

Three essays on financial risk

Abstract

The thesis contributes to the literature on behavioural finance and price jumps by moving beyond the traditional framework of the efficient market hypothesis. The aim of the thesis is to deepen the understanding of actual financial markets rather than the ideal world described by that hypothesis. This thesis empirically investigates three related topics: managerial traits; the incentives for risk-taking provided by managerial compensation packages; and price jumps.

The first empirical chapter of the thesis examines the varying effect of CEO overconfidence after the experience of a severe financial shock. It investigates the association between CEO overconfidence and a firm's risk-taking behavioural during pre- and post-crisis periods. We find that the association between CEO overconfidence and firms' risk-taking becomes weaker during the post-crisis period. This work contributes to the literature on the state dependence of executive managerial traits.

The second empirical chapter examines the association between components of managerial compensation packages that provide incentives for firms to undertake risky investments and default risk in the banking industry. It investigates the association between CEO vega (the sensitivity of CEOs' wealth to stock price volatility) and default risk in the US banks. We find that the positive association between CEO vega and default risk is mitigated by high leverage ratios. This work contributes to the literature on managerial compensation in different financial conditions.

The third empirical chapter examines the association between price jumps and market liquidity in the context of cross-listed stocks. It investigates intraday patterns in market liquidity and price jumps for cross-listed stocks during overlapping and non-overlapping trading hours. We find that the improved market liquidity during overlapping hours is associated with fewer price jumps. Moreover, we find that overlapping-hours phenomenon is sensitive to varying overlapping

hours caused by daylight-saving time. This work contributes to the literature on the incidence of price jumps for cross-listed stocks.

Collectively, the three studies empirically explore biased behaviours of CEOs and non-random-walk movements of stock prices, which cannot be well explained by the classical efficient market hypothesis.

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CHAPTER 1. Introduction

The efficient market hypothesis (EMH) was widely accepted in the 1970s. In his cornerstone paper, 'Efficient Capital Markets: A Review of Empirical Work', Fama (1970) defines an efficient financial market as one that is efficient in reflecting information about securities as well as the securities market. The EMH suggests that when information becomes available, it is quickly incorporated into the prices of securities. The EMH reaches great success both theoretically and empirically. Much empirical evidence supports the EMH. Indeed, Michel Jensen, albeit as one of the creators of EMH, declared that '*there is no other proposition in economics which has more solid empirical evidence supporting it than the Efficient Market Hypothesis*' (Jensen, 1978, pp. 95).

As Shiller (2003) suggests, while the EMH is a powerful tool that allows aspects of real-world financial markets to be quantified, anomalies have been observed that are not readily explained by the EMH. By the turn of the century, it had begun to be challenged. According to the weak form of the EMH, no excessive stock returns can be made based on past information. However, some empirical studies have produced results counter to this prediction. For instance, Bondt and Thaler (1985) form two portfolios – the best-performing and worst-performing stocks over the previous three years (the 'winner' and 'loser' portfolios, respectively) – and compare their performance over the following five years. The authors find that over thirty-six months post-formation period, the loser portfolio earned about 25% more than the winner portfolio. These results suggest that the momentum reverse itself over long periods of time. In contrast, over short periods of time such as six-month, this momentum seems to continue. For instance, Jegadeesh and Titman (1993) show that 'winning' stocks (those which have shown high six-month returns) continue to outperform 'losing' stocks (those which have shown low six-month returns) in the next six months. Both studies imply that there is at least a certain predictivity of stock prices over a certain period. Moreover, some empirical studies on security price behaviour identifies a few seasonal patterns in equity returns. Cross (1973), French (1980) and Keim and Stambaugh (1984) found that equity returns tend to be low on Mondays and Gibbons and Hess (1981) noted abnormal high return at the end of the week (the day-of-the-week effect).

Lakonishok and Smidt (1988) show that equity returns at the turn of the month are significantly higher than those during the rest of the year (the month effect). Rozeff and Kinney (1976) and Keim (1983) suggest that the US stock returns are significantly higher in January than in the rest of eleven months. These anomalies are not readily explained by the EMH.

The defenders of the EMH argue that these anomalies are only small deviations from an elegant explanation for many aspects of the financial system. However, as more and more anomalies between empirical results and the predictions of the EMH are found, some researchers have become dissatisfied with the EMH. As Akerlof and Shiller (2010) state in their book *Animal Spirit*, economists have traditionally sought to minimise any real-world deviations from the ideal system of Adam Smith and have therefore ignored the role of human psychology, which has, however, been taken up in the study of ‘behavioural finance’.

Behavioural finance was developed as an alternative view of the financial market to the EMH. As a pioneer of behavioural finance, Shiller (2000) suggests, in his seminal work ‘*Irrational Exuberance*’, that markets are not always efficient and stock prices do not always revert to their fundamental value. The authors also suggest that when stock prices generate positive returns, they promote ‘*word-of-mouth*’ enthusiasm, which leads to the expectation of future stock price increases. This expectation in turn increases demand for the stock in the next round. The feedback mechanism repeats itself and as a result generates ‘bubbles’. Behavioural finance provides a better explanation than the EMH for the dot-com bubble of 2000. As a result, it has attracted the attention of academia. Supporters of behavioural finance believe that the EMH offers an elegant framework for descriptions of how financial markets should work in an ideal world but behavioural finance, which takes account of the human psyche, can better describe how the financial market works in the real world.

One of key disagreements between the EMH and behavioural finance is over whether investors are rational. The EMH states that they are, and that irrational

individuals will eventually be eliminated from the markets. In contrast, behavioural finance suggests that investors could be irrational in certain scenarios.

An essential strand of behavioural finance concerns how the managerial traits of executives substantially influence the behaviour of firms. Some studies have found that one such trait, CEO overconfidence, is positively associated with firms' risk-taking behaviours (Li and Tang, 2010; Hirshleifer et al., 2012). These studies treat the effect of CEO overconfidence on firm risk-taking as fixed (i.e. it does not vary over time). More recent studies show that CEOs' personal experience also affects their choices in raising funds (Malmendier and Nagel, 2011), their expectation of future stock returns and bond returns (Malmendier et al., 2011) and their expectation of inflation rates (Malmendier and Nagel, 2016).

