEW	NCSKEW	NCSKEW
RPE	-0.045***	-0.045***	-0.042***
	(-7.03)	(-6.77)	(-6.25)
SIZE	0.019***	0.006**	0.014***
	(10.44)	(2.29)	(4.66)
FIRMAGE	0.000	-0.000	0.000
	(0.51)	(-0.05)	(0.83)
LEV	-0.080***	-0.038*	-0.045**
	(-3.95)	(-1.79)	(-2.07)
MTB	0.000	-0.000	0.000
	(0.20)	(-0.03)	(0.11)
ROA		0.071***	0.072***
		(3.26)	(3.24)
OPAQUE		0.013	0.013
		(0.80)	(0.84)
DTURN		0.139**	0.139**
		(2.51)	(2.51)
RET		-13.504**	-14.718***
		(-2.55)	(-2.75)
SIGMA		-2.118***	-2.291***
		(-3.83)	(-4.07)
CEOAGE			-0.001***
			(-8.40)
CEOFEMALE			0.014
			(0.54)
TENURE			0.001**
			(1.99)
CHAIR			0.003
			(0.14)
BOARDSIZE			-0.003*
			(-1.72)
BOARDINDEP			0.035*
			(1.95)
SKEWALL	0.981***	0.983***	0.983***
	(474.32)	(367.67)	(349.67)
Industry FE	Y	Y	Y
Year FE	Y	Y	Y
Observations	22,776	22,776	22,776
Number of Firms	3880	3880	3880
Adjusted R^2	0.23	0.23	0.23

Panel B: Control for backward-looking skewness			
	(1)	(2)	(3)
	NCSKEW	NCSKEW	NCSKEW
RPE	-0.032**	-0.035**	-0.033**
	(-2.18)	(-2.40)	(-2.24)
SIZE	0.010***	-0.004	-0.002
	(2.79)	(-0.94)	(-0.45)
FIRMAGE	0.000	0.000	0.000
	(0.59)	(0.48)	(0.50)
LEV	-0.087***	-0.042	-0.042
	(-3.29)	(-1.53)	(-1.50)
MTB	0.005***	0.004***	0.004***
	(3.94)	(3.50)	(3.49)
ROA		0.053**	0.053*
		(2.00)	(1.96)
OPAQUE		0.044**	0.044**
		(2.51)	(2.54)
DTURN		0.161***	0.161***
		(3.53)	(3.49)
RET		-21.830***	-22.207***
		(-3.86)	(-3.93)
SIGMA		-3.167***	-3.224***
		(-5.02)	(-5.10)
CEOAGE			-0.000*
			(-1.69)
CEOFEMALE			-0.015
			(-0.34)
TENURE			0.002*
			(1.72)
CHAIR			0.008
			(0.57)
BOARDSIZE			-0.000
			(-0.13)
BOARDINDEP			0.000
			(0.01)
SKEWROLL	1.065***	1.068***	1.068***
	(120.08)	(117.29)	(117.65)
Industry FE	Y	Y	Y
Year FE	Y	Y	Y
Observations	22,776	22,776	22,776
Number of Firms	3880	3880	3880
Adjusted R^2	0.42	0.42	0.42

Table 3.A.5 Sampling Criteria

This table presents the association between *RPE* and stock price crash risk for a sample of U.S. listed firms from 2009–2017, with samples in 2006, 2007, and 2008 excluded. The dependent variable is *NCSKEW* in year *t*+1. *NCSKEW* is the negative conditional skewness of firm-specific weekly returns. The main explanatory variable *RPE* is a dummy variable equal to one if the firm claims utilization of relative performance evaluation in the proxy statement and zero otherwise. The detailed definitions of other variables are presented in Table 3.A.1. All regressions include the lagged *NCSKEW*, industry and year fixed effects. The robust *t*-statistics clustered by the firm are reported in parentheses. ***, **, and * denote the significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)
	NCSKEW	NCSKEW	NCSKEW
RPE	-0.144***	-0.143***	-0.144***
	(-6.16)	(-6.19)	(-6.20)
SIZE	0.072***	0.064***	0.068***
	(11.82)	(8.12)	(8.21)
FIRMAGE	-0.000	-0.000	-0.001
	(-0.46)	(-0.45)	(-0.65)
LEV	-0.154***	-0.130***	-0.138***
	(-3.85)	(-3.02)	(-3.20)
MTB	0.005***	0.005***	0.005***
	(2.83)	(2.77)	(2.74)
ROA		0.070	0.078*
		(1.52)	(1.68)
OPAQUE		0.014	0.014
		(0.54)	(0.53)
DTURN		0.213***	0.215***
		(2.83)	(2.87)
RET		-14.322	-14.488
		(-1.10)	(-1.10)
SIGMA		-1.675	-1.644
		(-1.18)	(-1.13)
CEOAGE			-0.001*
			(-1.83)
CEOFEMALE			0.028
			(0.55)
TENURE			0.001
			(0.82)
CHAIR			0.120
			(1.33)
BOARDSIZE			-0.002
			(-0.35)
BOARDINDEP			0.122**
			(2.48)
NCSKEW	0.033***	0.035***	0.034***
	(3.50)	(3.51)	(3.43)
Industry FE	Y	Y	Y
Year FE	Y	Y	Y
Observations	17,310	17,310	17,310
Number of Firms	3446	3446	3446
Adjusted R^2	0.03	0.03	0.03

Table 3.A.6 Alternative Model Specifications

This table reports the association between *RPE* and *NCSKEW*, replacing 3-digit SIC with 4-digit SIC, FF48, and Industry-Year fixed effect. FF48 denotes Fama-French 48 industries. Industry-Year FE denotes the fixed effect of interaction between year and FF48. The detailed definitions of variables are presented in Table 3.A.1. All regressions include the lagged *NCSKEW*, industry and year fixed effects. The robust *t*-statistics clustered by the firm are reported in parentheses. ***, **, and * denote the significance at the 1%, 5%, and 10% levels, respectively.

	(1) 4-digit SIC	(2) FF48	(3) Industry-Year FE
RPE	-0.138***	-0.124***	-0.121***
	(-7.13)	(-6.54)	(-6.36)
SIZE	0.066***	0.060***	0.060***
	(9.66)	(9.60)	(9.47)
FIRMAGE	-0.001	-0.001	-0.001
	(-0.76)	(-0.85)	(-0.65)
LEV	-0.100***	-0.144***	-0.144***
	(-2.72)	(-4.08)	(-4.03)
MTB	0.003**	0.004**	0.004**
	(2.05)	(2.53)	(2.39)
ROA	0.086**	0.091**	0.081**
	(2.36)	(2.50)	(2.19)
OPAQUE	0.004	-0.016	-0.022
	(0.19)	(-0.76)	(-0.93)
DTURN	0.222***	0.214***	0.250***
	(3.68)	(3.55)	(4.06)
RET	-10.312	-0.984	0.883
	(-1.05)	(-0.11)	(0.10)
SIGMA	-1.515	-0.404	-0.183
	(-1.43)	(-0.46)	(-0.20)
CEOAGE	-0.001***	-0.001*	-0.001
	(-2.83)	(-1.66)	(-1.43)
CEOFEMALE	0.043	0.054	0.056
	(0.96)	(1.25)	(1.26)
TENURE	0.001	0.001	0.001
	(1.05)	(1.00)	(0.99)
CHAIR	-0.038	-0.043*	-0.044*
	(-1.60)	(-1.84)	(-1.83)
BOARDSIZE	-0.004	-0.002	-0.002
	(-1.13)	(-0.64)	(-0.45)
BOARDINDEP	0.155***	0.140***	0.148***
	(3.72)	(3.44)	(3.64)
NCSKEW	0.026***	0.037***	0.038***
	(3.15)	(4.71)	(4.64)
Industry FE	Y	Y	N
Year FE	Y	Y	Y
Industry-Year FE	N	N	Y
Observations	22,772	22,534	22,532
Number of Firms	3,876	3,833	3,833
Adjusted R^2	0.05	0.04	0.05

Table 3.A.7 Peer Propensity of Relative Benchmark and Stock Price Crash Risk

This table presents the association between *PEERPROP* and stock price crash risk for firms using relative performance evaluation. The dependent variables are crash risk measures in year *t*+1. The main explanatory variable *PEERPROP* measures firms' trade-off between self-selected peers benchmark and traditional indices benchmark. For each year, a firm's *PEERPROP* is the number of grants of which the performance is evaluated based on self-selected peers divided by the total number of grants based on all types of relative benchmarks. Therefore, a higher value of *PEERPROP* indicates more weight on the use of self-selected peer group benchmarks. The benchmark of relative performance evaluation for each grant is disclosed in the proxy statement. The detailed definitions of other variables are presented in Table 3.A.1. All regressions include the lagged *NCSKEW*, industry and year fixed effects. The robust *t*-statistics clustered by the firm are reported in parentheses. ***, **, and * denote the significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)
	NCSKEW	DUVOL	CRASH	COUNT
PEERPROP	-0.066***	-0.055***	-0.046***	-0.037**
	(-2.80)	(-3.71)	(-3.67)	(-1.98)
SIZE	0.045***	0.030***	0.013***	0.031***
	(6.73)	(8.50)	(5.10)	(7.44)
FIRMAGE	-0.001	-0.001	0.000	-0.000
	(-1.12)	(-1.59)	(0.58)	(-0.32)
LEV	-0.109***	-0.060***	0.004	-0.068***
	(-2.98)	(-2.79)	(0.23)	(-2.70)
MTB	0.003	0.002*	-0.001*	0.001
	(1.56)	(1.84)	(-1.80)	(1.27)
ROA	0.094***	0.065***	0.000	0.099***
	(2.58)	(3.05)	(0.01)	(4.06)
OPAQUE	-0.003	-0.001	0.002	-0.001
	(-0.13)	(-0.11)	(0.16)	(-0.07)
DTURN	0.224***	0.116***	0.069**	0.145***
	(3.66)	(3.13)	(2.49)	(3.26)
RET	-11.063	-6.007	1.629	1.376
	(-0.92)	(-1.19)	(0.62)	(0.32)
SIGMA	-1.507	-0.371	-0.185	-0.516
	(-1.13)	(-0.77)	(-0.65)	(-1.13)
CEOAGE	-0.001***	-0.001***	-0.000	-0.001**
	(-2.83)	(-2.81)	(-1.61)	(-2.22)
CEOFEMALE	0.058	0.031	0.042**	0.046
	(1.35)	(1.16)	(2.23)	(1.53)
TENURE	0.001	0.001	0.000	0.001
	(1.00)	(1.01)	(0.26)	(0.98)
CHAIR	-0.042*	-0.037**	0.006	-0.005
	(-1.75)	(-2.41)	(0.42)	(-0.24)
BOARDSIZE	-0.004	-0.002	-0.006***	-0.003
	(-1.01)	(-0.72)	(-3.43)	(-1.01)
BOARDINDEP	0.134***	0.064**	0.072***	0.094***
	(3.22)	(2.57)	(3.71)	(3.02)
NCSKEW	0.034***	0.019***	0.010***	0.010*
	(3.94)	(4.04)	(2.86)	(1.85)
Industry FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Observations	22,776	22,776	22,776	22,776
Number of Firms	3880	3880	3880	3880
Adjusted R^2	0.04	0.05	0.03	0.03

Table 3.A.8 Long-term Incentive Plans and Stock Price Crash Risk

This table presents the similar effects of *RPE* and *LTIP* on stock price crash risk for a sample of U.S. listed firms from 2006–2017. The dependent variable is *NCSKEW* in year *t*+1. *RPE* is a dummy variable that equals one if the firm claims utilization of relative performance evaluation in the proxy statement and zero otherwise. *LTIP* is a dummy variable that equals one if the firm has long-term incentive plans disclosed in the proxy statement and zero otherwise. *LTRPE* is a dummy variable that equals one if the RPE firm has long-term incentive plans disclosed in the proxy statement and zero otherwise. *STRPE* is a dummy variable that equals one if the RPE firm has no long-term incentive plans disclosed in the proxy statement and zero otherwise. The detailed definitions of other variables are presented in Table 3.A.1. All regressions include the lagged *NCSKEW*, industry and year fixed effects. The robust *t*-statistics clustered by the firm are reported in parentheses. ***, **, and * denote the significance at the 1%, 5%, and 10% levels, respectively.

	(1) NCSKEW	(2) NCSKEW	(3) NCSKEW	(4) NCSKEW
RPE	-0.132***		-0.101***	
	(-6.80)		(-4.37)	
LTIP		-0.108***	-0.055**	
		(-5.81)	(-2.51)	
LTRPE				-0.141***
				(-6.67)
STRPE				-0.116***
				(-4.72)
SIZE	0.063***	0.054***	0.064***	0.063***
	(8.45)	(7.50)	(8.49)	(8.44)
FIRMAGE	-0.001	-0.001	-0.001	-0.001
	(-0.73)	(-0.82)	(-0.69)	(-0.74)
LEV	-0.118***	-0.115***	-0.119***	-0.118***
	(-3.21)	(-3.13)	(-3.23)	(-3.21)
MTB	0.004**	0.003**	0.004**	0.004**
	(2.31)	(2.11)	(2.42)	(2.33)
ROA	0.082**	0.088**	0.081**	0.082**
	(2.25)	(2.40)	(2.21)	(2.25)
OPAQUE	-0.002	-0.000	-0.001	-0.001
	(-0.08)	(-0.01)	(-0.02)	(-0.06)
DTURN	0.222***	0.229***	0.225***	0.223***
	(3.63)	(3.74)	(3.68)	(3.65)
RET	-13.979	-13.048	-14.447	-14.081
	(-1.16)	(-1.07)	(-1.19)	(-1.16)
SIGMA	-1.793	-1.716	-1.849	-1.806
	(-1.35)	(-1.28)	(-1.38)	(-1.35)
CEOAGE	-0.001**	-0.001***	-0.001**	-0.001**
	(-2.54)	(-2.74)	(-2.53)	(-2.55)
CEOFEMALE	0.054	0.049	0.050	0.053
	(1.25)	(1.14)	(1.18)	(1.23)
TENURE	0.001	0.001	0.001	0.001
	(0.74)	(0.93)	(0.73)	(0.73)
CHAIR	-0.037	-0.034	-0.034	-0.036
	(-1.55)	(-1.45)	(-1.43)	(-1.51)
BOARDSIZE	-0.003	-0.003	-0.003	-0.003
	(-0.87)	(-0.72)	(-0.75)	(-0.83)
BOARDINDEP	0.134***	0.132***	0.134***	0.135***
	(3.25)	(3.19)	(3.25)	(3.27)
NCSKEW	0.033***	0.034***	0.033***	0.033***
	(3.80)	(3.80)	(3.75)	(3.79)
Industry FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Observations	22,776	22,776	22,776	22,776
Number of Firms	3880	3880	3880	3880
Adjusted R^2	0.04	0.04	0.04	0.04

Chapter 4

Relative performance evaluation and long-term acquisition performance

4.1 Introduction

A large literature documents the drivers of acquisition performance (e.g., Raghavendra Rau and Vermaelen, 1998; Mitchell and Stafford, 2000; Fu, Lin, and Officer, 2013; Ma et al., 2019; Hasan et al., 2020). However, despite its growing importance in agency theory, the role of executive performance evaluation in acquisition performance is not systematically studied. We focus on the effect of relative performance evaluation (RPE) utilization on long-term acquisition performance. As Gibbons and Murphy (1990) summarized, RPE could protect executive compensation from the market and industry shocks that also affect their peer firms. According to contract theory based on risk-sharing, eliminating common uncertainty beyond managers' control can help reduce agency costs and benefit shareholders (Holmstrom, 1979, 1982). Thus, during the last decades, the consensus is that RPE is beneficial for evaluating managers' performance and as a tool for constructing their compensation (Holmstrom, 1979, 1982; Antle and Smith, 1985, 1986; Gibbons and Murphy, 1990; Janakiraman, Lambert, and Larcker, 1992). To the best of our knowledge, this study is the first to demonstrate the effect of RPE in

firm policies on acquisition performance.

Previous studies test for the presence of RPE in compensation contracts (Aggarwal & Samwick, 1999b; Antle & Smith, 1986; Barro & Barro, 1990; Garen, 1994; Gibbons & Murphy, 1990; Janakiraman et al., 1992). Since 2006, due to changes in regulation, firms have been forced to disclose detailed information about compensation in their proxy statements. Thus, data availability allows direct observation of the listed firms' utilization of RPE. In recent years, the number of firms claiming RPE utilization has rapidly increased, with the relevant interest of academia arising. Bakke, Mahmudi, and Newton (2020) demonstrate that the proportion of RPE firms in the S&P 500 increased from 17% to 34% between 2006 and 2012. We obtain the acquisition data in the U.S. from 2006 to 2017 and confirm that the proportion of RPE acquirers has increased during the past few years.

