CORPORATE GOVERNANCE AND TOP MANAGEMENT FRAUD IN CONSTRUCTION COMPANIES: A CHINA STUDY

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Corporate Governance and Top Management Fraud in Construction Companies: A China Study

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CERTIFICATE OF ORIGINALITY

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ABSTRACT

Corruption in construction companies often leads to injuries and deaths. To explore the antecedents of corrupt practices in construction companies, most previous studies have emphasized the effects of operational managers while neglecting to examine the impact of top managers. As decision-makers in a firm, top managers can determine the establishment and dissolution of project teams and may force project managers to save costs excessively by cutting corners or remain silent when their subordinates engage in some unlawful practices.

This dissertation investigated the role of top manager characteristics, internal governance mechanisms, and the other organizational contexts in top management fraud in construction companies at the individual and corporate levels. Though a great number of factors have been identified as contributing to the possibility of engaging in fraudulent behaviors, minimal research has focused on ranking the importance of these factors and using them to predict corporate fraud in the construction industry. Thus, this dissertation also examined the most influential factors among organizational features and constructed a prediction model. A combination of statistical methods and machine learning tools was used in this dissertation. Hierarchical linear modeling was applied to explore the drivers of an individual executive's occupational fraud due to the multilevel, specifically individual and corporate level, structure of the data. Then a hierarchical logit regression model with fixed effects was adopted in investigating the determinants of corporate fraud. Random forest (RF), a machine learning tool, was introduced for ranking the importance of factors associated with corporate fraud. This tool was also used to construct a corporate fraud prediction model.

Using a multi-year sample of construction firms in China, this dissertation draws several important conclusions. First, regarding an

individual executive's fraudulent behaviors, executives near retirement are associated with a lower likelihood of occupational fraud, and this likelihood is further reduced if his/her firm has a less independent board or a higher percentage of shares held by the state. Second, corporate fraud is positively affected by top management team (TMT) compensation. Aspiration–performance discrepancies have an inverted V-shaped relationship with the probability of illegal activities. The positive relationship between TMT compensation and corporate fraud is strengthened by aspiration–performance discrepancies. Third, based on the variable importance analysis of RF, the 11 most important variables associated with an increased risk of corporate illegal activities were obtained. All 11 variables relate to corporate governance, rather than financial performance. Last, RF is recommended for detecting corporate fraud in the construction industry.

This dissertation facilitates our understanding of corruption in construction companies and contributes to academic theories in the fields of organization theory, strategic management, and business ethics. The used machine learning tools provide alternative ways for researchers to investigate and evaluate construction companies. The results are likely to be of interest to decision-makers including top managers, boards of directors, shareholders, investors, and relevant regulators.

PUBLICATIONS ARISING FROM THE STUDY

Journal Papers

[1] **Wang, R.**, Lee, C. J., Hsu, S. C., Zheng, S., & Chen, J. H. (2020). Effects of Career Horizon and Corporate Governance in China's Construction Industry: Multilevel Study of Top Management Fraud. *Journal of Management in Engineering*, 36(5), 04020057.

[2] **Wang, R.**, Lee, C. J., Hsu, S. C., & Chen, J. H. Preventing or Encouraging Illegal Activities by Construction Firms: Effects of Top Management Team Compensation and Aspiration-Performance Discrepancies. Engineering, Construction and Architectural Management (Accepted).

[3] **Wang, R.**, Asghari, V., Hsu, S. C., Lee, C. J., & Chen, J. H. (2020). Detecting corporate misconduct through random forest in China's construction industry. *Journal of Cleaner Production*, 268, 122266.

[4] **Wang, R.**, Lee, C. J., Hsu, S. C., & Lee, C. Y. (2018). Corporate Misconduct Prediction with Support Vector Machine in the Construction Industry. *Journal of Management in Engineering*, 34(4): 04018021.

[5] Lee, C. J., **Wang, R.**, Lee, C. Y., Hung, C. C., & Hsu, S. C. (2018). Board Structure and Directors' Role in Preventing Corporate Misconduct in the Construction Industry. *Journal of Management in Engineering*, 34(2), 04017067.

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Conference Papers

[7] **Wang, R.**, Lee, C. J., Hsu, S. C., & Lee, C. Y. (2018). Top Managers and Corporate Misconduct: An Application of SVM model in misconduct prediction. *2018 Academy of Management Meeting*, August 10~14, Chicago, IL, USA.

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LIST OF ACRONYMS

BI	Board Independence
CART	Classification and Regression Tree
CCER	China Centre for Economic Research
CEO	Chief Executive Officer
CF	Corporate Fraud
CH	Career Horizon
CNN	Cable News Network
CSMAR	China Stock Market and Accounting Research
CSR	Corporate Social Responsibility
CSRC	China Securities Regulatory Commission
CV	Control Variables
DER	Debt-to-Equity Ratio
DT	Decision Tree
DV	Dependent Variable
EBIT	Earnings before interest and taxes
FN	False Negative
FP	False Positive
HLM	Hierarchical Linear Modeling
ICC	Intra-Class Correlations
IV	Independent Variable
KNN	K-Nearest Neighbors
LR	Logistic Regression
MOHURD	Ministry of Housing and Urban-Rural Development
MV	Moderating Variables
NRP	Negative Relative Performance
NRP-DER	Negative Relative Performance for Debt-to-Equity Ratio
NRP-ROA	Negative Relative Performance for Return on Assets
OOB	Out-of-Bag
PRP	Positive Relative Performance
PRP-DER	Positive Relative Performance for Debt-to-Equity Ratio
PRP-ROA	Positive Relative Performance for Return on Assets
$\mathbf{R^2}$	Coefficient of Determination
R&D	Research and Development
RAM	Random Access Memory
RBF	Radial Basis Function
RF	Random Forest
ROA	Return on Assets
ROE	Return on Equity
SD	Standard Deviation
S.E.	Standard Error

SO	State Ownership
SMOTE	Synthetic-Minority Over-Sampling Technic
SVM	Support Vector Machine
TMT	Top Management Team
TN	True Negative
TP	True Positive
VIF	Variance Inflation Factor

CHAPTER 1 INTRODUCTION

1.1 Research Background

The construction sector greatly contributes to the national economy and influences human health and social activities. However, there are many paradoxes in the construction industry in terms of corporate social responsibility (CSR) (Lu *et al.*, 2016). Even though more and more academics and practitioners in the construction industry are emphasizing sustainable business (Chang *et al.*, 2018; Lu *et al.*, 2018; Nosratabadi *et al.*, 2019) and CSR (Liao *et al.*, 2018; Loosemore *et al.*, 2018; Xia *et al.*, 2018; Zhang *et al.*, 2019), the construction industry has a reputation for being irresponsible. It has been designated as one of the most corrupt industries (Transparency International, 2008) and faces many unlawful challenges (e.g., fraud, bid shopping) (Ho, 2011). Unlawful activities, such as using unqualified materials or equipment and faking financial statements, may occur when firms consider the upside benefits of those behaviors to exceed the downside risk (Mishina *et al.*, 2010).

Revelations of such corrupt practices have damaging consequences across multiple levels of the construction industry. The reputations of implicated managers are affected and they even may be dismissed (Agrawal *et al.*, 1999; Aharony *et al.*, 2015; Gomulya and Boeker, 2016). For the firm itself, once a firm's scandals become public knowledge, not only are stock prices slashed or billions of dollars in fines lost, but companies may also end up bankrupt (Davidson and Worrel, 1988; Firth *et al.*, 2011; Xu *et al.*, 2016). For the local community, associated tax revenue may decrease and unemployment rise, especially when the demand for related secondary businesses such as restaurants and gas stations decreases (Zahra *et al.*, 2005).

For society, confidence in the free market system is eroded (Klein, 1998; Paruchuri and Misangyi, 2015) and corruption may cause a depressed moral climate in a society (Shadnam and Lawrence, 2011; Szwajkowski, 1985).

In addition to these repercussions, corrupt practices in the construction industry can lead to injuries and death (Chan and Owusu, 2017; Transparency International, 2005). In Cambodia, a building under construction collapsed, killing at least 24 people and injuring 24 others, while the project was reported to have lacked required permits (Narin and Beech 2019). In India, 27 people were confirmed dead and at least 80 were injured due to the collapse of a flyover. Several top executives of the construction company were arrested, including its deputy general manager (The Indian Express, 2016). These events are also common in China. In 2019, 11 people were killed and 2 seriously injured in the collapse of an elevator at a construction site in Hebei Province (Xinhua, 2019). In 2016 in Jiangxi Province of China, a construction platform at Fengcheng Coal Power Plant toppled over, which killed 74 people and injured 2 others. The chairman, chief engineer, and project leaders of the construction company along with others were arrested on charges of collusion bidding, dereliction of duty, bribery, and embezzlement (CNN, 2016). The same year, 73 people were killed in Shenzhen because of a landslide of dirt and construction debris. 53 people were detained in connection with the disaster, including company executives and government officials, and 57 others faced disciplinary measures such as demotion. The investigation blamed shoddy oversight and negligence (Perlez 2016). Regrettably, financial misrepresentation, bribery, and other illegal activities have still been widely reported in the construction industry worldwide (Krista, 2017; Signor *et al.*, 2016; Transparency International, 2008).

These cases and more indicate that corruption in the construction sector is not something new to the various parties involved in this sector. Such corrupt activities leave other parties harmed or otherwise forced to deal with the consequences. Therefore, it is vital for researchers and practitioners (e.g., business owners and stakeholders) to propose and implement some measures to prevent corruption in the construction industry.

1.2 Problem Statement

In discussions of corruption involving business organizations, researchers usually refer either to "corrupt organizations" or "organizations of corrupt individuals" (Pinto *et al.*, 2008). While certain organizations may be so thoroughly infused with corrupt norms and behavior that they could be considered "corrupt" (Rusch, 2016), a growing body of research demonstrates dishonest behaviors are greatly influenced by business leaders without professional ethics and morals (Alkhatib and Abdou, 2018). Among the unethical leaders, operational level managers have been emphasized in previous studies (Ameyaw *et al.*, 2017; Bowen *et al.*, 2012; Owusu *et al.*, 2019). However, the fraudulent choices of operational level managers may be determined by multiple factors due to a company's hierarchy of reporting relationships. For example, top management, as the final decision makers in a firm, can force project managers to save costs excessively by cutting corners. Moreover, top managers can engage in criminal behavior themselves such as by misstating or hiding some financial standing, which may give rise to a league of acquiescent followers who also behave unethically or illegally (Owusu *et al.*, 2019). However, the fraudulent behaviors of top managers have been overlooked, especially in the context of the construction industry. Thus, it is vital to explore the antecedents of top management fraud in construction companies.

Previous studies have stated that an executive's choices, including whether to engage in fraudulent activities, may be affected by their characteristics (Baucus, 1994; Greve *et al.*, 2010; Zahra *et al.*, 2005). Among characteristics, their career horizon has been reported to have a significant impact on corporate strategic decisions and subsequent organizational outcomes (e.g., McClelland et al. 2012). Little research has examined the effects of executives' career horizons on top management fraud. Career horizon can particularly matter in relation to top management fraud since an executive's career horizon impacts his/her risk preferences and risk-taking behaviors (Matta and Beamish 2008). When executives approach retirement age, some risk-averse choices may be preferred to preserve a legacy of success. As such, it is reasonable to surmise that an executive's career horizon can play a critical role in whether the executive makes fraudulent choices. In addition, contextual factors (e.g., organizational factors) can exert an influence on the commitment of illegal acts (Zahra *et al.*, 2005). Either individual characteristics (Baucus, 1994; Troy *et al.*, 2011) or organizational factors (Lee *et al.*, 2018; Shi *et al.*, 2017) have been explored in prior studies, but few studies have considered both of them simultaneously. An individual with particular features may exhibit different behaviors in different contexts. Hence, in consideration of organizational factors, investigating the impact of an executive's career horizon on top management fraud seems essential and relevant due to the influence of career horizon on their risk preferences and strategic choices.

Apart from a top manager's individual choices, fraudulent behavior may be a result of group decision-making. Among the pertinent groups in question, the top management team (TMT) has been the focus of many studies (Heavey and Simsek, 2017; Li, 2018; Sahaym *et al.*, 2016; Yoo and Reed, 2015). Top managers often work collectively as a dominant coalition because managing a firm is a shared effort in general (Cyert and March, 1963). Considering their significant role in setting the overall direction of an organization, compensation packages and other corporate governance mechanisms have been proposed to mitigate possible moral hazards and to motivate executives (Conyon and He, 2011). Surprisingly, scholars have not reached a consensus about the effects of TMT compensation on organizational fraud. This may be at least in part because of insufficient attention to situational factors. One potentially relevant but neglected contextual factor is aspiration-performance discrepancies, given that executive compensation is often tied to firm performance and organizations strive to achieve their desired benchmarks (Harris and Bromiley, 2007). Therefore, it is essential to empirically explore whether the effects of TMT compensation are affected by performance discrepancies in making risky decisions, e.g. engaging in improper actions when a company is performing lower than acceptable level.

Clarifying the antecedents of corporate fraud is still far from effectively preventing its occurrence. Due to the limited budget and resources of a firm, attempting to taken into account all those factors in order to take appropriate action is very difficult. Though considerable effort has been poured into fraud prevention practices and research, corporate scandals continue to arise. Therefore, it is necessary to identify and rank the importance of contributing factors. By focusing on the most important factors, the effectiveness of fraud prevention could be improved and suitable countermeasures could be initiated in advance. Moreover, timely and accurate detection of illegal corporate behaviors once they have already occurred is also essential. This would enable regulators and investors to promptly identify violating companies so that proactive interventions may be implemented in a targeted manner.

The main objectives of this dissertation are:

(1) to explore the executive’s characteristics (i.e., career horizon) that induce a top manager’s fraudulent behavior at the individual level, taking organizational factors into consideration.

(2) to investigate the effects of TMT compensation on fraud at the corporate

level, considering aspiration-performance discrepancies as a situational factor.

(3) to construct a model to rank the importance of the possible factors and to predict the occurrence of corporate fraud in the construction industry.

1.3 Research Methodology

This study mainly employs several methods, including literature review, hierarchical linear modeling, hierarchical logit regression with fixed effects, and random forest. First, influential drivers of corruption in the construction industry, antecedents of top management fraud, and inputs and techniques for corporate fraud prediction were identified through a comprehensive literature review. The relevant theories were also reviewed. Second, regarding fraud at the individual executive level (Objective 1), hierarchical linear modeling was adopted to explore the antecedents of a top manager's fraud from individual executive and corporate level. Third, as for the fraud at the corporate level (Objective 2), hierarchical logit regression with fixed effects was applied to examine the moderating effect of aspiration-performance discrepancies on the relationship between TMT compensation and a corporate's fraud. Finally, in terms of ranking influential factors and predicting corporate fraud (Objective 3), random forest was used to identify the most important influential factors and to construct the corporate fraud detection model.

1.4 Dissertation Outline

After clarifying the general background for the research problems and the main aims and overviewing the research methodology briefly, the rest of the dissertation is organized as follows.

Chapter 2: Literature Review. This chapter reviews previous studies about corruption in the construction industry, describes in more detail aspects of top management fraud, reviews the antecedents of top management fraud as identified in previous studies, and then presents the theoretical foundation for this study.

Chapter 3: Research Methodology. This chapter provides the research design and several research methods applied in this study, including hierarchical linear modeling, hierarchical moderating logistic regression with fixed effects, and random forest.

Chapter 4: Occupational Fraud. Adopting hierarchical linear modeling, this chapter explores the potential relationship between an executive's career horizon and likelihood that he/she participates in occupational fraud. This chapter also considers how firm-specific variables, particularly board monitoring and ownership structure, may have a moderating effect on the relationship between career horizon and occupational fraud.

Chapter 5: Corporate Fraud. Using hierarchical moderating logistic regression, this chapter examines the relationship between TMT compensation and fraudulent corporate activities with consideration of the possible moderating effects of aspiration-performance discrepancies based on agency theory and behavioral theory of the firm.

Chapter 6: Corporate Fraud Detection. This chapter presents a random forest (RF) model to rank the importance of the variables about corporate governance and financial performance and use those variables to predict corporate fraud in the construction industry.

Chapter 7: Summary of Major Findings. This chapter summarizes the major findings in exploring the antecedents of top management fraud, identifying the most influential factors, and building corporate fraud detection model.

Chapter 8: Conclusion. This chapter discusses contributions, implications, and limitations of the present study and proposes possible future research directions.

The overall organization of the chapters in the dissertation is shown in Figure 1-1.

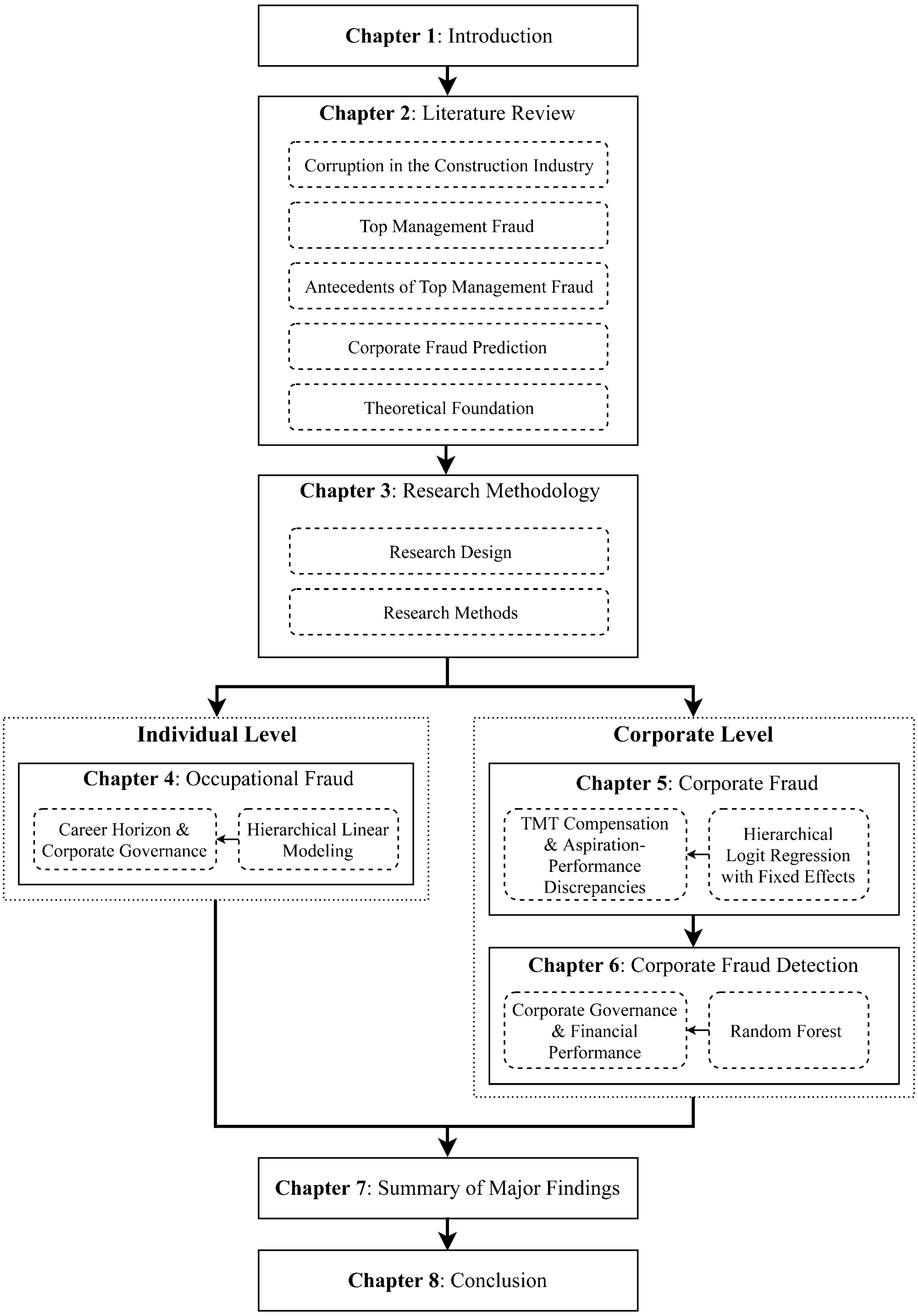


Figure 1-1. Organization of chapters in this dissertation

CHAPTER 2 LITERATURE REVIEW

2.1 Introduction

This chapter first reviews the existing studies about corruption in the construction industry. Then aspects of top management fraud are described, and the drivers of top management fraud as identified in prior research are reviewed. Next, previous research on corporate fraud prediction is summarized. Finally, several related theories in the field of corporate governance are introduced as the theoretical foundation of this work.

2.2 Corruption in the Construction Industry

As a result of rapidly changing and competitive environments (Reeves-Latour and Morselli, 2017), as well as project complexity and production uniqueness (Bowen *et al.*, 2012), the construction industry has been a markedly high-risk sector (Beltrão and Carvalho, 2019) and is considered as one of the most corrupt sectors in the world (Transparency International, 2011; Zhang *et al.*, 2017). Due to the fragmented nature of the construction industry involving several transaction parties (Ahmad *et al.*, 1995; Kenny, 2009), unethical actions may occur during any phase of a project (Tabish and Jha, 2011). Various forms of corruption have been identified, such as bid cutting (May *et al.*, 2001), collusive tendering (Dorée, 2004; Zarkada-Fraser and Skitmore, 2000), and setting up front/shell companies (Chan and Owusu, 2017). These behaviors may be attributed to underlying factors at different levels. From a macro perspective, flawed government regulation systems may elevate the chances of opportunistic behaviors, and a negative industrial climate may encourage bad practices (Le *et al.*, 2014a). A corrupt culture of the construction industry would normalize corrupt behaviors (Brown and Loosemore, 2015). Chao and Liou (2007) argued that intense market competition contributes to bid-cutting, which may lead to more incidents of collusive tendering. From a micro perspective, some scholars emphasize individual traits, like an attitude conducive toward corruption (Brown and Loosemore, 2015), egoism, and utilitarianism (Fan and Fox, 2009). From a meso perspective, economic pressures (Alutu and Udhawuve, 2009), board structure (Lee *et al.*, 2018), organizational corrupt culture (Liu, 2016), commitment to abide by ethical, building, or other codes (Alkhatib and Abdou, 2018; Ameyaw *et al.*, 2017), and other organizational factors may contribute to the occurrence of illegal behaviors. In particular, Kankaanranta and Muttilainen (2010) found that dealing in receipts (such as counterfeit invoicing) is one of the most common economic crimes committed by construction companies in Finland. The researchers also identified entrepreneurs and managers, who are upper-class members of society, as the first and third most common occupations for the suspects of economic crime, respectively.

Among managers in a firm, operational managers and professionals at the project level have been emphasized in previous literature (Ameyaw *et al.*, 2017; Bowen *et al.*, 2012; Owusu *et al.*, 2019; Sohail and Cavill, 2008). As frontline managers are responsible for day-to-day operations at construction sites, their deliberately negligent behaviors, including poor supervision, or use of substandard materials, can lead to substantial loss of life and property (Owusu *et al.*, 2019; Tabish and Jha, 2011). Although project leaders have plenty of opportunities to engage in corrupt practices, a company's hierarchy of reporting relationships makes unethical choices multi-determined (Kish-Gephart *et al.*, 2010). For example, top managers, who are the final decision makers in a firm, may pressure project managers to save costs excessively by cutting corners or remain silent when their subordinates engage in some corrupt practices. Given these considerations, it is essential to pay attention to top management’s bad behaviors and explore the drivers of top management fraud in the construction industry.

2.3 Top Management Fraud

Top management fraud refers to the deliberate actions taken by top managers to con, deceive, cheat or swindle investors or other stakeholders, with the purpose of benefiting the individual perpetrator and/or the corporation (Zahra *et al.*, 2005). It may have various forms, including insider trading, embezzlement, corruption, failure to or postponing disclose facts, misrepresentation and other fraudulent activities (Apostolou *et al.*, 2000; Moberg, 1997). Though top management fraud committed specifically in the construction industry has not been amply studied, wrongdoing committed by top management has captured the attention of a great number of researchers in other fields (Caplan, 1999; Mishina *et al.*, 2010; Williams *et al.*, 2000). According to the nature of the offense itself, top management fraud can be classified into two categories, occupational fraud and corporate fraud (Clinard and Quinney, 1967; Haß *et al.*, 2015; Holtfreter, 2005; Shepherd and Button, 2019; Zahra *et al.*, 2005). The former is committed on behalf of the individual offender while the latter is committed with the support of the corporate.

2.3.1 Occupational Fraud

Occupational fraud means those criminal actions committed for individual financial gains on behalf of the individual offender, in the context of a legitimate occupation (Friedrichs, 2002). Top managers are ultimately responsible for running a firm and making key decisions. Some of them may engage in fraudulent activities by abusing their positions and misusing or misapplying the organizations' resources or assets for direct or indirect personal enrichment (Association of Certified Fraud Examiners, 2014; Timofeyev, 2015). Occupational fraud in an organization is very common and may include many activities. These activities include stealing or misusing the firm's assets such as cash or other inventory. Top managers in the construction industry may also commit corrupt practices such as financial misrepresentation, misappropriation of project funds, insider trading, bribery, and nepotism (Le *et al.*, 2014b). Moreover, some managers may choose to manipulate revenue or other figures to cheat shareholders.

2.3.2 Corporate Fraud

Corporate fraud refers to the illegal activities taken by firms by raising revenues or reducing costs when they believe that the upside benefits of doing so will exceed the downside risks (Mishina *et al.*, 2010; Szwajkowski, 1985). A corporation should be regarded as moral agents (French, 1979, 1984), which means that corporations should be morally responsible for their behaviors and corresponding consequences. Corporate fraud should be considered as a group behavior, although represented by individuals (Meier, 2011). Given these considerations, this dissertation attributes corporate fraud to the top management team rather than to an individual top manager. Typical corporate fraud in the construction industry includes but is not limited to using substandard materials and equipment, major contractors extorting subcontractors, fictitious capital and profits, and evading taxes and mandatory fees.

2.4 Antecedents of Top Management Fraud

Regardless of occupational fraud or corporate fraud, there must be some individual actors to perform, approve or condone fraudulent activities. The perpetrators are often depicted as individuals who are highly educated and possess high-status occupations, which is in line with the work of Sutherland (1949). Studies usually explore the antecedents of top management fraud from the individual or organizational level.