This view that managerial traits are influenced by personal experience is consistent with a strand of the psychology literature on what is termed the availability heuristic. Tversky and Kahneman (1973) find that individual judgements of the probability of an event depend on how easily the individual can recall instances of similar events. An example is that individuals' subjective evaluation of the probability of a traffic accident rises after they have just seen a car accident. Tversky and Kahneman (1974) suggest that individuals tend to overestimate the probability of a nuclear war after seeing a picture related to nuclear war. Barberis and Kramer (2013) point out that high-impact events like financial crises usually generate vivid images and strong emotions. In this sense, the experience of the 2008 financial crisis should create a vivid image for CEOs.

Taking account of both the literature on CEO overconfidence and that on the availability heuristic, it is reasonable to expect that a high-impact event like the 2008 financial crisis would have influenced overconfident CEOs' risk-taking behaviour. Although prior studies such as Li and Tang (2010) and Hirshleifer et al. (2012) have shown that CEO confidence increases firms' risk-taking behaviour, few studies specifically explore whether the link between CEO overconfidence and a firm's risk-taking influenced by a financial crisis. The first empirical chapter

investigates the effect of CEO overconfidence on the risk-taking behaviour of companies before and after the 2008 financial crisis. The chapter thereby attempts to shed light on the effect of managerial traits of executives on firms' risk-taking behaviour.

Besides the managerial traits of executives, which might be thought as intrinsic or even instinctual, external factors such as incentives in the form of managerial compensation (i.e. the executive's pay arrangements) also influence CEOs' risk-taking behaviour. According to agency theory, the interests of shareholders and those of managers are not perfectly aligned (Jensen and Meckling, 1976). Managers are exposed to firm-specific risk and tend to be risk-averse if there are no incentives for them to be otherwise. Research on agency theory suggests that overcoming managers' risk aversion is an essential aspect in mitigating the agency problem (Jensen and Meckling, 1976; Huagen and Senbet, 1981; Smith and Stulz, 1985).

Studies on managerial compensation show that offering CEOs convex payments such as stock options can motivate them to implement risky investment projects. Convex managerial compensation means that CEOs can unlimitedly benefit from an increase in stock price in good times but only bear limited losses in bad times. The convexity of managerial compensation can be measured by 'CEO vega', which is the sensitivity of CEOs' wealth (or pay package) to stock price volatility. Empirical studies such as Smith and Stulz (1985), Core and Guay (1999) and Coles et al. (2006) show that the CEO vega is positively associated with firms' risk-taking.

The association between CEO vega and firm risk could be influenced by the firm's financial state. Jensen and Meckling (1976) introduced the risk-shifting problem: managers tend to take excessive risk when firms are financially distressed. Earlier studies on risk-shifting focus on the conflict of interest between shareholders and debtholders. It is notable that conflicts of interest also exist between shareholders and CEOs. For instance, Williamson (1988) shows that a CEO's human capital

increases with employment continuity, especially when human capital is specific to industries. Fox and Marcus (1992) argue that CEOs' human capital, including their skills, experience, ability and relationship, is highly valued in specific firms than in others. John and John (1993) demonstrate that managers benefit more for being in charge of their firms if their firms are in solvent states. These studies imply that the CEOs' utility is different in good times and bad times.

As CEOs' utility function is asymmetric, we expect that the incentives of CEO compensation should have varying effects on firms' default risk according to the firms' financial status. For instance, Brockman et al. (2010) find that short-term debts mitigate the positive effect of the effect of high-vega CEO pay schemes on a firm's bond yield. Kim et al. (2017) show that high leverage ratios have an attenuating impact on the relationship between incentives and risk-taking. Both of these studies suggest that the association between CEO vega and firm risk tends to become weaker when firms are close to defaulting on loans. Motivated by this view, the second empirical chapter explores the association between CEO vega and the default risk of banks. Specifically, we investigate whether the association between CEO vega and firm risk varies for firms in different financial states.

Another essential assumption of the EMH is that the stock return follows a random walk as new information is immediately reflected in stock prices. Recent studies like Todorov (2010) suggest that the variance can be decomposed into two parts: the well-known stochastic stock volatility; and jumps, which are extreme discontinuous shocks in stock returns. Empirical studies indicate that price jumps have characteristics that distinguish them from the well-known continuous movement. For instance, Bollerslev et al. (2014) show that jumps have different risk characteristics from stock volatility which is the conventional measure of firm risk. Cremers et al. (2015) suggest that aggregate jumps and continuous movement have different effects on expected stock returns and the effect of aggregate jumps is economically significant. Due to the importance of jumps, the determinants of price jumps also attract great interest within academia.

A strand of the literature shows that the incidence of price jumps is associated with market liquidity. For instance, Jiang et al. (2011) demonstrate that after controlling for the effect of information shocks, liquidity shocks in bid–ask spreads and market depth still have significant predictive power for price jumps. Evans (2011) finds that market liquidity, in terms of trading volume and the number of trading ticks, has a positive association with price jumps. Gilder et al. (2014) shows that liquidity variables like bid–ask spreads and numbers of transactions are the drivers for jumps. Christoffersen et al. (2016) prove that market illiquidity was the reason behind the ‘Flash Crash’ in the US stock market on 6 May 2010. These studies at least agree that there is a significant association between price jumps and market liquidity.

Earlier studies generally focus on non-cross-listed stocks, but a few studies do explicitly explore market liquidity in the context of cross-listed stocks. For cross-listed stocks (i.e. stocks traded on both domestic and overseas markets) traded in different time zones there may be ‘overlapping hours’ when the domestic and overseas are open at the same time. Moulton and Wei (2009) show that an ‘overlapping hour’ phenomenon exists for cross-listed stocks trading, whereby the intraday market liquidity for cross-listed stocks is significantly different during overlapping and non-overlapping hours. This provides an ideal model to investigate the association between price jumps and market liquidity. Taking the literature on the overlapping-hours phenomenon and price jumps together, the third empirical chapter explores the association between intraday market liquidity and the incidence of price jumps during overlapping and non-overlapping hours. The chapter sheds light on the incidences of price jumps by investigating the intraday price jumps in the trading of American Depositary Receipts (ADRs).