Previous work indicates that RPE disclosure in firms' proxy statements serves as a good proxy for RPE use in practice. Black, Dikolli, and Hofmann (2012) dispel the concern that RPE disclosure does not necessarily tie to a real utilization. They demonstrate that firms' RPE utilization aligns with their RPE disclosure in the proxy statements. Additionally, Gong et al. (2011) provide evidence of real RPE utilization in firms incorporating explicit RPE contract details rather than firms without those details.

We postulate that RPE improves long-term acquisition performance by introducing a more informative compensation evaluation, accompanied by

additional benefits from suppressing the agency problem of managerial myopia. Specifically, managers tend to make myopic decisions to achieve short-run benefits at the expense of the long-run interests of shareholders (Flammer & Bansal, 2017; Laverty, 1996; Marginson & McAulay, 2008; Narayanan, 1985; Porter, 1992; Shleifer & Vishny, 1990; Stein, 1988, 1989). The myopia problem is driven by a labor market consideration of managers to seek increases in their total expected incomes, despiting the infringement of shareholders' interests (Nagar, 1999; Narayanan, 1985, 1987). Holmstrom (1979, 1982) develops a moral hazard model and derives RPE as a more informative way to document optimal incentive contracts. Thus, agents rely less on short-term results to convince the labor market about their productive inputs (Narayanan, 1985). In contrast, RPE motivates managers to reduce their manipulation behaviors of information and time distribution of returns to protect their reputation (Kasznik & Lev, 1995; Kothari et al., 2009; Skinner, 1994). We discuss the theoretical channel in detail in the next section.

We find empirical evidence that RPE increases long-term acquisition performance. RPE utilization encourages 3.6% (6.8%) increase for 1-year (3-year) abnormal return of acquirers on average. The finding remains robust to using an endogenous treatment model estimation, PSM regression technique, alternative measures of long-term performance, sampling criteria, and alternative model specifications. The decomposition of RPE identifies that the results are mainly driven by performance benchmarks of self-selected peer groups instead of the

market and industry indices. In terms of heterogeneity, the effect of RPE on long-term acquisition performance is more pronounced in firms with higher market uncertainty, higher managerial myopia correctability, and lower external monitoring. Finally, we show that RPE is associated with lower short-term acquisition returns, confirming the short-term outperformance and long-term reversal of non-RPE firms due to managerial myopia. RPE is positively associated with the acquirer reference price ratio, indicating RPE firms mitigate agency problems through more active transaction timing.

Our study contributes to the literature in two ways. First, it relates to studies of agency problems and optimal contracts. Previous studies postulate that RPE can effectively control agency costs and benefit shareholders (Holmstrom, 1979; Antle and Smith, 1985, 1986; Gibbons and Murphy, 1990; Janakiraman, Lambert, and Larcker, 1992). We confirm the advantages of RPE in determining compensation contracts over non-RPE by demonstrating that RPE increases firms' acquisition performance. We emphasize that RPE insulates manager compensation from market uncertainty and controls the unnecessary systematic risk (i.e., the common fluctuation out of managers' control) to motivate favorable managerial factors, especially managerial long-termism.

Second, we contribute to the literature on long-term acquisition performance. Previous efforts to document the causes of long-term acquisition performance focus on stock valuation (Fu et al., 2013; Raghavendra Rau and Vermaelen, 1998),

acquirer reference prices (Ma et al., 2019), cash reserves (Harford, 1999b), etc. Moreover, Hasan et al. (2020) examine the association between labor and acquisition markets. Nevertheless, our focus is very different from theirs. Hasan et al. focus on within-firm tournament incentives by emphasizing the compensation gap between the CEO and other senior executives, despite the industry tournament incentives attracting more research attention (e.g., Chowdhury et al., 2020; Coles et al., 2018; Huang et al., 2019; Kubick & Lockhart, 2020). Our paper proposes another labor market-based factor as the cause of long-term acquisition performance, illustrating that RPE is an essential positive driver. We show that shareholders can benefit from the well-performed acquisitions undertaken by RPE managers.

The remainder of this paper is organized as follows. We review the literature and propose our testable hypotheses in Section 2. Section 3 shows the data and empirical models. In Section 4, we report the results and robustness checks. We further discuss two related interesting topics in Section 5. Finally, Section 6 concludes the paper.

4.2 Hypothesis Development

Academic researchers have highlighted the agency problem on acquisition performance. Jensen (1986), Lang, Stulz, & Walkling (1991), and Morck, Shleifer, & Vishny (1990) provide evidence that managers' acquisition choices are sometimes harmful to the interest of shareholders. Jensen (1986) discusses sub-optimal acquisition behaviors based on a free cash flow theory. That is, when companies

have excess funds after satisfying the needs of all net-present-value projects, managers tend to spend the excess cash on acquisitions instead of paying dividends to shareholders. The reinvestment behavior is because managers have strong incentives to grow firms beyond the optimal size to seek increasing power and compensation. Especially when firms have substantial free cash flows but few favorable investment opportunities, the cash will be spent on unprofitable projects that are beneficial to managers but harmful to shareholders. Lang, Stulz, & Walkling (1991) provide empirical evidence to support this hypothesis, using Tobin's q to measure the quality of investment opportunity. Morck, Shleifer, & Vishny (1990) document several types of bad acquisitions when acquirers overpay for targets. The evidence confirms the phenomenon of sub-optimal acquisitions that are profitable to the interest of managers but harmful to the interest of shareholders.

Agency problems are mostly derived from information asymmetry. Managers have more firm-specific information than shareholders and potential investors, i.e., information asymmetry exists. The asymmetrical information usually benefits the subjects with more information (Akerlof, 1970). Specifically, Myers and Majluf (1984) relate the information asymmetry and takeover market in theory and postulate that managers' behaviors can affect bidders' announcement returns (i.e., the interest of shareholders) due to their information advantages. For instance, the selection of common stock issuing to finance investment opportunities is more likely to incur negative returns than debt issuing, since investors recognize the stock

issuing as the managers' judgment on the overvaluation of bidder firms.

One important issue of conflicts between the interests of managers and shareholders is the managerial myopia problem, i.e., managers make decisions to achieve short-run benefits at the expense of the long-run interests of shareholders (Flammer & Bansal, 2017; Laverty, 1996; Marginson & McAulay, 2008; Narayanan, 1985; Porter, 1992; Shleifer & Vishny, 1990; Stein, 1988, 1989). Narayanan (1985, 1987) attributes the myopia problem to a labor market consideration that quick and positive returns facilitate the linkage between firms' good results and managers' investment decisions, which help prove their excellence to the labor market. The early increase of market perception about managers' ability benefits their total expected gains (see also Nagar, 1999). In particular, Campbell and Marino (1994) demonstrate that managers are able to take unpublic treatments to affect the temporal distribution of returns on company investments. Managers have a short-term orientation on selecting investment opportunities in order to show their high ability and become winners in the labor market, whereas the covered bad news and unfavorable private information are revealed in the long run. Thus, managers tend to undertake acquisitions with short-term positive returns that are value-destroying in the long run.

Fortunately, Mitchell & Lehn (1990) and Masulis et al. (2007) find that improving corporate governance can help mitigate the agency problem on takeover activities and increase the probability of undertaking value-enhance deals.

Specifically, Mitchell & Lehn (1990) find that the acquirers who take value-reducing deals are more likely to become subsequent targets. They regard this mechanism as a disciplinary role of acquisitions. Masulis et al. (2007) show antitakeover provisions can destruct the acquisition value. The results are robust after controlling for acquirers' other governance characteristics of CEO/Chairman duality, the board size, board independence, industry competitiveness, industry uniqueness, the percentage of equity-based compensation of CEOs, the shareholding of CEOs, and CEOs' wealth sensitivity to the stock price. While the studies discuss the mechanism based on corporate control, we focus on evaluating executive compensation performance.

Executive compensation design is a representative matter to reform corporate governance. One aspect of these efforts is to examine the effect of executive compensation structure on the firm performance (for example, Humphery-Jenner et al., 2016; Matolcsy & Wright, 2011; Mehran, 1995). The executive compensation structure is based on the trade-off between cash-based or equity-based compensation strategies. Meanwhile, we focus on how executive performance is evaluated (relatively or absolutely). The evaluation benchmark of RPE varies from absolute performance evaluation (APE, i.e., non-RPE). APE usually sets absolute values of either accounting metrics or stock price as the benchmarks to evaluate managers' performance during the assessment periods. RPE selects a group of comparable companies as the relative benchmarks, such as market indices, industrial indices, and groups of peer firms.

Holmstrom (1979, 1982) develops a moral hazard model to document optimal incentive contracts and derives RPE as a more informative method to evaluate managers' performance. The model claims that noisy signals carrying no information about agents' productive inputs should be excluded from the compensation contracts to achieve optimal informativeness. The systematic risk removed by RPE is a type of noisy signal out of managers' control, incurring unnecessary risk to managers. Hence, RPE is beneficial for aligning the interest between managers and shareholders, improving corporate governance, and controlling agency costs (Antle & Smith, 1985, 1986; Gibbons & Murphy, 1990; Holmstrom, 1979, 1982; Janakiraman et al., 1992). Specifically, RPE brings such a positive firm impact through mitigating the managerial myopia problem. As Narayanan (1985, 1987) stated, agents rely less on short-term results to convince the labor market when they have alternative ways to offer the information of productive inputs. In this case, RPE motivates managers to reduce their manipulation behavior of information and time distribution of returns to protect their reputation (Kasznik & Lev, 1995; Kothari et al., 2009; Skinner, 1994).

Based on our previous discussions, we expect our empirical results to be aligned with the risk-sharing predictions of Holmstrom (1979, 1982) that RPE is beneficial for evaluating executive performance by removing unnecessary systematic risk from agents' contracts. Specifically, our testable hypothesis is:

Relative performance evaluation is positively associated with the firms'

long-term acquisition performance.

4.3 Data and Methodology

4.3.1 Data

We download all acquisitions in the U.S. over the 2006-2017 period from the Thomson Reuters SDC Merger and Acquisitions Database. We exclude deals with the following criteria: i) deals undertaking the acquisition of assets; ii) deals undertaken by private acquirers; iii) buyback, repurchase, spinoff, split-off, divestiture, restructuring, self-tender, and recapitalization deals; iv) acquirers and targets belonging to the same parent firm. After merging with the acquirer's RPE data, our final sample consists of 6,811 M&A observations[26].

As required by the U.S. Securities and Exchange Commission (SEC), listed companies need to disclose detailed executive compensation information in their proxy statements. The statements are all available on SEC's official website. Institutional Shareholder Services (ISS) collects the proxy statements and produces standard datasets. Thus, we download our major data about RPE from ISS. Overall, there is over 20% observations disclosing RPE in the firm-year data of listed firms from 2006-2017 with over 60,000 observations in total. After merging with acquisition data, there is 6,811 observations in the sample. 34% in-the-sample firms use RPE, which percentage is available in Table 4.1 Panel A.

[26] The sample size of acquisitions is comparable to prior literature on acquisition performance using SDC. For example, Ma et al. (2019) include 19,119 U.S. acquisitions over the 1981-2014 period. We manually calculate the number of observations between 2006 and 2014, and find the total number is 4,449.

Additionally, we collect financial statement data from Compustat Funda, executive data from Compustat Execucomp, shareholding information from Thomson Reuters 13f Holdings, and stock returns from CRSP.

4.3.2 Measurements of Long-term Acquisition Performance

We follow Ma et al. (2019), Duchin and Schmidt (2013), Bouwman, Fuller, and Nain (2009), Mitchell and Stafford (2000), Lyon, Barber, and Tsai (1999), and Barber and Lyon (1997) to construct the conventional buy-and-hold abnormal return (*BHAR*) measure proxy for the long-term acquisition return. First, we use the reference portfolio approach to calculate the normal returns. We construct reference portfolios with the following process: i) each month, we sort all NYSE stocks into five quintiles based on market capitalization (the size factor); ii) for each size group, we sort the stocks into five quintiles based on the book-to-market ratio (the value factor) to get 25 size-value groups; iii) for each size-value group, we sort the stocks into five quintiles based on return over the past year (the momentum factor), and finally get 125 reference portfolios. The buy-and-hold returns of reference portfolios are calculated with equal-weighted returns as follows:

$$R_{pT} = \sum_{j=1}^{n_s} \frac{[\prod_{t=s}^{s+T}(1 + R_{jt})] - 1}{n_s} \quad (1)$$

where R_{pT} denotes the long-term buy-and-hold return of the reference portfolio *p* for *T* months after acquisition announcement month *s*, R_{jt} denotes the simple return of firm *j* at month *t*, n_s is the number of stocks of reference portfolio in month *s*.

Next, we adopt the average monthly return of each portfolio as the benchmark

for stocks listed on NYSE, Amex, and Nasdaq. For each month, every stock can be linked to a single reference portfolio based on market size, book-to-market ratio, and return over the past year. That is, the firm's each value of the three factors should fall into the corresponding range of the reference portfolio. We calculate the buy-and-hold abnormal return as the long-term buy-and-hold return of each acquirer less the long-term buy-and-hold return of its reference portfolio.

$$BHAR_{iT} = \prod_{t=s}^{s+T}(1 + R_{it}) - \prod_{t=s}^{s+T}(1 + R_{pT}) \quad (2)$$

where $BHAR_{iT}$ denotes the T-month buy-and-hold abnormal return for acquirer firm i, R_{it} is the simple return of firm i at month t, R_{pT} is the reference portfolio return as calculated in Equation (1), and T is the time-horizon in months over which BHAR are calculated. We use 12-month BHAR as the dependent variable in our baseline regressions.

We also provide the alternative measure of subsequent earnings announcement abnormal return (SEAR) proxy for the long-term acquisition performance in Table 4.A.2 to eliminate the concern of the bad-model problem (Fama, 1998). The calculation of BHAR is based on the expected (normal) returns. Specifically, we use the returns of our 125 reference portfolios as the expected returns for the stocks falling into the corresponding size-value-momentum group. The bad-model problem argues that all models for expected returns incompletely describe the common patterns of normal returns. The problem is serious in BHAR due to the accumulation of the measuring errors of normal returns over time. Fama (1998) indicates that the

event study methodology can mitigate the bad-model problem by focusing on short event horizons (typically a few days), thus limiting the measuring errors of expected returns. Studies develop the measure of SEAR to calculate the long-term stock performance using the event study methodology (e.g., Chopra et al., 1992; Jegadeesh and Titman, 1993; La Porta et al., 1997; Titman et al., 2004). Taking the subsequent earnings announcements after acquisition announcements as the underlying events, SEARs are equal to the short-window cumulative abnormal returns (CARs) around earnings announcements. Thus, we conduct robustness checks using the SEAR measure of long-term acquisition performance in Table 4.A.2.

4.3.3 Empirical Model

We conduct our baseline regression which examines the association between the RPE and acquisition performance with an OLS linear model with year and industry fixed effects:

$$BHAR_{iT} = \alpha + \beta RPE_{is} + \gamma X_{is} + \theta_s + \mu_d + \varepsilon_{iT}, \qquad (3)$$

where $BHAR_{iT}$ denotes the T-month buy-and-hold abnormal return of firm i, and T is 12 months in our baseline results. RPE_{is} is a dummy variable that equals one if the firm i claims the utilization of relative performance evaluation in the acquisition announcement month s. In further analyses, we replace RPE with some variables of our interest. θ_s and μ_d denote time and industry fixed effects, respectively. X_{is} includes a set of control variables. All variables are defined in Table 4.A.1.

We initially add two sets of most frequently used control variables of firm characteristics and deal characteristics in the acquisition literature (e.g., Fuller et al., 2002; Golubov et al., 2012; Golubov et al., 2015; Ma et al., 2019; Moeller et al., 2004, 2005). Firm characteristics include firm size (*SIZE*), firm age (*FIRMAGE*), firm leverage (*LEV*), book-to-market ratio (*BTM*), return on assets (*ROA*), and the acquirer's raw stock return over the past year before the takeover announcement month (*PASTRETURN*). Deal characteristics include all-stock payment (*STOCK*), all cash-payment (*CASH*), tender offer deal (*TENDER*), hostile deal (*HOSTILE*), public target (*PUBLIC*), intra-industry deal (*SAMEINDUSTRY*), toehold investment (*TOEHOLD*), and cross-border deal (*CROSSBORDER*).