2.4.1 Antecedents from the Individual Level

According to the review work by Treviño et al (2006), previous research on ethical decision-making often focuses on an individual's psychological status. Most research on individual ethical decision-making is based on James Rest's four-component framework. The four components are: moral awareness (an interpretative process of recognizing a situation as a moral problem or a moral principle associated with the circumstances), moral judgment (the decisions regarding which actions are morally right), moral motivation (an individual's degree of prioritizing moral values over other values), and moral behavior (the execution of moral intent) (Rest, 1986; Rest *et al.,* 1999). O'Fallon and Butterfield (2005) reviewed and analyzed the determinants of each of Rest's four variables. They found that individual-level influential factors mainly consist of locus of control, Machiavellianism, personal philosophy/value orientation, and other invisible psychological factors. Reynolds (2006) investigated the role of individual differences in ethical predispositions and preferences for utilitarian and formalistic ideals in moral awareness, the first component of James Rest's four-component analysis.

Other studies have looked to demographic characteristics to gain insights on less visible aspects of the psychological profiles of individual decision-makers. Grullon et al. (2009) provided evidence that people who are less religious are more likely to report or reveal fraud. Similarly, Chintrakarn et al. (2017) found that there is a significant negative relationship between religious piety and entrenched (staggered) boards of directors. Piff *et al.* (2012) demonstrated that an individual's social class can affect the likelihood of engaging in unethical behaviors and that upper-class individuals are more likely to commit wrongdoing than lower-class individuals. Williams et al. (2000) found that an executive's business school education and military service may exert an influence on the likelihood of carrying out criminal acts. Gender, education level, position, and other demographic properties have also been found to be related to the likelihood of engaging in corrupt activities (Collins *et al.*, 2009; Mocan, 2008; Timofeyev, 2015).

2.4.2 Antecedents from the Corporate Level

Organizational factors have been reported to be associated with an individual's fraudulent decisions and corporate fraud. In an organization, individuals' notions and behaviors are always associated with their leaders'. Thus, much research has concentrated on the role of leadership in encouraging unethical behaviors (Bonner *et al.*, 2016; Brown *et al.*, 2005; Mayer *et al.*, 2010). Furthermore, some studies have proposed that individuals' fraudulent behaviors are also influenced by their peers' ethical attitudes and behaviors. As the frequency and intensity of interactions between an individual and his/her peers increase, the influence is stronger (Zey-Ferrell and Ferrell, 1982). Weaver et al. (2005) provided empirical evidence on how others' ethical behaviors provides a model for a person's own ethical behavior.

Ethical climate and ethical culture are often considered as antecedents of organization members' fraudulent behaviors. Victor and Cullen (1988) introduced the idea of ethical climate and proposed that organization members' ethical-oriented attention and behaviors are affected by their perceptions of an organization's ethical climate. Lu and Lin (2014) reported there is a positive relationship between ethical climate and ethical behaviors. Andreoli and Lefkowitz (2008) provided evidence that ethical climate has a negative impact on fraud in organizations. Similarly, Kaptein (2011) explained fraudulent behaviors as a result of an organization's ethical culture and found that ethical culture is negatively related to fraudulent practices.

Top management fraud has also been attributed to corporate financial performance. There is the intuition that companies with poor performance are more likely to engage in fraud. That intuition was empirically supported by Alexander and Cohen (1996), who found that a low rate of sales was a predictor of corporate environmental crime. Hobson et al. (2012) and Dechow et al. (2011) also found that large firms exhibiting poor performance while operating in very volatile environments and under high growth expectations are more prone to financial restatements. Along these lines, Hill et al. (1992) argued that firms with poor financial performance may be more likely to commit corporate fraud due to financial strain. However, their results showed that there is no significant relationship between financial performance and corporate fraud. Similarly, Baucus and Baucus (1997) found that reduced financial performance did not necessarily correlate with corporate fraud. Moreover, even well-performing corporations may be sanctioned as violators of the law. Harris and Bromiley (2007), as well as Mishina et al. (2010) provided evidence that high-performing firms may engage in illegal activities. Firm performance also has the capacity to make a difference in chief executive officer (CEO) confidence and in turn heighten the pressure to misreport firm performance as more positive than it really is (Chen, 2010). In summary, there is a lack of consensus about how firm performance affects top management fraud.

Apart from financial performance, corporate fraud has been reported to be affected by corporate governance. Corporate governance is a particular configuration of internal and external mechanisms that condition how to generate and distribute residual earnings in corporations (Shleifer and Vishny, 1997). Dalton et al. (2007) suggest three main mechanisms: monitoring by a board of directors, incentive alignment through executive remuneration, and external market for corporate control. The first two internal mechanisms have been reported to be associated with the likelihood of top management fraud. Board of directors is the first line to reduce the interest conflict between top management and shareholders (Fama and Jensen, 1983a). It is expected to play the most important role in mitigating top management fraud. More independent directors could enhance the effectiveness of board monitoring and then decrease the likelihood of financial fraud (Beasley, 1996; Shan, 2013). A large board may be too unruly to achieve consensus and more likely to be controlled by CEO or top management (Bacon, 1993; Jensen, 1993). Board size has been found to has positive association with corporate fraud (Kassinis and Vafeas, 2002). Other board characteristics, like the frequency of board meeting (Salleh and Othman, 2016), have been reported to exert influences on corporate fraud. Apart from board of directors, incentive contract has been found to be related to corporate fraud (DuCharme *et al.*, 2001; Hass *et al.*, 2016).

Ownership structure has also been considered as an influential factor of corporate fraud. In China, the state still has influential ownership in about half of privatized listed firms (Shan, 2013). State ownership has been found to be associated with weakening internal monitoring mechanisms, increasing the chances of executives carrying out opportunistic activities (Hou and Moore, 2010). Thus, state ownership has been reported to have positive effects on corporate fraud (Shan, 2013). Besides state shareholders, many Chinese listed companies are controlled by blockholders (Xu, 2004). Blockholders are shareholders who hold at least 5% of the common shares in a firm (Connelly *et al.*, 2010). Prior studies argue that blockholders could exert influence on the decisions made by management due to their voting control (Connelly *et al.*, 2010; Jensen and Warner, 1988). Thus, blockholders have been found to be associated with earnings inflation (Guthrie and Sokolowsky, 2010), financial reporting fraud (Persons, 2006), and accrual earnings management (Lemma *et al.*, 2018).

2.5 Corporate Fraud Prediction

Apart from identifying the antecedents of corporate fraud, it is also important to swiftly and accurately detect unlawful corporate behaviors. Though research focused on corporate fraud prediction for the construction industry is limited, some scholars have attempted to create predictive models in the field of organizational management. Ravisankar et al. (2011) used a multilayer feed-forward neural network, support vector machine (SVM), genetic programming, logistic regression (LR), and a probabilistic neural network to identify fraud-committing companies with 18 financial items. Pai et al. (2011) constructed an SVM-based fraud warning model to detect top management fraud based on 16 financial features (related to the firm's profitability, leverage, liquidity, and efficiency) and 2 variables about the directors' shareholding. Lin et al. (2015) developed financial fraud detection tools with several data mining techniques (LR, decision trees [DT], and artificial neural networks) and analyzed their different performances in comparison with experts' judgments. Most of the variables used were relevant to financial/accounting performance and corporate governance. Throckmorton et al., (2015) compared the performance of a generalized likelihood ratio test with LR, naïve Bayes, and K-nearest neighbors (KNN) in financial fraud detection. Kim et al. (2016) established three multi-class prediction models using multinomial LR, SVM, and Bayesian networks. These models drew upon 49 variables, including off-balance sheet variables, nonfinancial measures, market variables, and governance measures. Sorkun and Toraman (2017) explored the use of linear regression, SVM, KNN, DT, and other data mining methods to detect financial fraud based on 9 financial features. Dong et al. (2018) adopted LR, SVM, DT, and neural networks as well as leveraged 3 categories of financial ratios and language-based features for financial misstatement detection.

Input variables used in prior literature can be classified into two categories, financial performance and corporate governance. First, most previous research has employed financial/accounting variables. These may be related to the reasons for engaging in corporate fraud. Unusual financial ratio values may represent a need to hide losses, to improve apparent stock market performance, and/or to satisfy investors and lenders so as to mitigate managerial pressure (Ravisankar *et al.*, 2011). Therefore, poor financial performance could be an incentive to commit corporate fraud. Second, some studies (e.g., Kim et al. 2016; Pai et al. 2011) add several corporate governance-related variables (e.g., CEO bonus and board shareholding) as input features. Fraud is conducted more often by top management (Zahra *et al.*, 2005). As the chief decision-makers, executives have the responsibility for setting the overall direction of an organization (Hambrick and Mason, 1984). Once they decide how to behave, corresponding proper or improper actions within the firm will follow. Thus, an array of studies attribute fraudulent corporate behaviors to the characteristics of top management (Schnatterly *et al.*, 2018; Shi *et al.*, 2016; Troy *et al.*, 2011). To reduce such behaviors by executives, a board of directors is appointed by a firm's owners to serve as a monitoring device (Fama and Jensen, 1983b). A board of directors can play an important role in supervising and guarding against opportunistic behaviors by top management. The effectiveness of this function is associated with board size, board independence, and other board properties (Lee *et al.*, 2018; Raheja, 2005).

As for classification techniques, previous studies have often used LR, KNN, SVM, and DT to construct their financial statement fraud detection models. Among them, LR is typically used as a benchmark (Ngai *et al.*, 2011; Tserng *et al.*, 2011). Though LR is easy to implement, it has difficulties handling complex issues, especially fraud detection (West and Bhattacharya, 2016). KNN is one of the most commonly used clustering techniques (Ngai *et al.*, 2011). This technique is non-parametric and thus there is no assumed model. However, its ability to detect fraud may be limited because this technique is based on the number of neighboring observations and can be negatively affected by an imbalanced number of observations per class (Throckmorton *et al.*, 2015). SVM is one of the most popular machine learning tools. It transforms the original data into a high dimensional space by nonlinear mapping and separates the data with a hyperplane. However, SVM is prone to overfitting (Pai *et al.*, 2011). More importantly, SVM lacks variable importance ranking. With its ability to predict and provide variable importance, DT is an easy-to-use predictive model that generates mapping from observations to possible consequences (Ngai *et al.*, 2011). It is constructed as a tree-like structure with attributes as branches and outcomes as leaves. When developing a predictive model, DT has no requirement for prior domain knowledge, making its implementation simple (Dutta *et al.*, 2017). However, DT may be unstable and risks overfitting if a single tree is used (Bhattacharyya *et al.*, 2011).

2.6 Theoretical Foundation

Considering the complicated nature of top management fraud, this dissertation draws upon three theories as its foundation, namely agency theory, upper echelons theory, and behavioral theory of the firm. Agency theory represents the combined disciplines of management and economic theory and functions as the overall foundation for analyzing top management fraud in this dissertation. Upper echelons theory focuses on the psychology and sociology of top management. Behavioral theory of the firm considers the context of top management fraud.

2.6.1 Agency Theory

Fundamental theories of corporate governance begin with agency theory. Agency theory addresses problems that arise due to differences between principals' (shareholders) and agents' (executives) goals or desires. The agency problem is primarily due to the separation of management from the wealth effects of ownership, as management staff may try to maximize their wealth at the expense of the stockholders (Jarrell *et al.,* 1988; Morck *et al.,* 1988), and attempt to insulate themselves from internal (Salancik and Pfeffer, 1980; Tosi and Gomez-Mejia, 1989) and external (Dann and DeAngelo, 1988) governance mechanisms. Executives' opportunism and expropriation, for example, fraudulent acts, may bring agency costs borne by shareholders. Such costs include expenditures to monitor and align the incentives of managers, as well as the residual loss of firm value that arises from conflicts of interest with managers (Jensen and Meckling, 1976).

To mitigate the agency problem and to reduce the residual loss of firm value, Dalton et al. (2007) suggest three main mechanisms: monitoring by a board of directors, incentive alignment through executive remuneration, and external market for corporate control. A board of directors, authorized by shareholders, is comprised of members independent of management and is able to monitor the performance of management to ensure that managers' interests do not differ substantially from those of shareholders (Fama, 1980; Fama and Jensen, 1983b; Jensen and Meckling, 1976; Mizruchi, 1983). The second approach is incentive alignment through executive remuneration, often in the form of equity. This approach proposes that managers possessing equity in the firm are more motivated to include other equity holders' interests and, as a result, to operate the firm to maximize the joint interests (Fama and Jensen, 1983a; Jensen and Meckling, 1976). The last mechanism for mitigating the agency problem is the external market for corporate control, which refers to when managers inappropriately leverage their agency advantage, they may be disciplined by corporate markets. That is, a firm with self-serving managers may be subjected to acquisition by other firms (Fama and Jensen, 1983b; Jensen and Ruback, 1983; Manne, 1965). Though these three mechanisms in corporate governance are rational in principle, their efficacy in practice remains under debate.

2.6.2 Upper Echelons Theory

Upper echelons theory, as put forward by Hambrick and Mason (1984), attributes organizational outcomes such as performance to the decision-making of the leaders. This theory is rooted in the behavioral theory of the firm (Nielsen, 2010), which holds that complex managerial choices including law-abiding or violating activities are not made according to a perfectly rational analysis on a foundation of complete information, but are influenced by an array of behavioral characteristics of managers (Cyert and March, 1963; March and Simon, 1958). These behavioral factors, including bounded rationality, multiple and conflicting goals, and various aspiration levels, result in strategic choices by top executives and consequently exert an influence on a firm's performance. Among numerous managerial characteristics, observable ones such as age, educational background, and other demographic characteristics, are recommended by Hambrick and Mason (1984) to be indicators of what a manager brings to a work setting. Their emphasis on observable background characteristics is in line with some previous studies in the field of marketing (Frank and Greenberg, 1979; Hornik and Schlinger, 1981), and the position of Weick (1969) that defining properties according to observable behaviors would produce a greater amount of empirically sound research. Compared to psychological dimensions, which are often difficult to reliably measure and validate or even ambiguous in their interpretation and meanings (Pfeffer, 1983), some background characteristics, for example tenure and functional background, are highly recommended because there are no close psychological analogs (Hambrick and Mason, 1984). For the unit of analysis, upper echelons theory concentrates primarily on the top management team rather than only on the chief executive. Managing a firm is generally a shared effort in which organizational outcomes are shaped by the collective work of a dominant coalition (Cyert and March, 1963). Drawing upon these arguments and findings, this dissertation explores the impact of an individual top manager’s psychological characteristics, represented by observable demographic background information, on occupational fraud, and considers the top management team when analyzing corporate fraud.

2.6.3 Behavioral Theory of the Firm

Developed by March and colleagues (Cyert and March, 1963; March and Simon, 1958), the behavioral theory of the firm argues that firms endeavor to achieve their set performance targets. When performance meets the organizational aspiration, firms are conservatively apt to maintain their current routines and unwilling to search for better alternatives. When the organizational aspiration is not achieved, firms actively make some changes and are greatly motivated to search for alternative paths of action to improve firm performance until it reaches an acceptable level. This argument is proposed on the basis of three assumptions. First, the decision-makers choose a satisfying alternative rather than maximizing one. The satisfying alternative can meet the aspiration level, which is set with reference to the firm’s historical performance and competitors’ performance (Gavetti *et al.,* 2012; Greve, 1998). Second, the searching process by organizations is burdensome and searching stops when expectations are achieved. Due to the lack of complete information regarding what a choice may lead to (Simon, 1947), individuals are bounded rational beings and search for a satisfying alternative from a narrow range of possible choices when a satisfactory outcome is not yet realized (Gavetti *et al.*, 2012). The search is according to the expectations of the firm, and depends on some "pattern-recognition variables (e.g. linear extrapolation) and the effect of hopes on expectations" (Cyert and March, 1963). Third, organizations prefer routines and standard operating procedures to foresight and anticipation of a distant future (Gavetti *et al.*, 2012). Rule-based behavior tends to draw upon historical experience even when some pressing problems occur, and organizations prefer a narrower search within the neighborhood of current alternatives (Cyert and March, 1963).

As mentioned previously, a firm's aspirations may be mainly derived from two aspects, the firm's own historical performance and competitors' performance (Cyert and March, 1963; Desai, 2016; Lant, 1992; March and Simon, 1993; Yang *et al.*, 2017). Both approaches to evaluating performance have been shown to impact an organization's aspirations (Bromiley and Harris 2014; Gaba and Bhattacharya 2012; Harris and Bromiley 2007). When the performance of a firm is higher than its past performance, its aspirations rise, and after a firm experiences a slide in performance, aspirations may fall. Similarly, if a firm's performance does not exceed competitors' performance, the firm's aspirations fall. Nonetheless, when firm performance is lower than the firm's aspirations, the top management team may engage in corporate fraud to improve the organizational performance because corporate fraud could be considered as part of the available choice set during the search process.

2.7 Summary

This chapter first summarized the previous studies about corruption in the construction industry. Then top management fraud was defined in this study and followed by its individual and corporate level antecedents discussed in prior studies. Apart from its antecedents, the corporate fraud detection models established in previous research were reviewed regarding the inputs and techniques. Finally, agency theory, upper echelons theory and the behavioral theory of the firm were introduced as the groundwork of the present study.

CHAPTER 3 RESEARCH METHODOLOGY

3.1 Introduction

This chapter starts with the presentation on research design used in this study. Then several research methods applied in this study are discussed. including literature review and several quantitative methods for data analysis. The quantitative methods are composed of hierarchical linear modeling, hierarchical logit regression with fixed effects, and random forest.

3.2 Research Design

Research design is a logic plan that deals with the topic under the investigation (Creswell, 2003). It addresses the four aspects: the questions to study, the relevant data, the methods for data collection, and the data analysis. This study aims to investigate the antecedents of top management fraud and to predict corporate fraud in terms of the Chinese construction firms. In line with studies about Chinese companies (Conyon and He, 2016; Hou and Moore, 2010), the data is mainly collected from the China Stock Market and Accounting Research Database (CSMAR) database and China Centre for Economic Research (CCER/Sinofin) database. In particular, the information about top management fraud was derived from enforcement data issued by the China Securities Regulatory Commission (CSRC), Ministry of Housing and Urban-Rural Development (MOHURD), and other governmental institutions. The enforcement information is comprised of the case description, supervisors, violation type, related laws and regulations, and other information. The violation type includes not only misleading statement and other false information disclosure, but also the usage of substandard construction materials and other criminal activities. To accurately assess fraudulent actions, the enforcement information had been carefully reviewed and the year when individual executives actually took part in fraudulent activities was identified.

This study mainly adopts quantitative methods to analyze the collected data in the following steps. First, using hierarchical linear modeling, this study explores the effects of top managers' career horizon on occupational fraud with the consideration of board of directors and shareholders as moderators. Second, hierarchical logit regression with fixed effects is conducted to examine the moderating effects of aspiration-performance discrepancies on the relationship between top management team compensation and corporate fraud. Last, random forest is employed to identify the importance of influential factors and to build the corporate fraud detection model.

3.3 Research Methods

The adopted research methods are determined by the depth and scope of the study (Knight and Ruddock, 2008). According to the research design, four methods are considered suitable and thus employed in this study, including literature review, hierarchical linear modeling, hierarchical logit regression with fixed effects, and random forest.

3.3.1 Literature Review

Comprehensive literature review is critical endeavor to obtain the in-depth understanding and what is already known on a research topic (Littau *et al.*, 2010). The literature review in this study concentrates on previous studies on corruption in the construction industry, the individual and organizational antecedents of top management fraud and corporate fraud detection. Three theories are introduced as the theoretical foundation as well. The groundwork laid by literature review are beneficial to build up a solid theoretical understanding for this study and to compare this study with previous studies to justify the contribution of this study.

3.3.2 Hierarchical Linear Modeling

Hierarchical linear modeling (HLM) is employed to explore the antecedents of occupational fraud from the individual executive and corporate level. Given the nested structure of data, traditional regression is inappropriate because of violating the necessary condition of independent and identically distributed random variables (Hofmann *et al.*, 2000). As such, HLM is employed (Raudenbush and Bryk, 2002). This method has a primary advantage that it explicitly recognizes and corrects for the problem of nested data (Holcomb *et al.*, 2010). Apart from the nested data structure, HLM is able to handle the cross-level moderation. The present study adopts a dataset containing a three-level hierarchical structure and is interested in cross-level interactions. Hence, HLM is an appropriate analytical technique.

3.3.3 Hierarchical Logit Regression with Fixed Effects

Hierarchical logit regression model with fixed effects is applied to test the moderating effects of aspiration-performance discrepancies on the relationship between TMT compensation and corporate fraud because it is able to deal with the dichotomous dependent variable (Christensen, 2016; Ege, 2015). Logit regression is robust in most situations because of its minimal set of assumptions. It does not require the distributional form of independent variables or the linear relationship between independent variable(s) and dependent variable (Hair *et al.*, 2014). Considering the panel structure of the data used in this study, there may be some unobserved characteristics for each firm that exert some influences on the independent variables. To address such potential bias, the fixed effect model is employed to specify the unobserved cross-sectional differences among firms (Chang and Chung, 2017).

3.3.4 Random Forest

Random forest (RF) is applied to rank the importance of influential factors and to establish the corporate fraud detection model. This method was introduced by Breiman (2001). As an ensembled tool, RF is composed of a set of trees generated by a classification and regression tree (CART) (Breiman *et al.*, 1984) and a combination of randomly chosen explanatory factors. This method inherits several advantages of decision tree (Sutton, 2005). First, RF can handle complex nonlinear high-order interactions among features and does not require feature selection. Feature selection is the process of selecting the most influential features or predictors to adequately capture the association between outcomes and predictors (Fallah *et al.*, 2019). RF is also robust even with outliers and irrelevant inputs, as well as able to avoid overfitting (Rodriguez-Galiano *et al.*, 2012). Next, there is no requirement for prior knowledge of underlying processes and no assumptions about the target function (Prinzie and Van den Poel, 2008). RF is among the most accurate general-purpose tools to date (Biau, 2012). More importantly, it provides useful estimates of variable importance (Breiman, 2001).

3.4 Summary

This chapter overviews the research methodology. It introduces and justifies the research design and methods to fulfill the research objectives. Research design was first introduced in this chapter and then the adopted methods were fully discussed, including literature review, hierarchical linear modeling, hierarchical logit regression with fixed effects and random forest.

CHAPTER 4 OCCUPATIONAL FRAUD

4.1 Introduction

Due to the multi-determined nature of unethical choice (Kish-Gephart *et al.*, 2010), it is important to take into consideration multiple-antecedent sets (Flannery and May, 2000) and develop a comprehensive model of organizational-and individual-level factors that are associated with top management fraud. Previous studies have not systematically investigated these two sets of drivers but generally only focused on a single level, either individual (Baucus, 1994; Troy *et al.*, 2011) or firm level (Lee *et al.*, 2018; Shi *et al.*, 2017). This may be because one fact has been overlooked that an individual with particular features may have different behaviors in different contexts. Managers with the same characteristics may make different decisions when they are exposed to different organizational environments. To address this gap, this chapter would examine the drivers of occupational fraud from two levels, individual-level and firm-level.

With regard to individual-level factors, this research focuses on top manager career horizon, which is the amount of time remaining until an executive reaches retirement age (Matta and Beamish, 2008). In addition to individual-level factor (i.e., career horizon), organizational-level factors might encourage or discourage executives to commit illegal acts (Zahra *et al.*, 2005). This chapter takes the characteristics of corporate governance into consideration and treats them as the boundary conditions of testing. That is, it is proposed the relationship between a top manager's career horizon and his/her criminal behavior may be moderated by organizational factors (i.e., board structure and ownership structure).

4.2 Hypotheses Development

Apart from profit or some other kind of material benefit gained by top managers, fraudulent behaviors may yield negative effects on the individual perpetrator as well. Once problematic managers are caught committing fraud, their reputations are affected and are sometimes terminated from employment (Gomulya and Boeker, 2016). Thus, considering the great uncertainty of outcomes involved in committing fraud, scholars treat executive fraud as a form of risky activity (Dong *et al.*, 2018; Hoskisson *et al.*, 2017).

To prevent such risky actions from occurring, numerous studies focused on the relationship between executive characteristics and their decision to commit fraud (Finkelstein *et al.*, 2009; Hoskisson *et al.*, 2017). Researchers have found associations between observable characteristics of an executive and fraud (e.g., Troy et al. 2011). Despite extensive research, little research has examined how psychological attributes influence top managers' illegal acts. To address this gap, this chapter investigates whether executives with different career horizons may make different choices about unacceptable behaviors.

4.2.1 Career Horizon Concerns

Career horizon concerns are mainly relevant to the career stage of an executive. When he/she becomes older and retirement gets closer, the career horizon becomes shorter. Researchers have predicted that career horizon would affect executives' priorities and incentives, which would then translate into their risk-seeking or risk-averse behaviors (Barker and Mueller, 2002). Older executives would generally prefer risk-averse strategies rather than those that would maximize shareholder benefit or long-term firm performance, leading to increases in agency cost (Davidson *et al.*, 2007). Hambrick and Mason (1984) list three possible reasons for the conservative attitude of older managers: less physical and mental stamina, greater preference for organizational status quo, and at a special point in their lives at which they highly value their financial security and career security. Matta and Beamish (2008) also mention that approaching retirement implies limited ability and time, and thus risk aversion is preferred.

Besides those reasons, legacy conservation is also considered a contributor to risk-aversion for executives with a short career horizon (Kang, 2016). The legacy is the imprint that a former executive bequeaths to a firm (Sonnenfeld, 1986). Though an executive may retire and leave the firm, he/she might want to still leave a lasting legacy to the firm for which he/she would be recognized. To preserve a legacy of success, some executives near retirement may exhibit myopic risk aversion, because risky actions may jeopardize the current firm performance and taint the executives' legacies (Kahneman and Lovallo, 1993). In fact, the perceptions of a successful executive with reputational and human capital are often associated with good firm performance (Harris and Helfat, 1997). Thus, to minimize the risk and preserve the executives' legacies, they would become more inclined to forgo some risky moves, particularly fraud. Those dishonest behaviors could erode the executives' reputations and the public's trust (Davies and Olmedo-Cifuentes, 2016). Some problematic managers would have to resign. Once executives with a short career horizon are fired, they would be less likely to find a similar position than those with long career horizons (McClelland *et al.*, 2012). Thus, top managers with a short career horizon are assumed to be less likely to engage in fraudulent behaviors than those with a long career horizon.

H1: There is a positive relationship between a top manager's career horizon and the likelihood of his/her engagement in fraudulent behaviors.