The rest of the thesis is organised as follows. Chapter 2 explores the association between firm risk and CEO overconfidence. Taking the 2008 financial crisis as an extreme shock, we investigate how the crisis affected the association between CEO overconfidence and firms’ risk-taking behaviour. The empirical results show that CEOs’ overconfidence has a positive association with a firm’s risk-taking

behaviour. Moreover, we find that after the 2008 financial crisis, overconfident CEOs tended to be more cautious with firms' risk-taking. The empirical results are robust to variations in the measures used to evaluate CEO overconfidence. This chapter contributes to the literature on the association between CEO overconfidence and firm risk-taking behaviour. It also supports the argument that the past experience of executive managers affects firms' risk-taking decisions.

Chapter 3 investigates the relationship between default risk (the risk of a bank defaulting, in this study) and CEO vega (i.e. the sensitivity of CEO wealth, or the CEO's compensation package, to stock price volatility) in the US banking industry. We apply the distance-to-default measure proposed by Bharath and Shumway (2008) to estimate the default risk. The empirical results show that CEO vega is positively associated with default risk. We also classify banks into high-leverage and low-leverage groups to investigate how different financial states influence the association between CEO vega and default risk. We find that the association between CEO vega and default risk is weaker among high-leverage banks. After controlling for variables linked to CEO compensation, the empirical results remain qualitatively the same. The chapter enriches the literature on the relationship between managerial pay packages and banks' default risk. The results have important implications for policymakers in the banking industry. We show that the incentives provided by managerial compensation schemes are affected by the firm's financial state, which should be considered in the design of managerial compensation packages.

Chapter 4 investigates the connection between overlapping hours of trading on exchanges in different time zones and price jumps in ADRs. Specifically, we measure the intraday market liquidity of ADRs with measures such as bid-ask spread, trading volume, number of transactions, average transaction size and market depth. We also employ Lee and Mykland's (2008) test to detect price jumps. We find that the market is more liquid during overlapping hours for ADR trading, and that the incidence of price jumps is lower during overlapping hours. These results suggest a negative association between market liquidity and price

jumps, which is consistent with the existing literature. We check the robustness of the empirical results by taking account of a change in overlapping hours caused by daylight-saving time. The results remain robust to differences in the number of overlapping hours. The chapter contributes to the rapidly developing literature on the relationship between price jumps and market liquidity. The research has implications for policy-makers and regulators. The overlapping-hours effect is evident in intraday price jumps as well as market liquidity. Specifically, a greater number of overlapping hours tends to increase market liquidity and reduce the incidence of price jumps. In this sense, the trading time of for ADRs should be taken into consideration in deciding when to issue new depositary receipts.

Chapter 5 summarises the main conclusions and the policy implications of the findings. Our empirical research tackles different aspects of financial risk beyond the classic framework of the EMH. We also discuss interesting areas for further studies on this topic, which may broaden our understanding of firms' risk-taking behaviours as well as price jumps in the real world.

CHAPTER 2. Firm risk, CEO overconfidence and the availability heuristic

2.1 Introduction

Overconfidence as a managerial trait has attracted great interest within academia. Recent empirical studies show that CEO overconfidence significantly influences corporate decision-making in areas such as investment (Malmendier and Tate, 2005), debt maturity (Huang et al., 2016), dividend policy (Deshmukh et al., 2013), innovation (Hirshleifer et al., 2012) and mergers and acquisitions (Malmendier and Tate, 2008). Firms' decision-making determines their risk-taking behaviour, which is essential in the survival and development of a firm (Shapira, 1995). Empirical studies such as Li and Tang (2010) and Hirshleifer et al. (2012) indicate that CEO overconfidence is positively associated with firms' risk-taking behaviour.

Some prior research such as Li and Tang (2010) and Hirshleifer et al. (2012) assumes that overconfidence is a consistent individual trait which does not vary over time. Other studies argue that executive managers' past experiences affect their beliefs and views about the future. For instance, Malmendier et al. (2011) show that CEOs who were born during the Great Depression are averse to debt and reluctant to use external loans. Malmendier and Nagel (2011) show that CEOs who have experienced low stock market returns are more pessimistic about future returns, and are less likely to participate in the stock market. In contrast, CEOs who have experienced low bond returns are less likely to participate in the bond market. Malmendier and Nagel (2016) suggest that CEOs who have experienced different inflation rates tend to have expectations of inflation rates.

The view that CEOs' beliefs are affected by their past experience is consistent with a phenomenon noted in the psychology literature termed the 'availability heuristic'. Tversky and Kahneman (1973) state that the availability heuristic denotes that people judge the probability of an event by how easy it is to recall instances of similar events. For instance, Tversky and Kahneman (1974) show that an individual's subjective evaluation of the probability of a traffic accident rises temporarily when he or she sees a car accident. Taking both the availability heuristic and the overconfidence literature together, a question naturally arises: do overconfident CEOs adjust their beliefs after they have just experienced an

economic shock? Billett and Qian (2008) find that executive managers develop overconfidence through their individual experiences. We investigate the risk-taking behaviour of overconfident CEOs before and after the 2008 financial crisis, as it is the most considerable economic shock in recent history. We measure CEO overconfidence using Campbell et al.'s (2011) method. The idiosyncratic risk of firms is estimated using Fama and French's (1993) three-factor model.

Our empirical results show that the financial crisis had a considerable impact on overconfident CEOs' risk-taking behaviours. The post-crisis indicator has a negative impact on overconfident CEOs' risk-taking, which suggests that overconfident CEOs tend to be more conservative after they have experienced a great economic shock. Besides Campbell et al.'s (2011) proxy for managerial overconfidence, we also construct different overconfidence measures, including relative ranks of option moneyness, investment levels and the interaction of the two. The empirical results remain consistent across these different measures of CEO overconfidence.

This chapter contributes to the developing literature on the impact of managerial traits. Consistent with Malmendier and Nagel (2011; 2016), and Giuliano and Spilimbergo (2013), we show that overconfident CEOs adjust their risk-taking behaviour after they experienced a great economic shock. Different from prior studies, we argue that it is reasonable to investigate overconfident CEOs' behaviour as a dynamic process rather than a fixed and permanent trait. This chapter has implications for financial practitioners regarding corporate governance. Our results suggest that it is essential to consider firms' current financial status when analysing the effect of CEO overconfidence. Overconfident CEOs tended to behave more cautiously after the 2008 financial crisis. This implies that the regulations and policies set to govern the effects of CEOs' levels of confidence might need to be adjusted after such a crisis.