In addition, the literature shows some other characteristics that may affect acquisition performance. We also include these factors in our control variables. Cai, Song, & Walkling (2011) demonstrate that market anticipation can increase the announcement returns, using a dormant period measure as the proxy for market anticipation. We follow their definition to construct a dummy variable of *DORMANT*. *DORMANT* equals one if peer firms in the same industry make no acquisition for at least one year before the current deal, and zero otherwise. Brown et al. (1991) and Moeller et al. (2007) highlight the role of information asymmetry in the M&A context. We follow Hutton et al. (2009) to generate the *OPAQUE* variable based on discretionary accruals to proxy the firms' opaqueness.

Finally, we follow El-Khatib et al. (2015) and Masulis et al. (2007) to control

for executive and board characteristics of CEO's age (*CEOAGE*), CEO's gender (*CEOFEMALE*), CEO's tenure (*TENURE*), the duality of CEO and chairman (*CHAIR*), number of directors (*BOARDSIZE*), and the independence of board (*BOARDINDEP*).

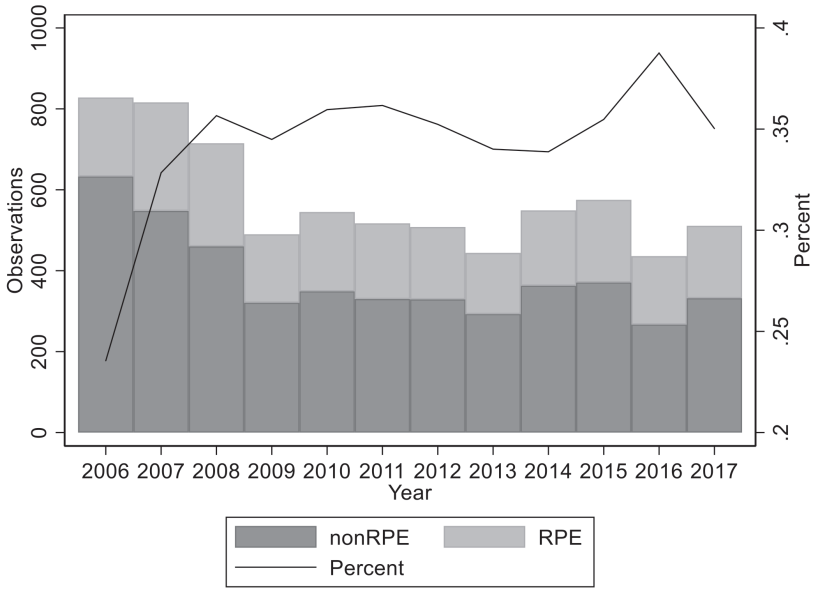

Figure 4.1 Time-Series Pattern of RPE

This figure presents the time-series pattern of RPE disclosing acquirers. The sample consists of acquisitions from 2006–2017. Since 2006, regulations have forced listed companies to disclose information of manager compensation in detail. We label the sample as RPE if the acquirer claims relative performance evaluation in the proxy statement at the acquisition announcement year and Non-RPE otherwise. Percent is the number of samples with RPE acquirers scaled by the total number of samples per year. We can notice an uptrend of RPE Percent during recent years.

4.3.4 Summary Statistics

We obtain data on acquisitions in the United States from 2006 to 2017. We report the time trend of the number and proportion of RPE acquirers in Figure 4.1. RPE acquirers undertake 2,338 acquisitions, and the proportion in the full sample is 34%. There is an obvious uptrend in the proportion of RPE disclosing acquirers during the sample period.

In Table 4.1, Panel A reports the sample description of the acquisition deals, and Panel B shows the summary statistics of RPE and non-RPE firms, respectively. The last column of Panel B presents the statistical difference of variables between RPE and non-RPE firms. The detailed definitions are presented in Table 4.A.1. The RPE acquirers are characterized by the larger firm size, higher profitability, larger board size, and higher board independence, indicating better corporate governance and firm operation. The findings confirm our intuition that developed and governed companies tend to use RPE to reduce agency problems. We have further discussions in the subsequent section of empirical results.

We offer the Spearman correlations among the main variables in Panel C. The correlation coefficients are small (generally less than 0.3), suggesting the correlation among company characteristics is modest and multicollinearity problems are not serious.

Table 4.1 Sample Description and Summary Statistics

This table presents the sample description and summary statistics for the 6,811 acquisition samples from 2006 to 2017. Panel A lists the year-by-year averages of sample characteristics. Panel B shows the mean and observations of the variables and reports the difference between the two part4.s based on RPE. Panel C provides Pearson pairwise correlation coefficients for the selected variables of interest. The detailed definitions of variables are presented in Table 4.A.1.

Panel A: Sample Description

Year	N	RPE	STOCK	CASH	TENDER	HOSTILE	PUBLIC
2006	806	0.24	0.07	0.30	0.05	0.09	0.38
2007	803	0.33	0.06	0.28	0.07	0.04	0.37
2008	701	0.36	0.06	0.24	0.06	0.10	0.36
2009	482	0.35	0.11	0.23	0.08	0.08	0.40
2010	526	0.37	0.05	0.27	0.06	0.08	0.36
2011	510	0.36	0.07	0.27	0.05	0.06	0.32
2012	501	0.35	0.06	0.27	0.04	0.05	0.33
2013	438	0.34	0.08	0.23	0.03	0.06	0.31
2014	541	0.34	0.09	0.25	0.05	0.05	0.32
2015	567	0.36	0.07	0.20	0.05	0.04	0.33
2016	432	0.38	0.06	0.18	0.03	0.04	0.34
2017	504	0.35	0.08	0.12	0.01	0.03	0.36
Total	6,811	0.34	0.07	0.24	0.05	0.06	0.35

Panel B: Summary Statistics

	Non-RPE		RPE			Total				
	Mean	N1	Mean	N2	Difference	N	Mean	SD	Min	Max
SIZE	7.87	4,497	9.50	2,314	-1.62***	6,811	8.43	2.433	0.47	15.07
FIRMAGE	8.45	4,497	7.47	2,314	0.98***	6,811	8.11	10.131	-1.00	68.00
LEV	0.56	4,497	0.60	2,314	-0.04***	6,811	0.57	0.251	0.00	3.30
BTM	0.37	4,497	0.43	2,314	-0.07***	6,811	0.39	0.593	0.00	24.61
ROA	0.01	4,497	0.05	2,314	-0.05***	6,811	0.02	0.165	-5.03	0.78
OPAQUE	0.34	4,497	0.33	2,314	0.01	6,811	0.33	0.408	0.00	8.55
PASTRETURN	0.18	4,497	0.15	2,314	0.03**	6,811	0.17	0.415	-2.61	6.06
CEOAGE	55.60	1,248	56.10	2,098	-0.50	3,346	55.91	6.991	30.00	87.00
CEOFEMALE	0.02	1,260	0.02	2,099	-0.01	3,359	0.02	0.143	0.00	1.00
TENURE	8.45	1,236	6.91	2,088	1.54***	3,324	7.48	7.301	-13.00	47.00
CHAIR	0.16	1,248	0.19	2,098	-0.04**	3,346	0.18	0.383	0.00	1.00
BOARDSIZE	8.65	2,562	10.66	2,228	-2.01***	4,790	9.59	2.859	3.00	33.00
BOARDINDEP	0.75	2,562	0.81	2,228	-0.06***	4,790	0.78	0.123	0.22	1.00
STOCK	0.09	4,497	0.04	2,314	0.04***	6,811	0.07	0.257	0.00	1.00
CASH	0.22	4,497	0.28	2,314	-0.06***	6,811	0.24	0.428	0.00	1.00
TENDER	0.04	4,497	0.07	2,314	-0.02***	6,811	0.05	0.219	0.00	1.00
HOSTILE	0.06	4,497	0.06	2,314	0.00	6,811	0.06	0.238	0.00	1.00
PUBLIC	0.33	4,497	0.39	2,314	-0.06***	6,811	0.35	0.477	0.00	1.00
SAMEINDUSTRY	0.57	4,497	0.55	2,314	0.03*	6,811	0.56	0.496	0.00	1.00
TOEHOLD	0.11	4,497	0.09	2,314	0.02**	6,811	0.10	0.300	0.00	1.00
CROSSBORDER	0.67	4,497	0.58	2,314	0.09***	6,811	0.64	0.480	0.00	1.00
DORMANT	0.13	4,497	0.16	2,314	-0.03***	6,811	0.14	0.346	0.00	1.00

Panel C: Spearman Correlation Matrix

	BHAR	RPE	SIZE	FIRMAGE	LEV	BTM	ROA	OPAQUE	PASTRETURN
BHAR12	1.00								
RPE	0.05***	1.00							
SIZE	0.06***	0.32***	1.00						
FIRMAGE	-0.00	-0.05***	0.10***	1.00					
LEV	0.00	0.07***	0.40***	-0.01	1.00				
BTM	-0.04***	0.05***	-0.14***	-0.11***	0.03**	1.00			
ROA	0.05***	0.13***	0.24***	0.04***	-0.18***	-0.03***	1.00		
OPAQUE	-0.03**	-0.01	-0.20***	-0.00	-0.23***	-0.09***	-0.08***	1.00	
PASTRETURN	-0.25***	-0.03***	-0.09***	0.00	-0.06***	-0.09***	0.14***	0.05***	1.00

4.4 Empirical Results

4.4.1 RPE and Long-term Acquisition Performance

As an initial step, we test the association between RPE and one-year buy-and-hold abnormal return (*BHAR12*), as used previously in equation (3). We use a sample of filtered 6,811 observations to run the regressions. Table 4.2 shows the empirical results. First, we test the relation between *RPE* and *BHAR12* with only industry and year fixed effects. The coefficient 2.805 is statistically significant at the 0.01 level. Next, in Column (2), we add manager characteristics with regard to CEOs (age, gender, tenure, and chairman duality) and the board (number of directors and board independence) as control variables. The coefficient of *RPE* on *BHAR12* remains significant, with t-statistics increasing from 2.91 to 3.67. The economic magnitude also increases from 2.805 to 4.377 (from 9 percent of a standard deviation to 14 percent of a standard deviation of *BHAR12*).

We further add firm characteristics and deal characteristics step by step in Columns (3) and (4). In Columns (3) and (4), the adjusted R-square substantially increases from 0.02 to 0.11, demonstrating strong and additional explanation power of control variables of firm characteristics. The association between *RPE* and *BHAR12* is still significant at the 0.01 level with a trivial reduction in coefficient. The economic magnitude of the coefficient is also significant that RPE encourages 3.5% increase for 1-year return of acquisitions, when the average return of acquirers is only -3.6%. Besides, the reversal effect aligns with the empirical findings of Ma et

al. (2019), indicated by the negative association between the one-year past returns (*PASTRETURN*) and the 1-year buy-and-hold abnormal returns of acquirers.

To dispel the data mining concern of the horizon selection of buy-and-hold abnormal returns, we examine the BHAR based on multiple periods except for the one-year baseline BHAR. Specifically, we test the BHAR with periods of 1-month, 6-month, 1-year, 2-year, and 3-year. Columns (1)-(5) of Table 4.3 report the empirical results, respectively. Column (1) shows no statistical evidence of an increasing effect of RPE on 1-month BHAR. Column (2) demonstrates that the acquisition outperformance of RPE firms starts to be statistically significant at six months after announcements. A positive coefficient of 1.632 is marginally significant at the 0.1 level. The last three columns indicate that the positive association between RPE and BHAR remains significant over the 6-month to the 3-year period after acquisition announcements. At the same time, the increasing effect of RPE on BHAR gets more substantial, and the explanatory power of regression (adjusted R^2) increases as the BHAR horizon expands[27]. The economic magnitude of the RPE coefficient is nontrivial that RPE utilization encourages 3.9% (6.8%) increase of 2-year (3-year) long-term return for acquisitions on average, when the mean return of acquirers is only -3.6% (-4.3%). Overall, the results show consistent effects of the RPE utilization on higher long-term acquisition returns. The effect is getting more evident over a longer horizon after acquisition announcements.

[27] Due to the influence of delisting and price data, observations of BHARs gradually decrease over time.

Table 4.2 RPE and Long-term Acquisition Performance

This table presents the association between *RPE* and long-term acquisition performance for a sample of 6,811 acquisitions from 2006–2017. The dependent variable is one-year buy-and-hold abnormal returns after acquisition announcements. The main explanatory variable *RPE* is a dummy variable equal to one if the firm claims utilization of relative performance evaluation in the proxy statement and zero otherwise. The detailed definitions of variables are presented in Table 4.A.1. All regressions include the industry and year fixed effects. The robust *t*-statistics clustered by the firm are reported in parentheses. ***, **, and * denote the significance at the 1%, 5%, and 10% levels, respectively.

	(1) BHAR12	(2) BHAR12	(3) BHAR12	(4) BHAR12
RPE	2.805***	4.377***	3.521***	3.569***
	(2.91)	(3.67)	(2.86)	(2.90)
CEOAGE		-0.006	-0.024	-0.025
		(-0.22)	(-0.89)	(-0.91)
CEOFEMALE		2.585	0.929	0.733
		(1.10)	(0.41)	(0.33)
TENURE		-0.007	0.038	0.039
		(-0.10)	(0.55)	(0.57)
CHAIR		-0.034	-0.822	-0.826
		(-0.02)	(-0.50)	(-0.50)
BOARDSIZE		-0.022	-0.070	-0.082
		(-0.12)	(-0.39)	(-0.46)
BOARDINDEP		-4.092	0.542	0.550
		(-1.50)	(0.18)	(0.19)
SIZE			-0.239	-0.167
			(-0.69)	(-0.48)
FIRMAGE			-0.073	-0.072
			(-1.62)	(-1.59)
LEV			-2.317	-2.266
			(-0.56)	(-0.54)
BTM			-4.910***	-4.924***
			(-5.81)	(-5.78)
ROA			14.321	14.234
			(1.31)	(1.28)
OPAQUE			-1.256	-1.263
			(-0.83)	(-0.83)
PASTRETURN			-22.637***	-22.662***
			(-4.93)	(-4.92)
STOCK				-0.277
				(-0.13)
CASH				-1.148
				(-1.40)
TENDER				-0.112
				(-0.07)
HOSTILE				0.885
				(0.68)
PUBLIC				-0.416
				(-0.47)
SAMEINDUSTRY				0.843
				(1.00)
TOEHOLD				-0.607
				(-0.49)
CROSSBORDER				0.442
				(0.53)
DORMANT				0.375
				(0.32)
Industry FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Observations	6,811	6,811	6,811	6,811
Number of Firms	2464	2464	2464	2464
Adjusted R^2	0.02	0.02	0.11	0.11

Besides, we find the acquirer valuation (*BTM*) is positively associated with two-year and three-year long-term acquisition performance. These findings align with previous evidence from Bouwman et al. (2009), Duchin and Schmidt (2013), and Lyon et al. (1999) that high-market acquisitions (i.e., lower BTM) leads to lower long-term BHARs.

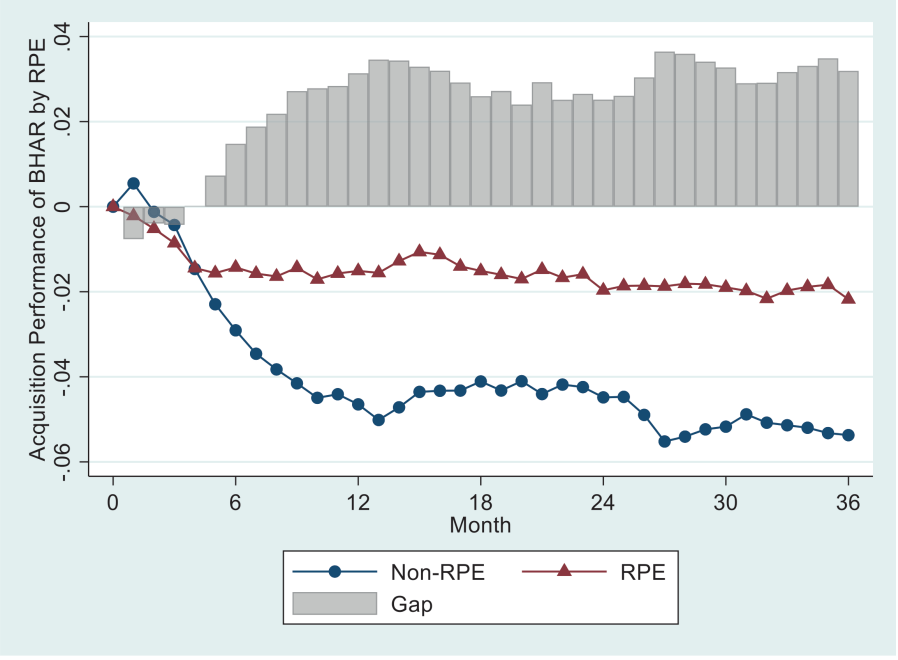

Figure 4.2 Time-Series Pattern of Acquirer BHAR

This figure presents the time-series pattern of acquirers' average buy-and-hold abnormal returns for RPE and non-RPE firms. RPE acquirers consistently outperform the non-RPE acquirers from the fifth month after the acquisition announcements (although still negative). The performance gap reaches a high point one year after the acquisition announcements.