4.2.2 Moderating Role of Board Monitoring

One of the most crucial corporate governance mechanisms is board monitoring, which refers specifically to the monitoring undertaken by a board of directors to safeguard the interests of shareholders and to mitigate the possible agency costs that arise from the separation of control and ownership (Fama and Jensen, 1983b). Ineffective implementation of their function could provide management with opportunities to commit fraudulent acts (Dechow *et al.*, 1996). To improve monitoring effectiveness, researchers and practitioners have advocated for board independence—absorbing outside directors that are independent from the listed companies and the major shareholders (CSRC, 2002; Mallette and Fowler, 1992). The independent directors are less likely to be influenced by executives and have more incentives to protect their reputation in the labor market. Thus they are expected to supervise the management's performance effectively (Fama and Jensen, 1983b). Previous research has reported a negative relationship between board independence and incidents of corporate fraud (Beasley, 1996). Some empirical research specifically focused on the construction industry has produced similar results about board monitoring (Rebeiz, 2001; Rebeiz and Salameh, 2006). Thus, it is expected that when a board is composed of more independent directors, monitoring effectiveness would be enhanced. Then the opportunities for managers to initiate some opportunistic activities (e.g., misconduct) would be constrained. Especially for those executives with long career horizons and a preference for risk-taking, their selfish decisions that may erode the firms' interests may be blocked by an independent board. On the other hand, an independent board may not find fault for older executives, who are more conservative and less likely to commit illegal behaviors. Thus, the relationship between career horizon and occupational fraud may be less positive in relation to monitoring by an independent board.

In addition, board monitoring effectiveness may be determined in part by its size. Some researchers argue that a large board may enlarge the pool of professional experts, expanding the scope of skills and experiences, and improving the quality of monitoring (Pfeffer, 1973). However, some other empirical studies suggest that the benefits could be outweighed by the costs of largeness because of the conflicts in interactions, additional challenges in coordination, and free-riding problems (Eisenberg *et al.*, 1998). According to Goodstein et al. (1994), it is easier for a large board to generate coalitions and more difficult to achieve consensus because directors on large boards may fail to exchange information or their ideas freely, and thus creating openings for managers to undertake some opportunistic behaviors. In contrast, a small board is considered to be more participative and cohesive. Their monitoring function is more likely to be implemented effectively. Extending the above reasoning procedure, it expects an executive's dishonest desires, driven by his/her career horizon, would be alleviated. On the one hand, the positive effect of career horizon on occupational fraud will be more salient when a firm has a larger board due to the reduced monitoring effectiveness resulting from communication barriers between directors; on the other hand, the association between career horizon and managerial wrongdoing can be mitigated because of the cohesion among board members.

H2a: Board independence weakens the positive effect of career horizon on occupational fraud.

H2b: Board size strengthens the positive effect of career horizon on occupational fraud.

4.2.3 Moderating Role of Blockholder Ownership

Blockholders are shareholders who hold at least 5% of the common shares in a firm (Connelly *et al.*, 2010). Prior studies argue that blockholders could exert influence on the decisions made by management due to their voting control (Connelly *et al.,* 2010; Jensen and Warner, 1988). This control may not only incentivize the large shareholders to supervise the managerial activities (Aoki, 1984), but also put great financial pressure on executives. The stakes for large shareholders are literally high, leading to their excessive emphasis on short-term financial earnings. Gorton and Schmid (2000) reported that the performance of firms with large shareholders would be improved. Guthrie and Sokolowsky (2010) found evidence that firms with large shareholders would inflate their earnings. Lemma et al. (2018) found that a large percentage of institutional ownership induces an increase of accrual earnings management. To protect their benefits, blockholders would put pressure on top managers and be likely to make a threat of intervention (e.g., decreasing the executives' compensation or dismissing someone) if the firm performance is lower than their desired level (Kaplan and Minton, 2012). This threat may incentivize executives to engage in risky behaviors, especially for those nearing retirement. They may become more worried about their career termination (i.e., forced retirement) in the presence of blockholder activism. To make matters worse, top managers with a short career horizon may have limited ability and time to improve firm performance and to satisfy blockholders (Matta and Beamish, 2008). Thus, fraud may be an available means for those approaching retirement. On the other hand, for those young managers, financial pressures from blockholders may make little difference because it may be easier for them to move on to other positions than for their older counterparts (McClelland *et al.,* 2012). Therefore, when there are high levels of blockholders, the effect of career horizon on fraud may be less positive.

H3: Blockholder ownership weakens the positive effect of career horizon on occupational fraud.

4.2.4 Moderating Role of State Ownership

In China, despite the privatization of state-owned-enterprises, the state still has influential ownership in about half of privatized listed firms (Shan, 2013). State ownership has been found to be associated with weakening internal monitoring mechanisms, increasing the chances of executives carrying out opportunistic activities (Hou and Moore, 2010). However, this may not be the case for executives near retirement when they are faced with state ownership. Unlike general shareholders, state shareholders emphasize less on maximizing shareholder wealth. Even though governmental bureaucrats are interested with pursuing profits, they are unwilling to consume much time and effort on supervising managerial activities because the involved cost is much higher than the political payoff (Shen and Lin, 2009). This reduces executives' financial pressure to some extent. As the result, executives with a short career have fewer incentives to engage in some risky behavior.

The goals of state shareholders and top managers can also be aligned. Instead of setting purely profit driven goals, state shareholders prefer to achieve various social and political purposes, such as controlling sensitive industries (Clarke, 2003) or reducing a local unemployment rate (Fan *et al.*, 2007). Especially for some megaprojects, benefiting the megaproject community is more attractive than pursuing rational economic benefit (Yang *et al.*, 2018). In parallel, executives, especially those near retirement age, often love to pursue socially responsible goals in order to build and preserve their legacy (Matta and Beamish, 2008). State shareholders' interest and management's aim to protect their reputations are aligned, incentivizing older executives to behave in a more politically- and morally-correct manner, and less likely to commit violations. Taken together, this research assumes that executives near retirement would be less likely to undertake fraudulent behaviors with the presence of high state ownership.

H4: State ownership strengthens the positive effect of career horizon on occupational fraud.

4.3 Method

This section first presents the used sample and data, followed by the measures of dependent variable, independent variables, moderating variables and control variables. Then the data analysis tool is introduced.

4.3.1 Sample and Data

To test the above hypotheses, this present study analyzed a sample of top management in the construction companies publicly listed in China from 2012 to 2017. Top management includes CEO and non-CEO executives, referring to individuals titled as executives in the annual report of the listed firm (Zhang *et al.*, 2011). In line with other studies about Chinese companies (Conyon and He, 2016; Hou and Moore, 2010), the data is mainly collected from the China Stock Market and Accounting Research Database (CSMAR) database. In particular, the information about occupational fraud was derived from enforcement data issued by the China Securities Regulatory Commission (CSRC). To accurately assess fraudulent actions, the enforcement information had been carefully reviewed and the year when individual executives actually took part in fraudulent activities was identified. Due to the data availability, firms newly listed after 2015 had to be removed to ensure the financial variables are known one year before the fraudulent activities they are used to explain. The removal is also because the observation period is too short to detect occupational fraud and the disclosure practice could not be assessed realistically in early years (Anh *et al.,* 2011). Thus, this research only included firms with more than two consecutive years of annual reports (Fama and French, 1992; Loughran, 1997). All the top managers in the remaining companies were considered including those leave their positions during the focal years. The final sample was comprised of 3722 individual-year observations. These observations are from 1052 executives in 70 firms. Among these 70 companies, there are 57.14% are state-owned companies. According to the main business, 72.86% companies belong to civil engineering construction industry, 1.43% to building construction industry, and 25.71% to architectural decoration and other construction industries. Subsequently, a panel dataset was employed that includes firms with various number of top managers every year.

4.3.2 Measures

The measures of the relevant variables are described, including dependent variable, independent variables, moderating variables, and control variables in multiple levels.

Dependent variable (DV)

As the dependent variable, *occupational fraud* is operationalized as a dummy variable indicating the fact whether a manager participated in fraudulent activities (e.g., financial misrepresentation, misappropriation of firm assets) in the focal year. The real perpetrator and the actual year when fraud was committed were identified according to announcements made by CSRC. In the sample there are a total number of 165 individual-year observations that engaged in wrongdoing. If a manager was involved in fraud in the focal year, this variable equals to 1, otherwise 0 (Shi *et al.,* 2017; Suh *et al.,* 2019).

Independent variable (IV)

Career horizon is the remaining number of years before a manager reaches retirement age. 70 was used as the reference point when a manager should retire, following Krause and Semadeni (2014) and Matta and Beamish (2008). Hence, career horizon is measured as 70 minus a manager’s age.

Moderating variables (MV)

Four moderators are considered regarding board and ownership characteristics. *Board independence* is represented by the percent of directors on the board who only have a directorial relationship with the firm (Lee *et al.,* 2018). *Board size* could exert an influence on the board's monitoring and advising function. This variable is defined as the total number of board members (Wang *et al.,* 2018). In many firms, including the ones that this research focuses on, it is more common to have several large shareholders than a single blockholder (Maury and Pajuste, 2005). Given that their interests are aligned to some extent, those several shareholders may choose to work together to implement their concentrated control. Thus, *blockholder ownership* is calculated as the sum of the shares held by blockholders. Though privatization has been extensively implemented in China, the state still exerts influence over the firms. *State ownership* is measured by the percent of shares held by governmental entities (Shen and Lin, 2009).

Control variables (CV)

Several variables are controlled about the individual top managers and the firms. At the individual level, *tenure* of a top manager is first considered because top managers with long tenure are generally more willing to persist with unchanged strategies and maintain the status quo (Finkelstein and Hambrick, 1990). It is represented by the number of months that a manager has held a position as senior management (Zhang *et al.,* 2011). Second, an executive's *gender* may be related to engaging in risky behaviors. Women managers have been found to be less overconfident than men managers in making decisions (Huang and Kisgen, 2013). The variable is given a value of 1 if an executive is a woman, 0 otherwise. Third, poor education has been regarded as an individual trait that may lead to unethical, even illegal, behaviors (Liu *et al.,* 2017). *Education level* is controlled by coding the highest educational level attained by an executive: 1= below junior college; 2 = a junior college degree; 3 = a bachelor’s degree; 4 = a master's degree; 5 = a doctoral degree (Fan *et al.,* 2007). Fourth, an executive may have the experience of serving as a current or former officer in the central or local governments or military. This has been considered as a proxy for government influences (Fan *et al.,* 2007), and an important reason why corruption is widely reported in the construction industry (Zhang *et al.,* 2017). A dummy variable is included to represent whether a top manager has such *political background* (1=Yes; 0=No). Fifth, executive compensation is taken into consideration because of its influence on the incentives to commit fraud (Conyon and He, 2016). The compensation is represented by the log of *total pay* and *ownership*. Total pay is the sum of salary, stipends, and bonus (Lu and Shi, 2018). Ownership is calculated as the number of shares held by an executive multiplied by the stock price per share on the last day of the stock market (Barker and Mueller, 2002). Sixth, the executive’s power is also controlled. Two dummy variables are added to indicate whether an executive has been a *CEO* or *board member*, respectively (1=Yes; 0=No).

For the firm level, the variables at the individual level are first aggregated to the top management team (TMT) level, representing the firm level, to capture the TMT average level or the TMT diversity. Thus, several variables were controlled including *average of tenure, standard deviation (SD) of tenure, percentage of women executives, average education level, education diversity, percentage of executives with political background, average total pay,* and *average ownership*. Among them, education diversity is calculated by the Blau’s index (Blau, 1977). It is operationalized as $1 - p_i^2$, where p_i is the percent of executives with ith education level. This index has been widely used for operationalizing the diversity of culture (Richard *et al.*, 2004), education background (Lee *et al.*, 2018) and other nominal features.

Then, this research includes the number of top managers on TMT to control for *TMT size* (Greve *et al.*, 2015) due to its influence on the decision-making dynamics (Amason and Sapienza, 1997). Next, firm size and firm performance are controlled. *Firm size* is measured as the log of the total number of employees (Matta and Beamish, 2008), which may impact managerial discretion (Finkelstein and Hambrick, 1990). Firm performance is indicated by the *return on equity (ROE)* in the last year. Poor performance may pressure managers to engage in problematic behavior (Krause and Semadeni, 2014). *Debt-to-equity ratio (DER)* is considered to control for organizational slack. A high ratio indicates less financial slack and less available resources (Kuusela *et al.*, 2017). Too high of a DER, which is common in the construction industry, creates pressure on managers. Last, five *year* dummies are created to include the unobserved heterogeneity rooted in the environments (Greve *et al.*, 2015).

Based on the four hypotheses and the above measures, the hypothesized model is shown in Figure 4-1.

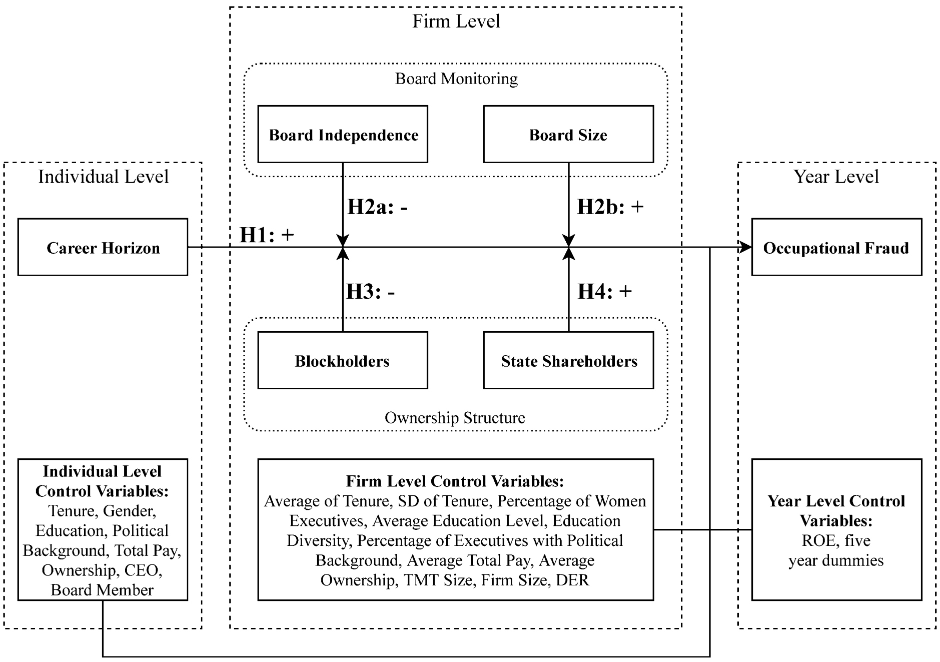


Figure 4-1. The hypothesized model

4.3.3 Hierarchical Linear Modeling

The data used encompasses three levels: year, individual executive, and firm. This represents a hierarchical structure as an individual-year observation's behavior is nested in an individual manager and then nested in a firm that employs the manager. The lowest level mainly includes the year dummies, examining the effect of time on a manager's decision about fraud. The second level involves the characteristics of a manager (e.g., career horizon). The third level considers a firm's features (e.g., board composition and ownership structure). The variables in the higher two levels are stable across years.

Given the nested structure, traditional regression is inappropriate because of violating the necessary condition of independent and identically distributed random variables (Hofmann *et al.*, 2000). As such, Hierarchical Linear Modeling (HLM) was employed (Raudenbush and Bryk, 2002). This method has a primary advantage that it explicitly recognizes and corrects for the problem of nested data (Holcomb *et al.*, 2010). Apart from the nested data structure, HLM was employed due to the cross-level moderation hypothesis (Hypotheses 2a-4). Though HLM has less been used in the fraud-related studies in the construction industry, it has been popular in psychology and the behavioral sciences (McNeish *et al.*, 2017), entrepreneurship research (Holcomb *et al.*, 2010) and management literature (Grosvold and Brammer, 2011; Mathieu and Chen, 2011). While the focuses of these fields are at one single level (i.e., individual or firm level), it is clear that individuals' or firms' behaviors or other outcomes are affected by individual, group, firm, industry and even national level drivers. Furthermore, researchers are often interested in the top-down influences of high-level factors on low-level factors or relationship (Zhang *et al.*, 2009). The present study adopted a dataset containing a three-level hierarchical structure and was interested in cross-level interactions. Hence, HLM is an appropriate analytical technique.

Before conducting HLM analysis, it is important to consider whether a variable should be entered at a lower level (i.e., year level here) or at a higher level (i.e., individual or firm level). For example, the raw data on an executive's career horizon and pay varied in different years, but this research wants to input this variable in Level 2 (individual level) so that the variance between individual top managers could be considered. Thus, intra-class correlations (ICC) testing was performed. This testing is one of the most commonly used procedures that is able to justify aggregating year-level data to individual- or firm- level units and thus to provide the assessment of the extent to which the year-level data are homogeneous within an individual or a firm unit (Klein and Kozlowski, 2000; LeBreton and Senter, 2008). ICC(1) estimates the proportion of a variable's total variance that is attributed to the unit membership while ICC(2) examines the reliability of the aggregated variable. High ICC(1) and ICC(2) indicate the values within each group are similar but differ across groups and thus the aggregation is reliable. The ICC(1) and ICC(2) of all the time-variant variables were calculated and shown in Table 4-1. Except ROE, all of the variables about individuals and firms are justified in aggregation because (1) their ICC(1) values exceed 0.25 (LeBreton and Senter, 2008); (2) the corresponding F tests for ICC(1) are significant (Klein and Kozlowski, 2000); (3) their ICC(2) values are above 0.7 (Bliese *et al.,* 2002; Klein and Kozlowski, 2000). Thus, this research used their corresponding mean value among the focal years as the input of HLM analysis. ROE was added in the lowest level due to its large variance across years.

Another noteworthy point is the appropriate centering because the intercept and slopes in lower level of HLM model will become the dependent variables in higher level, and different centering decisions may result in different interpretations (Raudenbush and Bryk, 2002). Considering that the Level 2 (individual-level) predictors indicate the individual variance and are of interest, this study chose to group mean center all the continuous and ordinal variables in Level 2 (individual level), and to grand mean center all the continuous variables about the TMT or firm mainly in Level 1 (year level) and Level 3 (firm level) (Ou *et al.*, 2017). The dichotomous variables including year dummies were uncentered to guarantee these variables' interpretability (Lander *et al.*, 2019). The above centering is necessary to avoid multilinearity when testing the cross-level moderating effect of career horizon.

Table 4-1. Intra-class correlations (ICC) of relevant variables

Var.	ICC(1)	F Ratio for ICC(1)	ICC(2)
Individual Level			
Career horizon	0.9117	62.95***	0.9844
Tenure	0.7228	16.64***	0.9433
Total pay	0.3566	4.33***	0.7712
Ownership	0.8485	34.60***	0.9712
Firm Level			
Board independence	0.8221	28.74***	0.9652
Board size	0.6863	14.13***	0.9294
Blockholder ownership	0.8503	35.08***	0.9715
State ownership	0.5135	7.33***	0.8636
TMT size	0.7356	17.69***	0.9435
Firm size	0.9261	76.24***	0.9869
ROE	0.0152	1.09	0.0822
DER	0.7217	16.56***	0.9397
Percent of political	0.4025	5.04***	0.8075
Percent of female	0.7416	18.22***	0.9451
Average education	0.8066	26.02***	0.9617
Education diversity	0.5453	8.20***	0.8780
Average tenure	0.6189	10.74***	0.9070
SD of tenure	0.4523	5.95***	0.8351
Average total pay	0.6943	14.63***	0.9327
Average ownership	0.8187	28.10***	0.9644

Notes: *** $p<0.001$.

A binary outcome was adopted as the dependent variable. Thus, a multilevel logit model is the most suitable for the present study (Greve *et al.*, 2015). To avoid unwieldy models, the random intercept model was applied to limit the number of random parameters. That is, only intercepts in low levels are allowed to vary, and the intercept in Level 3 and all the slopes remain constant. Its general model is shown as follows:

$$\log\left[\frac{p_{ijk}}{(1-p_{ijk})}\right] = \eta_{ijk} = \pi_{0jk} + \sum_P \pi_{Pjk} * a_{Pijk} \qquad \text{(Level 1)} \qquad (1)$$

$$\pi_{0jk} = \beta_{00k} + \sum_q \beta_{0qk} * X_{qjk} + r_{0jk} \qquad \text{(Level 2)} \qquad (2)$$

$$\beta_{00k} = \gamma_{000} + \sum_s \gamma_{00s} * W_{sk} + u_{00k} \qquad \text{(Level 3)} \qquad (3)$$

where p_{ijk} is the probability that an executive j in firm k participated in violating activities in year i, and error terms r_{0jk} and u_{00k} represent the unique effects relevant to individual j and firm k. There is no random error term in Level 1 of the model because of the assumption that the total variance in this level is included in the estimated value η_{ijk} (Hox *et al.*, 2017). This multilevel logit model was implemented in HLM6, a software that is able to handle the analysis of hierarchically structured data. First, the moderators (board independence, board size, blockholder ownership, state ownership) and the control variables including the five year dummies were added into Level 3 (firm level) of the model. Next, the independent variable (career horizon) was included in Level 2 (individual level) of the model. Then, the slope of the independent variable was constructed as a function of moderators before a full model was estimated.

4.4 Results

Table 4-2 displays the information on the descriptive statistics among the variables in the three levels: year, individual, and firm level. Table 4-3 presents collinearity diagnostics and the correlations for the three-level data. To check for potential multicollinearity, variance inflation factor (VIF) was calculated among the explanatory variables. All of the VIF values are lower than 10, indicating that there is no serious collinearity issue (Hair *et al.*, 2014). Besides, there is no high dependence among the variables. The hypotheses for occupational fraud were tested by hierarchical linear modeling and the results are summarized in Table 4-4.

Table 4-2. Descriptive statistics

Var.	N	Mean	SD	Minimum	Maximum
Year Level					
Fraud	3722	0.04	0.21	0.00	1.00
ROE	3722	0.09	0.5	-1.20	14.78
Individual Level					
Career horizon	1052	22.34	6.88	-5.00	43.50
Tenure	1052	49.08	40.96	0.00	228.00
Gender	1052	0.12	0.33	0.00	1.00
Education	1052	3.3	0.88	1.00	5.00
Political	1052	0.08	0.27	0.00	1.00
Total pay	1052	12.64	1.74	0.00	14.91
Ownership	1052	5.17	7.29	0.00	23.08
CEO	1052	0.16	0.36	0.00	1.00
Board member	1052	0.32	0.47	0.00	1.00
Firm Level					
Board independence	70	0.4	0.07	0.33	0.69
Board size	70	8.56	1.36	5.67	13.83
Blockholder ownership	70	47.68	15.59	10.34	90.87
State ownership	70	0.06	0.12	0.00	0.57
TMT size	70	8.95	3.46	2.67	21.83
Firm size	70	7.91	1.86	2.70	12.57
DER	70	2.51	2.08	0.30	13.82
Percent of political	70	0.06	0.08	0.00	0.36
Percent of female	70	0.13	0.12	0.00	0.45
Average education	70	3.26	0.45	2.24	4.12
Education diversity	70	0.52	0.11	0.06	0.69
Average tenure	70	59.12	20.42	23.60	125.79
SD of tenure	70	34.76	13.98	9.36	76.38
Average total pay	70	12.96	0.54	11.50	14.13
Average ownership	70	10.06	7.59	0.00	20.60

Table 4-3. Collinearity diagnostics and Pearson correlations

Var.	VIF	1 Fraud	2 ROE	3 Career horizon	4 Tenure	5 Gender	6 Education	7 Political	8 Total pay	9 Ownership	10 CEO	11 Board member	12 Board independence	13 Board size
2	1.019	-0.008	-											
3	1.3	0.114***	-0.003	-										
4	1.502	-0.087***	-0.017	-0.281***	-									
5	1.183	0.079***	-0.015	0.167***	-0.030†	-								
6	1.377	-0.008	-0.008	0.037*	-0.063***	0.064***	-							
7	1.164	0.023	-0.003	-0.056**	0.070***	0.025	0.111***	-						
8	1.276	-0.003	0.018	-0.042*	0.063***	-0.004	0.029†	0.052**	-					
9	1.912	-0.053**	0.035*	-0.037*	0.221***	0.076***	-0.075***	0.051**	0.190***	-				
10	1.488	0.071***	0.004	-0.070***	0.120***	-0.093***	0.012	0.056**	0.072***	0.118***	-			
11	1.588	0.107***	0.009	0.001	0.170***	-0.01	0.018	0.060***	0.059***	0.160***	0.550***	-		
12	2.534	-0.015	0.006	-0.251***	-0.049**	-0.071***	0.190***	0.040*	0.030†	-0.02	-0.023	-0.129***	-	
13	1.639	-0.050**	-0.016	0.018	0.064***	-0.023	-0.060***	-0.088***	-0.026	-0.021	0.001	0.062***	-0.486***	-
14	2.039	0.02	0.005	-0.135***	-0.068***	-0.077***	0.125***	-0.003	0.067***	-0.01	-0.036*	-0.046**	0.353***	-0.232***
15	2.171	-0.080***	-0.029†	-0.166***	-0.075***	-0.120***	0.111***	-0.038*	-0.151***	-0.335***	-0.036*	-0.094***	0.281***	-0.069***
16	1.646	-0.035*	-0.027	-0.135***	-0.017	-0.108***	0.036*	-0.015	-0.076***	0.003	-0.139***	-0.216***	0.274***	0.062***
17	3.625	-0.155***	0.011	-0.316***	0.066***	-0.140***	0.141***	0.035*	0.130***	0.074***	-0.068***	-0.159***	0.578***	-0.120***
18	1.737	-0.096***	-0.035*	-0.186***	0.121***	-0.129***	0.051**	0.044**	-0.001	-0.168***	-0.026	-0.046**	0.137***	0.128***
19	1.336	0.105***	-0.016	0.039*	-0.02	0.023	0.089***	0.332***	0.008	-0.061***	0.007	0.004	0.070***	-0.223***
20	1.548	0.196***	-0.042*	0.210***	-0.055**	0.355***	-0.016	-0.011	0.021	0.201***	0.050**	0.101***	-0.199***	-0.068***
21	2.179	-0.063***	-0.007	-0.142***	-0.049**	-0.018	0.494***	0.069***	0.098***	-0.085***	0.002	-0.058***	0.402***	-0.129***
22	1.382	-0.001	0.069***	0.01	0.026	-0.01	-0.144***	0.044**	0.021	0.122***	-0.032†	-0.087***	0.068***	-0.076***
23	2.49	-0.154***	0.016	-0.197***	0.468***	-0.030†	-0.057**	0.01	0.095***	0.096***	-0.025	-0.033*	-0.110***	0.133***
24	2.567	-0.099***	-0.013	-0.065***	0.305***	0.002	-0.098***	-0.046**	0.018	-0.091***	0.001	-0.045**	-0.206***	0.182***
25	2.095	-0.116***	-0.008	-0.151***	0.055**	-0.013	0.169***	0.038*	0.421***	0.289***	-0.014	-0.044**	0.271***	-0.139***
26	2.599	-0.051**	0.028†	0.121***	-0.037*	0.096***	-0.099***	0.050**	0.181***	0.591***	0.003	0.052**	-0.189***	0.007

Table 4-3. Collinearity diagnostics and Pearson correlations (Continued)

Var.	13 Board size	14 Blockholder ownership	15 State ownership	16 TMT size	17 Firm size	18 DER	19 Percent of political	20 Percent of female	21 Average education	22 Education diversity	23 Average tenure	24 SD of tenure	25 Average total pay	26 Average ownership
13	-													
14	-0.232***	-												
15	-0.069***	0.362***	-											
16	0.062***	0.183***	0.333***	-										
17	-0.120***	0.500***	0.390***	0.481***	-									
18	0.128***	0.059***	0.365***	0.220***	0.443***	-								
19	-0.223***	-0.015	-0.088***	-0.036*	0.01	0.014	-							
20	-0.068***	-0.206***	-0.334***	-0.294***	-0.387***	-0.363***	0.051**	-						
21	-0.129***	0.264***	0.225***	0.074***	0.301***	0.102***	0.145***	-0.052**	-					
22	-0.076***	-0.016	0.005	0.244***	0.158***	-0.070***	0.125***	-0.01	-0.273***	-				
23	0.133***	-0.146***	-0.173***	-0.057**	0.128***	0.249***	-0.006	-0.096***	-0.104***	0.023	-			
24	0.182***	-0.456***	-0.146***	-0.046**	-0.097***	0.224***	-0.095***	-0.008	-0.190***	-0.026	0.648***	-		
25	-0.139***	0.293***	-0.008	0.021	0.408***	0.033*	-0.035*	-0.027	0.383***	0.011	0.118***	-0.078***	-	
26	0.007	-0.097***	-0.522***	-0.053**	-0.068***	-0.286***	-0.006	0.264***	-0.191***	0.048**	-0.053**	-0.137***	0.291***	-

Notes: † $p < 0.10$; * $p<0.05$; ** $p<0.01$; *** $p<0.001$. All variables in the three levels are included here. For collinearity diagnostics and Pearson correlations, the data in individual level and firm level was disaggregated to year level (Ou *et al.*, 2017). Thus, N=3722 observations for the two tests.