The rest of the chapter is organised as follows. In Section 2.2 we review the related literature and present the two hypotheses tested in the study. In Section 2.3,

we discuss our data and methodology. In Section 2.4, we present the empirical results. Section 2.5 sets out the conclusions.

2.2 Literature review

2.2.1 Overconfidence and risk-taking

The literature on CEO overconfidence stems from a social psychology phenomenon termed the ‘better-than-average effect’, which suggests that people tend to attribute good outcomes to their abilities but bad outcomes to bad fortune. An extension of the effect is when an overconfident individual tends to overestimate the return and underestimate the probability of failure (Malmendier and Tate, 2005). Since CEOs can strongly influence firms’ business policies, their overconfidence influences corporate policies in different respects. For instance, Malmendier and Tate (2005) show that CEO overconfidence accounts for corporate investment distortions, i.e. overconfident CEOs overestimate future returns from their companies and tend to overinvest if they have sufficient internal funds. If overconfident CEOs do not have sufficient internal funds, they are reluctant to use external financing as they believe that their own firm’s stocks are undervalued. Thus, overconfident CEOs forego investment opportunities when they require external financing. Moreover, overconfidence also influences merger and acquisition decisions. Malmendier and Tate (2008) demonstrate that as overconfident CEOs overestimate their abilities to generate income, they tend to undertake value-destroying mergers by overpaying for target companies. Ferris et al. (2013) also present evidence that overconfident CEOs are more likely to make value-destroying decisions in international mergers.

Li and Tang (2010) summarise three mechanisms through which overconfidence influences CEOs’ strategic choices. First, overconfident CEOs tend to overestimate their personal problem-solving ability. For instance, they may exaggerate the potential return of a strategic decision, say, paying a higher price for acquisitions (Hayward and Hambrick, 1997), or undertake excessive business entries in a target market (Camerer and Lovallo, 1999). Second, overconfidence

could drive CEOs to underestimate the resource required for new projects and overestimate the resource endowment of firms. Malmendier and Tate (2005) state that overconfident CEOs tend to believe that their internal financing will be sufficient for new investment projects. Third, an overconfident CEO tends to underestimate the uncertainty in the firm's operating activities. Chatterjee and Hambrick (2007) suggest that overconfident CEOs believe that they hold more information than is the case, and that their own information is more valuable than external information.

Through these mechanisms, overconfident CEOs tend to overestimate the return on a project and underestimate the corresponding risk (Li and Tang, 2010). Since risk-taking plays a fundamental role in the survival and development of a firm (Shapira, 1995), the effect of CEO overconfidence on firms' risk-taking has attracted great academic interest. Empirical studies demonstrate that CEO overconfidence is positively associated with firms' risk-taking. For instance, Li and Tang (2010) use R&D expenditure as a proxy for a firm's risk-taking and observe a positive association with CEO overconfidence. Hirshleifer et al. (2012) also provide evidence that overconfidence is positively associated with risk-taking, which they measured with reference to total stock volatility. The research question in this study is to explore the associations between CEO overconfidence and firms' risk-taking before and after the financial crisis. Since CEOs are involved in firms' decision-making, only the firm-specific risk is expected to be associated with CEO overconfidence. Therefore, we measure a firm's risk-taking as idiosyncratic risk which is measured by the residual term in the Fama–French three-factor model. To check the robustness of the empirical results, we also measure firms' risk-taking with reference to overall stock return volatility, as done by Hirshleifer et al. (2012).

2.2.2 Personal experience affects belief

Earlier research on CEO overconfidence such as Malmendier and Tate (2005, 2008) has assumed that overconfidence is a stable trait and has not accounted for the fact that it may be altered by individual experiences. More recent studies have

argued that individual experience affects executive managers' beliefs and views about the future. For instance, Malmendier et al. (2011) find that macroeconomic shocks affect the risk-taking behaviours of those who experience them. Specifically, CEOs who were born during the Great Depression are found to be more averse to debt and reluctant to use external loans. Malmendier and Nagel (2011) show that individuals' willingness to take risks is affected by the macroeconomic history they have experienced over their lifetime. The authors document that individuals who have experienced low stock market returns are more reluctant to take risk, more pessimistic about future returns and are less likely to participate in the stock market. Giuliano and Spilimbergo (2013) document that individuals who grew up during a recession are more likely to believe that economic success in life depends more on luck than effort and tend to support more government redistribution. Malmendier and Nagel (2016), using microdata on inflation expectations from 1953 to 2009 in the US, present evidence that individuals' inflation experiences affect their inflation expectations

These studies imply that managerial traits are affected by the exogenous environment. Specifically, empirical studies show that CEO overconfidence can be developed by individuals' experiences. Individuals are subject to self-attribution bias, which means people tend to attribute the good outcome to their ability but attribute the bad outcome to bad luck. For instance, Billett and Qian (2008) suggest that CEOs who experienced a positive acquisition were more likely to make further acquisitions, but those proved to be disproportionately value-destructive. The authors argue that self-attribution causes individuals to learn to be overconfident rather than converging to an accurate self-assessment.

2.2.3 The availability heuristic

The view that CEO traits are influenced by their environment is consistent with the psychology literature on the availability heuristic. Tversky and Kahneman (1973) state that individuals' judgements are influenced by the ease with which relevant instances come to mind. For instance, people are likely to increase their subjective

evaluation of the probability that a nuclear war will start accidentally after they have just seen a vivid image related to nuclear war.

Additionally, Tversky and Kahneman (1974) suggest that people judge the probability of an event by how easy it is to recall the instances of similar events. Specific, more recent events associated with a vivid image are easier to recall. For instance, people's evaluation of the probability of a traffic accident rises temporarily after they have recently seen a car accident (Tversky and Kahneman, 1974). Barberis (2013) shows that the availability heuristic can explain why people underestimate the probability of extreme events such as a financial crisis. Before the 2008 financial crisis, the US security market experienced a long period of growth. It was hard for people to recall a financial crisis. The severe consequences of the 2008 financial crisis were disproportionately reported by media, and an enormous amount of coverage was given to events such as the failure of Lehman Brothers. As a result, individuals who experienced that financial crisis should subsequently have vivid associated images and the experience of that financial crisis should increase the degree to which CEO overconfidence induces risk-taking behaviour.