Table 4.3 Term Structure of Acquirer BHAR

This table presents the association between *RPE* and long-term acquisition performance for a sample of 6,811 acquisitions from 2006–2017. The dependent variable is the buy-and-hold abnormal returns after acquisition announcements from 1-month to 3-year. $BHAR_T$ denotes the *T*-month BHAR. The main explanatory variable *RPE* is a dummy variable equal to one if the firm claims utilization of relative performance evaluation in the proxy statement and zero otherwise. The detailed definitions of variables are presented in Table 4.A.1. All regressions include the industry and year fixed effects. The robust *t*-statistics clustered by the firm are reported in parentheses. ***, **, and * denote the significance at the 1%, 5%, and 10% levels, respectively.

	(1) BHAR1	(2) BHAR6	(3) BHAR12	(4) BHAR24	(5) BHAR36
RPE	0.250	1.632*	3.569***	3.878**	6.812***
	(0.55)	(1.77)	(2.90)	(2.57)	(3.62)
CEOAGE	-0.014	-0.006	-0.025	-0.057*	0.031
	(-1.28)	(-0.30)	(-0.91)	(-1.78)	(0.71)
CEOFEMALE	0.122	1.678	0.733	4.170	-4.868
	(0.12)	(0.75)	(0.33)	(0.77)	(-1.03)
TENURE	0.030	0.020	0.039	0.071	0.025
	(1.00)	(0.37)	(0.57)	(0.81)	(0.22)
CHAIR	0.941	-0.359	-0.826	0.205	1.446
	(1.36)	(-0.25)	(-0.50)	(0.08)	(0.52)
BOARDSIZE	0.001	0.028	-0.082	-0.234	-0.885***
	(0.01)	(0.19)	(-0.46)	(-1.08)	(-3.03)
BOARDINDEP	-0.871	-1.550	0.550	-1.664	-7.577
	(-0.57)	(-0.64)	(0.19)	(-0.45)	(-1.51)
SIZE	-0.171	-0.395	-0.167	0.724	0.674
	(-1.01)	(-1.44)	(-0.48)	(1.62)	(1.16)
FIRMAGE	-0.010	-0.032	-0.072	-0.108*	-0.254***
	(-0.44)	(-0.89)	(-1.59)	(-1.86)	(-3.63)
LEV	0.174	-1.876	-2.266	-0.370	5.670
	(0.07)	(-0.55)	(-0.54)	(-0.09)	(1.22)
BTM	-0.046	-2.418***	-4.924***	4.772**	10.586***
	(-0.10)	(-3.68)	(-5.78)	(2.14)	(4.46)
ROA	-6.315	10.315	14.234	-27.995***	-50.943***
	(-1.19)	(1.41)	(1.28)	(-2.83)	(-5.58)
OPAQUE	0.034	0.350	-1.263	-1.469	-2.893
	(0.05)	(0.17)	(-0.83)	(-1.04)	(-1.17)
PASTRETURN	10.063**	-12.840***	-22.662***	-25.530***	-30.535***
	(2.53)	(-2.92)	(-4.92)	(-4.85)	(-14.27)
STOCK	-1.467	-4.604***	-0.277	0.821	2.393
	(-1.26)	(-2.74)	(-0.13)	(0.33)	(0.83)
CASH	0.433	-0.358	-1.148	-0.225	-1.827
	(1.17)	(-0.51)	(-1.40)	(-0.21)	(-1.38)
TENDER	-0.677	-0.794	-0.112	1.569	1.888
	(-1.15)	(-0.64)	(-0.07)	(0.90)	(0.88)
HOSTILE	-0.710	0.093	0.885	-1.713	-2.416
	(-1.38)	(0.08)	(0.68)	(-1.04)	(-1.39)
PUBLIC	-0.395	-0.537	-0.416	-1.817*	-2.216
	(-1.08)	(-0.80)	(-0.47)	(-1.65)	(-1.64)
SAMEINDUSTRY	-0.046	0.541	0.843	-1.944*	-1.417
	(-0.12)	(0.76)	(1.00)	(-1.79)	(-0.99)
TOEHOLD	-0.297	0.723	-0.607	1.248	1.536
	(-0.50)	(0.70)	(-0.49)	(0.82)	(0.95)
CROSSBORDER	0.153	-0.620	0.442	0.255	0.104
	(0.40)	(-0.90)	(0.53)	(0.25)	(0.08)
DORMANT	-0.078	0.274	0.375	0.305	-0.258
	(-0.16)	(0.26)	(0.32)	(0.20)	(-0.14)
Industry FE	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y
Observations	6,811	6,808	6,811	6,433	5,695
Number of Firms	2464	2462	2464	2283	2033
Adjusted R^2	0.08	0.06	0.11	0.14	0.18

To visualize the BHAR difference between RPE and non-RPE acquirers, we plot the time-series pattern of acquirer BHAR in Figure 4.2. The red line is the average BHAR of RPE acquirers, and the blue line is the average BHAR of non-RPE acquirers. We find RPE acquirers consistently outperform the non-RPE acquirers from the fifth month after the acquisition announcements (although still negative). The finding is aligned with our previous empirical testing of the BHAR term structure. The grey bars indicate the performance gap between RPE and non-RPE acquirers for each month (the average BHAR of RPE firms minus the average BHAR of non-RPE firms). The performance gap reaches a high point one year after the acquisition announcements.

The results confirm our hypothesis that relative performance evaluation can increase the firms' long-term acquisition performance. RPE is not surprisingly to exhibit significantly positive effects on long-term acquisition performance as a signal of corporate governance improvement. Consistent with the risk-sharing predictions of agency theory (Holmstrom, 1979, 1982; Jensen & Meckling, 1976; Ross, 1973), RPE are advantageous to mitigate agency costs due to the removal of systematic risk that is out of managers' control.

Besides, we test the results by constructing an alternative continuous measure of RPE to replace the baseline dummy measure in Table 4.A.3. Companies provide multiple grants to executives with different award types and various benchmarks each year. APE firms set absolute benchmarks for all grants. RPE firms set relative

benchmarks for some grants, and may also set absolute benchmarks for the other grants. For each sample, we calculate the RPE propensity (*RPEPROP*) as the number of grants using relative benchmarks scaled by the total number of grants at that year. Thus, *RPEPROP* measures the firms' propensity of using RPE relative to APE. Table 4.A.3 demonstrates the test results, showing that *RPEPROP* is positively associated with *BHAR* (statistical significance increases over time), aligning with our baseline findings.

4.4.2 Identification Issues

4.4.2.1 Endogenous Treatment

Our previous findings may raise potential endogeneity issues. Omitted factors can simultaneously drive long-term acquisition performance and firms' RPE use. Although there is a special compensation committee for each firm that is accountable to the board to determine the executive compensation issues, managers can intercommunicate with the committee members and affect their decisions in practice. For example, Bakke, Mahmudi, and Newton (2020) show that executives impact the selection of peers under RPE utilization to form underperforming benchmarks. Thus, the use of relative or absolute performance valuation is also possibly influenced by managers. Relative evaluation is not randomly assigned to firms if managers with the potential good performance following acquisition tend to choose RPE. To address the potential endogeneity concern, we conduct an endogenous treatment test to examine the problem.

Table 4.4 Endogenous Treatment Model Estimation

This table presents the effect of *RPE* on acquirer's one-. two-, and three-year *BHAR*, with endogenous treatment model estimation being applied. *NCA.INDEX* is the 2009 NCA enforceability index as in Starr (2019). A high value of *NCA.INDEX* indicates a higher enforceability of NCA. The detailed definitions of variables are presented in Table 4.A.1. All regressions include the industry and year fixed effects. The robust *t*-statistics clustered by the firm are reported in parentheses. ***, **, and * denote the significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)
	BHAR12	BHAR24	BHAR36
RPE=1	42.366***	51.464***	67.418***
	(7.45)	(8.09)	(14.03)
Manager Characteristics	Y	Y	Y
Firm Characteristics	Y	Y	Y
Deal Characteristics	Y	Y	Y
Year FE	Y	Y	Y
Industry FE	Y	Y	Y
RPE			
SIZE	0.212***	0.210***	0.201***
	(11.29)	(10.76)	(10.44)
FIRMAGE	-0.007	-0.006	-0.006
	(-1.46)	(-1.28)	(-1.27)
NCA.INDEX	0.296**	0.286**	0.237**
	(2.37)	(2.31)	(2.30)
Observations	6812	6443	5702
Number of Firms	2,465	2,291	2,037
Log Likelihood	-36476.44	-35531.83	-32023.31

Chowdhury et al. (2020) and Huang et al. (2019) demonstrate that the enforceability of non-competition agreement (NCA) is an efficient exogenous variable affecting the labor market. On the other hand, the firm-level acquisition performance is not likely to affect the states' policymaking. We use the NCA enforceability index of Starr (2019) as the endogenous treatment factor, which measures the different levels of NCA enforceability among the U.S. states. Lower NCA enforceability indicates a higher possibility of manager mobility

(Balasubramanian et al., 2022; Rubin and Shedd, 1981). Thus, under low NCA enforceability, managers are more likely to be job-hopping instead of reform-promoting to seek a more beneficial contract. In the first stage estimation, we predict a higher probability of RPE use for firms with stronger NCA enforceability. Based on the endogenous treatment, we expect the previous finding of the positive association between RPE and acquisition performance to remain robust in the second stage estimation.

Table 4.4 reports the two-stage results of endogenous treatment model estimation. We find a positive association between the NCA enforceability and RPE. Based on the estimated RPE, the positive relations between *RPE* and acquisition performances (*BHAR12*, *BHAR24*, and *BHAR36*) remain robust. The results confirm our predictions.

4.4.2.2 Propensity Score Matching

To further address endogenous concerns, we apply the popular propensity score matching (PSM) approach to see whether the RPE-performance relation remains after adjusting the sample differences led by RPE. Treatment groups (RPE firms) and control groups (non-RPE firms) are extremely close on covariates through sample matching. Thus, the RPE firms can be regarded as randomly assigned to mitigate the endogeneity concern.

We follow Shipman et al. (2017) to undertake the PSM regression. First, we take a logit regression using all control variables in our previous baseline regressions

to create the propensity score of the probability of RPE, with RPE being the dependent variable. The control variables include managerial characteristics (*CEOAGE, CEOFEMALE, TENURE, CHAIR, BOARDSIZE,* and *BOARDINDEP*), firm characteristics (*SIZE, FIRMAGE, LEV, BTM, ROA, OPAQUE, and PASTRETURN*), and deal characteristics (*STOCK, CASH, TENDER, HOSTILE, PUBLIC, SAMEINDUSTRY, TOEHOLD, CROSSBORDER, DORMANT*). All variables are defined in Table 4.A.1.

Second, we match the samples based on the propensity score. We perform a nearest 1-to-1 matching without replacement. The calliper of maximum distance is 0.01. After matching, the sample size decreases from 6,811 to 1,747. In Panel A of Table 4.5, the covariate balance demonstrates the effectiveness of sample matching. The difference between control and treatment groups for all variables becomes insignificant after matching.

Finally, we redo the baseline OLS regression based on the matched samples to examine the association between RPE and one-year BHAR. The results are shown in Panel B of Table 4.5. The RPE-performance relation remains significantly positive at a 0.01 level after controlling for management, firm, and deal characteristics. In terms of the economic magnitude, the coefficient of RPE on BHAR12 is 4.44, higher than that of the previous baseline regression 3.57. The increase of the coefficient indicates that the PSM technique eliminates the underestimation of the increasing effect of RPE on acquisition performance.

Table 4.5 Propensity Score Matching

This table presents regression estimates of the baseline model using the propensity score matching (PSM) regression technique. We use all variables of managerial, firm, and deal characteristics to generate the propensity score. We take the nearest one-to-one matching with 0.1 maximum distance of controls. Panel A reports the sample means for variables from the full sample and those from the matched sample. Panel B shows the baseline regression of *RPE* on one-year *BHAR* based on the matched sample. The detailed definitions of variables are presented in Table 4.A.1. All regressions include the industry and year fixed effects. The robust *t*-statistics clustered by the firm are reported in parentheses. ***, **, and * denote the significance at the 1%, 5%, and 10% levels, respectively

Panel A: Covariate Balance

	Sample	Control	Treatment	Diff	T-stats
CEOAGE	Full	55.60	56.10	-0.50	-1.87
	Matched	41.23	41.52	-0.28	-0.24
CEOFEMALE	Full	0.02	0.02	-0.01	-1.37
	Matched	0.01	0.01	-0.00	-0.21
TENURE	Full	8.45	6.91	1.54	5.70
	Matched	5.76	6.17	-0.42	-1.19
CHAIR	Full	0.16	0.19	-0.04	-2.71
	Matched	0.11	0.12	-0.01	-0.89
BOARDSIZE	Full	8.65	10.66	-2.01	-25.84
	Matched	8.17	8.24	-0.07	-0.37
BOARDINDEP	Full	0.75	0.81	-0.06	-18.01
	Matched	0.68	0.69	-0.01	-0.86
SIZE	Full	7.87	9.50	-1.62	-30.03
	Matched	8.34	8.26	0.08	0.91
FIRMAGE	Full	8.45	7.47	0.98	4.08
	Matched	8.40	8.45	-0.05	-0.12
LEV	Full	0.56	0.60	-0.04	-6.11
	Matched	0.58	0.58	-0.00	-0.04
BTM	Full	0.37	0.43	-0.07	-4.87
	Matched	0.41	0.43	-0.02	-1.07
ROA	Full	0.01	0.05	-0.05	-13.83
	Matched	0.03	0.04	-0.00	-0.68
OPAQUE	Full	0.34	0.33	0.01	0.66
	Matched	0.32	0.33	-0.01	-0.58
PASTRETURN	Full	0.18	0.15	0.03	2.91
	Matched	0.16	0.17	-0.01	-0.54
STOCK	Full	0.09	0.04	0.04	6.80
	Matched	0.08	0.06	0.01	1.11
CASH	Full	0.22	0.28	-0.06	-5.40
	Matched	0.27	0.26	0.01	0.59
TENDER	Full	0.04	0.07	-0.02	-3.75
	Matched	0.05	0.05	0.00	0.33
HOSTILE	Full	0.06	0.06	0.00	0.32
	Matched	0.05	0.05	0.00	0.00
PUBLIC	Full	0.33	0.39	-0.06	-4.50
	Matched	0.38	0.36	0.02	0.94
SAMEINDUSTRY	Full	0.57	0.55	0.03	2.08
	Matched	0.62	0.58	0.04	1.75
TOEHOLD	Full	0.11	0.09	0.02	3.03
	Matched	0.08	0.08	-0.01	-0.53
CROSSBORDER	Full	0.67	0.58	0.09	7.35
	Matched	0.66	0.66	-0.00	-0.15
DORMANT	Full	0.13	0.16	-0.03	-3.53
	Matched	0.17	0.15	0.01	0.71

Panel B: Baseline regression based on matched samples				
	(1)	(2)	(3)	(4)
	BHAR12	BHAR12	BHAR12	BHAR12
RPE	3.103*	3.251*	4.366***	4.442***
	(1.90)	(1.95)	(2.71)	(2.75)
CEOAGE		-0.085*	-0.028	-0.031
		(-1.79)	(-0.66)	(-0.73)
CEOFEMALE		4.179	1.037	1.275
		(1.05)	(0.26)	(0.32)
TENURE		0.129	0.075	0.081
		(1.31)	(0.78)	(0.84)
CHAIR		0.294	0.099	-0.102
		(0.10)	(0.04)	(-0.04)
BOARDSIZE		-0.289	-0.348	-0.383
		(-0.93)	(-1.23)	(-1.38)
BOARDINDEP		3.776	5.906	6.162
		(0.74)	(1.17)	(1.21)
SIZE			-0.542	-0.494
			(-0.72)	(-0.65)
FIRMAGE			-0.123	-0.124
			(-1.56)	(-1.57)
LEV			-4.280	-4.149
			(-0.87)	(-0.84)
BTM			-8.037***	-8.081***
			(-3.41)	(-3.42)
ROA			-26.126*	-26.230*
			(-1.89)	(-1.91)
OPAQUE			1.538	1.412
			(0.58)	(0.54)
PASTRETURN			-29.679***	-29.685***
			(-9.65)	(-9.69)
STOCK				-1.731
				(-0.66)
CASH				0.623
				(0.41)
TENDER				-2.466
				(-0.80)
HOSTILE				2.683
				(1.13)
PUBLIC				-0.218
				(-0.14)
SAMEINDUSTRY				-0.716
				(-0.53)
TOEHOLD				-0.125
				(-0.06)
CROSSBORDER				1.299
				(0.96)
DORMANT				1.714
				(0.86)
Industry FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Observations	1,747	1,747	1,747	1,747
Number of Firms	924	924	924	924
Adjusted R^2	0.02	0.02	0.18	0.17

4.4.3 Benchmark Selection

Companies face subsequent choices after deciding to use RPE. One typical issue is selecting an appropriate benchmark. The traditional RPE benchmarks are S&P 500, Nasdaq 100, Russell 2000, industrial indices, etc. An alternative way is to select a basket of peer firms by compensation committee to construct a homemade index as the relative benchmark for a grant, the self-selected peer group. The ISS database records the benchmark selection details of listed firms.