Table 4-4. Results of hierarchical linear modeling for occupational fraud

Var.	Model 1		Model 2		Model 3		Model 4		Model 5		Model 6		Model 7	
	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.
Intercept	-7.043***	0.851	-7.303***	0.858	-7.350***	0.867	-7.300***	0.856	-7.286***	0.861	-7.469***	0.890	-7.720***	0.937
Firm Level														
Firm size	-0.341	0.234	-0.349	0.241	-0.347	0.243	-0.347	0.241	-0.349	0.242	-0.360	0.242	-0.380	0.244
Board size	0.184	0.259	0.167	0.267	0.157	0.270	0.160	0.268	0.169	0.265	0.190	0.267	0.225	0.278
Board independence	8.710	5.590	8.379	5.788	8.629	5.885	8.344	5.792	8.417	5.746	9.421†	5.523	11.343*	5.335
TMT size	0.065	0.113	0.066	0.115	0.070	0.117	0.066	0.116	0.067	0.115	0.069	0.117	0.083	0.121
State ownership	-10.287*	4.555	-11.132*	4.729	-11.308*	4.757	-11.113*	4.713	-11.099*	4.744	-14.697**	4.569	-17.620**	4.932
DER	0.356*	0.163	0.376*	0.169	0.384*	0.172	0.376*	0.169	0.374*	0.168	0.350*	0.172	0.324†	0.178
Percent of political	1.043	4.367	0.051	4.517	0.088	4.566	0.094	4.556	0.079	4.497	-0.283	4.444	-1.267	4.545
Percent of female	5.381†	3.055	5.511†	3.126	5.460†	3.178	5.495†	3.127	5.637†	3.064	5.653†	3.082	6.002†	3.100
Average education	-1.791†	0.931	-1.882†	0.955	-1.888†	0.965	-1.884†	0.956	-1.872†	0.959	-1.917*	0.947	-1.947†	0.973
Education diversity	2.166	4.448	2.596	4.656	2.697	4.774	2.588	4.659	2.620	4.646	2.577	4.603	3.079	4.781
Average tenure	-0.044	0.027	-0.046	0.028	-0.047	0.029	-0.046	0.028	-0.046	0.028	-0.045	0.028	-0.045	0.028
SD of tenure	0.012	0.038	0.009	0.039	0.011	0.039	0.009	0.039	0.010	0.038	0.009	0.038	0.010	0.037
Average total pay	0.585	0.656	0.673	0.670	0.683	0.678	0.668	0.672	0.663	0.671	0.672	0.663	0.641	0.666
Average ownership	-0.073	0.055	-0.083	0.057	-0.080	0.057	-0.082	0.056	-0.082	0.057	-0.088	0.057	-0.094	0.057
Blockholder ownership	0.032	0.029	0.034	0.030	0.034	0.031	0.034	0.030	0.032	0.029	0.033	0.029	0.032	0.030

Table 4-4. Results of hierarchical linear modeling for occupational fraud (Continued)

Var.	Model 1		Model 2		Model 3		Model 4		Model 5		Model 6		Model 7	
	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.
Individual Level														
Career horizon			0.060**	0.018	0.061**	0.017	0.060**	0.018	0.061**	0.020	0.094***	0.020	0.115***	0.021
Tenure	-0.011†	0.006	-0.009†	0.006	-0.009	0.005	-0.009†	0.005	-0.010†	0.005	-0.009	0.006	-0.010†	0.006
Gender	0.632*	0.308	0.595*	0.284	0.596*	0.273	0.592*	0.278	0.560†	0.294	0.583*	0.292	0.571*	0.285
Education	-0.029	0.114	-0.049	0.115	-0.070	0.115	-0.053	0.121	-0.045	0.114	-0.072	0.121	-0.095	0.119
Political	0.399	0.519	0.711	0.533	0.664	0.544	0.682	0.519	0.750	0.503	0.626	0.536	0.768	0.556
Total pay	1.443**	0.494	1.596**	0.502	1.652**	0.514	1.598**	0.501	1.581**	0.514	1.539**	0.491	1.614**	0.526
Ownership	-0.023	0.027	-0.022	0.027	-0.019	0.026	-0.022	0.027	-0.015	0.028	-0.029	0.027	-0.016	0.028
CEO	0.063	0.287	0.265	0.339	0.282	0.333	0.270	0.342	0.212	0.354	0.392	0.351	0.398	0.376
Board member	0.871*	0.346	0.779*	0.323	0.747*	0.323	0.777*	0.321	0.806*	0.331	0.732*	0.335	0.697*	0.349
Year Level														
ROE	0.145	0.136	0.145	0.138	0.149	0.140	0.146	0.139	0.143	0.137	0.135	0.133	0.125	0.130
Year dummies	Yes		Yes		Yes		Yes		Yes		Yes		Yes	
Cross-Level Interactions														
Career horizon × Board independence					-0.606*	0.303							-1.222*	0.48
Career horizon × Board size							0.003	0.017					-0.023	0.016
Career horizon × Blockholder ownership									0.002	0.002			0.002	0.001
Career horizon × State ownership											0.952*	0.401	1.401**	0.49
-2 log likelihood	7993.678		8027.562		8094.456		8070.414		7950.706		7887.768		7818.618	

Notes: † $p < 0.10$; * $p<0.05$; ** $p<0.01$; *** $p<0.001$. The results of multilevel logit modeling are reported, and the coefficients are generated from the estimation of the unit-specific model with robust standard errors. The robust standard errors are shown in parentheses. The sample sizes are 3722 in year level, 1052 in individual level, and 70 in firm level.

According to Table 4-4, Model 1 estimates the influences of control variables on occupational fraud. To test Hypothesis 1 about the positive effect of career horizon, career horizon (IV) was introduced in Model 2. The results indicate that career horizon does have a positive effect ($\gamma = 0.060; \mathrm{p} < 0.01$), supporting Hypothesis 1. Hypothesis 2 emphasizes the moderating effects of board monitoring. The coefficient of the interaction term of career horizon (IV) and board independence (MV) in Model 3 is significantly negative ($\gamma = -0.606; \mathrm{p} < 0.05$). This shows that the positive effect of career horizon is weakened with an independent board, which is consistent with Hypothesis 2a. The interaction term of career horizon (IV) and board size (MV) was included in Model 4 and the interaction term is statistically insignificant ($\gamma = 0.003; \mathrm{NS}$). Hypothesis 2b is hence not supported. Hypothesis 3 predicts that blockholder ownership would weaken the relationship between career horizon and occupational fraud. As indicated in Model 5, the interactive effect of blockholder ownership (MV) on that relationship is not significant either ($\gamma = 0.002; \mathrm{NS}$), rejecting Hypothesis 3. Next, the positive relationship between career horizon and occupational fraud is assumed to be strengthened by state ownership in Hypothesis 4. It is supported in Model 6 given the significant positive interaction term of career horizon (IV) and state ownership (MV) ($\gamma = 0.952; \mathrm{p} < 0.05$). Finally, Model 7 shows the full model including the four interaction terms, generating results similar to those found for Models 2-6.

To interpret the significant moderating effects of board independence and state ownership further, this chapter plotted the relationship between career horizon and occupational fraud with different levels of moderators (± one standard deviation) following common guidelines (Aiken *et al.*, 1991). However, one negative standard deviation goes beyond the value range of state ownership. Its lowest value was chosen as the low level of state ownership. Figure 4-2 and Figure 4-3 present the moderating effect of board independence and state shareholder on that relationship. When the board independence (MV) is higher, the relationship between career horizon (IV) and occupational fraud (DV) is less positive. This trend is in line with Hypothesis 2a. When more shares are held by the state (MV), the effect of career horizon (IV) on occupational fraud (DV) is more positive and the likelihood of participating in dishonest actions appears to decrease. This result confirms Hypothesis 4.

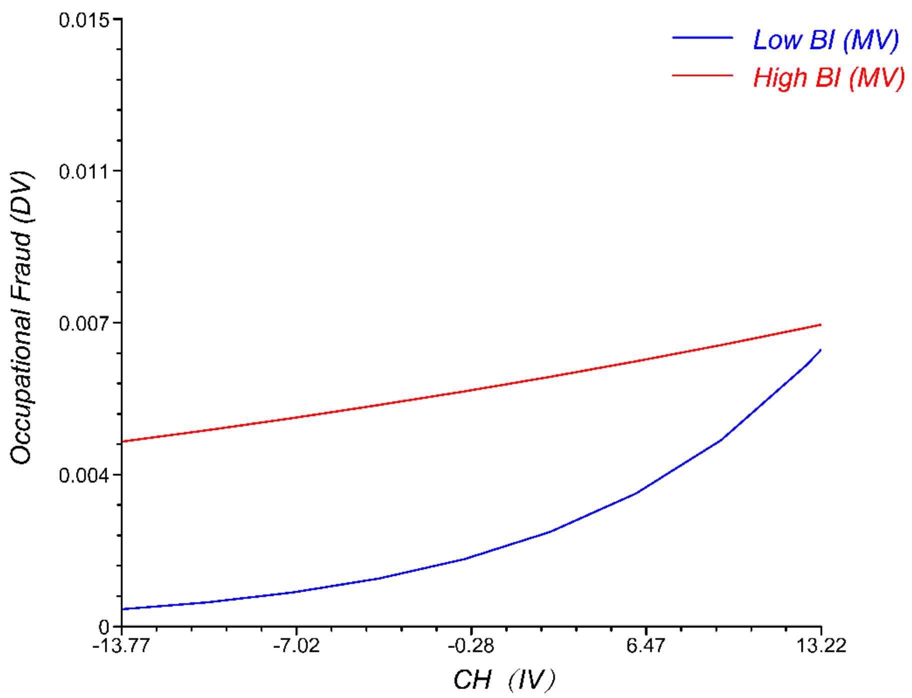


Figure 4-2. Moderating effect of board independence (BI) on career horizon (CH)-occupational fraud relationship

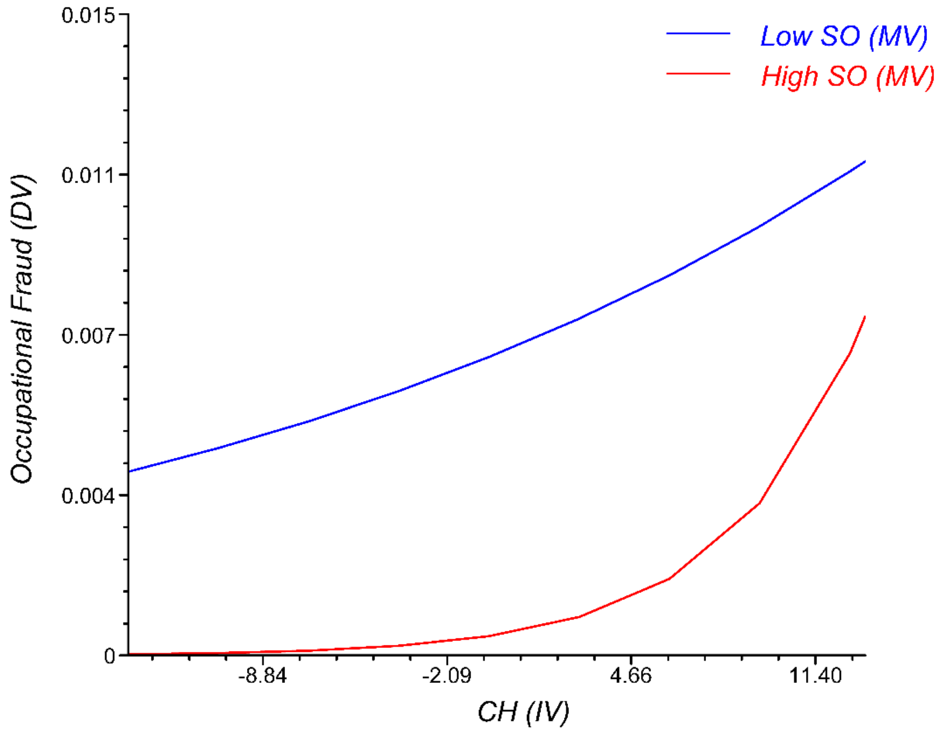


Figure 4-3. Moderating effect of state ownership (SO) on career horizon (CH)-occupational fraud relationship

4.5 Discussion

Under the context of construction industry, the findings present several insights into top managers' violating behaviors in construction companies. First, it is found that the likelihood of occupational fraud being committed decreases as a manager's career horizon becomes shorter. Due to considerations of legacy conservation, executives near retirement become more risk averse. Approaching retirement, an executive may strive to preserve a legacy of success and avoid risky actions (e.g., fraud) that could jeopardize their legacy. This is in line with existing studies on career horizon (Kang, 2016; Matta and Beamish, 2008). While the findings may contradict some studies (e.g., Antia et al. 2010), indicating retirement draws short-term earnings at the expense of long-term performance, most researchers will agree that executives approaching retirement tend to have more risk-averse mindsets, especially in the context of China. An individual's risk perception in China has been found to be different than those in Western countries due to cultural differences (Weber and Hsee, 1998). Particularly, construction practitioners are inclined to be risk-averse (Zou *et al.*, 2009). Thus, the Chinese context may increase the conservative nature of executives near retirement.

Second, such risk aversion is found to be contingent upon board monitoring. As expected, board independence weakens the positive relationship between career horizon and occupational fraud. That is, when board independence is low, the impact of career horizon on whether an executive commits wrongdoing is more prominent. While the moderating effect of board independence is verified by the empirical results in this chapter, it may not necessarily play a role in preventing managers from engaging in fraudulent behavior. This may be explained by the construction industry's characteristics, which emphasizes professional skills and knowledge (Edum-Fotwe and McCaffer, 2000). Many construction firms employ lawyers, accountants and bankers as independent directors (Rebeiz, 2001), who have less tacit knowledge and experiences about the firm and its environment than top managers due to the information asymmetry. Thus, a board with too many independent members may have inadequate information to implement its monitoring function. Executives near retirement are likely to have strived for many years in the firms or in the construction industry. This means that they may have the advantage of possessing important knowledge (Rebeiz, 2001) and even dominate the board (Stiles, 2001). Apart from information asymmetry, the selection procedure by which board members are chosen may be another reason that top management may dominate the board. In many cases, the selection procedure is controlled by top management and thus independent directors are less likely to criticize top managers for fear of losing the prestige and financial rewards (Pfeffer, 1972; Stiles, 2001). Further, board size has no significant effect on the career horizon-occupatioanl fraud relationship. The insignificant effect may be attributed to the ambiguous effects of board size. A large board may be beneficial to obtain some technical or business information (Pfeffer, 1973), which may be significant for the construction industry. A large board may also facilitate free-riding problems and group faultlines (Eisenberg *et al.,* 1998). Thus, simply increasing board independence or board size may not be effective in preventing an executive near retirement from committing deviant behaviors. This finding extends the current understanding of the effects of board monitoring on top management fraud.

Finally, the findings also suggest that the relationship between career horizon and occupational fraud is moderated by ownership structure. Blockholders and state shareholders were considered given whether these stakeholders emphasize profitability or not. Regarding blockholders, this research argued that they would put great financial pressure on executives and thus force some executives approaching retirement to fulfill blockholders' goals even through illicit means. However, it did not find a significant moderating effect of blockholders. This is consistent with studies about large shareholders (e.g., Oh et al. 2016). It may be explained by the mixed roles of blockholders. Considering the conflicts between blockholders and minority shareholders (Thomsen *et al.,* 2006), the effects of blockholders may be complex and uncertain. Concerning state ownership, as predicted, the results indicate that state shareholders exert less financial pressure and thus executives with short career horizons have less external incentive to engage in undesired activities to fulfill financial goals. Nevertheless, state shareholders exert less of an influence on executives with a long career horizon. This may be because the main drivers of wrongdoing for those young managers is not external financial pressure but personal wealth maximization. Though state shareholders could intervene via termination and replacement of executives, Shen and Lin (2009) found that state ownership is negatively related to top management turnover. That is, the likelihood of forced retirement is less if the firm's shares are held by the state. Hence, dishonest actions of executives near retirement is mitigated by the existence of state shareholders.

4.6 Summary

To advance a multilevel understanding of occupational fraud in construction companies, an executive's career horizon was introduced as a possible antecedent of his/her fraudulent activities. Its varied effects were investigated with different cross-level moderators related to board monitoring and ownership structure. Using a multilevel dataset involving 3722 individual-year observations about 1052 executives from 70 construction firms in China, this chapter employed a multilevel research method, HLM, to explore the combined effects of individual- and firm-level characteristics. This chapter found that a manager with a shorter career horizon would be less likely to engage in unacceptable behaviors. This likelihood is further reduced (1) if the board has fewer independent directors, and (2) if more firm's shares are held by the state. However, board size and blockholder ownership have no significant moderating effect on the relationship between managers' career horizon and their wrongdoing.

The application of HLM contributes to the research methods in the field of fraudulent behaviors in organizations. Considering the nested nature of organizational data, traditional regression is inappropriate because the condition of independent and identically distributed random variables is violated (Hofmann *et al.,* 2000). HLM is capable of handling organizational data, which is characterized as hierarchical nature (Gavin, 2004). The present study provides an example of how multilevel methods could be adopted to identify the antecedents and mechanisms of occupational fraud.

There also exists several limitations. First, as mentioned in the introduction section, an individual's traits (e.g., moral intention and attitude) have been found to be associated with an individual's unethical decisions in the construction industry (Alkhatib and Abdou, 2018; Liu *et al.*, 2017). This chapter relies on the observable variables (e.g., career horizon) to capture the executives' invisible psychological status. This approach has been criticized by some scholars (e.g., Carpenter *et al.*, 2004). This approach has to be employed because those intra-psychological processes toward fraud are difficult to obtain. Future studies may adopt other research methods, like field surveys and case interviews, to collect more detailed information on executives' thought processes. Second, in terms of board role in preventing occupational fraud, only two classic but simple indicators of monitoring effectiveness were applied. In subsequent studies, researchers may use more sophisticated and advanced indicators to explore board governance quality.

CHAPTER 5 CORPORATE FRAUD

5.1 Introduction

Given the severe consequences and frequent occurrence, the underlying factors that may lead to committing fraudulent acts have drawn the attention of scholars. Some environmental factors, such as environment turbulence (Silvestre *et al.*, 2018) and industrial climate (Le *et al.*, 2014a) are addressed while more and more researchers consider the internal characteristics of firms such as firm size (Baucus and Near, 1991), and board structure (Lee *et al.*, 2018; Wang *et al.*, 2018). However, as organizations are legal fiction after all, and activities are indeed conducted by individuals. It is difficult and inadvisable to analyze organizational misconduct without considering individuals. From the standpoint of the individual level, a great number of studies have been generated to explore the antecedents of organizational wrongdoing. These studies have been classified into five theories, namely rational-choice perspectives (Grossman and Hart, 1983; Milgrom and Roberts, 1988), strain theory (Agnew *et al.*, 2009; Langton and Piquero, 2007), culture theories (Ashkanasy *et al.*, 2006; Kulik, 2005), network theories (Brass *et al.*, 1998; Briscoe and Safford, 2008) and accidental misconduct perspective (Cohan, 2009; Vaughan, 1999). Besides the role of a single individual, groups in an organization could not be neglected because groups are generally subject to majority-rule and their decisions are riskier (Zaleska, 1976). Thus, organizational wrongdoing is likely to be a result of group decisions.

Among the groups in an organization, one particularly important is the top management team (TMT). Top managers often work collectively as a dominant coalition because managing a firm is a shared effect in general (Cyert and March, 1963). Thus, TMT rather than an individual executive has been a focus of many studies (Heavey and Simsek, 2017; Li, 2018; Sahaym *et al.*, 2016; Yoo and Reed, 2015). The critical role of TMT in determining organizational outcomes has been emphasized by upper echelons theory and related studies (Hambrick and Mason, 1984; Strand, 2013; Zhang *et al.*, 2015). Their role in corporate fraud is also salient because TMT is often the initiator of organizational misconduct and can make individual or group wrongdoing become an organizational phenomenon (Greve *et al.*, 2010). Thus, it has become a consensus that corporate fraud is more often the result of actions or inactions, deliberate or inadvertent, of top managers in organizations (Collins *et al.*, 2009; Daboub *et al.*, 1995; Zahra *et al.*, 2005). TMT has the responsibility for setting the overall direction of an organization (Hambrick and Mason, 1984), and once the team decides how it will behave, corresponding actions and even corporate fraud may follow. This belief seems to be the legal basis for holding business executives personally liable and subject to fines or potential incarceration. To solve the possible moral hazards and to motivate executives, firms design executive compensation packages as an important mechanism to align shareholder and managerial interest and motive managers (Conyon and He 2011). It includes performance-based pay, stock options, and restricted stock and other elements (Devers *et al.*, 2007), which are aimed to reward executives for gains in shareholder value so that the benefits of shareholders and managers can be aligned (Wowak et al. 2015).

It is surprising, however, scholars have not yet reached a consensus about the effect of executive compensation system (Devers *et al.*, 2007). Its association with firm performance may be positive (Nyberg *et al.*, 2010), insignificant (Carpenter and Sanders, 2004) and negative (Hanlon *et al.*, 2003). Similarly, the relationship between TMT compensation and corporate illegal behaviors is not concurred either (O'Connor *et al.*, 2006; Schnatterly *et al.*, 2018; Shi *et al.*, 2016). It has been reported that compensation is positively associated with corporate fraudulent behaviors (Minor, 2016; Wowak *et al.*, 2015) as well as negatively associated (Armstrong *et al.*, 2010; Conyon and He, 2016). Due to the influence of industrial culture and other industry characteristics, it is worth a revisit to unveil the effects of compensation design/system in the construction industry. Thus, the first emphasis in this study is to investigate whether improving TMT pay level could reduce the incidence of corporate fraud in the context of the construction industry.

The inconsistency on the effect of TMT compensation may be, at least in part, because of neglecting the situational factors. Situations may affect both an organization's structural choices and strategies and thus the most desirable strategy needs to alter relying on certain contextual factors (Donaldson, 1996; Roh *et al.*, 2016; Zott and Amit, 2008). Simpson (2002) also claims that organizational wrongdoing has much to do with organizational contingencies. Similarly, contextual factors may exert influences on the effects of compensation on corporate illegal behaviors. O'Connor et al. (2006) found larger stock options for a CEO may lead to a higher incidence of fraudulent reporting and sometimes a lower incidence, depending on whether the CEO and chairman positions are separated. Besides CEO duality, another potential but neglecting contextual factor is relative firm performance given that executive compensation is often tied to firm performance and organizations strive to achieve their desired level (Harris and Bromiley, 2007). Therefore, this research argues that a firm's performance gap relative to its desired level may influence the relationship between executives' compensation and corporate fraud. The second emphasis in this study is to investigate the moderating effect of performance discrepancies on the relationship between TMT compensation and corporate fraud. Performance discrepancies refer to the gap between a construction company's performance and its aspiration level (Lant, 1992; Yang *et al.*, 2017). The aspiration level is "the smallest outcome that would be deemed satisfactory by the decision maker" (Greve, 2003a; Schneider, 1992). Exploring whether the effects of TMT compensation would be affected by performance discrepancies may facilitate the understanding of how to make good use of TMT compensation to alleviate the commitment of illegal activities.

5.2 Hypotheses Development

This section begins by presenting the hypothesis for TMT compensation's influences on corporate fraud. The following hypotheses build on the behavioral theory of the firm and address the effect of aspiration-performance discrepancies. Particularly, the possible moderating effects of aspiration–performance discrepancy on the relationship between TMT compensation and corporate fraud are emphasized.

5.2.1 TMT Compensation

Prior work on predicting and preventing corporate criminal activities has evidenced the role of executive compensation (Johnson *et al.*, 2009; Peng and Röell, 2008). In the absence of complete information and credibly enforceable-contracts, agents (i.e., top managers) might potentially behave opportunistically at the expense of principal (i.e., shareholders). As a vital effort to mitigate the agency cost resulting from the separation of control and ownership, TMT compensation is designed to align the interests of multiple participants. When executives are well-compensated and the majority of their wealth is closely linked to a company, they are expected to act in the company's best interest, engage in fewer opportunistic actions, and be less likely to behave wrongfully or illegally at work (Jensen and Meckling, 1976; Jensen and Murphy, 1990).