Though CEO overconfidence has been found to be positively correlated with firms' risk-taking, few studies have explored whether and how the effect of CEO overconfidence on firms' risk-taking varies over time. This chapter investigates how the effect of CEO overconfidence is influenced by economic shocks. This issue is essential because if CEO overconfidence is not unchanging and innate, then monitoring activities and compensation incentives should be adjusted according to CEOs' experiences. We choose to focus on the effect of the 2008 financial crisis as it is the largest shock in the US stock market in recent decades. According to the availability heuristic literature, more recent experience has more impact on individuals' expectations. Therefore, we believe that the 2008 financial crisis should have had a negative effect on CEOs' risk-taking behaviour. The hypothesis is stated as follows.

Hypothesis: Firms with overconfident CEOs tended to be less risk-taking after the 2008 financial crisis than before.

2.3 Data description and summary statistics

We begin with data on CEO characteristics for all CEO-firm years in the Standard & Poor's Execucomp database between 1992 (the earliest availability of the data) and 2014. We obtain accounting data from Standard & Poor's Compustat database. The stock price data are obtained from the Centre for Research in Security Price (CRSP) database. The data for the Fama–French three factors are downloaded from Kenneth French's website. After merging the data, the sample contains 3,347 firms with 42,048 observations. We exclude financial service firms (Standard Industrial Classification, hereafter SIC, codes between 4900 and 4999) and utility firms (SIC codes between 6000 and 6999). This procedure reduces our sample to 2,395 firms with 27,152 observations. Firms without valid managerial option information are excluded. Since we require that each firm has valid observations for at least 2 years, we exclude 122 firms which have only one year of data.

To prevent the influence of outliers, we winsorise the variables as follows. The variables market to book ratio, return on assets, property, plant, and equipment to asset ratio, stock return, sales, sales growth, cash holding and leverage ratio are winsorised at the 0.5% level. These percentages for winsorising are chosen not only to mitigate the influence of outliers but also to maximise the sample size. Finally, we exclude the missing observations. These criteria result in 2,048 firms with 16,144 observations in total. The data selection procedures are stated in Table 2.1. Following Hirshleifer et al. (2012), we standardised all continuous independent variables. That means we subtract the mean from the variable and divide the result by the standard deviation.

Table 2.1 Data selection procedures

	Observations	No. firms
All CEOs available both in Execucomp database from 1992 to 2014	42048	3347
Less: with SIC codes 4000-4999 and 6000-6999	14896	952
Subtotal	27152	2395
Less: without valid option data or moneyiness data	3962	116
Subtotal	23190	2279
Less: winsorise the independent variables	31	0
Subtotal	23159	2279
Less: firms with only 1 year of data	122	122
Subtotal	23037	2157
Less: Missing observations	6893	109
Subtotal	16144	2048

Notes: This table summarises the steps of sampling managerial compensation data from the Execucomp database and company data from the CRSP/Compustat merged database from 1992 to 2014. We exclude financial firms (SIC codes 6000–6999) and utilities firms (4000–4999).

Table 2.2 Summary statistics

	Mean	SD	Min	Q 0.25	Median	Q 0.75	Max	Range	Skew	Kurtosis
Idiosyncratic risk	0.80	0.60	-1.65	0.41	0.73	1.08	4.60	6.26	1.58	5.78
ocyear	0.25	0.44	0.00	0.00	0.00	1.00	1.00	1.00	1.13	-0.73
OC	0.39	0.49	0.00	0.00	0.00	1.00	1.00	1.00	0.47	-1.78
rt_ocyear	0.20	0.40	0.00	0.00	0.00	0.00	1.00	1.00	1.52	0.30
rt_OC	0.30	0.46	0.00	0.00	0.00	1.00	1.00	1.00	0.87	-1.24
ir_oc	0.20	0.40	0.00	0.00	0.00	0.00	1.00	1.00	1.53	0.34
ir_oc2	0.03	0.18	0.00	0.00	0.00	0.00	1.00	1.00	5.10	24.06
ir_rt	0.07	0.26	0.00	0.00	0.00	0.00	1.00	1.00	3.37	9.33
Log sales	7.19	1.65	2.35	6.10	7.15	8.27	11.58	9.23	0.06	0.08
Leverage	0.21	0.17	0.00	0.05	0.19	0.32	0.94	0.94	0.90	1.18
MB	0.00	1.01	-1.00	-0.58	-0.31	0.19	6.05	7.04	2.96	11.37
ROA	0.01	0.98	-6.74	-0.15	0.15	0.44	2.27	9.01	-3.12	16.03
Return	0.00	1.00	-1.69	-0.57	-0.13	0.33	6.66	8.35	2.67	13.06
Log PPE	6.27	1.86	1.51	4.98	6.24	7.51	10.98	9.48	0.06	-0.25
Cash	0.16	0.18	0.00	0.03	0.09	0.24	0.97	0.97	1.58	2.20
Sale growth	0.12	0.29	-0.59	-0.01	0.08	0.19	2.04	2.63	2.60	13.84
Log delta	6.84	1.60	0.42	5.73	6.82	7.94	13.44	13.02	0.03	0.00
Log vega	3.81	2.50	0.00	1.66	3.92	5.75	11.31	11.31	0.06	-1.01
Log tenure	1.75	0.85	0.00	1.10	1.79	2.40	3.66	3.66	-0.16	-0.46

Notes: The definitions of variables are stated in Table 2.3.