The literature discusses the difference between traditional indices and self-selected peer groups and agrees that self-selected peer groups can perform better in evaluating corporate managers (Albuquerque, 2009; Albuquerque et al., 2013; Jayaraman et al., 2020). Albuquerque (2009) and Jayaraman et al. (2020) suggest that traditional relative benchmark groups based on market and industry indices are inefficient in seizing the main features of relative benchmarking and seek development based on industry-size factors and product similarity, respectively. Furthermore, Gong et al. (2011) demonstrate that stronger evidence of RPE utilization is confirmed using self-selected peer groups rather than benchmark groups based on an industry-size factor, highlighting the benefit of effectively isolating common exogenous shocks. They conclude that self-selected peer group benchmarks are more efficient[28]. Thus, we expect the self-selected peer group is the better choice for benchmark-setting while using RPE.

[28] Although the selection of rivals can have bias. For example, Bakke, Mahmudi, and Newton (2020) show that executives impact the selection of peers under RPE utilization to form underperforming benchmarks.

Table 4.6 Benchmark Selection and Long-term Acquisition Performance

This table presents the association between relative benchmark types and long-term acquisition performance. *PEER* is a dummy variable that equals one if the firm utilizes a relative benchmark of self-selected peers, and zero otherwise. *INDEX* is a dummy variable that equals one if the firm utilizes a relative benchmark of traditional market or industry indices, and zero otherwise. The dependent variable is one-year buy-and-hold abnormal returns after acquisition announcements. The detailed definitions of variables are presented in Table 4.A.1. All regressions include the industry and year fixed effects. The robust *t*-statistics clustered by the firm are reported in parentheses. ***, **, and * denote the significance at the 1%, 5%, and 10% levels, respectively.

	(1) BHAR12	(2) BHAR12	(3) BHAR12
PEER	2.701**		2.690**
	(2.14)		(2.11)
INDEX		-0.413	-0.216
		(-0.32)	(-0.17)
CEOAGE	-0.010	-0.006	-0.010
	(-0.39)	(-0.21)	(-0.38)
CEOFEMALE	0.312	0.676	0.288
	(0.14)	(0.31)	(0.13)
TENURE	0.030	0.017	0.029
	(0.43)	(0.25)	(0.43)
CHAIR	-0.917	-0.821	-0.926
	(-0.56)	(-0.50)	(-0.56)
BOARDSIZE	-0.025	-0.005	-0.024
	(-0.14)	(-0.03)	(-0.13)
BOARDINDEP	1.159	1.220	1.158
	(0.40)	(0.42)	(0.40)
SIZE	0.041	0.104	0.043
	(0.12)	(0.32)	(0.13)
FIRMAGE	-0.075*	-0.079*	-0.075*
	(-1.66)	(-1.76)	(-1.66)
LEV	-2.255	-2.343	-2.251
	(-0.54)	(-0.56)	(-0.54)
BTM	-5.013***	-5.026***	-5.014***
	(-5.81)	(-5.81)	(-5.81)
ROA	14.139	14.040	14.140
	(1.28)	(1.27)	(1.28)
OPAQUE	-1.319	-1.252	-1.316
	(-0.87)	(-0.83)	(-0.87)
PASTRETURN	-22.648***	-22.644***	-22.648***
	(-4.92)	(-4.92)	(-4.92)
STOCK	-0.199	-0.203	-0.199
	(-0.09)	(-0.10)	(-0.09)
CASH	-1.165	-1.152	-1.163
	(-1.42)	(-1.41)	(-1.42)
TENDER	-0.133	-0.141	-0.132
	(-0.09)	(-0.09)	(-0.09)
HOSTILE	0.848	0.874	0.848
	(0.65)	(0.67)	(0.65)
PUBLIC	-0.311	-0.306	-0.313
	(-0.35)	(-0.35)	(-0.35)
SAMEINDUSTRY	0.866	0.846	0.869
	(1.02)	(1.00)	(1.02)
TOEHOLD	-0.622	-0.638	-0.624
	(-0.50)	(-0.51)	(-0.50)
CROSSBORDER	0.306	0.329	0.308
	(0.37)	(0.39)	(0.37)
DORMANT	0.388	0.372	0.386
	(0.34)	(0.32)	(0.33)
Industry FE	Y	Y	Y
Year FE	Y	Y	Y
Observations	6,811	6,811	6,811
Number of Firms	2464	2464	2464
Adjusted R^2	0.11	0.11	0.11

In this subsection, we disassemble RPE based on the selection of relative benchmarks. Since there are usually multiple grants for a firm each year, the grants can be appropriate for different benchmark settings. We conduct two dummy variables based on different benchmark selections. One is *PEER* which equals one if the RPE firm uses self-selected peer groups as the RPE benchmark for at least one grant, and zero otherwise. The other is *INDEX* which equals one if the firms use RPE, however, without applying self-selected peer groups, and zero otherwise. That is, the RPE firms labelled as *INDEX* use traditional market and industry indices as the relative benchmarks for their all grants. We expect the association between *PEER* and acquisition performance is stronger than that of *INDEX*. Results in Table 4.6 confirm this prediction.

Column (1) shows the significant and positive association between *PEER* and *BHAR12*. Column (2) indicates no significant impact of *INDEX* on *BHAR12*. In terms of economic magnitude, the coefficient on *PEER* is about 700% larger than the coefficient on *INDEX*. Next, we simultaneously add *PEER* and *INDEX* in the same OLS regression and find the previous results remain as shown in Column (3). The results support our argument that relative benchmarks of self-selected peers are more pronounced in increasing acquisition performance. We find similar regression results using two-year and three-year BHAR, which are available upon request.

We also test the propensity of firms' utilization of self-selected peer groups in Table 4.A.7. For each sample, we calculate the peer benchmark propensity

(*PEERPROP*) as the number of grants using self-selected peer benchmarks scaled by the total number of grants using relative benchmarks at that year. Thus, *PEERPROP* measures the firms' weights on the benchmark utilization of self-selected peers relative to traditional indices. Table 4.A.7 demonstrates the test results, showing that *PEERPROP* is positively associated with BHAR, aligning with our previous benchmark selection finding.

4.4.4 Cross-Sectional Analyses

In this subsection, we study the heterogeneity in RPE across the different groups with various market uncertainty, managerial myopia correctability, and external monitoring. Market uncertainty is commonly measured by the implied market volatility derived from the well-known Black-Scholes-Merton Model and option prices in the real market. The managerial myopia correctability is the expected tenure of managers, implying their expected horizon to make corporate decisions. External monitoring is the level of supervision power from outside that are not participating in the operation of companies, such as shareholders, analysts, and media.

4.4.4.1 Market Uncertainty

RPE mainly differ from APE by removing systematic uncertainty (Holmstrom, 1982). Thus, we expect the RPE effect is stronger when market uncertainty is higher. Specifically, we predict the increasing effect of RPE on BHAR is stronger during high market uncertainty periods. As customary, we use the CBOE volatility index

(VIX) to proxy for market uncertainty (Bhagwat, Dam, & Harford, 2016; Bonaime, Gulen, & Ion, 2018). We construct two sample groups based on the high-VIX and low-VIX periods.

Columns (1)-(2) of Table 4.7 indicate that the association between RPE and BHAR12 is pronounced for deals undertaken during high-volatility periods. The coefficient equality between two sub-samples is also remarkably significant at the 0.01 level. In terms of economic magnitude, the coefficient of RPE for the high-VIX sub-sample is 7.42, which is about 108% larger than that of the full sample (3.57). The results support our expectations.

4.4.4.2 Managerial Myopia Correctability

Next, we conduct cross-sectional analyses based on the CEOs' expected tenure, which implies the correctability of the managerial myopia problem. Managers who are expected to retire soon have less motivation and gain lower potential benefits to overcome the myopia problem. Thus, a shorter expected tenure implies a more stubborn myopia problem, and a longer expected tenure indicates a higher probability of amendable managerial myopia. Antia, Pantzalis, & Park (2010) demonstrate that longer expected tenure is associated with fewer agency costs and higher long-term value creation. Flammer and Bansal (2017) support this view by showing that managers' long-term orientation can increase firm value and operating performance.

Table 4.7 Sub-Sample Analyses

This table reports the sub-sample analysis results with samples being divided into two parts based on the degree of sub-periods based on the market volatility index (*VIX*), managerial myopia (*Career Horizon),* and institutional holding (*Institutional Shares*). *VIX* is the CBOE volatility index. *Career Horizon* is the CEOs' expected career horizon that proxies for the expected remaining tenure of managers. *Institutional Shares* is the firms' proportion of shares held by institutions. The detailed definitions of variables are presented in Table 4.A.1. All regressions include the industry and year fixed effects. The robust *t*-statistics clustered by the firm are reported in parentheses. ***, **, and * denote the significance at the 1%, 5%, and 10% levels, respectively.

	VIX		Career Horizon		Institutional Shares	
	(1)	(2)	(3)	(4)	(5)	(6)
	Low	High	Low	High	Low	High
RPE	1.229	7.417***	1.150	7.172***	7.002***	2.286*
	(0.85)	(3.32)	(0.90)	(3.03)	(2.63)	(1.69)
CEOAGE	0.014	-0.067	-0.019	-0.021	-0.017	-0.019
	(0.31)	(-1.59)	(-0.65)	(-0.44)	(-0.37)	(-0.55)
CEOFEMALE	-0.841	1.471	1.100	2.161	3.618	-0.121
	(-0.31)	(0.41)	(0.35)	(0.64)	(0.93)	(-0.05)
TENURE	-0.082	0.572*	0.077	0.038	0.032	0.022
	(-1.06)	(1.77)	(0.93)	(0.32)	(0.26)	(0.28)
CHAIR	-1.781	-1.623	-4.389*	2.318	-0.535	0.917
	(-0.89)	(-0.51)	(-1.83)	(1.04)	(-0.14)	(0.50)
BOARDSIZE	-0.060	-0.193	-0.206	0.014	-0.367	-0.016
	(-0.30)	(-0.58)	(-0.97)	(0.05)	(-1.24)	(-0.09)
BOARDINDEP	-0.977	2.171	2.901	-3.184	4.408	-0.321
	(-0.29)	(0.45)	(0.90)	(-0.64)	(0.92)	(-0.10)
SIZE	0.610	-0.737	0.066	-0.754	-0.346	-0.124
	(1.34)	(-1.42)	(0.17)	(-1.16)	(-0.67)	(-0.31)
FIRMAGE	-0.108*	-0.004	-0.119*	-0.020	0.005	-0.114**
	(-1.85)	(-0.05)	(-1.94)	(-0.25)	(0.06)	(-2.03)
LEV	0.328	-4.640	-9.965**	7.478	-3.100	-6.302**
	(0.10)	(-0.78)	(-2.26)	(1.26)	(-0.52)	(-2.08)
BTM	-5.081***	-6.998***	-7.566***	-4.561***	-5.007***	-6.379***
	(-5.61)	(-4.27)	(-4.65)	(-4.74)	(-5.13)	(-4.71)
ROA	-2.363	17.084	23.106*	-5.275	20.221*	-2.460
	(-0.18)	(1.42)	(1.96)	(-0.69)	(1.77)	(-0.30)
OPAQUE	3.268*	-3.809**	-2.528	0.582	-0.408	-1.201
	(1.95)	(-2.21)	(-1.58)	(0.23)	(-0.20)	(-0.60)
PASTRETURN	-28.481***	-19.784***	-20.445**	-24.731***	-20.060***	-32.642***
	(-8.87)	(-2.71)	(-2.30)	(-6.62)	(-3.04)	(-14.58)
STOCK	0.653	-1.047	-1.543	-1.533	1.189	-3.606*
	(0.32)	(-0.32)	(-0.66)	(-0.45)	(0.39)	(-1.72)
CASH	-0.836	-1.650	-0.840	-1.400	-1.406	-0.286
	(-0.80)	(-1.22)	(-0.83)	(-1.01)	(-1.08)	(-0.28)
TENDER	-2.474	1.870	-0.779	1.396	4.002	-3.574*
	(-1.12)	(0.84)	(-0.38)	(0.55)	(1.59)	(-1.82)
HOSTILE	0.008	1.816	-0.714	2.157	0.589	2.586
	(0.00)	(0.92)	(-0.47)	(1.06)	(0.35)	(1.32)
PUBLIC	2.207**	-3.112**	0.013	-1.733	-1.963	1.611
	(2.05)	(-2.26)	(0.01)	(-1.17)	(-1.43)	(1.57)
SAMEINDUSTRY	1.161	0.772	-0.200	2.429*	1.411	0.723
	(1.09)	(0.57)	(-0.20)	(1.70)	(0.97)	(0.81)
TOEHOLD	-1.200	-0.700	1.104	-1.114	-1.310	-0.703
	(-0.79)	(-0.37)	(0.76)	(-0.53)	(-0.81)	(-0.43)
CROSSBORDER	-0.486	1.250	0.832	-0.135	-0.006	0.925
	(-0.47)	(0.91)	(0.87)	(-0.09)	(-0.00)	(1.01)
DORMANT	0.251	-1.019	1.073	0.502	-5.094**	3.058***
	(0.19)	(-0.44)	(0.71)	(0.24)	(-2.13)	(2.61)
Industry FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Observations	3,453	3,334	3,753	3,015	3,370	3,400
Number of Funds	1,211	1,541	1,785	1,492	1,270	1,342
Adjusted R^2	0.18	0.09	0.10	0.15	0.12	0.19
Coefficient Equality						
(1) vs. (2)	0.01					
(3) vs. (4)	0.01					
(5) vs. (6)	0.08					

We follow Antia et al. (2010) and Lee et al. (2018) to construct the measure *Career Horizon*, which is calculated as the difference between managers' current tenure and the industrial average tenure. A higher *Career Horizon* implies longer expected tenure and higher managerial myopia correctability. If RPE increases acquisition performance by dispersing managers' short-termism, the coefficient on RPE should be more significant for firms with high correctability of managerial myopia.

Columns (3)-(4) of Table 4.7 demonstrate the subsample results. We find the association between RPE and acquisition performance is pronounced for firms with high *Career Horizon*. The coefficient equality between Columns (3) and (4) is statistically significant at a 0.01 level. The economic magnitude of the RPE coefficient for the high *Career Horizon* group (7.17) is also significant, which is 100% larger than the RPE coefficient in full sample regression (3.57). The test results confirm our expectation that the increasing effect of RPE on acquisition performance is more pronounced for executives with higher correctability of managerial myopia.

4.4.4.3 External Monitoring

Finally, we study the heterogeneity in RPE across the different levels of external monitoring. Since firms with high external monitoring already have good corporate governance and information symmetry, we expect the RPE effect to be stronger for firms with lower external monitoring. We follow Kim et al. (2011b) and

Yu (2008) to use the proportion of institutional shares to measure the level of external monitoring. The measure is calculated as the number of shares held by institutions scaled by the total number of outstanding shares.