From the labor market perspective, Jensen (1993) argues competition in the managerial labor market promotes effective corporate governance and plays an important role in disciplining top executives. Managers involved in criminal activities tend to lose their jobs and have difficulty finding another one. If top executives are held accountable for the violations of their firms, it is expected that managers losing their jobs would suffer a larger compensation penalty when their compensation is higher. The firing mechanism to discipline senior executives could contribute to the change of risk attitude of managers. When violations are financially costly (Firth *et al.,* 2011), executives may become risk-averse (Jensen and Meckling, 1976), such that their desire to reduce their loss outweighs that to increase their gain (Kahneman and Tversky, 1979). Therefore, to avoid the loss of their wealth, managers may be reluctant to engage in the risky illegal behaviors.

Conversely, an argument could be made that executive compensation increases the probability of corporate fraud. Although previous studies on executive compensation typically draw on agency theory, bounded rationality perspective indicates that rewards for specific outcomes increase the probability that individuals work toward those outcomes. Since the primary mechanism by which top managers are evaluated is by firm performance (Arthaud-Day *et al.*, 2006), executives may constantly feel pressured to report consistent and positive firm performance to stockholders. Thus they may be tempted to cover up problems, take excessive risks, or exaggerate performance potential to present their work in the best possible light (Zahra *et al.*, 2005). DuCharme et al. (2001) found some managers would purposely manipulate earnings or misrepresent the firm's financial outcomes to maximize individual benefit.

Empirical studies also have demonstrated that executive compensation may be positively associated with corporate fraud. Harris and Bromiley (2007) suggest that higher compensation increases the likelihood of financial misrepresentation. Efendi et al. (2007) provided empirical evidence that higher CEO compensation increases greatly the probability of misstated financial statement. When highly compensated managers have a strong incentive to protect their income, they might attempt to window-dress financial statements via illicit actions. Although managers generally behave ethically, the likelihood of doing business illegally rises with the level of compensation. It is easy to be ethical if a small portion of one's pay is at stake; it is hard when a substantial amount is influenced through illegal behaviors.

That is, executives may prefer honesty, but the incentives of gaining more personal wealth may promote corporate wrongdoing.

In summary, the effects of TMT compensation may vary in different decision-making scenarios, depending on losing the existing wealth or gaining more coming benefits. Based on the two competing incentives, we thus propose the null hypothesis.

Hypothesis 1: TMT compensation has no significant bearing on the likelihood of corporate fraud because of the diverse perception of executives.

5.2.2 Aspiration-Performance Discrepancies

Prior studies (Hill *et al.*, 1992; Schnatterly *et al.*, 2018) show that firms with the low or declining performance or suffering from problems (e.g., losing a competitive position) are more likely to be involved in illegal activities. However, other studies report a contradictory finding that high performing organizations are more likely to engage in illegal behaviors after achieving higher performance than their peers (Mishina *et al.*, 2010). Although scholars have provided sensible explanations of apparently contradictory findings, it remains the fact that some studies show that declining performance leads to illegal activities, while others indicate that improving performance leads to violating the laws. Acknowledging the inconsistent findings, Gavetti et al., (2012) suggest that the conflicting results might be achieved by considering the role of managerial aspiration levels.

Different from the classic economic theories assuming that a firm's goal is to maximize its profits, the behavioral theory of the firm (Cyert & March 1963; March & Simon 1958) suggests that firms endeavor to achieve their target on performance evaluation. The target level, or say aspiration, is mainly derived from two aspects, the firm's historical performance and the competitors' performance (Desai, 2016). Firms compare their performance with their past achievements and then adjust their goals for future development (March and Simon, 1958). They also evaluate their performance by comparing it with their peers' or competitors' according to social comparison theory (Festinger, 1954).

Following the behavioral theory, a discrepancy between performance and aspirations signifies that the status is problematic, and new solutions are needed. Then firms will initiate problematic search and are willing to seek changes and even risky ways to improve the current performance (Brown and Loosemore, 2015; March and Shapira, 1987). This process also exerts influences on bank lending practices (McNamara and Bromiley, 1999), innovation (Greve, 2003a), safety initiatives (Baum and Dahlin, 2007) and acquisitions (Iyer and Miller, 2008). In parallel with these previous studies, this study argues that corporate fraud are also among available options when firms initiate a problematic search. Firms may engage in corporate wrongdoing to increase the performance to a satisfactory level.

If the current performance is better than aspiration, firms would perceive the status as a success. Since organizations guide their behaviors by encoding the references from history into the routine (Levitt and March, 1988), firms may be reluctant and even averse to engaging in any risky activities that may change the current success (Gavetti *et al.*, 2012). Among the risky activities, illegal actions are very costly. For fear of penalty and other possible economic and reputation loss (Williams and Barrett, 2000), firms tend to keep the routine with the least possible changes and have far much incentive to reduce fraud. The inertial forces would counteract the risky illegal actions when performance is above aspiration but not work when performance is below aspiration. Then the effects of performance on illegal activities are weaker for performance greater than aspiration. Taken together, when firms' performance relative to aspirations increases, the likelihood of corporate fraud decreases. The decrease would be more rapid when firms' performance above aspirations than when performance below aspirations. The following hypotheses are developed.

Hypothesis 2a: The likelihood of corporate fraud decreases as aspiration-performance discrepancies increases.

Hypothesis 2b: The decrease is more rapid for firms' performance is above aspirations than for performance below aspirations.

5.2.3 Moderating Effects of Aspiration–Performance Discrepancies

Prior research on corporate fraud has addressed many factors like firm performance, firm structure, and executive compensation that are associated with unethical or illegal activities (e.g., Harris & Bromiley, 2007; Johnson et al.,2009). Among theories of fraudulent behaviors, strain perspective builds on the premise that firms are more likely to behave wrongfully when individuals suffer from performance pressure (Hill *et al.*, 1992; Schnatterly *et al.*, 2018). When an organization is under strain, individuals who internalize the achievement gap may be motivated to commit illegal activities. That is, organizational wrongdoing not only is influenced by an employee's needs (i.e., financial wellness) but has a lot to do with organizational contingencies, priorities, and goals (Simpson, 2002). A firm's performance relative to aspiration reflects the degree to which managers are aware of strain, as well as the extent to which they view it as relevant.

When performance is lower than aspiration, top managers are under intense pressure to drive growth and deliver strong results to meet shareholders' expectations (Arora and Dharwadkar, 2011). Those with high compensation and thus with potentially the most to lose will have a strong motivation to take fraudulent activities. That is, the potential costs of not meeting aspirations increase the likelihood of illegal behavior, and that likelihood is even greater when a firm is under strain. This implies managers under performance pressure will be more likely to believe their financial well-being would be affected or even their positions are threatened. Then, the likelihood of engaging in corporate fraud would increase.

When performance exceeds aspiration, managers would prefer taking fewer risks to maintain their existing success (March and Shapira, 1987). Under this circumstance, a manager's position, reputation, and economic benefit would be retained and the motivation to engage in fraudulent activities would be lower. They may even have some inertial forces to counteract fraudulent doings. Hence, the relation between TMT compensation and corporate fraud would be weaker. The following hypotheses are constructed.

Hypothesis 3a: As performance falls below aspirations, it strengthens the relationship between TMT compensation and the likelihood of corporate fraud.

Hypothesis 3b: As performance increases above aspirations, it weakens the relationship between TMT compensation and the likelihood of corporate fraud.

5.3 Method

5.3.1 Sample and Data

The samples are made up of publicly traded construction companies in China. The data is derived mainly from the CSMAR (GTAFE) and CCER (Sinofin) database. By primarily searching the listed construction companies in these databases, this study focused on the enforcement information announced by the China Securities Regulatory Commission (CSRC), Ministry of Housing and Urban-Rural Development (MOHURD), and other governmental institutions. The enforcement information is comprised of the case description, supervisors, violation type, related laws and regulations, and other information. The violation type includes not only misleading statement and other false information disclosure, but also the usage of substandard construction materials and other criminal activities. Through carefully reviewing the violation cases, this study identifies the year in which illegal events occurred rather than the date of announcement used by prior studies (e.g., Chen et al., 2016; Hass et al., 2016). In a few cases where the fraudulent activities last for several years (e.g. using poor materials in a project), this study assumes that the companies could have stopped the illegal behavior at any time so that they are regarded as guilty each year. For the cases for which it is difficult to identify the period, this study assumes the behavior was detected by the CSRC as soon as it occurred. Due to data availability, 36 companies were selected as the final sample. Among the 36 companies, 52.78% are state-owned enterprises. According to main business, 69.44% companies belong to civil engineering construction industry and the other companies belong to architectural decoration and other construction industries. To capture as many observations as possible and to get a more generalized result, the period from 2011 to 2017 was used. Thus, this study yielded a final total of 252 firm-year observations.

5.3.2 Measures

This section provides the measures of dependent variable and independent variables. To verify the moderating effects of aspiration-performance discrepancies, several interaction terms are included. Then the measures of control variables are presented.

Dependent Variable

As the dependent variable, *corporate fraud (CF)* is a dichotomous variable, operationalized by whether violations were committed by firms in a focal year. When a company is convicted of being a violator in a focal year, the CF is coded 1 and otherwise 0 (Baucus and Baucus, 1997; Harris and Bromiley, 2007). Among our samples, the most frequent type of violations was delayed disclosure, and the second and third frequent types were serious loopholes and false records. Besides, a company was found guilty of using poor materials and another company was found guilty of illegal emission of pollutants.

Independent Variables

The measurement of *TMT compensation* has not achieved consensus (Devers *et al.*, 2007). Although in many studies (Devers *et al.*, 2007; Harris and Bromiley, 2007) restricted stock and stock options were used to compute incentive compensation, they are rarely used in Chinese firms. Consistent with recent studies in China (Conyon and He, 2012, 2016; Lu and Shi, 2018), this study measured compensation as the average of total pay in TMT. Total pay is defined as the sum of basic salary, stipends, and bonus. A bonus is determined based on firm performance, though the calculation process and the actual bonus information are unveiled (Firth *et al.*, 2007a). To deal with the fact that pay is positively skewed (Conyon and He, 2011, 2012, 2016), this study uses its natural logarithm transformation.

Aspiration–performance discrepancy is calculated based on performances relative to social and historical aspiration mentioned in previous literature (Bromiley and Harris, 2014; Gaba and Bhattacharya, 2012). These two aspirations were combined by the weighted average model (Greve, 2003a; O'Brien and David, 2014). This model assumes there is a single goal for a period. This is consistent with corporate practice and this single goal is established based on the balance of industrial and historical performance. More importantly, this model is considered to align most closely with the behavioral theory proposed by Cyert and March (1963). Their original model constructs aspiration as a linear mixture of a firm's past aspiration, historical performance, and its competitors' average performance in the last year. By mathematically transforming the original model, the formulation of the weighted average model could be generated.

Specifically, aspiration–performance discrepancy equals the difference of the current performance and the two aspirations, shown as follows:

$$RP_{i,t} = P_{i,t} - A_{i,t} \tag{1}$$

where relative performance $RP_{i,t}$ denotes aspiration–performance discrepancy for firm i at time t, $P_{i,t}$ is the current performance, and $A_{i,t}$ is aspiration that is calculated as follows:

$$A_{i,t} = a_1 SoA_{i,t} + (1 - a_1) SeA_{i,t} \tag{2}$$

where $SoA_{i,t}$ is social-referent aspiration and $SeA_{i,t}$ represents self-referent aspiration. Their calculation equations are as follows:

$$SoA_{i,t} = IP_{i,t} = \left(\sum_{i \neq j} P_{j,t}\right)/(N - 1) \tag{3}$$

$$SeA_{i,t} = a_2 SeA_{i,t-1} + (1 - a_2) P_{i,t-1} \tag{4}$$

where $IP_{i,t}$ is the industry performance. Equation 3 shows that social aspiration, equaling the industry performance, is the average performance in the industry excluding the focal company. Equation 4 demonstrates self aspiration is determined by the weighted sum of self-referent aspiration and performance in the last year. Specifically, self aspiration is operationalized as an exponentially weighted moving average of historical performances. For example, the self aspiration in the Year 2011 (the first year we investigate) is calculated based on performance in the Year 2010 and Year 2009. Therefore, the overall equation of aspiration–performance discrepancy is as follows:

$$RP_{i,t} = P_{i,t} - a_1 IP_{i,t} - (1 - a_1)(1 - a_2) \sum_{j=0}^{\infty} a_2^j P_{i,t-1-j} \tag{5}$$

The two parameters a_1 and a_2 in the above equation can be estimated by grid search (Rhee *et al.*, 2019; Vissa *et al.*, 2010). Each time, a_1 and a_2 are assigned a value randomly from the set [0, 0.1, 0.2, …, 0.9, 1] (in increments of 0.1). This leads to 121 sets of aspiration–performance discrepancies. Using one set of constructed aspiration–performance discrepancies each time, this study estimates hundreds of full models (Model 5 below) and selects the one with the maximum likelihood. $a_1 = 0.2$ and $a_2 = 0.9$ provide the best model fit. $a_1 = 0.2$ means that self comparison dominates this blended measure of aspirations. This is in line with Rowley et al. (2017) which also found that firms would react to the performance goals depending more strongly on the historical performance rather than their competitors' performance. Especially when they are claimed to undertake some unique strategies, their performance changes are more meaningful to take as the referent point. $a_2 = 0.9$ represents the updating of self aspiration relies more on past performance rather than recent performance (Greve 1998, 2003b). This is reasonable considering the greater payback period for the construction industry than other service industries (Alfeld, 1988).

Following many studies based on the behavioral theory of the firm (Bromiley and Harris, 2014; Greve, 1998, 2003a), a spline function is employed to determine whether performance greater or lower than aspirations has different impacts on corporate fraud. In mathematics, the slope for performance above aspiration may be different from that for performance below aspiration. To do so, the aspiration–performance discrepancy is split into positive and negative. The positive aspiration-performance discrepancy, also called positive relative performance (PRP), indicates the status when the discrepancies are above zero, while negative aspiration–performance discrepancy or say negative relative performance (NRP) represents the status when discrepancies are below zero. The following two continuous but censored variables are constructed.

$$Positive\ RP_{i,t} = \begin{cases} P_{i,t} - A_{i,t},\ if\ P_{i,t} > A_{i,t} \\ 0,\ if\ P_{i,t} \le A_{i,t} \end{cases} \tag{6}$$

$$Negative\ RP_{i,t} = \begin{cases} 0,\ if\ P_{i,t} \ge A_{i,t} \\ P_{i,t} - A_{i,t},\ if\ P_{i,t} < A_{i,t} \end{cases} \tag{7}$$

Two kinds of performance were considered, Return on Assets (ROA) and Debt-to-Equity Ratio (DER). ROA is commonly used (Chen *et al.*, 2009; Shen and Lin, 2009). Higher ROA represents better profitability. DER signifies firm leverage (Ferguson and Shockley, 2003; Schmukler and Vesperoni, 2006) and also reflects organizational slack, the stock of available resources that can be diverted or redeployed for an organization to achieve their goals (Arora and Dharwadkar, 2011; Kuusela et al., 2017). This study added DER because of a distinctive feature of the construction industry—most construction companies are operated on borrowings. This sector is considered a high-risk one because DER in many construction companies is too high (Rebeiz and Salameh, 2006). Compared with non-financial listed companies in other industries in China, DER in the construction industry is the highest from 2002 to 2016 (Roberts and Zurawski, 2016). As DER rises, financial risks grow (Edum-Fotwe *et al.*, 1996) and the probability of firm bankruptcy increases (Easterbrook, 1984). A high DER also represents high expected costs of financial distress, bankruptcy, or liquidation (Margaritis and Psillaki, 2010). Moreover, DER has been treated as a natural proxy for the risk of common equity of a firm (Bhandari, 1988).

Combining positive and negative relative performance (PRP and NRP) with ROA and DER, four variables are constructed to measure aspiration–performance discrepancy. They are *positive relative performance for ROA (PRP-ROA), negative relative performance for ROA (NRP-ROA), positive relative performance for DER (PRP-DER), and negative relative performance for DER (NRP-DER)*. PRP-ROA and NRP-DER reflect performance above aspiration, while NRP-ROA and PRP-DER imply performance below aspiration.

Interaction Terms

To test hypotheses 3a to 3b, this study constructed several interaction terms showing the moderating effect of aspiration–performance discrepancy on the relationship between TMT compensation and corporate fraud. The interaction term is calculated by multiplying aspiration–performance discrepancy and TMT compensation. To avoid multicollinearity and unstable regression estimates resulting from the fact that interaction terms are always highly associated with its constituents, this study followed the "centering" (or say demeaning) procedures (Aiken *et al.*, 1991). Specifically, the mean of each variable was subtracted from the raw value for each observation before the multiplying process. Through the above procedures, four interaction terms were created, including *Compensation×PRP-ROA, Compensation×NRP-DER, Compensation×NRP-ROA, and Compensation×PRP-DER.*

Control Variables

The estimating model also includes several control variables, including firm size, TMT size, CEO duality, number of female managers, stock ownership by TMT, average tenure, and tenure variance. They have also been used as control variables in some studies about executives' compensation (Al-Shaer and Zaman, 2019; Hou *et al.*, 2017; Shi *et al.*, 2016; Wowak *et al.*, 2015). A larger firm has been evidenced empirically to be related to executives' compensation (Tosi and Gomez-Mejia, 1994) and more likely to commit corporate fraud (Baucus and Near, 1991). *Firm size* is controlled and operationalized by the natural log of the number of employees (Lee *et al.*, 2018). TMT size may influence a firm's decision-making process. A larger team has more potential for dissimilarity and is likely to have conflicting thinking (Wiersema and Bantel, 1992). This may result in the reduction of corporate wrongdoing. *TMT size* is measured as the number of top managers in total (Dauth *et al.*, 2017). CEO duality is considered due to the CEO's influence (Shi *et al.*, 2016). When a CEO serves as chairman inboard, he/she has more power in decision-making and can increase information asymmetry. This would lead to the board of directors failing to block his/her violating decisions (Sharma, 2004). *CEO duality* equals to 1 if the CEO holds the chairman seat inboard and otherwise 0. *The number of female managers* is also controlled (Jurkus *et al.*, 2011) because women are less overconfident, more risk-averse, and less likely to conduct fraudulent activities (Cumming *et al.*, 2015). The *stock ownership* by TMT has been reported to exert an influence on the attitude of risk-taking and thus on the likelihood of corporate fraud (Troy *et al.*, 2011). It was operationalized by the percentage of total shareholdings by top managers (Shi *et al.*, 2017). Besides, this study controlled *average tenure* and *tenure variance*, operationalized by the average of the number of years when top managers served in the focal company and its variance (Zhang *et al.*, 2015). With increasing tenure, executives may be prone to strategic inertia (Hambrick and Mason, 1984). That is, they would unlike some risky strategies, such as risky fraudulent activities. Thus, TMT tenure is expected to be negatively associated with corporate fraud (Daboub *et al.*, 1995). Tenure variance represents the heterogeneity of TMT, which has been found to affect group decision-making (Pfeffer, 1983). A heterogenous TMT is expected to hinder deviant decisions and generate acceptable and lawful solutions (Daboub *et al.*, 1995).

5.3.3 Analysis

Since this research involves a dichotomous dependent variable (corporate fraud), a categorical control variable (CEO Duality), as well as other continuous variables, the hierarchical logit regression model with fixed effects, was applied (Christensen, 2016; Ege, 2015). Logit regression is robust in most situations because of its minimal set of assumptions. It does not require the distributional form of independent variables or the linear relationship between independent variable(s) and dependent variable (Hair *et al.*, 2014). Considering the panel structure of the data, there may be some unobserved characteristics for each firm that exert some influences on the independent variables. To address such potential bias, the fixed effect model was employed to specify the unobserved cross-sectional differences among firms (Chang and Chung, 2017). To check for possible multicollinearity, collinearity diagnostics were run. The variance inflation factors (VIFs) were below the threshold of 10 (ranging from 1.094 to 1.740), implying no significant collinearity (Hair *et al.*, 2014). The analysis procedure included three steps. The first step examined the relationship between the dependent variable and the control variables only. Then this study tested the effects of independent variable and the moderator—TMT compensation and aspiration–performance discrepancy—on the dependent variable. In the last step, moderated regression was employed, and a set of interaction terms was entered to test whether aspiration–performance discrepancy could moderate the relationship between TMT compensation and corporate illegal activities.

5.4 Results

Tables 5-1 and 5-2 provide descriptive statistics and a correlation matrix, while Table 5-3 presents the results of hierarchical logit regression. In Table 5-3, the first column reports estimates with control variables only. The second column reports estimate considering the independent variables. The third and fourth columns present the respective effects of four moderators. The last column provides the results of the full model.

Table 5-1. Descriptive statistics

Variable	Mean	SD	Minimum	Maximum
CF	0.33	0.47	0	1
Firm Size	7.60	1.74	2.30	11.76
CEO Duality	0.24	0.43	0	1
TMT Size	7.92	3.38	2	20
Female Managers	1.00	0.92	0	4
Average Tenure	4.57	1.81	1.00	9.38
Tenure Variance	6.57	6.18	0.00	30.78
Stock Ownership by TMT	0.06	0.14	0.00	0.57
Compensation	12.81	0.69	10.69	14.07
PRP-ROA	0.01	0.02	0.00	0.14
NRP-ROA	-0.03	0.05	-0.55	0.00
PRP-DER	0.48	0.80	0.00	4.97
NRP- DER	-0.63	1.19	-7.86	0.00

Note: N = 252. Means and standard deviations are presented in decimal form of percentages, except for Firm Size and Average of Total Pay which are in natural log form, CEO Duality which is a dummy variable, and Average Tenure and Tenure Variance which are in years.

Table 5-2. Correlation matrix of variables

Variable	1	2	3	4	5	6	7	8	9	10	11	12	13
CF	1												
Firm Size	0.07	1											
CEO Duality	-0.12*	-0.25***	1										
TMT Size	-0.04	-0.23***	0.35***	1									
Female Managers	0.01	0.15**	-0.09	0.09	1								
Average Tenure	-0.11*	-0.19***	0.19***	0.07	-0.24***	1							
Tenure Variance	-0.08	-0.29***	0.20***	0.25***	-0.05	0.53***	1						
Stock Ownership by TMT	-0.02	0.47***	-0.17***	-0.11*	0.23***	-0.19***	-0.21***	1					
Compensation	-0.08	-0.23***	0.40***	0.15**	0.07	0.16**	0.04	-0.06	1				
PRP-ROA	-0.01	0.04	-0.06	0.04	0.03	-0.12*	-0.01	-0.03	-0.16**	1			
NRP-ROA	0.07	0.03	-0.08	0.08	0.03	0.01	0.10	-0.03	-0.04	0.22***	1		
PRP-DER	-0.01	-0.08	0.20***	0.18***	-0.06	0.07	0.26***	-0.13**	0.05	0.07	-0.01	1	
NRP- DER	0.09	0.09	-0.32***	0.05	-0.02	0.02	0.14**	0.00	-0.14**	0.07	0.12*	0.32***	1

Note: N = 252; *p < 0.10; **p < 0.05; ***p < 0.01.

Table 5-3. Hierarchical logit regression results

Variables	Model 1	Model 2	Model 3	Model 4	Model 5	
	Coef.	Coef.	Coef.	Coef.	Coef.	Odds Ratio
Firm Size	-0.09	-0.13	-0.07	-0.11	-0.03	0.97
	(0.24)	(0.22)	(0.24)	(0.24)	(0.25)	(0.24)
CEO Duality	1.07*	1.35**	1.26**	1.63**	1.60**	4.94**
	(0.57)	(0.62)	(0.63)	(0.67)	(0.69)	(3.42)
TMT Size	-0.08	-0.09	-0.09	-0.04	-0.03	0.97
	(0.10)	(0.10)	(0.10)	(0.10)	(0.10)	(0.10)
Female Managers	-0.21	-0.27	-0.31	-0.35	-0.41	0.66
	(0.27)	(0.27)	(0.28)	(0.28)	(0.29)	(0.19)
Stock Ownership by TMT	-0.73	-0.39	-0.60	-0.41	-0.68	0.51
	(1.83)	(1.90)	(1.93)	(2.01)	(2.05)	(1.04)
Average Tenure	-0.19	-0.22	-0.21	-0.29**	-0.30**	0.74**
	(0.13)	(0.13)	(0.14)	(0.14)	(0.15)	(0.11)
Tenure Variance	-0.05	-0.05	-0.07*	-0.05	-0.07	0.93
	(0.04)	(0.04)	(0.04)	(0.04)	(0.05)	(0.04)
Compensation		0.70	0.59	1.08**	1.03**	2.81**
		(0.43)	(0.45)	(0.51)	(0.53)	(1.48)
PRP-ROA			-5.59		-6.03	2.41E-03
			(7.33)		(7.47)	(0.02)
NRP-ROA			3.48		3.01	20.20
			(4.48)		(4.61)	(93.05)
Compensation ×PRP-ROA			16.86		19.79	3.92E+08
			(12.52)		(12.58)	(4.93E+09)
Compensation ×NRP-ROA			0.52		-0.30	0.74
			(7.33)		(7.61)	(5.64)
PRP-DER				-0.63	-0.71*	0.49*
				(0.40)	(0.43)	(0.21)
NRP- DER				0.72**	0.74**	2.09**
				(0.36)	(0.37)	(0.78)
Compensation ×PRP- DER				1.01*	1.22*	3.38*
				(0.59)	(0.65)	(2.19)
Compensation ×NRP- DER				0.26	0.27	1.31
				(0.39)	(0.38)	(0.50)
Log likelihood	-94.99	-93.63	-91.02	-89.30	-86.25	
Pseudo R^2	0.04	0.05	0.06	0.09	0.11	
Wald chi-square	13.07	15.80	21.01	24.45	30.55	
	(7)	(8)	(12)	(12)	(16)	
Prob > chi-square	0.07	0.05	0.05	0.02	0.02	

Note: N = 252; *p < 0.10; **p < 0.05; The figures in the parentheses in the rows of the variables are standard errors while those in the Wald chi2 row are the degree of freedom.

According to Table 5-3, the results of Model 2 support Hypothesis 1 indicating that TMT compensation has an insignificant influence on the likelihood of corporate fraud (0.70, $p>0.1$). When considering performance discrepancies (in particular DER) simultaneously, the coefficient of TMT compensation is significantly positive (1.08, $p<0.05$; 1.03, $p<0.05$), shown in Model 4 and Model 5. This verifies the relationship between TMT compensation and corporate fraud is affected by the situational factors (i.e., aspiration-performance discrepancies). Hypothesis 2a and 2b argue that the likelihood of fraudulent activities would decrease as aspiration-performance discrepancy increase and the decrease would be more rapidly for positive aspiration-performance discrepancy than negative aspiration-performance discrepancy. The coefficients of NRP-ROA and PRP-ROA are both insignificant, the coefficient of PRP-DER is significantly negative (-0.71, $p<0.1$), and the coefficient of NRP-DER is positive at the significance of 5% (0.72, $p<0.05$; 0.74, $p<0.05$). Thus, Hypothesis 2a is supported when performance is above aspiration. Hypothesis 2b is not fully supported because the coefficient signs for performance above and below aspiration are different, and the likelihood of corporate fraud surprisingly increases as performance below aspiration increases, which is out of our expectation.