Table 2.3 Definitions of variables

Idiosyncratic risk	The annualised standard deviation of residuals from the regression of daily stocks return on the Fama–French three factors estimated over the fiscal year.
Total risk	The annualised standard deviation of daily stock returns on the Fama–French three factors model estimated over the fiscal year.
ocyear	Equal to 1 when the moneyiness of CEO's vested option is greater than 100% in that year; otherwise, 0. The detailed calculation of moneyiness of CEO option is in section 2.3.1.
OC	If a CEO postpones exercising vested options at or beyond 100% moneyiness at least twice in the sample period, this CEO is identified as 1 on the OC measure from the first time they exceed the threshold; otherwise, 0.
rt_ocyear	Equal to 1 when the moneyiness of CEO's vested option are in the top quintile among all CEOs in that year; otherwise, 0.
rt_OC	Equal to 1 when the moneyiness of CEO's vested option are in the top quintile among all CEOs at least twice; otherwise, 0.
ir_oc	Equal to 1 if a CEO whose firm's investment rate, which is defined as capital expenditures divided by beginning-of-year property, plant and equipment, is in the top quintile of the industry-adjusted investment rate; otherwise, 0.
ir_oc2	Equal to 1 if a CEO whose firm's investment rate, which is defined as capital expenditures divided by beginning-of-year property, plant and equipment, is in the top quintile of the industry-adjusted investment rate for two years; otherwise, 0.
ir_rt	Equal to 1 if the moneyiness of CEO vested option is more than 100% and the industry-adjusted investment ratio of the firm is in the top quintile for that year; otherwise, 0.
Sales	Total revenue of firm in millions of dollars. Calculated as variable revt in Compustat database.
Leverage	The book value of long-term debt plus the debt in current liabilities divided by total assets. Calculated as variables in Compustat database $(dlc + dlta)/at$.
MB	The market value of the firm divided by book value of assets. Calculated as variables $(prcc_f * csho + lt)/at$ in Compustat database.
ROA	Return on assets, the ratio of operating income before depreciation to book assets. Calculated as Compustat variables ni/at .
Stock return	The firm's annual stock return during the fiscal year.
PPE	The total value of property, plant and equipment in millions of dollars, calculated as variables (ppegt) in Compustat database.
Cash	The book value of cash and short-term investments divided by the book value of assets. Calculated as variables in Compustat database che/at .
Sales growth	The percentage increase in total revenue of firm (Compustat variable revt) from prior year to current year.
Delta	The dollar changes in CEO stock and option portfolio for a 1% change in stock price (in \$1000s).
Vega	The dollar changes in CEO option holdings for a 1% change in stock return volatility (in \$1000s).
Tenure	The number of years that the CEO has been CEO of the firm.

The descriptive statistics are presented in Table 2.2. Our final sample consists of firm-year observations from 1992 to 2014 for which the required data are available. The logarithm form of idiosyncratic risk has an approximately normal distribution. The mean and median of log idiosyncratic risk are 0.80 and 0.73 respectively. The mean and median of the logarithm form of sales is 7.19 and 7.15. Our sample consists of the listing firms and relatively small firms are not included in our samples. The mean of log delta is 6.84 and the median is 6.82. The mean of log vega is 3.81 and the median is 3.92. As Core and Guay (1999), Coles et al. (2006) and Armstrong and Vashishtha (2012) suggested that both original form of delta and vega are highly skewed, so we take the logarithm form of delta and vega. The definitions of variables are provided in Table 2.3. The detailed calculation procedures for delta and vega are stated in Appendix 2.A to this chapter. Following Hirshleifer et al. (2012), we normalise the control variables such as cash holdings, stock returns, return on assets, and sales growth rates. The correlation matrix of variables is stated in Table 2.13 in Appendix 2.B.

2.3.1 Overconfidence measured as absolute moneyness

Malmendier and Tate (2005) propose a measure of CEO overconfidence based on CEOs' beliefs reflected in their option holding decisions. This measure stems from CEOs' overexposure to idiosyncratic risk. According to Jensen and Meckling's (1976) agency theory, the interests of managers and those of shareholders are misaligned. Investors can diversify their investments by selling or purchasing stocks of different firms. CEOs invest their human capital in their own firms. Moreover, their personal wealth, in the form of stocks, options, or cash bonuses for example, is closely tied to the firm's performance. As CEOs cannot short-sell the stocks of their own firms, they are largely exposed to the idiosyncratic risk of their firms (Malmendier and Tate, 2005). Due to their overexposure to idiosyncratic risk, CEOs should exercise their in-the-money options early, to diversify their portfolios. For instance, Huddart and Lang (1996) document that managers tend to exercise options relatively early in their term, even when the underlying stock pays no dividends.

Meulbroek (2001) shows that managers are reluctant to hold equity-based compensation for a long time.

It is generally true that risk-averse and under-diversified CEOs tend to exercise their options early (Malmendier and Tate, 2005). Based on this idea, Malmendier and Tate (2005) propose a measure of CEOs' overconfidence that is based on their beliefs as reflected in their option-holding decisions. The authors state that overconfident CEOs tend to overestimate the future returns on and underestimate the risk of their investment projects. Therefore, overconfident CEOs are more likely to believe that their stocks are undervalued by the market and expect that their stock's price will increase under their management. Malmendier and Tate (2005) argue that, to maximise the value of their options with the expected future gains, overconfident CEOs are more likely to postpone exercising their options. The authors examine the first year in which all the packages with vesting paid out periods and then compute the percentage in-the-money for each option. Due to their risk aversion and under-diversification, CEOs should exercise options when the vesting period expires if the moneyness of those options exceeds a reasonable level. Hall and Murphy (2002) propose a theoretical guide to choosing a rational benchmark for the percentage in-the-money at or above which executives should exercise their vested option packages. Malmendier and Tate (2005) propose that a rational threshold for the percentage in-the-money should be 67%. The authors identify an overconfident CEO as one who, at least twice, holds options which are valued above the threshold. From the first instance when a CEO holds options above the threshold and onward, the CEO is categorised as overconfident. This method identifies those CEOs who habitually postpone exercising their options. In other words, it captures the permanent rather than transitory effect of CEO overconfidence.

Malmendier and Tate's (2005) measure of overconfidence is limited by the dataset, because it is difficult to obtain detailed data for CEO options holdings. Campbell et al. (2011) provide a modified method of calibrating CEOs' overconfidence based on stock option holding and exercising behaviours. This chapter follows Campbell et al.'s (2011) approach to calculate option moneyness. Since the dataset from Execucomp does not contain specific

exercise prices for each option granted, we need to estimate the average exercise price for the aggregated options. Core and Guay (2002) propose an approximation approach of estimating the exercise prices of aggregated options. According to their approach, the realisable value per option is computed as the total value of unexercised exercisable ($OPT_UNEX_EXER_EST_VAL$) divided by the number of unexercised exercisable options ($OPT_UNEX_EXER_NUM$). Then, we subtract the realisable value per option from the stock price at the fiscal year end ($PRCCF$). We focus on the unexercised exercisable options as we are interested in the options which CEOs can exercise but voluntarily postpone exercising. The procedure yields an estimation of the average exercise price of the options. The average percentage in-the-money is the realisable value per option divided by the average exercise price for aggregated options. Malmendier and Tate (2005) use 67% as the threshold for the option moneyness, Campbell et al. (2011) use 30% and 100% as two thresholds to classify CEO overconfidence into three categories: low, moderate and high. Those authors in fact test different upper cut-off points, namely 100%, 150% and 250%. Given that their three categories beyond a 100% moneyness cut-off point appear to give qualitatively the same results, the authors combine the three categories into one overconfidence measure, which is holding options at or above 100% moneyness. Additionally, Campbell et al. (2011) document that only high-overconfident CEOs are likely to exhibit overconfident behaviours. This chapter also applies 100% moneyness as the threshold for identifying CEO overconfidence.