In Columns (5) and (6) of Table 7, we show the RPE impact is strongly significant for low-institutional holding firms at 0.01 level (*t*-statistics = 2.63) and weakly significant for high-institutional holding firms at 0.1 level (*t*-statistics = 1.69). In terms of economic magnitude, the RPE coefficient for firms with low-institutional shares (7.00) is much higher than that of high-institutional shares (2.29) and that of full samples (3.57). The finding confirms our expectation that RPE is more effective in increasing acquisition performance for firms with low external monitoring.

4.4.5 Robustness Checks

4.4.5.1 Alternative Measures of Long-term Acquisition Performance

In Table 4.A.2, we re-define the measure of long-term acquisition performance to remove the concern of the bad-model problem (Fama, 1998). Following Field and Mkrtchyan (2017) and Ma et al. (2019), we adopt the [-1, +1] three-day window to calculate the abnormal returns surrounding the subsequent earnings announcement (*SEAR*) following the acquisition announcement. The subsequent earnings announcement is the first periodic report (10-K or 10-Q) over the six-month to one-year period after the acquisition announcement. We redo the OLS regression to examine the association between RPE and SEAR based on the alternative measure

of long-term acquisition performance. The results are presented in Table 4.A.2. We adopt three ways to adjust the raw returns. $SEAR^{VW}$, $SEAR^{EW}$, and $SEAR^{SP}$ denote the subsequent earnings announcement returns adjusted by CRSP value-weighted market returns, CRSP equal-weighted market returns, and S&P 500 market returns separately. RPE is positively associated with all three long-term acquisition performance SEAR measures, which supports our baseline findings.

4.4.5.2 Alternative Constructions of BHAR

In our baseline results, BHAR is calculated using size, value, and momentum factors. We use two additional ways to construct BHAR and repeat the regressions. The results are reported in Table 4.A.4. In Panel A, BHAR is constructed based on market model. In Panel B, we construct reference portfolios using industry factor before size/value/momentum factors to generate BHAR. The positive association between RPE and BHAR remains, with similar economic magnitude to our baseline results. Particularly, the coefficients of *SIZE* are significantly negative in Panel A, which are insignificant in baseline results. This demonstrates that our baseline construction of BHAR removes the size anomaly of stock returns. Besides, some variables of deal characteristics become significant in Panel B. When we generate BHAR using industry factor, *HOSTILE* and *SAMEINDUSTRY* decrease the long-term returns of acquirers.

4.4.5.3 Sampling Criteria

We conduct extension tests based on our baseline results. In Table 4.A.5, we

exclude samples in certain years. Since listed firms are forced to disclose executive compensation details in the proxy statements from 2006, it's possible that the RPE features are not stable for the first few years. Figure 4.1 indicates a rapid uptrend of the proportion of RPE firms. The firms who take the lead in disclosing RPE utilization could be more representative among all RPE firms, thus being the elephant in the house. To avoid representative bias, we exclude the samples during 2006-2008. Table 4.A.5 reports the results after applying sampling criteria. Our finding of the positive association between RPE and BHAR is robust. The significance and economic magnitude of the RPE coefficient are both similar to the baseline regression results in Table 4.2.

4.4.5.4 Alternative Model Specifications

Table 4.A.6 reports the test results of alternative model specifications, replacing 3-digit SIC with 4-digit SIC, FF48, and Industry-Year fixed effect. FF48 denotes Fama-French 48 industries. Industry-Year FE denotes the fixed effect of interaction between year and FF48. The results support our main findings.

4.5 Further Discussions

4.5.1 Managerial Myopia

The managerial myopia problem is our major concern through which RPE affects long-term acquisition performance. We further test the existence of non-RPE firms' myopic acquisition performance. Since non-RPE firms preserve the common uncertainties and the conflict of interests between managers and shareholders, they

tend to have a higher degree of managerial myopia than RPE firms. Thus, we expect the short-term acquisition performance is higher for non-RPE acquirers. Given RPE acquirers reversely outperform in the long run, we highlight the benefit of RPE utilization to mitigate managerial myopia and reduce agency cost.

As we previously explained, the short-termism of managers is an important issue in the research field of agency problems. Agents tend to pursue short-term goals that serve their own interests. Conversely, the short-term goals of managers are not aligned with the long-run interests of principals. Narayanan (1985) states the conflict of interests between firm managers and stockholders incurred by managerial incentives of self-interest when managers have private information about the firms' decisions. Holmstrom & Costa (1986) and Hirshleifer & Thakor (1992) support this view by providing an additional concern based on managerial reputation. Moreover, Campbell & Marino (1994) elaborately document the myopic investment decisions of corporate managers. Eventually, managerial myopia can impair firms' long-term value and increase agency costs (Antia, Pantzalis, & Park, 2010; Flammer & Bansal, 2017).

To examine managerial myopia, we further study the RPE effect on acquirers' short-run performance after acquisition. Suppose non-RPE firms tend to achieve their short-term targets and pursue instant gains. In that case, the non-RPE acquirers using absolute executive performance evaluation methods should outperform RPE acquirers on short-term cumulative abnormal returns.

Table 4.8 Managerial Myopia

This table presents the association between *RPE* and short-run acquisition performance for a sample of 6,811 acquisitions from 2006–2017. The dependent variable is [0, +10] cumulative abnormal returns around acquisition announcements. The main explanatory variable *RPE* is a dummy variable that is equal to one if the firm claims utilization of relative performance evaluation in the proxy statement, and zero otherwise. The detailed definitions of variables are presented in Table 4.A.1. All regressions include the industry and year fixed effects. The robust *t*-statistics clustered by the firm are reported in parentheses. ***, **, and * denote the significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Acquirer CAR Adjusted by Market Model				
	(1)	(2)	(3)	(4)
	CAR	CAR	CAR	CAR
RPE	-0.746**	-0.811**	-0.699**	-0.705**
	(-2.38)	(-2.42)	(-2.13)	(-2.17)
Manager Characteristics	N	Y	Y	Y
Firm Characteristics	N	N	Y	Y
Deal Characteristics	N	N	N	Y
Industry FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Observations	5,382	5,382	5,382	5,382
Number of Firms	2023	2023	2023	2023
Adjusted R^2	0.04	0.04	0.07	0.07

Panel B: Acquirer CAR Adjusted by Fama-French 3 Factors Model				
	(1)	(2)	(3)	(4)
	CAR	CAR	CAR	CAR
RPE	-0.902***	-0.973***	-0.865***	-0.864***
	(-2.82)	(-2.88)	(-2.63)	(-2.66)
Manager Characteristics	N	Y	Y	Y
Firm Characteristics	N	N	Y	Y
Deal Characteristics	N	N	N	Y
Industry FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Observations	5,382	5,382	5,382	5,382
Number of Firms	2023	2023	2023	2023
Adjusted R^2	0.04	0.04	0.07	0.07

We conduct a traditional event study method using [0, +10] cumulative abnormal returns around acquisition announcements as the proxy for the short-term acquisition performance. We adjust the post-acquisition returns using the market and Fama-French three factors models to generate the CAR[0, +10]. Table 4.8 illustrates the testing results. Panel A indicates the results with CAR adjusted by the market model. Panel B indicates the results with CAR adjusted by Fama-French three factors model. In both panels, RPE is negatively associated with short-term

acquisition performance.

The empirical results confirm our expectation that non-RPE acquirers perform better in the short run after undertaking acquisition deals due to their incentives of pursuing short-term gains. Whereas, the acquisition performance reverse over the next several months that RPE acquirers start to outperform, as shown in our baseline findings. The reverse indicates the effectiveness of RPE in mitigating managerial myopia, aligning the interest between managers and shareholders, and controlling agency costs.

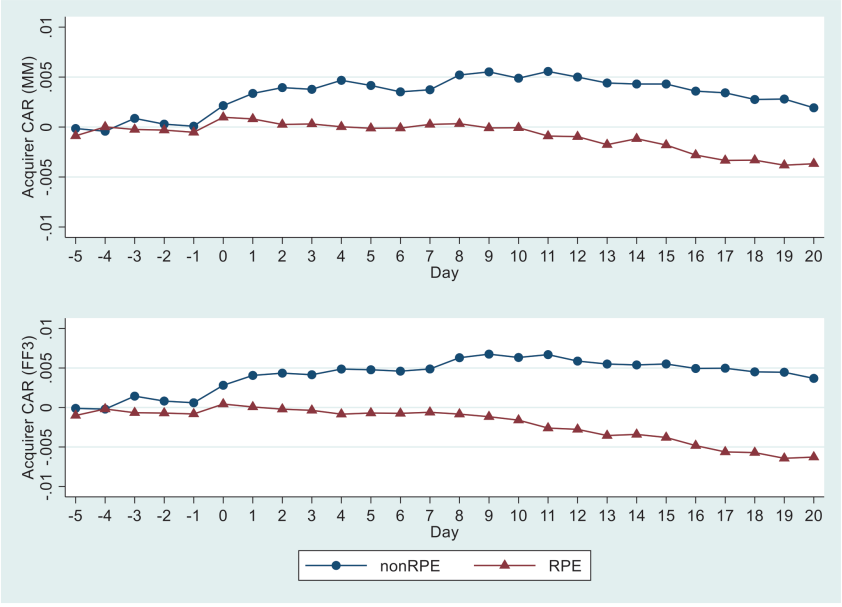

Figure 4.3 Acquirer CAR

The figure presents the time-series pattern of acquirer cumulative abnormal returns adjusted by the market model (MM) and Fama-French three factors model (FF3), respectively, around the acquisition announcement date. RPE acquirers underperform the non-RPE acquirers.

We also provide a graph showing the short-term returns of RPE and non-RPE firms around the announcement day. The event window of this graph is [-5, +20]. Figure 4.3 demonstrates that RPE acquirers steadily underperform non-RPE acquirers in the short run. CARs based on Market model and Fama-French Three Factors model generate similar results.

4.5.2 Acquirer Transaction Timing

This subsection explains that RPE managers can take advantage of their own high valuation through more active and adequate transaction timing. Heath, Huddart, & Lang (1999) provide evidence that executives are keeping their eyes on the past 52-week high price and will have a strong willingness to exercise their options while the stock price exceeds its past 52-week high. This indicates managers have the ability to grab the better timing to execute investment decisions. As for why it is better to take action when the stock price approaches or exceeds its past 52-week high, George & Hwang (2004) explain that the 52-week reference price ratio is more informative. Relative to the conventional momentum measurements based on the past return quantiles among stocks or industries, the momentum measurement based on a 52-week high has a more effective and robust prediction power that does not reverse in the long run. George, Hwang, & Li (2018) extend this discussion to fundamental aspects, showing that the 52-week high reference price ratio (current price divided by the past 52-week high) is positively associated with firms' expected profitability, expected investment growth, and the consequent stock returns. Ma et al.

(2019) and Baker et al. (2012) investigate the effect of the reference price ratio on mergers and acquisitions, focusing on the reference price of targets and acquirers, respectively. More closely to our research, Ma et al. (2019) show higher long-term buy-and-hold abnormal returns for acquirers with higher acquirer RPR.

Consistent with the empirical results of George, Hwang, & Li (2018) and Ma et al. (2019), we postulate that RPE is positively associated with RPR due to more active and beneficiary transaction timing, which eventually increases the long-term acquisition performance.

As Ma et al. (2019) demonstrated, lower RPR incurs investors' positive responses in short-run price due to anchoring influence and perceived valuation hypothesis. Whereas we claim that higher RPR can provide real benefits in the long run. We discuss two additional advantages associated with high RPR besides the profitability and investment aspects demonstrated by George, Hwang, & Li (2018). On the one hand, high RPR offer acquirers the opportunity to spend fewer costs to make the stock payments for target assets (Shleifer and Vishny, 2003; Dong et al., 2006; Savor and Lu, 2009). On the other hand, a higher valuation of own company can loosen the financing restrictions and avoid the exhaustion of operating capital, which is harmful to acquirers in the long run (Jensen, 1986; Lang, Stulz, & Walkling, 1991). These fundamental mechanisms can all bring real benefits for corporations operating in the long run instead of grabbing the investors' behavioral pricing to achieve short-term goals. Thus, an outperforming long-term performance exists for

RPE firms through more active and adequate transaction timing measured by the reference price ratio.

Table 4.9 shows the empirical results. The dependent variable is RPR for all three columns. Following Ma et al. (2019), our dependent variable RPR[-6/-258] is calculated as the acquirers' closing price six days before the announcement date divided by the highest closing price over the previous 252 trading days (52 weeks)[29]. RPR approaches one if the price is near the 52-weeks high.

Column (1) of Table 4.9 includes all acquisition samples. The positive association between RPE and RPR confirms our prediction that RPE firms can take actions with a higher reference price ratio. Additionally, we test whether the effect is stronger for deals with the composition of stock payments. Column (2) includes all-cash payment deals samples, and Column (3) includes samples that are all- or partial-stock payment deals. We find the positive association only remains significant in Column (3) that acquisition deals contain stock payment composition and provide the basis for benefiting from RPR timing. The finding indicates that RPE managers take more active timing through seizing higher reference price ratios when they select (at least partially) stock payment to execute acquisition transactions, which is easily reconciled with Shleifer and Vishny (2003) and Dong et al. (2006).

[29] We also test the association based on RPR at difference days, such as RPR[0,-252] and RPR[-3, -255]. The findings are consistently similar. Results are available upon request.

Table 4.9 Acquirer Transaction Timing

This table presents the association between RPE and acquirers' reference price ratio (RPR) for a sample of acquisitions during 2006-2017. Following Ma et al. (2019), our dependent variable RPR[-6/-258] is calculated as the acquirers' closing price on six days before the announcement date divided by the highest closing price over the previous 252 trading days (52 weeks). RPR approaches one if the price is near the 52-weeks high. Column (1) includes all acquisition samples. Column (2) includes samples that are all-cash payment deals. Column (3) includes samples that are all- or partial-stock payment deals. The detailed definitions of variables are presented in Table 4.A.1. All regressions include the industry and year fixed effects. The robust *t*-statistics clustered by the firm are reported in parentheses. ***, **, and * denote the significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)
	Whole Sample	All-Cash Payment	Not All-Cash Payment
RPE	0.080***	0.050	0.087***
	(3.47)	(1.36)	(3.44)
CEOAGE	0.001	0.002**	0.000
	(1.34)	(2.01)	(0.50)
CEOFEMALE	0.116**	0.129	0.116**
	(2.36)	(1.14)	(2.36)
TENURE	0.001	-0.003	0.003
	(0.74)	(-1.16)	(1.57)
CHAIR	-0.070**	-0.058	-0.079**
	(-2.49)	(-1.21)	(-2.43)
BOARDSIZE	0.008**	0.008	0.008**
	(2.35)	(1.18)	(2.33)
BOARDINDEP	0.018	0.010	0.024
	(0.40)	(0.11)	(0.51)
SIZE	-0.009	-0.007	-0.010*
	(-1.61)	(-0.82)	(-1.66)
FIRMAGE	-0.002	-0.002	-0.002
	(-1.58)	(-1.48)	(-1.26)
LEV	-0.059	-0.056	-0.055
	(-1.40)	(-0.78)	(-1.21)
BTM	-0.050***	-0.021	-0.056***
	(-3.46)	(-0.71)	(-3.31)
ROA	0.229***	0.159	0.238***
	(3.64)	(1.46)	(3.48)
OPAQUE	-0.056***	-0.087***	-0.048**
	(-3.11)	(-2.82)	(-2.37)
PASTRETURN	0.069***	0.076**	0.068***
	(4.32)	(2.49)	(3.89)
TENDER	0.037	-0.002	0.077*
	(1.50)	(-0.05)	(1.72)
HOSTILE	-0.019	-0.034	-0.012
	(-0.84)	(-0.87)	(-0.41)
PUBLIC	0.011	0.024	0.004
	(0.79)	(0.94)	(0.25)
SAMEINDUSTRY	0.010	0.044*	-0.001
	(0.72)	(1.69)	(-0.07)
TOEHOLD	-0.014	-0.052	0.002
	(-0.80)	(-1.40)	(0.11)
CROSSBORDER	0.001	0.009	-0.005
	(0.08)	(0.35)	(-0.30)
DORMANT	-0.008	-0.041	0.003
	(-0.50)	(-1.30)	(0.17)
Industry FE	Y	Y	Y
Year FE	Y	Y	Y
Observations	6,811	1,638	5,167
Number of Firms	2464	990	2119
Adjusted R^2	0.11	0.12	0.11

4.6 Conclusions

We provide an additional explanation of the causes of acquisition performance based on firms' design of managerial performance evaluation. Specifically, we focus on the effect of RPE utilization on long-term acquisition performance. RPE eliminates common uncertainties that are out of managers' control, thus being more informative in evaluating managers' performance and suppressing the agency problem of managerial myopia. We test this proposition using a sample of 6,811 acquisitions recorded in SDC from 2006 to 2017.