For the moderating effect of aspiration–performance discrepancy on the relationship between TMT compensation and corporate fraud, only the interaction term of PRP-DER and TMT compensation has a significant positive coefficient (1.01, $p<0.1$; 1.22, $p<0.1$), consistent with Hypothesis 3a. However, Hypothesis 3b is not supported considering the interaction term of NRP-DER and TMT compensation, as well as the interaction term of PRP-ROA and TMT compensation, which is insignificant. Figure 5-1 is a diagram depicting the joint effect of TMT compensation and PRP-DER using the odds ratio in Model 5. The value of compensation in this plot ranges from a standard deviation below the mean to a standard deviation above (Dawson, 2014). The value of high PRP-DER equals a standard deviation above the mean, while that of low PRP-DER equals 0 given that a standard deviation below is not in the range of the central value. According to Figure 1, whether the PRP-DER is low or high, the likelihood of corporate wrongdoing increases as TMT compensation rises, but the increasing speed of the likelihood of illegal practices is higher when PRP-DER is high, supporting Hypothesis 3a.

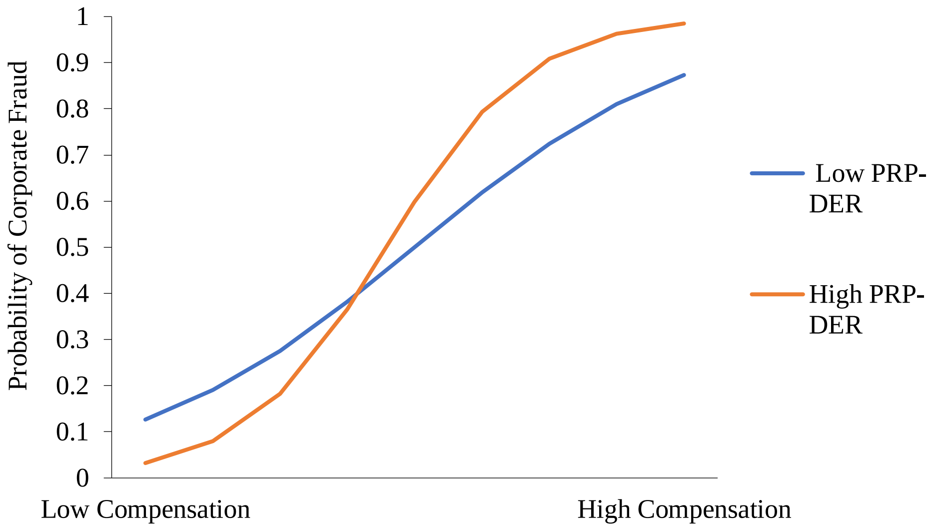


Figure 5-1. Moderating effect of PRP-DER on compensation-fraud relationship

5.5 Discussion and Summary

Executive compensation has drawn considerable attention, but there remains much disagreement about its role in preventing fraudulent actions (Conyon and He, 2012; Crutchley and Minnick, 2012; Devers *et al.*, 2007). This may be due to the neglecting contextual factors, which may have impacts on the effects of the compensation system and the TMT's decision-making. Basing on the behavioral theory of the firm, this study empirically explored the effects of TMT compensation and aspiration–performance discrepancy on the likelihood of corporate fraud. In particular, it studied the moderating effect of aspiration–performance discrepancies on the relation between TMT compensation and corporate fraud. Using data on publicly traded construction companies in China from 2011 to 2017, this study tested the above hypotheses. Some of them are supported.

Though it first found TMT compensation has an insignificant impact on corporate fraud in Model 2, a significantly positive relationship between them was then obtained in Model 5 which also considers performance discrepancy. This finding verifies the impact of situational factors on TMT compensation. This positive relationship corresponds to the notion that executive compensation may provide managers with incentives to improve the firm's short-term performance to maximize their interest at the expense of the firm's long-term growth (O'Connor *et al.*, 2006; Peng and Röell, 2008). This finding is consistent with previous studies about the relationship between incentive compensation and fraudulent decisions (DuCharme *et al.*, 2001; Harris and Bromiley, 2007; O'Connor *et al.*, 2006).

Second, aspiration–performance discrepancy, especially when characterized as relative DER, was found to have influences on the likelihood of corporate fraud. When performance is above aspiration, that is when DER is lower than the weighted industrial and historical level (i.e., NRP-DER), the firm is less likely to conduct violations. This is in line with the notion that the incidence of organizational change decreases when firms consider themselves successful (Fiegenbaum, 1990; Greve, 1998). To avoid anticipating a distant future, firms are willing to maintain a status quo and unwilling to change (Gavetti *et al.*, 2012). They would rely on their standard operating procedures and prefer seeking in the neighborhood of current alternatives and solutions (Cyert and March, 1963). When performance is below aspiration (DER is above the acceptable level, i.e., PRP-DER), the probability of corporate fraud is lower as relative DER increases, contrary to our expectation. This may be explained by the threat-rigidity effects generated by obvious failure (Gaba and Bhattacharya, 2012; Greve, 1998). Unsatisfactory performance, as a threat, may contribute to limited information processing, centralized decision making, strengthened organizational rigidity, narrow alternatives considered, and thus the decreasing likelihood of change (Staw *et al.*, 1981). Subsequently, firms become averse to taking risks (Chattopadhyay *et al.*, 2001). They would maintain their routines and be reluctant to commit wrongdoing.

Third, this research indicates that performance below aspirations (DER is higher than the desired level, i.e., PRP-DER) strengthens the effect of TMT compensation on fraudulent behaviors. As TMT compensation increases, the incidence of fraudulent activities grows fast. It is higher for firms with lower relative performance (higher PRP-DER) if compensation climbs high enough. This may be associated with increasing incentives for changes. Managers are expected to lose much financially if performance is below the acceptable level. Considering that their desire to reduce losses overwhelms that to increase gains, managers may become greater risk-taking under strains such as performance shortfalls (Kahneman and Tversky, 1979). This corresponds to the idea under the behavioral theory that failing to attain a satisfactory outcome generates incentives for problematic search and some risky alternatives may be selected due to bounded rationality (Cyert and March, 1963; Gavetti *et al.*, 2012). Executives might attempt to improve short-term performance and to avoid possible financial loss through illicit means.

Fourth, the insignificant effect of ROA on corporate fraud may be related to the pressure degree. ROA represents profitability, and making profits is a long-lasting activity. That is, performance below aspiration in a short period may not be urgent in the construction industry, in which the payback period is always longer than other service industries (Alfeld, 1988). Indeed, some construction firms would take some megaproject initiatives that are not in pursuit of rational economic benefits (Yang *et al.*, 2018). Thus, ROA below or above the past level or the competitors' level may not provide strong incentives for TMTs and firms to commit wrongdoing. On the other hand, DER shows the degree of debt versus wholly owned funds when a company is financing its operations. This variable reflects organizational slack, the stock of available resources that can be diverted or redeployed for an organization to achieve its goals (Arora and Dharwadkar, 2011; Kuusela *et al.*, 2017). When DER is high (e.g., the current level in our samples), the debt-related agency cost would increase, and consequently, the cost of capital would increase. This, in turn, raises the pressure to improve the current status (Bertero and Rondi, 2000). Simultaneously, TMTs and firms may confront resource scarcities and experience difficulties in adopting internal or external strategies (Bourgeois, 1981; Li *et al.*, 2017). Then they may have heavy performance pressure and strong incentives to conduct a problematic search even via financial statement fraud and other illicit means (Finney and Lesieur, 1982; Vaughan, 1985, 1999). When DER is low, there is still organizational slack and abundant resources to enable firms to adopt strategic adjustments to achieve organizational goals (Arora and Dharwadkar, 2011; Li *et al.*, 2017). There is no necessity and motivation to take any risky fraudulent activities, which may change the current success once these scandals are known by the public. However, the DER of construction industry has been relatively high as most firms are operated on borrowings (Rebeiz and Salameh, 2006; Roberts and Zurawski, 2016). Though there may be many reasons why a construction firm has high debt, high debt may result in undesirable consequences and activities, such as corporate scandals. Hence, construction firms need to pay more attention to DER.

This study has several practical implications. First, it confirms the contextual effect of aspiration–performance discrepancy on the relation of TMT compensation and corporate fraud. This implies that excessive executive pay does play a role in committing fraudulent activities when a firm faces a gap between goal and actual achievement. The design of executive compensation needs to be reconsidered by the compensation committee, which is responsible for design the reward structure and guaranteeing the executive compensation systems work effectively and equitably to protect shareholders' profits (Daily *et al.*, 1998; Kolev *et al.*, 2019; Laux and Laux, 2009). Using high total pay to align the interest of managers with firms might not be prudent to reduce the occurrence of corporate violations. In particular, there is no optimal compensation system for all organizations and/or all the time. The compensation system needs to alter to fit with the changing situational factors, such as aspiration-performance discrepancies. Second, while aspiration–performance discrepancy serves as a situational factor to moderate the association between compensation and corporate violation, companies should carefully monitor TMT, especially when performance is lower than the desired level (e.g., DER is above historical and industrial aspiration). The significant influence of DER rather than ROA may bring new insights to decision makers (i.e., investors, lenders, and regulators) when evaluating firms' performance and considering preventing fraudulent activities. For construction firms in China, DER deserves more attention in suppressing corrupt practices.

Though this study has significant theoretical and practical implications, several limitations exist. First, this research used the performance data before the year of initiating fraudulent behavior. It is implicitly assumed the fraudulent actions were taken one year after the unsatisfactory performance was detected. However, an aggressive manager may choose to violate options in the same year when signs of poor performance appear while a conservative manager may choose to ride the fence on unsatisfactory performance for years. Second, only TMT total pay was used to measure executive compensation. Though restricted stock, stock options, and long-term incentive plans are commonly treated as measures of compensation, they are seldom adopted in China, especially in the construction industry. Their effects on corporate fraud in this context may need further exploration.

CHAPTER 6 CORPORATE FRAUD DETECTION

6.1 Introduction

Preventing corporate fraud has been a top priority among practitioners and academics. A growing body of studies (Le *et al.*, 2014a; Liu *et al.*, 2017; Owusu *et al.*, 2019; Shan *et al.*, 2017) has focused on identifying causal factors of corruption and generated numerous noteworthy factors. The incidence of organizational wrongdoing is associated with financial problems (Clinard and Yeager, 1980; Greve *et al.*, 2010; Simpson, 2002; Staw and Szwajkowski, 1975). Corporate fraud is more prevailing for firms with high-performance pressures, low or declining profits, or undergoing other problems such as threats to the competitive position (Harris and Bromiley, 2007; Vaughan, 1999). Some other empirical studies on the construction industry show similar results. Through a questionnaire survey, Liu et al., (2017) identified cost pressures as the most influential inducers of contractors' unethical behaviors in the Chinese construction industry. Locatelli et al., (2017) suggested that lack of frequency of projects may affect the survival or profitability of contractors and thus provide a motive to engage in bribes. Zhang et al., (2017) found that illegitimate gains, as well as lack of competitive and equitable bidding practices, can cause business-to-government corruption.

However, due to the limited budget and resources of firms, coping with all those factors is very difficult. Even though a great deal of effort has been put into fraud prevention practices and research, corporate scandals continue to arise. Therefore, it is essential to identify and rank the importance of possible factors. By focusing on the most important factors, construction firms could take effective measurements to prevent corporate fraud in a targeted manner. Investors, regulators, and other stakeholders could improve the effectiveness of fraud detection and other critical evaluations.

Though recognizing those important risk factors could assist in mitigating corporate misbehaviors, timely and accurate detection of corporate fraud is also essential. However, accurately detecting corporate fraud is a serious challenge. Some studies (Ngai *et al.*, 2011; West and Bhattacharya, 2016) claim that data mining approaches may be useful for detecting small anomalies because such approaches can extract and identify relevant information otherwise hidden in large volumes of data. Support vector machine (SVM) and other machine learning tools have been employed in the analysis of construction cost, injury, contractor default, and other areas of the construction industry (Cao *et al.*, 2014; Movahedian Attar *et al.*, 2013; Tixier *et al.*, 2016). Some studies also have adopted logistic regression (LR), k-nearest neighbors (KNN), SVM, decision tree (DT) and other tools to detect financial restatement or managerial fraud (Dong *et al.*, 2018; Pai *et al.*, 2011). The use of these tools, however, remains limited in the domain of corporate fraud prediction in the construction industry. More importantly, few tools are capable of providing variable importance, which would facilitate the decision making by construction firms, investors and regulators. Wang et al. (2018) developed an SVM model to predict the occurrence of corporate misconduct in Taiwan based on several variables related to the board of directors. The study explored the role of statistically insignificant variables by comparing models with and without those variables, while also failing to provide a ranking of all variables, let alone the significant ones. In particular, when the number of factors is large, the manual comparison would be time-consuming and inefficient. This chapter draws upon a large quantity of data related to corporate governance and financial performance to rank feature importance and to construct a data mining-based prediction model. By identifying the most influential factors, the prediction model is expected to provide firms themselves, regulators, investors, and securities agencies with an effective and early fraud detection tool.

6.2 Method

To explore the most influential factors of corporate fraud in the construction industry, this study introduces RF, which could provide variable importance and is capable of predicting corporate fraud accurately. To assess the prediction performance of RF, LR, KNN, SVM, and DT are employed as a comparison reference. They have been commonly used in corporate fraud detection.

6.2.1 Random Forest

Random forests (RF) was introduced by Breiman (2001). As an ensembled tool, RF is composed of a set of trees generated by a classification and regression tree (CART) (Breiman *et al.,* 1984) and a combination of randomly chosen explanatory factors. This method inherits several advantages of DT (Sutton, 2005). First, RF can handle complex nonlinear high-order interactions among features and does not require feature selection. Feature selection is the process of selecting the most influential features or predictors to adequately capture the association between outcomes and predictors (Fallah *et al.,* 2019). RF is also robust even with outliers and irrelevant inputs, as well as able to avoid overfitting (Rodriguez-Galiano *et al.*, 2012). Next, there is no requirement for prior knowledge of underlying processes and no assumptions about the target function (Prinzie and Van den Poel, 2008). RF is among the most accurate general-purpose tools to date (Biau, 2012). It additionally provides useful estimates of variable importance (Breiman, 2001).

RF model has been applied in various fields of science and engineering, including flash-flood hazard assessment (Hosseini *et al.,* 2020; Liu *et al.,* 2020), pan evaporation prediction (Shabani *et al.,* 2020), atmospheric pollutants forecasting (Feng *et al.,* 2019), and credit risk assessment (Tang *et al.,* 2019). Some studies in the construction industry also employed RF model.

For instance, Tixier et al. (2016) developed a model to predict construction injury based on RF and Stochastic Gradient Tree Boosting with a set of features and safety outcomes extracted from textual injury reports. Liu et al. (2018) explored the impacts of outdoor ambient environment on scaffolding construction productivity via RF and a generalized additive model. Poh et al. (2018) presented an RF tool to explore safety leading indicators. Following this line of research, this study applies RF to corporate fraud factor identification and prediction in the construction industry.

Random forest is an ensemble of small trees trained on a randomly selected sub-sample of a dataset through bootstrap aggregating or bagging (Breiman, 1996). Each tree is trained through recursive partitioning of features to a certain level of depth, d. During this process, the randomly selected observations at each node are partitioned into subgroups to make a prediction (Breiman, 2001). The exact partitioning position and the selection of features rely heavily on the distribution of observations (Strobl *et al.*, 2009). The features, partitioning by which provides the most information regarding the observations, are chosen for this process. Several criteria are used for partitioning, but the most frequent ones are Gini Index (Breiman *et al.*, 1984) for classification.

For each tree T_i $(i = 1,2, \dots, n_{tree})$, a new training data set S_i is generated by randomly resampling the original training data set $S = \{(x_t, y_t), t = 1,2, \dots, N\}, (X, Y) \in R^K \times R$. Although these sub-samples are different from each other, they must have a similar distribution. Then tree T_i is created with the set S_i, by the above-mentioned methodology and without pruning. In this process, some data will be used repeatedly while others might be "left out" and considered as out-of-bag (OOB) samples. This OOB data is used to evaluate the internal performance of each tree and to determine the variable importance (Breiman, 2001). To increase the diversity of these trees further, m_{try} input variables are randomly selected from the K variables.

Considering the m_{try} input variables and their linear combinations, a tree grows by searching the best split based on the generated training dataset and random variable set. In the same way, all the n_{tree} trees are constructed and trained. They are expected to be independent from each other because of the randomization of training data and input variables. Finally, all the constructed trees are collected into the RF model and vote for the outcomes. The RF algorithm could be described by the following steps:

Step 1: From the original training data set S, randomly draw N subsets $\{S_1, S_2, \dots, S_N\}$ with replacement. This sampling procedure is usually called bootstrap aggregating.

Step 2: For each subset S_i, build the corresponding decision tree model without pruning based on a given number of m_{try} input variables. These variables are randomly selected from the K variables. Beginning in the root node, the subset S_i is separated using some split function into two disjoint sets. Compute all the possible split at each node. Then according to Gini Index, choose the best split to generate the child node.

Step 3: Recursively repeat this process until no further split is possible and the tree grows to the maximum depth d.

Step 4: Repeat Step 1-3 until all n_{tree} decision tree models are established. Combine all the trees $\{T_1, T_2, \dots, T_{n_{tree}}\}$ into an ensemble and adopt the majority vote among the trees. The final decision function for classification is as follows:

$$f(x_t) = majority\ vote\{T_i(x_t)\}_{i=1}^{n_{tree}} \tag{1}$$

The above steps could be presented in Figure 6-1.

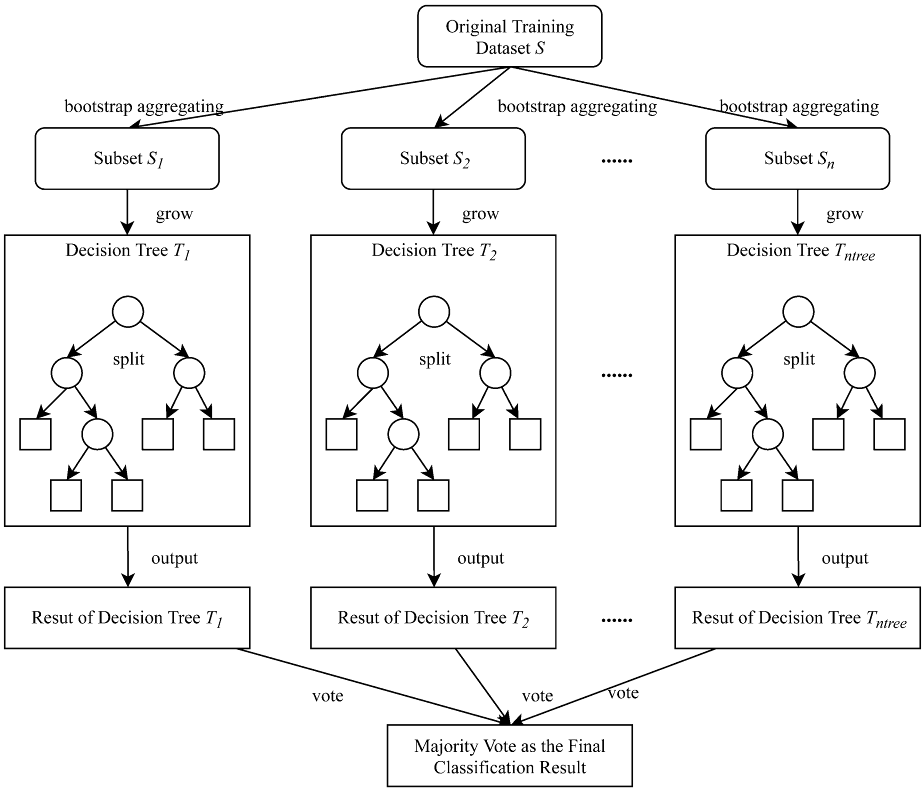


Figure 6-1. Random forest algorithm

To understand the computational efficiency of RF, time and space complexity are presented. As the first and immediate aspects of the computational complexity of RF, time complexity analyzes the asymptotic behavior of RF concerning the size N of its input and its hyperparameters. This complexity is the number of operations required for building models and making predictions in three cases: best case, worst case, and average case. The best case shows the most efficient induction procedure when the node subset could always be split into two balanced sets. Opposite to best case, the worst case describes the context that the splits are unbalanced and thus the induction procedure is efficient. The average case presents the average time complexity, which is derived based on all possible learning sets and all random seeds. Let $T(N)$ represents the time complexity of RF for learning,

$$T(N) = \begin{cases} \Theta\left(n_{tree} k \widetilde{N} log^2 \widetilde{N}\right), if\ in\ the\ best\ case; \\ O\left(n_{tree} k \widetilde{N}^2 log \widetilde{N}\right), if\ in\ the\ worst\ case; \\ \Theta\left(n_{tree} k \widetilde{N} log^2 \widetilde{N}\right), if\ in\ the\ average\ case. \end{cases} \quad (2)$$

where $O(\cdot)$ expresses an asymptotic upper bound on the growth rate of the number of steps in RF algorithms; $\Theta(\cdot)$ represents the case when the asymptotic upper bound equals to the lower bound; n_{tree} is the number of randomized trees; k denotes the number of variables randomly selected at each node; $\widetilde{N} = 0.632N$, reflecting that 63.2% of the original training dataset is drawn as bootstrap samples (Louppe, 2014). The computational complexity for making predictions is $O(N \cdot d)$. If the trees are not balanced, the computational cost would be lower. The other important complexity is memory space. It is an exponential function of the depth of the tree $O(2^d)$.

6.2.2 Variable Importance

One of the most desirable characteristics of RF is its ability to generate variable importance. To compute the importance of a variable, RF first randomly permutes the value of a variable and keeps the others unchanged. Then a set of new trees is established. A set of accuracies corresponding to the modified OOB data is generated and compared with accuracies corresponding to the original OOB data with all of the variables. Their differences are calculated and averaged. The average value indicates the importance of that permuted variable. The larger the absolute value of the average of the differences is, the more important that variable is. The underlying rationale is that the data permutation of a variable would break its association with the output, and as a result, there would be a decrease in the accuracy if the permuted data were used as an input (Strobl *et al.*, 2009). That is if there is indeed a relationship between a variable and the output, replacing the original data with the permuted data would lead to a significant decrease in the accuracy, otherwise, the replacement would make no difference to the accuracy. By doing so, RF reveals the variable importance and the association with the output. In particular, this association takes into consideration interactions with other variables (Strobl *et al.*, 2009; Tsanas and Xifara, 2012). The redundant variables are not given a priority even if they have a high correlation with the output. This function of RF facilitates research with high-dimensional data as is the case with the present study analyzing dozens of variables about financial performance and corporate governance.

Apart from variable importance ranking, another desirable characteristic of RF is accurate prediction even when the data has the multicollinearity, outliers and other issues (Tang *et al.*, 2019). To examine whether such characteristic holds true in the prediction of construction corporate fraud, this study would construct the predictive RF model. To assess the performance of the constructed RF model, this study compares it with LR, KNN, SVM, and DT. These four techniques are popular in financial fraud detection as mentioned in Section 2.5.

6.2.3 Logistic Regression

Unlike generalized linear regression models, logistic regression models describe the relationship between the probability of dependent variable and independent variables considering dependent variable is a binary variable, equaling to 0 or 1. The model function is

$$C(Y|X) = Prob\{Y = 1|X\} = (1 + exp\,(-X\beta - a))^{-1} \tag{3}$$

where β is the change in log odds that $Y = 1$ per unit change in X and a is a constant. These two parameters are estimated by maximum likelihood estimation. When the following log-likelihood function is maximum, the values of the two parameters are obtained.

$$L(x_1, \cdots, x_n|\beta, a) = \sum_{i=1}^{n} y_i logp_i + (1 - y_i)\log\,(1 - p_i) \tag{4}$$

where p_i refers to $Prob\{Y = 1|x_i\}$.

6.2.4 K-Nearest Neighbors

KNN is an instance-based method (Aha *et al.*, 1991) and assigns a label to the test case via finding a group of k cases in training dataset that are closest to that test case and classify that test case based on the majority of class of the nearest neighbors. Specifically, for all the training cases $D =$

$(\boldsymbol{x}, y)$ and a test case $z = (\boldsymbol{x}', y')$, this algorithm first computes the distance (usually Euclidean distance) between z and $(\boldsymbol{x}, y)$ to select its nearest-neighbor list D_z and then assigns the label of the test case as the majority label of the nearest neighbors:

$$Majority\ Voting: y' = \underset{v}{\operatorname{argmax}} \sum_{(x_i, y_i) \in D_z} I(v = y_i) \tag{5}$$

where $\boldsymbol{x}$ is the data of the training case, y is the label of the training case, $\boldsymbol{x}'$ is the data of the testing case, y' is the label of the testing case, v is a class label, y_i is the label of the ith nearest neighbors, $I(\cdot)$ is an indicator function that equals to 1 if the argument is true and 0 otherwise.

6.2.5 Support Vector Machine

Through finding an optimal margin hyperplane as the decision boundary, SVM separates a binary-class dataset according to the principle of structural risk minimization (Cortes and Vapnik, 1995). Let $D = \{(x_i, y_i) | x_i \in R, y_i \in [-1,1]\}_{i=1}^{n}$ as the training data. The optimal margin hyperplane would be obtained by minimizing the following function:

$$\begin{gathered} \min_{W, W^T, b, \xi} \frac{\|W\|^2}{2} + c \sum_{i=1}^{n} \xi_i \\ s.t. \quad y_i(W^T x + b) \geq 1 - \xi_i \\ \xi_i \geq 0, i = 1, 2, \dots, n \end{gathered} \tag{6}$$

where c is a penalty factor, usually equal to a constant. c may become very large when diminishing the misclassification errors. However, to alleviate overfitting, c is usually set to a low value. ξ indicates slack variables, measuring the degree of misclassification of x_i.

In Equation (6), minimizing the left part $\frac{\|W\|^2}{2}$ amounts to maximizing the margin while minimizing the right part $\sum_{i=1}^{n} \xi_i$ equals to minimizing the associated error. The parameter c determines the tradeoff between maximizing the margin and minimizing the associated error. After dealing with Equation (6), the final decision function can be generated as follows:

$$f(x) = sgn\left(\sum_{i=1}^{n} y_i \alpha_i K(x, x_i) + b\right) \tag{7}$$

where α_i is a Lagrange multiplier and $K(x, x_i)$ is a kernel function. There are several kernel functions for SVM, including Linear Kernel, Polynomial Kernel, Sigmoid Kernel, and Radial Basis Function (RBF) Kernel. This study used the RBF because it is able to address the nonlinear relationship as well as a high dimensional problem (Keerthi and Lin, 2003). Equation (8) shows the RBF kernel.

$$\mathrm{K}(x_i, x_j) = \exp\left(-\gamma\|x_i - x_j\|^2\right) \tag{8}$$

where the parameter $\gamma > 0$.