The first overconfidence measure, *OC*, is identified as follows. If an overconfident CEO postpones exercising vested options at or beyond 100% moneyness at least twice in the sample period, we identify this CEO as 1 on the *OC* measure from the first time they exceed the threshold. For those CEOs with information about options but who do not meet the *OC* measure standard, we classify them as 0 on the *OC* measure. We exclude those CEOs who do not have information on option holdings.

Malmendier and Tate (2005, 2008) and Campbell et al. (2011) assume that managerial overconfidence is a persistent trait (i.e. it remains stable over time). If a CEO is classified as overconfident on this measure, he or she is identified

as overconfident for the rest of the sample period. This procedure is consistent with Landier and Thesmar (2009) and Ben-David et al. (2013).

Our second measure of CEO overconfidence is based on the moneyness of CEO options but with a different assumption. Prior studies such as Malmendier et al. (2011), Giuliano and Spilimbergo (2013) and Malmendier and Nagel (2016) suggest that individuals' financial beliefs can be influenced by their personal experience. Motivated by this view, our second measure of managerial overconfidence allows it to vary over time. The overconfidence measure *ocyear* is defined as follows. First, we calculate the moneyness of unexercised exercisable executive options following the same approach used for the *OC* measure. That is, we define an overconfident CEO as one who holds executive options that are at least 100% in-the-money for each year. This measure allows CEO overconfidence to vary over time rather than be fixed during the whole sample period. In other words, the *ocyear* measure allows the situation where a non-overconfident CEO can become overconfident from one year to another, and vice versa. Unlike the *OC* measure, the *ocyear* measure captures temporary overconfident behaviours rather than a long-lasting personal trait. The mean values of *OC* and *ocyear* across different years are presented in Table 2.10 in Appendix 2.B to this chapter.

2.3.2 Overconfidence measures based on relative moneyness

Though the absolute moneyness measures *OC* and *ocyear* provide stable measures for CEO overconfidence in ordinary times, there is a potential concern: the value of executive option-based compensation which depends on stock prices will be influenced to a large extent by variations in the stock market. When the stock market fluctuates considerably, an absolute measure may run the risk of under-identifying overconfidence when the stock market drops systemically. For instance, during the 2008 financial crisis, when the US stock market experienced a large decline, the mean values of managerial option moneyness for all CEOs decreased.

To mitigate the risk of under-identifying, we propose a new overconfidence measure, based on a ranking of CEO option moneyiness rather than the absolute option moneyiness. This relative overconfidence measure, rt_oc , is calculated as follows. We first calculate the percentage in-the-money of CEOs' options and sort the samples on the moneyiness for each year. For each year, we identify the overconfident CEOs as those who hold unexercised exercisable options which are in the top quintile for that year, otherwise, the CEOs are denoted as non-overconfident. Like the permanent requirement applied with the OC measure, we also define an overconfidence measure, rt_OC , which captures those CEOs who 'habitually' hold executive options which are in the top quintile at least twice. The rt_OC measure avoids identifying CEOs who postpone exercising their options just by chance. We use both rt_oc and rt_OC as measures for overconfidence to check the validity of our empirical results. The means of rt_OC and rt_oc across different years are presented in Table 2.11 in Appendix 2.B to this chapter.

2.3.3 Control variables

We include the following control variables, as used in prior studies: firm size, book leverage ratio, market to book ratio, return on assets (ROA), cash holding, CEO delta and CEO vega.

Firm size. Core and Guay (1999), Guay (1999) and Low (2009), among others, show that a firm's risk-taking is negatively associated with firm size. We therefore incorporate firm size as a control variable. It is measured as the natural logarithm of the firm's total annual revenue.

Book leverage ratio. This is the ratio of long-term debt to total assets. Leland (1998) shows that a high leverage ratio motivates executives to transfer wealth from bondholders to shareholders. Hirshleifer et al. (2012) find a positive relationship between leverage ratio and a firm's risk-taking.

Investment opportunities. Guay (1999) argues that managers who have larger investment opportunities tend to be more risk-taking than those managers who

have smaller investment opportunities. To control for firms' investment opportunities, we include market to book ratio, the net investment in property, plant and equipment, and the sales growth rate as control variables. Following Armstrong and Vashishtha (2012) and Hirshleifer et al. (2012), we predict that firm risk-taking is positively associated with these three variables.

Return on assets. Armstrong and Vashishtha (2012) and Hirshleifer et al. (2012) document that firms with poor past performance such as return on assets tend to take more risks. Therefore, we include firms' previous stock return and return on assets (ROA) as proxies for firms' previous performance.

Cash holding. Opler et al. (1999) argue that managers who have access to more cash are more likely to investment in risky projects. Opler et al. (1999) and Hirshleifer et al. (2012) both find that firms with large cash holdings tend to be more risk-taking.

CEO tenure. To capture the impact of CEOs' individual characteristics, we include their length of CEO tenure as a proxy for their risk aversion following Hirshleifer et al. (2012).

CEO delta and vega. Following Hirshleifer et al. (2012), we include CEO delta and vega as control variables. We derive CEO delta and vega using the Black and Scholes (1973) option pricing model as modified by Merton (1973). CEO delta is the dollar change in wealth associated with a 1% change in the firm's stock price (in \$1000s). CEO delta captures the incentive to align the interests of shareholders and those of CEOs provided by the CEO's compensation package. CEO vega is the dollar change in wealth associated with a 1% change in the standard deviation of the firm's returns (in \$1000s). CEO vega captures the incentive to take risks provided by the CEO's compensation package.

Postcrisis is a dummy to identify the post financial crisis period. As the variables in the are recorded in fiscal year, so fiscal year 2010 refers to 2009 July to 2010 June. Therefore, *Postcrisis* equals to 1 for the year from 2010 and onward; otherwise, equals to 0.