First, we find RPE increases long-term acquisition performance. The effect exists (at least) over six months to three years after the acquisition announcement. RPE utilization encourages 3.6% (6.8%) increase for 1-year (3-year) long-term return of acquirers on average. The finding is robust to using alternative measures of long-term acquisition performance, sampling criteria, and alternative model specifications. To address endogeneity issues, we use the endogenous treatment and propensity score matching techniques to conduct further tests. The results support our main findings.

Next, we disassemble RPE based on the selection of relative benchmarks and find that benchmarks self-selected peers mainly drive the results. The finding is consistent with previous results of Albuquerque (2009), Gong et al. (2011), Albuquerque et al. (2013), and Jayaraman et al. (2020) that self-selected peers are superior in evaluating managers' relative performance. In terms of heterogeneity, the

increasing effect of RPE on long-term acquisition performance is more pronounced for firms with higher market uncertainty, higher managerial myopia correctability, and lower external monitoring.

Finally, we provide further discussion about managerial myopia and acquirer transaction timing. We find a reversal of acquisition performance in that non-RPE acquirers exceeds RPE acquirers in the short run, confirming the short-termism of non-RPE firms. Besides, RPE associates with higher reference price ratio before takeover announcement, indicating better transaction timing for RPE managers given the positive association between reference price ratio and long-term performance (Ma et al., 2019).

Overall, long-term acquisition performance can result from the insulation of common uncertainties in managers' compensation. RPE reconciles the interest between principals and agents and reduces agency costs. The possible explanations are that RPE mitigates the managerial myopia problem and motivates managers to capture better transaction timing. Our research provides important implications for understanding optimal contracting, managerial short-termism, and post-acquisition performance.

Appendix

Table 4.A.1 Variable Names and Definitions

BHAR	*The buy-and-hold abnormal return proxy for the long-term acquisition performance. $BHAR_T$ denotes the T-month buy-and-hold abnormal return for acquirers. For instance, BHAR12 is the one-year BHAR used as the dependent variable in our baseline regressions.*
BOARDINDEP	*The board independence that calculated as the proportion of independent board members*
BOARDSIZE	*The firm's number of board members.*
BTM	*The book value of equity over market capitalization.*
CAR	*The [0, +10] cumulative abnormal return of acquirers around acquisition announcements adjusted by market model or Fama-French three factors model.*
Career Horizon	*The CEO's expected tenure which is calculated as the industry average CEO tenure and age minus the firm's current CEO tenure and age, following Antia, Pantzalis, & Park (2010) and Lee, Park, & Folta (2018).*
CASH	*A dummy variable equals one if the percentage of consideration paid in cash is 100 in the SDC and zero otherwise.*
CEOAGE	*The natural logarithm of the CEO's age, as recorded in the Compustat Execucomp.*
CEOFEMALE	*A dummy variable that equals one if the CEO is female and zero otherwise, as recorded in the Compustat Execucomp.*
CHAIR	*A dummy variable that equals one if the CEO is also the chairman of the board and zero otherwise.*
CROSSBORDER	*A dummy variable that equals one if the acquirer and target are not from the same country and zero otherwise.*
DORMANT	*A dummy variable that equals to one if there is no acquisition made by peer firms in the same industry for at least one year prior to the current deal, and zero otherwise. The industry is based on the 4-digit SIC code.*
FIRMAGE	*The number of years after a firm's IPO date.*
HOSTILE	*A dummy variable that equals one if the deal attitude is hostile or unsolicited in SDC and zero otherwise.*
INDEX	*A dummy variable that equals one if the firm utilizes a relative benchmark of*

	traditional market or industry indices for all RPE grants, and zero otherwise.
Institutional Shares	*The firms' proportion of shares held by institutions.*
LEV	*The book value of all liabilities scaled by total assets.*
NCA.INDEX	*The NCA enforceability index of Starr (2019) that measures the different levels of NCA enforceability among the U.S. states. Higher NCA.INDEX indicates higher enforceability of non-competition agreement.*
OPAQUE	*The moving sum of the previous three years' absolute value of discretionary accruals.*
PASTRETURN	*The acquirer's raw stock return over the past year before the takeover announcement month, as in Ma, Whidbee, and Zhang (2019).*
PEER	*A dummy variable that equals one if the firm utilizes a relative benchmark of self-selected peers for at least one RPE grant, and zero otherwise, as recorded in ISS.*
PEERPROP	*The propensity of using self-selected peers as the relative benchmark. We calculate the peer benchmark propensity for each sample as the number of grants using self-selected peer benchmarks scaled by the total number of grants using relative benchmarks at that year. Thus, PEERPROP measures the firms' weights on the benchmark utilization of self-selected peers relative to traditional indices. The benchmark of relative performance evaluation for each grant is reported in the firm's proxy statement, as recorded in the ISS.*
PUBLIC	*A dummy variable that equals one if the target is a public firm and zero otherwise*
ROA	*The firm's net income scaled by total assets.*
RPE	*A dummy variable that is equal to one if the firm claims utilization of relative performance evaluation in the proxy statement.*
RPEPROP	*The propensity of using relative performance evaluation (RPE). We calculate the RPE propensity for each sample as the number of grants using relative benchmarks scaled by the total number of grants at that year. Thus, RPEPROP measures the firms' weights on utilization of RPE relative to APE. The performance evaluation method for each grant is reported in the firm's proxy statement, as recorded in the ISS.*
SAMEINDUSTRY	*A dummy variable that equals one if the acquirer and target firms share the same two-digit SIC code and zero otherwise*
SEAR	*The alternative measure of long-term acquisition performance that removes the concern of the bad-model problem (Fama, 1998). Following Field and Mkrtchyan (2017) and Ma et al. (2019), we adopt a [-1, +1] three-day window to calculate the abnormal returns surrounding the subsequent earnings announcement following the acquisition announcement. The subsequent earnings*

	announcement is the first periodic report (10-K or 10-Q) over the six-month to one-year period after the acquisition announcement. We adopt three ways to adjust the raw returns. $SEAR^{VW}$, $SEAR^{EW}$, and $SEAR^{SP}$ denote the subsequent earnings announcement returns adjusted by CRSP value-weighted market returns, CRSP equal-weighted market returns, and S&P 500 market returns separately.
SIZE	*The natural logarithm of the acquirer's total asset.*
STOCK	*A dummy variable that equals one if the percentage of consideration paid in stock is equal to 100 in SDC and zero otherwise.*
TENDER	*A dummy variable that equals one if the deal is a tender offer, and zero otherwise.*
TENURE	*The natural logarithm of the CEO's past tenure, which calculated as the number of years since she or he becomes CEO.*
TOEHOLD	*A dummy variable that equals one if the percentage of shares acquirer held at the announcement date is no less than 5% and zero otherwise.*
VIX	*The CBOE volatility index.*

Table 4.A.2 Alternative Measures of Long-term Acquisition Performance

This table presents the association between *RPE* and long-term acquisition performance for acquisition samples from 2006–2017. This table is directly comparable to Table 4.2 in the main paper, except the dependent variable is the [-1, +1] subsequent earnings announcement abnormal return *(SEAR)*. The subsequent earnings announcement is the first periodic report (10-K or 10-Q) over the six-month to one-year period after the acquisition announcement. $SEAR^{VW}$, $SEAR^{EW}$, and $SEAR^{SP}$ denote the subsequent earnings announcement returns adjusted by CRSP value-weighted market returns, CRSP equal-weighted market returns, and S&P 500 market returns separately. The detailed definitions of variables are presented in Table 4.A.1. All regressions include the industry and year fixed effects. The robust *t*-statistics clustered by the firm are reported in parentheses. ***, **, and * denote the significance at the 1%, 5%, and 10% levels, respectively.

	(1) $SEAR^{VW}$	(2) $SEAR^{VW}$	(3) $SEAR^{EW}$	(4) $SEAR^{EW}$	(5) $SEAR^{SP}$	(6) $SEAR^{SP}$
RPE	0.869***	0.781**	0.826**	0.753*	0.864***	0.775**
	(2.68)	(1.99)	(2.54)	(1.90)	(2.66)	(1.97)
CEOAGE		-0.005		-0.006		-0.006
		(-0.58)		(-0.64)		(-0.58)
CEOFEMALE		0.225		0.174		0.212
		(0.27)		(0.21)		(0.25)
TENURE		0.042		0.046		0.041
		(1.42)		(1.53)		(1.40)
CHAIR		0.483		0.517		0.489
		(0.82)		(0.87)		(0.83)
BOARDSIZE		0.017		0.013		0.016
		(0.37)		(0.29)		(0.35)
BOARDINDEP		0.401		0.442		0.413
		(0.44)		(0.49)		(0.46)
SIZE		-0.125		-0.131		-0.122
		(-1.19)		(-1.25)		(-1.17)
FIRMAGE		0.026		0.027		0.026
		(1.53)		(1.60)		(1.52)
LEV		0.545		0.598		0.553
		(0.59)		(0.65)		(0.60)
BTM		-1.620***		-1.589***		-1.620***
		(-3.41)		(-3.33)		(-3.41)
ROA		2.786*		2.769*		2.772*
		(1.87)		(1.87)		(1.86)
OPAQUE		-1.138**		-1.097**		-1.133**
		(-2.16)		(-2.10)		(-2.13)
PASTRETURN		-0.505		-0.459		-0.532
		(-1.22)		(-1.13)		(-1.27)
STOCK		0.006		-0.005		-0.005
		(0.01)		(-0.01)		(-0.01)
CASH		-0.487		-0.495		-0.501
		(-1.49)		(-1.51)		(-1.53)
TENDER		-0.733		-0.676		-0.738
		(-1.15)		(-1.09)		(-1.15)
HOSTILE		-1.041*		-1.024*		-1.025*
		(-1.78)		(-1.75)		(-1.76)
PUBLIC		0.472*		0.455*		0.471*
		(1.74)		(1.68)		(1.72)
SAMEINDUSTRY		0.542*		0.566*		0.545*
		(1.70)		(1.77)		(1.71)
TOEHOLD		0.508		0.499		0.510
		(1.39)		(1.38)		(1.39)
CROSSBORDER		-0.348		-0.362		-0.360
		(-1.19)		(-1.22)		(-1.23)
DORMANT		0.811**		0.765**		0.820**
		(2.17)		(2.05)		(2.18)
Industry FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Observations	6,681	6,681	6,681	6,681	6,681	6,681
Number of Firms	1862	1862	1862	1862	1862	1862
Adjusted R^2	0.04	0.06	0.04	0.06	0.04	0.05

Table 4.A.3 RPE Propensity and Long-term Acquisition Performance

This table presents the association between *RPEPROP* and acquirer's one-, two-, and three-year *BHAR*. The main explanatory variable *RPEPROP* measures firms' propensity of using RPE in grants. For each year, a firm's *RPEPROP* is the number of grants based on relative benchmarks scaled by the total number of grants. Thus, *RPEPROP* measures the firms' propensity of using RPE relative to APE. The benchmark of performance evaluation for each grant is disclosed in the proxy statement. The detailed definitions of variables are presented in Table 4.A.1. All regressions include the industry and year fixed effects. The robust *t*-statistics clustered by the firm are reported in parentheses. ***, **, and * denote the significance at the 1%, 5%, and 10% levels, respectively

	(1) BHAR12	(2) BHAR24	(3) BHAR36
RPEPROP	1.675	3.671*	7.131***
	(1.09)	(1.84)	(2.85)
CEOAGE	-0.027	-0.017	0.106*
	(-0.93)	(-0.45)	(1.93)
CEOFEMALE	0.594	-4.338	-5.239
	(0.26)	(-0.97)	(-1.04)
TENURE	-0.057	-0.129	-0.330**
	(-0.71)	(-1.14)	(-1.98)
CHAIR	1.572	1.183	0.686
	(0.87)	(0.40)	(0.20)
BOARDSIZE	-0.059	-0.531**	-1.290***
	(-0.30)	(-2.00)	(-3.47)
BOARDINDEP	1.360	-1.753	-8.484
	(0.41)	(-0.39)	(-1.37)
SIZE	-0.544	-0.256	-1.051
	(-1.45)	(-0.50)	(-1.49)
FIRMAGE	-0.078	-0.110*	-0.271***
	(-1.64)	(-1.69)	(-3.11)
LEV	-2.274	-4.876	4.164
	(-0.54)	(-1.04)	(0.70)
BTM	-5.551***	1.479	8.702***
	(-6.03)	(0.69)	(3.39)
ROA	22.296*	-7.880	-26.514**
	(1.88)	(-0.68)	(-2.32)
OPAQUE	-1.334	-1.512	-0.066
	(-0.80)	(-0.79)	(-0.02)
PASTRETURN	-9.436**	-11.746**	-20.302***
	(-2.10)	(-2.17)	(-8.13)
STOCK	1.184	0.898	1.168
	(0.53)	(0.31)	(0.33)
CASH	-0.156	-0.031	-0.862
	(-0.17)	(-0.02)	(-0.55)
TENDER	-0.939	0.539	0.422
	(-0.61)	(0.27)	(0.17)
HOSTILE	-0.346	-4.231**	-5.172**
	(-0.23)	(-2.21)	(-2.22)
PUBLIC	-0.241	-0.090	-0.296
	(-0.26)	(-0.07)	(-0.19)
SAMEINDUSTRY	-0.800	-2.910**	-3.425**
	(-0.87)	(-2.35)	(-2.03)
TOEHOLD	-0.668	0.037	0.582
	(-0.51)	(0.02)	(0.27)
CROSSBORDER	-0.515	-0.865	-0.050
	(-0.57)	(-0.68)	(-0.03)
DORMANT	-0.956	0.413	1.424
	(-0.76)	(0.24)	(0.61)
Industry FE	Y	Y	Y
Year FE	Y	Y	Y
Observations	6,556	6,196	5,508
Number of Firms	2326	2151	1924
Adjusted R^2	0.05	0.05	0.09

Table 4.A.4 Alternative Constructions of BHAR

This table presents the association between *RPE* and long-term acquisition performance with the *BHAR* measure based on alternative constructions. In Panel A, *BHAR* is constructed based on market model. In Panel B, we construct reference portfolios using industry factor before size/value/momentum factors to generate *BHAR*. The detailed definitions of variables are presented in Table 4.A.1. All regressions include the industry and year fixed effects. The robust *t*-statistics clustered by the firm are reported in parentheses. ***, **, and * denote the significance at the 1%, 5%, and 10% levels, respectively.