6.2.6 Evaluation Metrics

Some studies (Bhattacharyya *et al.*, 2011; Hajek and Henriques, 2017) claim the cost of misidentifying lawful corporate behaviors as wrongful is much higher than that of neglecting to identify wrongful behaviors. This present study proposes that the cost of incorrectly classifying a lawful company as a violating one should not be overlooked as well. When a company is considered violating, the subsequent investigation can be undertaken. If such actions are wasted on a lawful company, a fraudulent company would remain at large because of the limited resources of regulators. Moreover, investors would prefer to identify a trustworthy firm than a questionable one to achieve profits from their investments. Therefore, this study attempts to assess the performance of RF on both violating and lawful observations.

Whether the evaluated company is violating or lawful, the metrics used in this study are calculated mainly based on the confusion matrix shown in Figure 6-2.

	Predicted Positive	Predicted Negative
Actual Positive (P)	True Positive (TP)	False Negative (FN)
Actual Negative (N)	False Positive (FP)	True Negative (TN)

Figure 6-2. Confusion matrix

If the aim is to evaluate the performance of RF on violating observations, the violating companies are considered as positive while the lawful ones would be negative. Then TP is the number of violating observations classified correctly as violating. FN is the number of violating observations classified incorrectly as lawful. FP is the number of lawful companies falsely classified as violating while TN is the number of lawful companies accurately classified as lawful. On the other hand, if the aim is to evaluate the performance of RF on lawful companies, then the lawful companies are considered as positive while the violating one would be negative. TP and FN are the numbers of lawful observations correctly classified as lawful and wrongly classified as violating, respectively. FP and TN are the numbers of violating companies incorrectly classified as lawful and rightly classified as violating, respectively.

Based on the above confusion matrix, the metrics applied in this study include accuracy, precision, recall, and F1-score. These metrics can be formulated as follows:

$$Accuracy = \frac{TP+TN}{P+N} \tag{9}$$

$$Precision = \frac{TP}{TP+FP} \tag{10}$$

$$Recall = \frac{TP}{P} \tag{11}$$

$$F1 - score = 2 \times \frac{Precision \times Recall}{Precision + Recall} \tag{12}$$

6.2.7 Sample and Data

The samples consist of all the publicly traded construction companies listed on the Shenzhen Stock Exchange and Shanghai Stock Exchange in China. All of these companies' information is derived from the China Stock Market and Accounting Research (CSMAR) database. This database collects financial and governance data mainly from the companies' annual, semi-annual, and quarterly reports. Some governance data is complemented by interim announcements by the board of directors, the board of supervisors, and shareholder meetings. Regarding violation information, a list of violating companies was extracted from enforcement information published by the China Securities and Regulatory Commission (CSRC). By examining the violating cases carefully, this study identifies the year when violating behaviors are taken. If a fraudulent activity lasts for several years, we treat the company as a violator each year on the assumption that the activity could have been stopped at any time. If the date when a firm participated in fraud is not mentioned in the violating cases, it is assumed that the violation was detected immediately after the action took place. Though the CSMAR database collects enforcement information from 1994 to date, most records about construction companies begin after 2000. Thus, this study focuses on 93 construction companies over the period 2000-2018 to capture as much available data as possible. Among the 93 companies, 47.31% are state-owned enterprises. According to the main business, 65.59% belong to civil engineering construction industry, 3.23% to building construction industry, 1.08% to construction installation industry, and the rest to architectural decoration and other construction industries. After data points with missing values were excluded, 953 final observations are yielded. Among them, 170 observations engaged in fraud have been reported.

6.2.8 Measures

As the output, corporate fraud is operationalized by a binary variable indicating whether an observation engaged in corporate fraud or not. If yes, the observation is considered as violating and its label equals 1. Otherwise, the observation is considered lawful and its label is 0. This study employed 60 variables as the input, shown in Table 6-1.

Table 6-1. Summary of input variables

Variable	Description
X0: Capital structure change	Whether there is any change in the company's equity structure during the reporting period. 1 = unchanged, 2 = changed
X1: Relationship of top 10 shareholders	Whether top 10 shareholders are unrelated, related, or unconfirmed
X2: Firm size	Number of employees
X3: CEO duality	Whether CEO or president serves as the board chairman:1 = yes, 2 = no
X4: Board of directors' size	Number of directors
X5: Board independence	Number of independent directors
X6: Board of supervisors' size	Number of supervisors
X7: TMT size	Number of executives
X8: Board of directors' ownership	Number of shares held by board of directors
X9: Board of supervisors' ownership	Number of shares held by board of supervisors
X10: TMT ownership	Number of shares held by executives
X11: Total pay for two boards and TMT	Total annual emolument of directors, supervisors, and executives
X12: Board of directors' total pay	Total emolument of top 3 directors
X13: TMT total pay	Total annual emolument of top 3 executives
X14: Directors, supervisors, and executives with no salary	Number of directors, supervisors, and executives not receiving emolument
X15: Directors with no salary	Number of directors not receiving emolument
X16: Supervisors with no salary	Number of supervisors not receiving emolument
X17: Board committees	Total number of committees established
X18: The four board committees	Number of audit commission, strategic commission, nomination commission, and remuneration and evaluation commission established
X19: Other board committees	Number of other commissions established
X20: Working places consistency	Whether independent directors work in the same, different or unconfirmed place with the firm. When the number of independent directors is zero, the value is null
X21: Directors' meetings	Number of board of directors meetings
X22: Supervisors' meetings	Number of board of supervisors meetings
X23: Shareholders' meetings	Number of shareholder meetings
X24: Current assets ratio	Total current assets / total assets
X25: Ratio of working capital	(Current assets - current liabilities) / current assets
X26: Fixed assets ratio	Net fixed assets / total assets

Table 6-1. Summary of input variables (Continued)

Variable	Description
X27: Ratio of shareholders' equity to fixed assets	Shareholders' equity/net fixed assets
X28: Current liabilities ratio	Total current liabilities / total liabilities
X29: Current ratio	Current assets / current liabilities
X30: Quick ratio	(Current assets – inventories) / current liabilities
X31: Times interest earned	(Net profits + income tax + financial expenses) / financial expenses
X32: Net cash flow from operating activities / current liabilities	Net cash flow from operating activities / total current liabilities
X33: Ratio of debt to assets	Total liabilities / total assets
X34: Ratio of long-term borrowings to total assets	Fixed assets / operating income
X35: Ratio of liabilities to tangible assets	(Total liabilities) / (total assets - net intangible assets - net goodwill)
X36: Ratio of equity to debt	Total owners' equity / total liabilities
X37: Growth rate of total assets	(Ending total assets - beginning total assets) / beginning total assets
X38: Ratio of accounts receivable to income	Accounts receivable / operating income
X39: Accounts receivable turnover	Operating income / ending accounts receivable
X40: Ratio of inventories to income	Inventories / operating income
X41: Inventories turnover	Operating costs / ending inventories
X42: Accounts payable turnover	Operating costs / ending accounts payable
X43: Current asset turnover	Operating income / ending balance of current assets
X44: Ratio of fixed assets to income	Fixed assets / operating income
X45: Fixed asset turnover	Operating income / ending balance of net fixed assets
X46: Total assets turnover	Operating income / ending balance of total assets
X47: Earnings per share	Net profits / ending paid-in capital
X48: Net assets per share	Ending owners' equity at period-end / ending paid-in capital
X49: Net cash flow from operating activities per share	Net cash flow from operating activities / ending paid-in capital
X50: Return on assets	Net profits / balance of total assets
X51: Net profits margin of current assets	Net profits / balance of current assets
X52: Net profits margin of fixed assets	Net profits / balance of fixed assets
X53: Return on equity	Net profits / balance of shareholders' equity

Table 6-1. Summary of input variables (Continued)

Variable	Description
X54: Ratio of net profits to total profits	Net profits / total profits
X55: Ratio of total profits to EBIT	Total profits / EBIT
X56: Ratio of EBIT to total assets	EBIT / total assets
X57: Gross operating margin	(Operating income - operating costs) / operating income
X58: Selling expense ratio	Selling expenses / operating income
X59: Operating margin before interest and taxes	(Net profits + income tax expense + financial expenses) / operating income

Among them, 24 were about corporate governance and the remaining were financial variables. These variables were selected because they encompass a wide cross-section of corporate governance information and financial ratios. Governance variables (X0-X23) show the structure, compensation, and other related information about the shareholders, board, and TMT. They have been reported to be related to illegal corporate behaviors (Chen *et al.*, 2006; Dechow *et al.*, 1996; Harris, 2008; Jia *et al.*, 2009; Kesner *et al.*, 1986; Lee *et al.*, 2018; Schnatterly *et al.*, 2018; Sen, 2007; Wowak *et al.*, 2015; Zahra *et al.*, 2005). Financial ratios included several financial aspects of the construction companies, i.e., structure ratios (X24-X28), liquidity ratio (X29-X36), growth capability (X37), operating capacity (X38-X46), per-share indexes (X47-49), and profitability capacity (X50-X59). The financial variables were adopted mainly based on previous studies on fraudulent statement detection (Dutta *et al.*, 2017; Hajek and Henriques, 2017; Kim *et al.*, 2016; Kirkos *et al.*, 2007; Lin *et al.*, 2015; Pai *et al.*, 2011; Perols, 2011; Ravisankar *et al.*, 2011). Their calculation was based on the definition of CSMAR. Table 6-2 gives the descriptive statistics of the 60 variables.

Table 6-2. Descriptive statistics (Mean ± SD) of the 60 variables

Variable	Mean ± SD	Variable	Mean ± SD
X0	1.6±0.49	X30	1.13±1.67
X1	2.38±0.61	X31	5.15±90.72
X2	14012.61±46830.75	X32	0.01±0.39
X3	1.82±0.38	X33	0.61±0.21
X4	9.03±2.02	X34	0.06±0.09
X5	3.16±0.97	X35	0.64±0.24
X6	3.86±1.23	X36	1.15±2.5
X7	7.41±3.3	X37	0.26±0.64
X8	45083015.2±129657700.54	X38	0.37±0.81
X9	758886.74±2416806.31	X39	10±46.31
X10	13762504.74±51422956.64	X40	0.56±1.55
X11	4382752.79±3968282.48	X41	11.63±53.33
X12	1295546.33±1068322.87	X42	4.29±5.28
X13	1361851.89±1096064.19	X43	0.95±0.54
X14	3.67±3.38	X44	0.43±1.13
X15	2.26±2.32	X45	24.83±277.42
X16	1.31±1.36	X46	0.61±0.33
X17	3.34±1.43	X47	0.31±0.5
X18	3.3±1.42	X48	3.9±2.63
X19	0.04±0.2	X49	0.21±1.36
X20	1.41±0.77	X50	0.02±0.18
X21	9.59±3.96	X51	0±0.5
X22	5.26±2.33	X52	-13.53±630.38
X23	2.99±1.63	X53	0.06±0.7
X24	0.67±0.21	X54	0.8±0.4
X25	0.15±0.24	X55	0.87±1.22
X26	0.14±0.14	X56	0.04±0.19
X27	87.55±1586.87	X57	0.17±0.14
X28	0.87±0.15	X58	0.02±0.03
X29	1.59±1.78	X59	0.06±0.82

6.2.9 Model Development

This section includes three parts. This first part describes the process of data preprocessing. The last two part presents the hyperparameters tuning for RF and the parameters tuning for the other four methods, LR, KNN, SVM and DT.

Data preprocessing

The special characteristics of some input variables make data preprocessing essential before modeling any machine learning model. Categorical variables, skewed variables, and imbalanced labels are three main matters that need to be carefully addressed in this study. One-hot encoding has been used to encode categorical variables into new ones. For example, X1, the relationship code of the top 10 shareholders, has three categories: related, unrelated, unconfirmed. Within this process, new binary vectors corresponding to each sample are created. When the value of a sample equals to a category label, say X1=related, then the 'related' element of the encoded vector will be 1 and 'unrelated' and 'unconfirmed' elements will be zero (i.e. X1=related turns to [1,0,0]) Some of the variables are skewed because of the size of the company. For example, small companies could have less than 100 employees while giant companies could have thousands of employees. This skewness impedes machine learning models to train well on the dataset. These variables, such as X2 (the number of employees) and X8 (number of shares held by the board of directors) are transformed into categorical variables by expert judgment (e.g. small, medium, and big). Then, one-hot encoding has been applied to them. After this process, the newly generated dummy variables are presented in Table 6-3. Thus, 85 variables in total (including 37 newly generated in data preprocessing) were used in this study. The number of lawful companies is much more than the unlawful ones, the situation which is called imbalanced data. This issue, alongside others, lowers the quality of a trained model. Oversampling the minority label is one of the effective methods for dealing with imbalanced datasets. Synthetic-minority over-sampling technic (SMOTE) was used in this study to overcome the aforementioned problem. Mathematical details of this method could be found in Chawla et al. (2002).

Table 6-3. The list of generated dummy variables

Original Variable	Generated Variable	Description
X0	X0-1	There is change(s) in the company's equity structure during the reporting period.
	X0-2	There is no change in the company's equity structure during the reporting period.
X1	X1-1	The top 10 shareholders are unrelated.
	X1-2	The top 10 shareholders are related.
	X1-3	The relationship of the top 10 shareholders is unconfirmed.
X2	X2-1	The number of employees is below 100.
	X2-2	The number of employees is in the range of [100, 999].
	X2-3	The number of employees is in the range of [1000, 9999].
	X2-4	The number of employees is not less than 10000.
X3	X3-1	CEO or president does not serve as the board chairman.
	X3-2	CEO or president serves as the board chairman.
X8	X8-1	The number of shares held by board of directors is lower than 1000.
	X8-2	The number of shares held by board of directors is in the range of [1000, 99999].
	X8-3	The number of shares held by board of directors is not lower than 100000.
X9	X9-1	The number of shares held by board of supervisors is lower than 1000.
	X9-2	The number of shares held by board of supervisors is in the range of [1000, 99999].
	X9-3	The number of shares held by board of supervisors is not lower than 100000.
X10	X10-1	The number of shares held by executives is lower than 1000.
	X10-2	The number of shares held by executives is in the range of [1000, 99999].
	X10-3	The number of shares held by executives is not lower than 100000.
X11	X11-1	The total annual emolument of directors, supervisors, and executives is lower than 1000000.
	X11-2	The total annual emolument of directors, supervisors, and executives is in the range of [1000000, 3999999].
	X11-3	The total annual emolument of directors, supervisors, and executives is not lower than 4000000.

Table 6-3. The list of generated dummy variables (Continued)

Original Variable	Generated Variable	Description
X12	X12-1	The total emolument of top 3 directors is lower than 1000000.
	X12-2	The total emolument of top 3 directors is in the range of [1000000, 1999999].
	X12-3	The total emolument of top 3 directors is not lower than 2000000.
X13	X13-1	The total annual emolument of top 3 executives is lower than 1000000.
	X13-2	The total annual emolument of top 3 executives is in the range of [1000000, 1999999].
	X13-3	The total annual emolument of top 3 executives is not lower than 2000000.
X20	X20-1	The number of independent directors is zero.
	X20-2	Independent directors work in the same place with the firm.
	X20-3	Independent directors work in the different place with the firm.
	X20-4	Whether independent directors work in the same or different place with the firm is unconfirmed.
X27	X27-1	The ratio of shareholders' equity/net fixed assets is lower than 0.
	X27-2	The ratio of shareholders' equity/net fixed assets is in the range of [0,10], excluding 10.
	X27-3	The ratio of shareholders' equity/net fixed assets is in the range of [10,100], excluding 100.
	X27-4	The ratio of shareholders' equity/net fixed assets is not lower than 100.

All the 866 observations in 2000-2017 were randomly and proportionally split into two parts. 80% were used as the training data (692 observations, 133 with corporate fraud) while the other 20% were the testing data (174 observations, 30 with corporate fraud). The training data was used to establish the learning model, and then the performance of the established model was evaluated adopting the testing data. All the variables were input without feature selection because of RF's ability to handle higher-order interactions among features. To assess the robustness of the constructed RF model further, the 87 observations in 2018 were used as the validating data.

Hyperparameters tuning for RF

Like other machine learning models, RF has several hyperparameters which need to be tuned (Breiman, 2001; Ma and Cheng, 2016). Previous studies (Poh *et al.*, 2018) have mainly focused on the number of trees n_{tree} while other hyperparameters need to be meticulously tuned. In addition to the number of trees n_{tree}, the maximum depth which each tree will be split d, minimum number of samples on a node for branching S_n, the minimum number of samples in a final leaf S_l, and features being considered for branching at each step m_{try} are of equal importance. The sampling method could possibly affect the performance of RF. There is no effective method for simultaneous hyperparameter tuning of this model to the best of authors' knowledge. Therefore, grid search, a greedy search algorithm, was adopted for this study. This method has been one of the most typical methods for parameter tuning. More importantly, it is easy to implement. In grid search, all possible initial values of hyperparameters are tested. Table 6-4 presents the list of hyperparameters and the search space of each one. Each sample of the search space represented a possible set of hyperparameters.

Table 6-4. Results of hyperparameters tuning

Hyperparameter	Value	Search Space
n_{tree}	100	[50, 100, 150, 200, 250, 300,..,1000]
d	5	[3, 5, 7, …., 21] + [None]
S_n	2	[1, 3, 5, 7, 10]
S_l	1	[1, 3, 5, 7, 10],
$mtry$	All features	[Sqrt (features), Log_2(features), All features]
Sampling Method	Bootstrap	With/Without Bootstrap (sampling with replacement)

The steps for implementing a grid search with 5-fold cross-validation is as follows:

Step 1: Assign a set of values chosen from the search space to those 6 hyperparameters including the sampling method.

Step 2: Randomly shuffle the original training dataset and split it into 5 parts. One part is kept as the new testing set and the remaining as the new training set. Based on the new training set and these selected values in Step 1, construct an RF model according to the steps of RF algorithms.

Step 3: With the inputs of the new testing set in Step 2, use the constructed RF model to predict the labels of that new testing set in Step 2. Compare the predicted labels with those original labels of that new testing set in Step 2 and assess the performance of the constructed RF model.

Step 4: Use another part in Step 2 as the new testing set and the remaining as the new training set. Remaining the values of those 6 hyperparameters in Step 1 the same, repeat Step 3 and construct another RF model. After all the 5 parts generated in Step 2 are used as the new testing set respectively, 5 RF models are created, and their performance is assessed. Calculate the average of the 5 RF models' performance and treat the average value as the overall performance of that set of values for those 6 hyperparameters.

Step 5: Repeat Step 1-4 and obtain the performance of all the possible combinations of values for those 6 hyperparameters.

Step 6: Choose the best candidate with the highest prediction as to the final hyperparameter set.

According to the above procedures, the final values of those hyperparameters were obtained and presented in Table 6-4. The processing time of this grid search by using scikit-learn, a library for machine learning algorithms with python (Pedregosa *et al.*, 2011), took nearly 7.3 hours on a Core i7-8700T and 8.00 GB of RAM. The code for RF is available online[1].

[1] The code can be found online in this link: https://github.com/vd1371/Detecting-Corporate-Misconduct-through-Random-Forest-in-China-Construction-Industry.

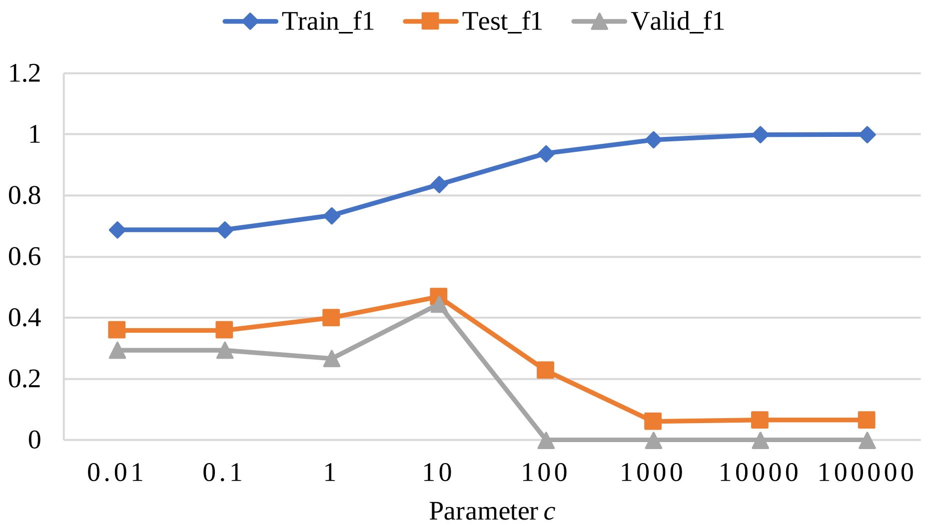
Parameters tuning for KNN, SVM, and DT

As mentioned in Section 6.2.3, the parameters of LR are estimated based on maximum likelihood estimation and thus there are no parameters needed to be tuned manually.

There is a parameter for KNN, the number of neighbors k. It was determined by the elbow method. This method considers the change of error rate as k rises and selects the optimal value of k when the error rate begins to increase. The results show that the optimal $k = 7$.

In implementing SVM, two parameters were optimized, namely the penalty constant c and the radial basis function (RBF) kernel parameter γ. c was determined by grid search and 5-fold cross-validation. That is, c was assigned a value from {0.01, 0.1, …, 100000} with 10 as the step and then was tested by 5-fold cross-validation. c is usually set to a low value because it is easy to have the overfitting problem when c is large. Figure 6-3 depicts the selection of the parameter c. When $c = 10$, the F1-scores (label=1) for testing data and validation data are both the highest and the difference between F1-score (label=1) for training data and that for testing or validation data is the lowest. Thus, the optimal c value was 10. γ equals the reciprocal of the number of used features. That is, $\gamma = \frac{1}{number\ of\ features} = \frac{1}{85} = 0.01$. SVM was implemented by LibSVM provided by Chang and Lin (2001)[2].

[2] LibSVM was implemented under the Copyright (c) 2000-2019 Chih-Chung Chang and Chih-Jen Lin.



Note: f1 refers to F1-score when label = 1.

Figure 6-3. Selection of the parameter c in SVM

For DT, the default value of the related parameters was employed. That is, the maximum depth of the tree d equals to the one when the nodes are expanded until all leaves contain less than the minimum number of samples required to split an internal node $S_n = 2$. The minimum number of samples in a final leaf S_l equals to 1. Features being considered for branching at each step m_{try} includes all the features.

6.3 Results and Discussion

6.3.1 Variable Importance Analysis

Variable importance as ranked by RF has the potential to facilitate the analysis of the role of input variables in corporate fraud prediction. To determine the number of the top important variables that need more attention, this study calculated the change of RF's prediction accuracy as the number of top variables identified by RF increases, shown in Figure 6-4. When only the top 1 important variable is considered, the accuracy of RF is 61.46%. When the top 10 important variables are considered, the accuracy of RF is 79.61%. When the first top 11 variables are considered, the accuracy of RF is 81.09%, which is higher than the acceptable level of 80% for prediction. When all the 85 variables (including 37 newly generated in data preprocessing) are considered, the accuracy is 82.76%. Thus, the first top 11 variables contribute to 97.99% of the overall accuracy and are regarded as the most important influential factors that need more attention by firms. Figure 6-5 presents the following 11 variables which are the most influential: number of supervisors (X6), number of employees in the range of [1000, 9999] (X2-3), number of shares held by the board of supervisors lower than 1000 (X9-1), total annual emolument of top 3 executives not lower than 2000000 (X13-3), number of directors (X4), number of shares held by executives lower than 1000 (X10-1), independent directors working in the same place with the firm (X20-2), number of supervisors not receiving emolument (X16), number of shareholders' meeting (X23), number of shares held by the board of directors lower than 1000 (X8-1), an unconfirmed relationship of the top 10 shareholders (X1-3). All the top 11 features are related to corporate governance. Corporate governance makes a significant difference in corporate fraud prediction.

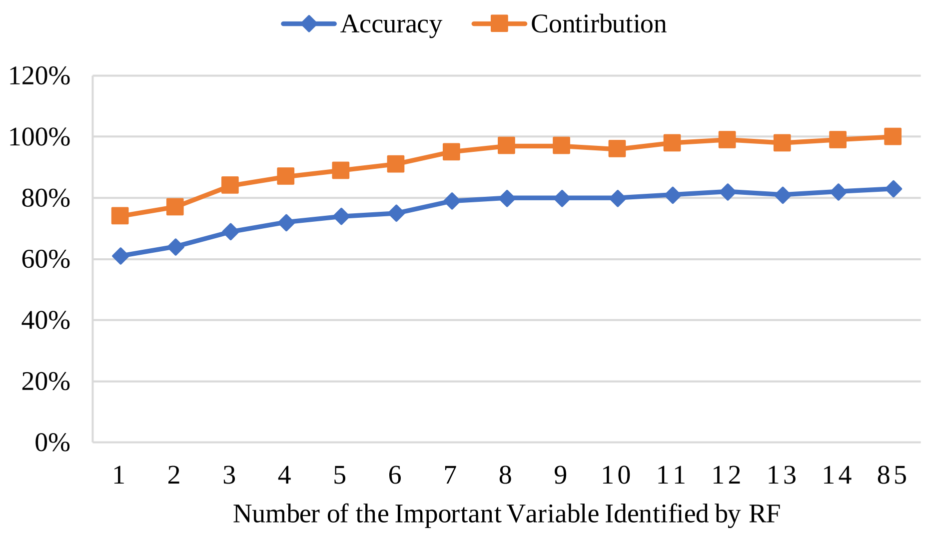


Figure 6-4. Selection of number of the top important variable identified by RF

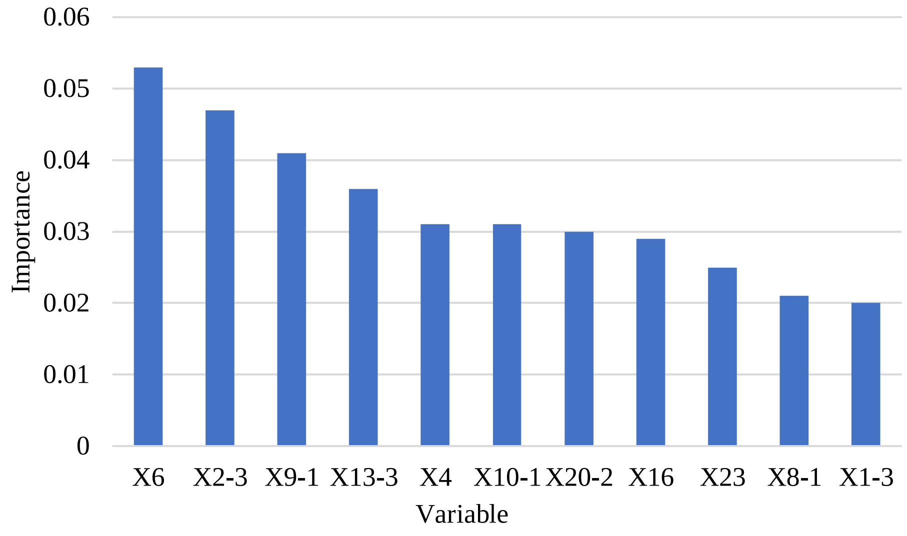


Figure 6-5. Importance ranking of the top 11 variables

The most important variable is the number of supervisors (X6). The listed companies in Chine have adopted a two-tier board structure, board of directors and board of supervisors (Dahya *et al.*, 2003; Ran *et al.*, 2015). They are functioning as dual monitoring organs. The major responsibility of the board of directors is to manage the firm on a day-to-day basis while the board of supervisors is to monitor top management and board of directors. In general, an effective board of supervisors is expected to improve the quality of corporate governance and exert influences in preventing corporate fraud (Shan, 2013). As the number of supervisors increases, the board of supervisors is more likely to be equipped with appropriate professional knowledge or work experience, which can provide effective corporate governance (Firth *et al.*, 2007b; Jia *et al.*, 2009). Better governance has been reported to be associated with less likelihood of fraud (Beasley, 1996). Besides, the compensation and shareholdings of supervisors make the supervisors' interest consistent with shareholders' and may provide supervisors incentives to supervise board of directors and top management (Ran *et al.*, 2015). Then, some fraudulent behaviors by directors or managers may be inhibited by supervisors. This may explain the third importance of number of shares held by board of supervisors (X9) and the eighth importance of number of supervisors not receiving emolument (X16).

The second important variable is number of employees (X2). This variable is always used to reflect firm size (Barnett *et al.*, 2018). Large firms are likely to be more complex and difficult to manage effectively (Agrawal *et al.*, 1999; Aharony *et al.*, 2015). Such a "deep pocket" makes it easy to be seedbeds for opportunistic behaviors (Strahan, 1998). Thus, firm size may exert positive influences on the occurrence of fraud.

The fourth important variable is the total annual emolument of the top 3 executives (X13) and the sixth important variable is the number of shares held by executives (X10). The former represents the compensation of top managers while the latter represents their shareholdings. Both could provide executives with incentives for maximizing their profits, and then raise the commitment of corporate misbehaviors (Conyon and He, 2016; Johnson *et al.*, 2009).

The fifth important variable is the number of directors (X4). As mentioned, the board of directors acts as a managerial decision-making unit in China. A large board is expected to possess sufficient information and is less likely to be deceived by some bad top managers (Pfeffer, 1973). However, more studies reported that board size is negatively related to firm value (Eisenberg *et al.*, 1998; Mak and Kusnadi, 2005). This may be because of the conflicts in communications, free-riding problems and additional challenges in coordination (Eisenberg et al. 1998). Besides, the number of shares held by the board of directors (X8) is also important, ranking tenth. It offers motivations for directors to reject some violating decisions and protect shareholders' benefits.

Other variables regarding shareholders and independent directors' workplace also play a significant role in corporate fraud. The above results have important implications in the process of feature selection when establishing a model for predicting construction corporate fraud.

6.3.2 Model Performance

According to the procedure described in model development, RF was trained, tested, and then compared with LR, KNN, SVM, and DT to assess prediction performance. Table 6-5 shows the prediction results of these five tools. For the testing data, the accuracy of only RF is above 80% and higher than the other four tools, indicating its overall performance is more feasible in predicting corporate fraud. As we mentioned before, identifying both violating companies and lawful ones is meaningful. When predicting violating observations (label = 1), RF performs somewhat better than the other four tools in terms of precision (0.50). The results show that RF identifies more actual violating observations than the other four tools among all the observations classified as violating. The recall of KNN (0.73) is the highest among all the five tools, reflecting KNN performs the best in accurately identifying the violating observations among all the actual violators. When predicting lawful companies (label = 0), RF performs better than the other four tools in terms of recall and F1-score (0.94; 0.90). Overall, RF has a better performance in corporate fraud detection in the construction industry.

Moreover, almost all the five tools have higher precision, recall, and F1-scores when the label is 0 than when the label is 1, showing that all perform better in identifying lawful observations than violating ones. This may be attributed to the fact that the number of violating observations is much smaller than that of lawful ones. Due to the somewhat limited sample size of violating companies, correctly predicting a violating company is more complex than predicting a lawful company using machine learning tools. As a result, it is difficult to precisely identify those violating companies. Nevertheless, accurately distinguishing lawful companies from those questionable ones is still meaningful. By giving those lawful companies an analog clearance certificate, the regulators could reduce the scale of investigation. Thus, the effectiveness of recognizing corporate fraud may be subsequently improved.

Simultaneously, investors could have greater confidence in their decision-making when selecting companies for investment.

Table 6-5. Prediction performance summary of RF, LR, KNN, SVM and DT

Tool	Label	Precision	Recall	F1-Score	Accuracy
			Training		
RF	1	0.95	0.94	0.94	94.45%
	0	0.94	0.95	0.94	
LR	1	0.73	0.79	0.76	74.81%
	0	0.77	0.70	0.74	
KNN	1	0.80	0.98	0.88	87.13%
	0	0.98	0.76	0.86	
SVM	1	0.76	0.87	0.81	80.09%
	0	0.85	0.73	0.79	
DT	1	1.00	1.00	1.00	100%
	0	1.00	1.00	1.00	
			Testing		
RF	1	0.50	0.30	0.38	82.76%
	0	0.87	0.94	0.90	
LR	1	0.33	0.43	0.38	75.29%
	0	0.87	0.82	0.85	
KNN	1	0.31	0.73	0.43	66.67%
	0	0.92	0.65	0.76	
SVM	1	0.38	0.43	0.41	78.16%
	0	0.88	0.85	0.87	
DT	1	0.14	0.17	0.15	68.39%
	0	0.82	0.79	0.81	

6.3.3 Model Validation

To validate the predictive capability of RF, this study reruns the RF model using the data in 2018. The validation results are presented in Table 6-6. The accuracy is 93.10%, a bit higher than that of the RF model using data in 2000-2017 in Table 6-5. When predicting violating observations (label = 1), the precision, the recall, and the F1-score are 0.57, 0.57 and 0.57 respectively. When predicting law-abiding observations (label = 0), the precision, the recall, and the F1-score are 0.96, 0.96 and 0.96 respectively. All of the three metrics are a bit higher than the corresponding metrics of the RF model using data from the year 2000 to 2017. Generally speaking, the results are similar or even better than those of RF in Table 6-5. This indicates that RF is robust in predicting construction corporate fraud. This study also used the same validation data and rerun LR, KNN, SVM, and DT to examine their robustness. The results shown in Table 6-6 indicate that the overall performance of RF is the best in terms of F1-score and accuracy. RF also has the best performance in terms of precision when predicting violating observations (label = 1). Overall, the performance of RF is better and more robust than the other four methods.

Table 6-6. Validation Results of RF, LR, KNN, SVM and DT

Tool	Label	Precision	Recall	F1-Score	Accuracy
RF	1	0.57	0.57	0.57	93.10%
	0	0.96	0.96	0.96	
LR	1	0.33	0.14	0.20	90.80%
	0	0.93	0.98	0.95	
KNN	1	0.18	0.86	0.29	66.67%
	0	0.98	0.65	0.78	
SVM	1	0.50	0.14	0.22	91.95%
	0	0.93	0.99	0.96	
DT	1	0.09	0.29	0.14	71.26%
	0	0.92	0.75	0.83	

6.4 Summary

Corporate fraud can result in severe consequences, especially in the construction industry. Though previous studies have identified a great number of factors associated with corporate fraud, ranking their importance and using them to predict corporate fraud in the construction industry has been previously overlooked. To identify the most influential factors, this study developed an RF-based model employing a dataset about 953 observations from 93 China construction companies in 2000-2018. Among the 85 used variables (including 37 newly generated in data preprocessing), this study identified the top 11 variables, of which all represent corporate governance, with the greatest association with corporate fraud.

In light of these findings, several suggestions could be proposed. First, firms need to keep their eyes open on corporate governance. In particular, firms should not overlook the board of supervisors. Instead of playing a "rubber stamp" role (Shan, 2013), the board of supervisors needs to sufficiently fulfill their role to alleviate the likelihood of corporate legal violations. Similarly, the board of directors cannot be neglected. They have the right to determining the executives' compensation and appointing and dismissing executives (Lu and Shi, 2018; Shan, 2013). Thus, to mitigate the corporate scandals, firms need to reconsider the board size of supervisors and directors. Second, firms themselves need to rethink the compensation mechanisms for managers, directors, and supervisors. Annual emolument and shareholding would provide the board of supervisors and directors with incentives to improve the quality of corporate governance while providing managers with incentives to maximize their profits. Hence, it is imperative to design a more effective and targeted compensation structure.

This chapter is expected to theoretically contribute to the field of corporate fraud prediction. Using variable importance ranking of RF to explore the most influential factors, this study presents a method for locating key factors of corporate fraud and for facilitating a greater understanding of corporate misbehavior. In particular, the role of corporate governance deserves more attention in alleviating corporate fraud. By employing RF and comparing it with LR, KNN, SVM, and DT, this research demonstrates the feasibility of RF in predicting corporate fraud in the Chinese construction industry. RF may provide a new option for researchers to more effectively identify questionable construction companies.

Not only researchers but also practitioners including construction firms themselves, regulators and investors have been concerning the corporate scandals. This chapter provides some practical implications for the application of RF. First, RF could be applied to identify important factors and urgent issues. Since every company's resource is limited, how to effectively allocate resources within an organization is critical for sustainable development. Especially for the construction industry which recognized as a high-risk sector for corruption (Lee *et al.*, 2018), inappropriate resource allocation not only causes financial loss for construction firms but makes the firms difficult to focus on pressing issues such as corporate fraud detection and prevention. This may be alleviated by exploring the most influential factors using RF, which differentiates RF from many machine learning tools. According to the results in this study, construction firms in China need to pay more attention to the set of top 11 variables indicating corporate governance to timely detect corporate fraud. Second, RF could be an effective tool for regulators and investors to identify both law-abiding and violating firms. Through the comparative analysis among RF, LR, KNN, SVM, and DT, the performance of RF is better than the other four tools. Besides, the validation using the data in 2018 also indicates RF is robust and the best. Taking reliability into consideration, RF is more recommended for regulators and investors to predict corporate fraud.

Though this research has included dozens of variables about corporate governance and financial performance, adding more features about projects, the firm itself, and its external environment may enhance the accuracy of corporate fraud prediction in the construction industry. The variables used in this study were mainly extracted from a firm's annual reports, which also contain a textual description of a firm. Thus, combing for sentiment analysis with text mining tools could help identify violating construction firms.

CHAPTER 7 Summary of Major Findings

7.1 Introduction

This chapter summarizes the overall research findings in this dissertation. First, the antecedents of occupational fraud are presented from individual and corporate level. Second, the drivers of corporate fraud are reported considering some contextual factors. Finally, the most important influential factors of corporate fraud are summarized and a random forest model for corporate fraud detection model is constructed.

7.2 Summary of Major Findings

This dissertation explored influential factors that impact the likelihood of fraud by of top management of construction companies in China at the individual and organizational level. The overall findings in this dissertation are summarized as follows.

First, at the individual level, a top manager's occupational fraud is reported to be affected by his/her career horizon as well as by the corporate governance in the firm where he/she has a position. Specifically, executives with a shorter career horizon are associated with a reduced likelihood of individual occupational fraud. Executives near retirement are even less likely to engage in fraudulent actions if their firms have a less independent board and a higher percent of shares held by the state. In addition, board size and blockholders ownership were found to have an insignificant moderating effect on the relationship between a manager's career horizon and his/her wrongdoing.

Second, at the corporate level, TMT total pay is found to be positively related to the occurrence of corporate fraud. The present study also found that aspiration–performance discrepancies have an inverted V-shaped relationship with the probability of fraudulent activities. Moreover, the positive relationship between TMT total pay and fraud is strengthened by aspiration–performance discrepancies.

Last, as identified through a machine learning approach rather than through classical statistical methods, corporate fraud was verified to be associated with dozens of internal factors at the corporate level. The top 11 influential variables on corporate fraud were obtained using RF variable importance analysis. These 11 variables, all related to corporate governance, rather than to the financial performance of the firm. In addition, RF was found to be suitable for predicting corporate fraud in the construction industry.

7.3 Summary

This chapter provided a summary of the major findings obtained in this study. The major findings include the recognized antecedents of occupational fraud and corporate fraud. The most important factors influencing corporate fraud and a corporate fraud prediction model were also summarized as parts of major findings.

CHAPTER 8 CONCLUSION

8.1 Introduction

This chapter discusses the theoretical contributions and practical implications of the major findings summarized in the above chapter. The theoretical contributions include six aspects from literature on corrupt practices in the construction industry, upper echelons theory, agency theory, the behavioral theory of the firm, multilevel framework for top management fraud, and methodological standpoint. This study offers practical implications that firms need to mount a three-pronged attack on corruption. Despite of several contributions and implications, there are three limitations in this study, related to the concealed nature of top management fraud, the measure of top management fraud and the data availability. Lastly, possible future research is proposed to deepen the understanding of top management fraud.

8.2 Contributions and Implications

8.2.1 Theoretical Contributions

Regarding the major findings, this dissertation offers several important theoretical contributions. First, this dissertation supplements the growing body of literature on corrupt practices in the construction industry. Prior works (Alutu and Udhawuve, 2009; Ameyaw *et al.*, 2017; Brown and Loosemore, 2015; Zhang *et al.*, 2017) emphasize the roles of professionals (e.g., engineers and architects) and middle managers (e.g., project managers) in corruption while neglecting to examine the impact of top managers. This dissertation suggests that top managers also play a strong role in determining whether fraud occurs in construction companies. On the one hand, this dissertation addresses individual differences between each top manager, a topic that has not been as thoroughly considered in the literature. The findings described in Chapter 3 indicate that occupational fraud is affected by an individual executive's characteristics, consistent with some existing studies (Zahra *et al.,* 2005). On the other hand, this dissertation follows in the footsteps of some previous studies (e.g., Kang 2008; Shi et al. 2017) and regards corporate fraud as a result of decisions made by the whole TMT. Chapters 4 and 5 both support the notion that the TMT is liable for corporate fraud.

Second, this dissertation suggests that top managers' psychological attributes (e.g., career horizon) play a role in top management fraud, extending the scope of upper echelons theory. Prior literature has proposed that background and demographic characteristics of CEOs exert an influence on firms' strategic outcomes, including international acquisitions (Matta and Beamish 2008), research and development (R&D) spending (Cazier, 2011) and the commitment of CSR (Kang 2016). The findings presented in Chapter 3 align with and augment upper echelons theory by demonstrating that fraudulent behaviors are among the outcomes of top management decision-making.

Third, the findings of this dissertation indicate that the effects of executive attributes are influenced by corporate governance mechanisms, contributing to the agency theory literature. All of the top 11 factors influencing corporate fraud are associated with corporate governance, underscoring the important role of such governance. Historically, researchers have perceived board monitoring and executive compensation as two major mechanisms for dealing with the agency problem (Dalton *et al.,* 2007). However, as shown in this dissertation, board monitoring has limited effects on keeping top managers from engaging in fraudulent behaviors. The compensation mechanism also does not work well in aligning the interests of executives and shareholders but instead appears to provide incentives for executives to engage in illegal activities. Taken together, the design of corporate governance mechanisms deserves reconsideration in preventing top management fraud in terms of both what we suppose matters and what really matters.

Fourth, this dissertation provides evidence that the ineffectiveness of corporate governance mechanisms may be attributed to another contingent factor, aspiration-performance discrepancy, which has implications for the behavioral theory of the firm. Previous research has cast search as constructs including exploration and exploitation, as empirically supported for R&D investment and mergers and acquisitions (Alessandri and Pattit, 2014; Greve, 2003a; Kuusela *et al.*, 2017). The findings in Chapter 4 extend the relevance and applicability of the theory by establishing that illegal corporate behaviors are another relevant type of search. That is, when initiating problem-solving searches, construction companies may choose unlawful solutions rather than simply pursuing legitimate firm responses, with consideration of various degrees of risk. Apart from directly affecting organizational behaviors, aspiration-performance discrepancies could be a new and potentially important contingency in conceptualizing corporate fraud.

Fifth, this dissertation provides a multilevel framework for unpacking the mechanisms involved when top managers engage in fraudulent behaviors. There have been many attempts to identify the mechanisms on a single level. Traditional studies (e.g., Sen 2007; Shi et al. 2017) tend to focus solely on the characteristics of managers or firms, overlooking the fact that an individual with particular features may have different behaviors in different environments. Taking the nested structure of data into consideration, Chapter 3 presents an analysis of the combined effects of temporal, individual, and organizational-level factors simultaneously. This multilevel framework responds to the need for a cross-level and hierarchical understanding of top management fraud not otherwise pursued in previous studies (Kish-Gephart *et al.*, 2010; Piquero and Piquero, 2001; Zahra *et al.*, 2005). The potential of multilevel modeling to enrich the research about top management fraud is also highlighted in Chapter 3.

Finally, from a methodological standpoint, this dissertation combines statistical analysis with machine learning tools. This provides researchers with more methodological options and enriches the algorithms used in empirical studies exploring the drivers of fraud in construction companies. To investigate the determinants of fraud, prior literature (Hou and Moore, 2010; Mishina *et al.*, 2010; Ndofor *et al.*, 2015; Shi *et al.*, 2016, 2017) has usually used logit regression, probit regression, and other statistical models. These models are capable of identifying factors having statistically significant positive or negative effects and aid in explaining the mechanisms and relationships between influential factors and outcomes. However, a critique of the logit model is that its assumptions like variation homogeneity are too strong so that its application is limited (Chou *et al.*, 2004). Moreover, statistical significance does not equal practical importance (Gelman and Stern, 2012; Stark *et al.*, 2004) and statistically insignificant factors may still make a difference. Thus, to investigate the importance of influential factors, including those found to be insignificant from a statistical analysis, the present study applied machine learning tools. Many machine learning tools do not require prior domain knowledge, making their implementation simple. They are able to accurately predict outcomes, making them practical. Some techniques (e.g., RF) can also rank variable importance, providing a new way to identify the most influential factors undergirding fraud in corporate companies. Though a 'black-box'-like computational analysis is useful, the predictions can be difficult to explain and the underlying mechanisms may remain unclear, or in other words, the outputs of machine learning often leave the associations between outcomes and predictor variables hidden. A combination of machine learning tools and statistical analysis can facilitate the identification of influential factors, uncover the effects of those influential factors on outcomes, and inform the design of mechanism models. Thus, this dissertation offers a way to explore what factors matter and how they matter for fraud in construction companies.

8.2.2 Practical Implications

In addition to the theoretical contributions, the findings of the present study have several practical implications. Briefly, firms need to mount a three-pronged attack on corruption by considering executives' psychological attributes, internal governance mechanisms (i.e., board monitoring and compensation) and ownership structure. This can enable decision makers, including investors, regulators, and top managers themselves, to better understand and reduce corporate scandals.

First, this dissertation underscores the need for stakeholders in the construction industry to pay attention to top management. In particular, more attention needs to be paid to an executive's psychological attributes, represented by career horizon. Thus, firms need to be more careful when selecting or dismissing top managers to prevent fraudulent activities.

Second, firms in the construction industry need to rethink the role of internal governance in alleviating top management fraud. This dissertation revisits two mechanisms of internal governance, namely interest alignment through executive remuneration and monitoring by a board of directors. Though executive compensation may be intended to mitigate the agency problem arising from the separation of security ownership and control (Fama, 1980), the results presented in Chapter 4 and 5 indicate that TMT total pay may provide executives with incentives to do business via illicit means. Thus, redesigning the executive compensation system is needed. Board monitoring is another important mechanism of corporate governance. Though previous studies (Anderson *et al.*, 2004; Fernández-Gago *et al.*, 2018; Rao *et al.*, 2012; Sharma, 2004) have argued that strengthening board independence could improve the quality of corporate governance, the results presented in Chapter 3 reveal that board independence has a limited effect on top management fraud. Similar findings described in Chapter 5 demonstrate that board independence is not among the 11 most influential factors associated with committing fraud. Thus, to improve monitoring effectiveness, firms may want to shift some attention away from board independence and towards other means, such as board ownership, which in the present study was found to be the most influential factor.

Third, as for ownership structure, the findings presented in Chapter 3 reinforce the importance of interest alignment. When the interests of management and state shareholders are consistent, the likelihood of top management fraud decreases. Retaining executives with shorter career horizons for a firm with a larger percent of state shares could discourage unlawful behavior carried out by executives. Firms may need to align the executives' psychological profile with internal contingencies to diminish the occurrence of fraudulent activities.

Finally, the prediction model constructed in this dissertation could enable regulators and investors to detect problematic firms. This model does not require prior knowledge so that even those who are not professionals in top management fraud can understand the outputs. This model has the potential to assist regulators and investors in shortening the search for appropriate candidates for investigation. Regulators could apply it to support its decisions regarding "gray area" firms, which may need to be further inspected for fraud and other unlawful behaviors. Investors could apply it to identify firms with a lower risk of experiencing a plunge in share prices, which often occurs once a corporate scandal becomes known to the public.

8.3 Limitations

Though the present study makes a number of theoretical contributions and offers several practical insights, it still has several limitations. First, fraud is usually concealed. Top managers who have committed fraudulent behaviors are unlikely to announce to the public what they have done. Simultaneously, investigation of "hidden" management acts by shareholders or regulatory bodies is usually not immediately disclosed to outsiders. Thus, not every case of fraud will be detected. This study has to rely on publicly available information about fraudulent cases with the risk of overlooking those undiscovered cases and those executives or companies that were not reported to be involved in fraudulent cases remain regarded as law-abiding.

Second, as the outcome variable, top management fraud is operationalized by a dummy variable indicating whether fraudulent activities are committed or not in the period studied. This work fails to measure the seriousness of violating activities because there are several types of penalties in China, including circulation of a notice of criticism, warning, serious warning, public condemnation, fines, confiscation of illegal gains, confiscation of unlawful property or things of value, temporary suspension or rescission of a permit, temporary suspension or rescission of a license, and banning entry into the securities market. More than one type of penalty may be used by regulators to penalize those violators and it is difficult to measure the severity of two or more penalties as well as the severity of the particular amount of a fine. For example, a firm may be given a temporary suspension of a permit and a serious warning while another firm may be fined a large amount of money, and without further examination it remains unclear from the penalties which firm's behavior was worse. Clearly defining the seriousness of illegal activities may be more meaningful and thus recommended for future studies.

Third, due to data availability, this study has to neglect many possible influential factors. Executives' invisible psychological status, in particular the risk preference (aggressive or conservative) may exert great influences on top management fraud. Then religion and other observable characteristics are not included either because Chinese listed companies do not reveal executives' religion and consider religion as executives' privacy. Besides, industrial and organizational culture is also neglected because it is invisible and difficult to measure.

8.4 Future Research

Due to the separation of management from the wealth effects of ownership and the subsequent differences between principals (shareholders) and agents' (CEOs') goals or desires, management staff may try to maximize their wealth at the expense of stockholders (Fama and Jensen, 1983b; Young *et al.*, 2000). Corporate boards, appointed by the principals, have been viewed as the most important mechanism to reduce such conflict of interest (Fama and Jensen, 1983b). A corporate board is conferred with the responsibilities of assisting and monitoring management as part of their fiduciary duty to maximize shareholders' wealth (Fama and Jensen, 1983b; Mace, 1971; Pearce and Zahra, 1991; Vance, 1964). However, a board of directors may not be able to exert a great influence on decision-making. A board may be dominated by CEOs and the top management team (D'Aveni and Kesner, 1993; Kosnik, 1987; Mallette and Fowler, 1992; Stiles, 2001) because directors have been chosen by management themselves or have inadequate knowledge of the workings of the corporation. These issues, in turn, raise questions regarding board effectiveness and board structure.

Apart from the internal governance and organizational contexts, a firm is also embedded in the external market and policy environments. These environments are constantly changing, challenging a firm's ability to promptly detect and respond to these changes. Failure to cope with these environmental circumstances may result in lost opportunities to expand a firm's operations, reduce its profitability, and create pressure to engage in unlawful behavior (Szwajkowski, 1985). Moreover, dynamic environments may increase an executive's advantage in possessing more information about projects and firms than do the board of directors and supervisors and may enable executives' ability to conceal fraudulent acts by management. Thus, external environments, especially their dynamism, are likely to affect the choices of managers by creating conditions that force, induce, and even facilitate managerial fraud. Therefore, taking external environments into consideration, it is necessary to explore what characteristics executives and board members should possess so as to decrease the occurrence of corporate scandals.

Studies have introduced a diverse range of theories in the field of managerial fraud, along with numerous variables and models with varying degree of effectiveness in explaining fraudulent acts committed by top managers. However, resources are limited and coping with all the variables is difficult. Therefore, it is vital to identify the most influential factors as well as select or develop theories with the greatest explanatory power. To promptly detect urgent issues and help organizations effectively allocate resources, future studies are needed to compare the effectiveness of different theories and tools and determine the most effective combinations of theory and tools in fraud prediction.

Last, different kinds of fraud may have different levels of severity. Once illegal activities are detected by governmental regulatory departments, corresponding enforcement actions follow. More importantly, in light of a corporate scandal, a firm's reputation may suffer (Williams and Barrett, 2000), its stock value may decrease (Chen *et al.*, 2005) and other adverse outcomes may occur. It is a difficult and often long-term process for a firm to recover its reputation and regain the trust of shareholders and stakeholders (Dietz and Gillespie, 2012; Gaines-Ross, 2008). To reduce associated economic losses and the extent of reputational damage, various crisis response strategies may be carried out, such as corrective action, compensation, bolstering, shifting blame, simple denial, and so on (Ferguson *et al.*, 2018). These crisis response strategies differ in their impact on shareholders' judgement of problematic firms and on a firm's efforts to restore its reputation. Thus, it is important to investigate what crisis response strategy should be applied after specific scandals occur.

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