Panel A: BHAR based on Market Model			
	(1)	(2)	(3)
	BHAR12	BHAR24	BHAR36
RPE	2.722*	4.146*	6.144**
	(1.81)	(1.75)	(2.10)
CEOAGE	-0.025	0.038	0.162**
	(-0.74)	(0.70)	(2.29)
CEOFEMALE	-1.113	-2.992	-2.898
	(-0.39)	(-0.52)	(-0.44)
TENURE	0.119	0.085	0.035
	(1.24)	(0.57)	(0.19)
CHAIR	-0.505	-2.181	-6.370
	(-0.23)	(-0.63)	(-1.51)
BOARDSIZE	0.058	0.314	0.152
	(0.24)	(0.80)	(0.28)
BOARDINDEP	4.416	8.222	6.718
	(1.10)	(1.29)	(0.78)
SIZE	-1.459***	-2.397***	-4.861***
	(-3.25)	(-3.42)	(-5.72)
FIRMAGE	-0.088	-0.087	-0.188
	(-1.49)	(-0.96)	(-1.55)
LEV	-4.767	-7.372	0.318
	(-1.02)	(-1.14)	(0.04)
BTM	-14.657***	-29.026***	-28.007***
	(-7.16)	(-10.79)	(-8.73)
ROA	38.920***	21.068*	11.225
	(4.88)	(1.72)	(0.76)
OPAQUE	-0.248	-4.747	-5.022
	(-0.12)	(-1.55)	(-1.30)
PASTRETURN	9.431**	5.622	-0.895
	(2.16)	(0.99)	(-0.28)
STOCK	-0.608	0.731	0.005
	(-0.22)	(0.18)	(0.00)
CASH	-0.237	0.683	1.252
	(-0.21)	(0.40)	(0.57)
TENDER	0.846	2.292	4.190
	(0.42)	(0.76)	(1.17)
HOSTILE	-0.337	-1.731	0.471
	(-0.20)	(-0.70)	(0.14)
PUBLIC	0.944	0.989	0.791
	(0.84)	(0.58)	(0.35)
SAMEINDUSTRY	1.970*	1.329	2.596
	(1.76)	(0.82)	(1.25)
TOEHOLD	-2.460	-1.005	2.552
	(-1.51)	(-0.43)	(0.96)
CROSSBORDER	0.314	2.228	4.905**
	(0.28)	(1.34)	(2.27)
DORMANT	-0.338	0.209	-0.474
	(-0.22)	(0.09)	(-0.15)
Industry FE	Y	Y	Y
Year FE	Y	Y	Y
Observations	6,617	6,253	5,538
Number of Firms	2395	2220	1976
Adjusted R^2	0.12	0.12	0.13

Panel B: BHAR based on Additional Industry Factor			
	(1)	(2)	(3)
	BHAR12	BHAR24	BHAR36
RPE	2.168*	3.492*	6.096***
	(1.68)	(1.90)	(2.59)
CEOAGE	-0.032	-0.021	0.104*
	(-1.08)	(-0.55)	(1.87)
CEOFEMALE	0.569	-4.423	-5.504
	(0.25)	(-0.99)	(-1.10)
TENURE	-0.053	-0.129	-0.330*
	(-0.66)	(-1.12)	(-1.94)
CHAIR	1.685	1.410	0.923
	(0.94)	(0.48)	(0.27)
BOARDSIZE	-0.070	-0.533**	-1.275***
	(-0.36)	(-2.02)	(-3.44)
BOARDINDEP	1.161	-1.860	-8.369
	(0.35)	(-0.41)	(-1.35)
SIZE	-0.604	-0.290	-1.049
	(-1.60)	(-0.55)	(-1.45)
FIRMAGE	-0.075	-0.106	-0.265***
	(-1.59)	(-1.63)	(-3.02)
LEV	-2.342	-4.985	4.043
	(-0.55)	(-1.06)	(0.68)
BTM	-5.536***	1.472	8.600***
	(-6.04)	(0.69)	(3.38)
ROA	22.357*	-7.823	-26.429**
	(1.88)	(-0.67)	(-2.32)
OPAQUE	-1.330	-1.490	-0.026
	(-0.79)	(-0.78)	(-0.01)
PASTRETURN	-9.451**	-11.783**	-20.407***
	(-2.11)	(-2.18)	(-8.17)
STOCK	1.154	0.870	1.203
	(0.51)	(0.30)	(0.34)
CASH	-0.180	-0.100	-0.991
	(-0.19)	(-0.08)	(-0.63)
TENDER	-0.930	0.550	0.351
	(-0.60)	(0.28)	(0.15)
HOSTILE	-0.308	-4.140**	-5.018**
	(-0.21)	(-2.16)	(-2.14)
PUBLIC	-0.262	-0.097	-0.241
	(-0.28)	(-0.08)	(-0.16)
SAMEINDUSTRY	-0.807	-2.927**	-3.495**
	(-0.88)	(-2.36)	(-2.07)
TOEHOLD	-0.677	0.018	0.536
	(-0.51)	(0.01)	(0.25)
CROSSBORDER	-0.469	-0.808	-0.010
	(-0.52)	(-0.63)	(-0.01)
DORMANT	-0.919	0.509	1.591
	(-0.73)	(0.30)	(0.68)
Industry FE	Y	Y	Y
Year FE	Y	Y	Y
Observations	6,556	6,196	5,508
Number of Firms	2326	2151	1924
Adjusted R^2	0.05	0.05	0.09

Table 4.A.5 Sampling Criteria

This table presents the association between *RPE* and acquirer' one-year *BHAR* for acquisition samples from 2009–2017. This table is comparable to Table 4.2 in the main paper, except samples in 2006, 2007, and 2008 have been excluded. The main explanatory variable *RPE* is a dummy variable equals to one if the acquirer claims utilization of relative performance evaluation in the proxy statement and zero otherwise. The detailed definitions of variables are presented in Table 4.A.1. All regressions include the industry and year fixed effects. The robust *t*-statistics clustered by the firm are reported in parentheses. ***, **, and * denote the significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)
	BHAR12	BHAR12	BHAR12	BHAR12
RPE	3.072***	4.875***	3.987***	4.059***
	(2.77)	(3.69)	(3.02)	(3.06)
CEOAGE		-0.000	-0.018	-0.021
		(-0.01)	(-0.60)	(-0.68)
CEOFEMALE		2.705	1.331	1.393
		(1.11)	(0.55)	(0.57)
TENURE		-0.036	-0.017	-0.013
		(-0.44)	(-0.21)	(-0.17)
CHAIR		-2.781	-3.186	-3.349
		(-0.40)	(-0.40)	(-0.42)
BOARDSIZE		0.035	0.088	0.095
		(0.17)	(0.41)	(0.45)
BOARDINDEP		-6.179*	-2.950	-2.872
		(-1.91)	(-0.85)	(-0.85)
SIZE			-0.441	-0.379
			(-1.09)	(-0.92)
FIRMAGE			-0.053	-0.053
			(-1.02)	(-1.01)
LEV			-1.078	-1.008
			(-0.21)	(-0.19)
BTM			-5.223***	-5.169***
			(-4.79)	(-4.70)
ROA			18.934	18.733
			(1.24)	(1.20)
OPAQUE			-1.667	-1.651
			(-0.97)	(-0.96)
PASTRETURN			-17.925***	-17.920***
			(-2.79)	(-2.78)
STOCK				-0.006
				(-0.00)
CASH				-0.225
				(-0.24)
TENDER				-0.707
				(-0.38)
HOSTILE				0.634
				(0.42)
PUBLIC				-1.565
				(-1.52)
SAMEINDUSTRY				1.457
				(1.37)
TOEHOLD				0.608
				(0.41)
CROSSBORDER				-0.409
				(-0.40)
DORMANT				0.072
				(0.05)
Industry FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Observations	4,490	4,490	4,490	4,490
Number of Firms	1876	1876	1876	1876
Adjusted R^2	0.03	0.03	0.09	0.09

Table 4.A.6 Alternative Model Specifications

This table reports the association between *RPE* and acquirer's one-year *BHAR*, replacing 3-digit SIC with 4-digit SIC, FF48, and Industry-Year fixed effect. FF48 denotes Fama-French 48 industries. Industry-Year FE denotes the fixed effect of interaction between year and FF48. The detailed definitions of variables are presented in Table 4.A.1. All regressions include industry and year fixed effects. The robust *t*-statistics clustered by the firm are reported in parentheses. ***, **, and * denote the significance at the 1%, 5%, and 10% levels, respectively.

	(1) 4-digit SIC	(2) FF48	(3) Industry-Year FE
RPE	3.508***	3.030**	2.778**
	(2.65)	(2.57)	(2.25)
CEOAGE	-0.021	-0.023	-0.029
	(-0.73)	(-0.87)	(-1.08)
CEOFEMALE	0.904	0.436	-1.789
	(0.40)	(0.19)	(-0.72)
TENURE	0.060	-0.002	0.027
	(0.83)	(-0.03)	(0.39)
CHAIR	-0.296	-0.911	-0.083
	(-0.18)	(-0.57)	(-0.05)
BOARDSIZE	-0.103	-0.042	-0.020
	(-0.54)	(-0.23)	(-0.11)
BOARDINDEP	0.231	-0.154	-0.348
	(0.08)	(-0.05)	(-0.11)
SIZE	-0.248	0.115	0.160
	(-0.66)	(0.36)	(0.46)
FIRMAGE	-0.076	-0.051	-0.054
	(-1.45)	(-1.09)	(-1.13)
LEV	-1.903	-0.677	-0.449
	(-0.42)	(-0.16)	(-0.11)
BTM	-4.801***	-3.717***	-3.312***
	(-5.60)	(-3.82)	(-3.40)
ROA	14.459	14.924	15.227
	(1.26)	(1.30)	(1.39)
OPAQUE	-1.477	-1.124	-2.094
	(-0.98)	(-0.75)	(-1.25)
PASTRETURN	-22.404***	-22.521***	-21.718***
	(-4.74)	(-4.93)	(-4.31)
STOCK	-0.461	0.113	0.295
	(-0.22)	(0.05)	(0.14)
CASH	-1.312	-1.079	-0.399
	(-1.59)	(-1.33)	(-0.47)
TENDER	-0.071	0.201	0.346
	(-0.05)	(0.13)	(0.22)
HOSTILE	0.701	1.079	0.485
	(0.52)	(0.84)	(0.36)
PUBLIC	-0.451	-0.802	-1.213
	(-0.51)	(-0.93)	(-1.38)
SAMEINDUSTRY	0.769	1.118	0.795
	(0.90)	(1.36)	(0.97)
TOEHOLD	-0.530	-0.773	-0.374
	(-0.42)	(-0.57)	(-0.29)
CROSSBORDER	0.245	0.588	0.317
	(0.29)	(0.70)	(0.36)
DORMANT	0.193	0.926	0.621
	(0.16)	(0.79)	(0.53)
Industry FE	Y	Y	N
Year FE	Y	Y	Y
Industry-Year FE	N	N	Y
Observations	6,790	6,683	6,625
Number of Firms	2,443	2,428	2,409
Adjusted R^2	0.11	0.09	0.13

Table 4.A.7 Peer Propensity and Long-term Acquisition Performance

This table presents the association between *PEERPROP* and acquirer's one-, two-, and three-year *BHAR* for firms using relative performance evaluation. The main explanatory variable *PEERPROP* measures firms' trade-off between self-selected peers benchmark and traditional indices benchmark. For each year, a firm's *PEERPROP* is the number of grants of which the performance is evaluated based on self-selected peers scaled by the total number of grants using relative benchmarks. Thus, *PEERPROP* measures the firms' weights on the benchmark utilization of self-selected peers relative to traditional indices. The benchmark of relative performance evaluation for each grant is disclosed in the proxy statement. The detailed definitions of variables are presented in Table 4.A.1. All regressions include the industry and year fixed effects. The robust *t*-statistics clustered by the firm are reported in parentheses. ***, **, and * denote the significance at the 1%, 5%, and 10% levels, respectively.

	(1) BHAR12	(2) BHAR24	(3) BHAR36
PEERPROP	2.750**	3.141*	5.008**
	(2.10)	(1.79)	(2.33)
CEOAGE	-0.010	-0.043	0.054
	(-0.38)	(-1.31)	(1.24)
CEOFEMALE	0.293	3.640	-5.757
	(0.13)	(0.67)	(-1.25)
TENURE	0.030	0.063	0.011
	(0.43)	(0.71)	(0.09)
CHAIR	-0.928	0.094	1.337
	(-0.56)	(0.04)	(0.48)
BOARDSIZE	-0.025	-0.172	-0.769***
	(-0.14)	(-0.80)	(-2.62)
BOARDINDEP	1.163	-0.939	-6.061
	(0.40)	(-0.26)	(-1.23)
SIZE	0.041	0.950**	1.073**
	(0.12)	(2.28)	(2.00)
FIRMAGE	-0.075*	-0.110*	-0.257***
	(-1.66)	(-1.94)	(-3.66)
LEV	-2.259	-0.346	5.623
	(-0.54)	(-0.08)	(1.21)
BTM	-5.012***	4.580**	10.136***
	(-5.81)	(2.05)	(4.26)
ROA	14.140	-27.961***	-50.550***
	(1.28)	(-2.84)	(-5.54)
OPAQUE	-1.313	-1.544	-3.020
	(-0.87)	(-1.08)	(-1.22)
PASTRETURN	-22.651***	-25.521***	-30.476***
	(-4.92)	(-4.85)	(-14.18)
STOCK	-0.198	0.910	2.580
	(-0.09)	(0.37)	(0.89)
CASH	-1.164	-0.244	-1.859
	(-1.42)	(-0.23)	(-1.40)
TENDER	-0.120	1.541	1.891
	(-0.08)	(0.89)	(0.88)
HOSTILE	0.849	-1.731	-2.417
	(0.65)	(-1.05)	(-1.39)
PUBLIC	-0.316	-1.699	-2.028
	(-0.36)	(-1.55)	(-1.50)
SAMEINDUSTRY	0.870	-1.904*	-1.320
	(1.02)	(-1.74)	(-0.92)
TOEHOLD	-0.620	1.239	1.506
	(-0.50)	(0.81)	(0.93)
CROSSBORDER	0.309	0.109	-0.146
	(0.37)	(0.11)	(-0.11)
DORMANT	0.389	0.304	-0.257
	(0.34)	(0.20)	(-0.14)
Industry FE	Y	Y	Y
Year FE	Y	Y	Y
Observations	6,811	6,433	5,695
Number of Firms	2464	2283	2033
Adjusted R^2	0.11	0.14	0.18

Chapter 5

Conclusions

This dissertation studies the agency problem, addressing the issues of incentives contracts, M&As, and firm risk. It provides empirical evidence of agency costs by demonstrating that high manager sentiment drives takeover activities and decreases the long-term acquisition performance. Moreover, high-sentiment managers tend to undertake large deals, decrease the all-stock payment, acquire hard-to-value targets, and offer high target valuation, which implies the over-investment channel for the underperformed high-sentiment deals. This study helps us understand the unfavorable impacts of high manager sentiment, a managerial trait proxy for managerial optimism, on the causes and consequences of takeovers.

Furthermore, this dissertation examines the effects of RPE on stock price crash risk and long-term acquisition performance, indicating its effectiveness in mitigating agency costs. On the one hand, RPE decreases stock price crash risk. The RPE-crash risk relation mainly manifests in firms with higher managerial ability, systematic uncertainty, industry competition, and managerial myopia correctability. The decreased market pressure is the primary channel through which RPE affects crash risk. RPE firms are associated with higher information disclosure quality and lower analyst optimism. On the other hand, RPE improves long-term acquisition

performance. In terms of heterogeneity, the increasing effect of RPE on long-term acquisition performance is more pronounced for firms with higher market uncertainty, higher managerial myopia correctability, and lower external monitoring. The possible explanations are that RPE mitigates the managerial myopia problem and motivates managers to capture better transaction timing.

Overall, RPE reconciles the interests between principals and agents and reduces agency costs. The findings provide important implications for understanding optimal incentive contracts, managerial short-termism, and information disclosure. It helps investors build awareness of managers' unfavorable takeover activities and information manipulation behaviors. Besides, the dissertation provides useful implications for regulatory agencies to establish appropriate supervisory procedures for corporate governance and firm policies. The incentive contracts of RPE are useful to suppress value-reducing M&As and control the stock price crash risk, which is highly relevant to firm value and financial market stability. Regulatory agencies should understand why takeover activities are sometimes overheated and value-destroying, which may damage firm value and economic growth. Thus, they are able to avoid unfavorable activities promptly and effectively. Firms should evaluate managers using informative ways and encourage managers to be cautious and rational when evaluating investment opportunities.

While this dissertation demonstrates the favorable impacts of RPE on stock price crash risk and long-term acquisition performance, its effects on other

managerial behaviors such as firm innovation, tax avoidance, and financial distress remain open questions. Future research can explore the positive round impacts of informative contracts on reducing agency costs. At the same time, other contractual factors potentially beneficial to build more informative contracts are worth studying in-depth.

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The three essays collected in this PhD dissertation concern agency costs, incentive contracts, mergers and acquisitions, and firm risk. The first essay demonstrates that manager sentiment, a managerial trait proxy for managerial optimism, can incur agency costs. The second and third essays state incentive contracts as an effective way to suppress agency problems and reduce agency costs. Specifically, the second essay demonstrates that firms using relative performance evaluation exhibit lower stock price crash risk and the third essay finds that relative performance evaluation increases long-term acquisition performance.

Suwei An (1992) received his Bachelor's degree at Central University of Finance and Economics in 2014, majoring in Human Resource Management and minoring in Finance. He obtained his Master's degree in Finance at The University of Melbourne in 2016. He has been engaged in investment work for several years. He currently takes charge of the Strategic Investment of the People's Daily Media of China. He previously acted as director, senior analyst, analyst of the Investment and Financing division of Beijing Fangshan Future City Investment. He also served as a supervisor of Beijing Fund Town.

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