2.4 Empirical results

Prior studies like Hirshleifer et al. (2012) use the volatility of the firm's stock return as a proxy for total risk-taking by the firm, which is measured by the annualised standard deviation of the residuals from the regression of daily stock return from the Fama–French three-factor model. We decompose total risk into its idiosyncratic and systematic components using Fama and French's (1993) method, as follows:

$$r_{j,t} = \beta_{0,j} + \beta_{1,j}r_{MKT,t} + \beta_{2,j}r_{SMB,t} + \beta_{3,j}r_{HML,t} + e_{j,t} \quad (2.1)$$

The idiosyncratic risk component is the annualised standard deviation of the residual $e_{j,t}$.

We follow Hirshleifer et al. (2012)'s model, which applies OLS regression based on the following equation:

$$\begin{aligned} idio_{risk_{i,t}} = & OC_{i,t-1} + OC_{i,t-1} * Post_{crisis} + Post_{crisis} + controls_{i,t-1} \\ & + Industries + Year \end{aligned} \quad (2.2)$$

where OC denotes the measure of CEOs' overconfidence and $Post_{crisis}$ denotes a year dummy variable for years after the 2008 financial crisis. Besides the control variables discussed above, we also include a year fixed effect and an industry fixed effect. The standard errors are clustered at the firm level.

The empirical results of OLS regressions are presented in Table 2.4. The coefficient on the *ocyear* term is 0.064, which suggests that CEO overconfidence is positively associated with idiosyncratic risk. This result implies that firms with overconfident CEOs tend to take more risk than firms with non-overconfident CEOs during the common period. The *ocyear_postcrisis* is the interaction term of post-financial crisis and CEO overconfidence. This term captures the impact of overconfident CEOs on the firm's risk-taking during the post-crisis period. The coefficient on *ocyear_postcrisis* is -0.059, which suggests that during the post-crisis period overconfident CEOs become more cautious in terms of risk-taking. These results support the availability heuristic argument. The experience of the

financial crisis is a shock for overconfident CEOs. Before the crisis, overconfident CEOs tend to underestimate risk whereas after the crisis they behave more cautiously. Non-overconfident CEOs tend to be moderate in their risk-taking before the crisis. Thus, the margin for the non-overconfident CEOs to become more cautious is limited. This result implies that the financial crisis had a negative effect on overconfident CEOs' risk-taking behaviour. Therefore, during the post-crisis period, the overconfident CEOs' risk-taking behaviour become more modest than during pre-crisis period.

Table 2.4 OLS for the absolute option moneyness measure of overconfidence

	<i>Dependent variable: Idiosyncratic risk</i>			
	(1)	(2)	(3)	(4)
ocyear	0.064*** (-0.01)	0.052*** (-0.01)		
ocyear_postcrisis	-0.059*** (-0.018)	-0.054*** (-0.018)		
OC			0.035*** (-0.009)	0.030*** (-0.009)
OC_postcrisis			-0.072*** (-0.015)	-0.054*** (-0.015)
Postcrisis	-0.062 (-0.042)	0.038 (-0.043)	-0.054 (-0.042)	0.041 (-0.043)
Log sales	-0.074*** (-0.005)	-0.046*** (-0.005)	-0.073*** (-0.005)	-0.046*** (-0.005)
Leverage	0.086*** (-0.022)	0.096*** (-0.022)	0.081*** (-0.022)	0.092*** (-0.022)
MB	-0.038*** (-0.004)	-0.023*** (-0.005)	-0.033*** (-0.004)	-0.020*** (-0.005)
ROA	-0.132*** (-0.004)	-0.114*** (-0.004)	-0.131*** (-0.004)	-0.113*** (-0.004)
Stock return	0.009** (-0.004)	0.009** (-0.004)	0.011*** (-0.004)	0.011*** (-0.004)
PPE	-0.065*** (-0.004)	-0.046*** (-0.004)	-0.065*** (-0.004)	-0.046*** (-0.004)
Cash	0.198*** (-0.025)	0.230*** (-0.025)	0.192*** (-0.025)	0.225*** (-0.025)
Sales growth	0.065*** (-0.013)	0.043*** (-0.013)	0.071*** (-0.013)	0.048*** (-0.013)
Log delta		-0.004 (-0.004)		-0.003 (-0.004)
Log vega		-0.060*** (-0.002)		-0.060*** (-0.002)
Log tenure		0.015*** (-0.004)		0.014*** (-0.004)
Industry fixed effect	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes
Observations	16,144	15,306	16,144	15,306
Adjusted R ²	0.471	0.499	0.470	0.499

Notes: ocyear equals to 1 when the moneyness of CEO's vested option is greater than 100% in that year; otherwise, 0. OC equals to 1 if a CEO postpones exercising vested options at or beyond 100% moneyness at least twice in the sample period, the CEO is identified as 1 on the OC measure from the first time they exceed the threshold; otherwise, 0. Postcrisis is a dummy for the year from 2010 and onward. Log sales is the logarithm of sales revenue. Leverage denotes the book value of long-term debt plus the debt in current liabilities divided by total assets. ROA denotes the return on assets, the ratio of operating income before depreciation to book assets. Stock return is the firm's annual stock return during the fiscal year. Sales growth is the percentage increase in sales from prior year to current year. PPE is the property, plant and equipment divided by total assets. Cash is the book value of cash and short-term investments divided by book value of assets. Log delta is the dollars change in CEO stock and option portfolio for a 1% change in stock price (in \$1000s). Log vega is the logarithm form of the dollars change in CEO option holdings for a 1% change in stock return volatility (in \$1000s). Log tenure is the logarithm form of the number of years that the CEO has been CEO of the firm. Except log tenure, all independent variables are lagged by one year. *p<0.1; **p<0.05; ***p<0.01.

The coefficient on log sales is -0.074. It suggests that larger firms tend to take less risk. The coefficient on the book leverage ratio is 0.086, which suggests higher book leverage results in more risk-taking. The coefficient of ROA is -0.132. This result implies that, for those firms which already have very high profitability (i.e. higher ROA) are reluctant to take further risk as the marginal return of undertaking more innovative projects is lower than for firms with low profitability. Cash holding is positively associated with risk-taking. CEOs in firms which hold a large amount of cash are more likely to invest in innovative projects. Sales growth is also positively associated with risk-taking. These results suggest that overconfident CEOs are more likely to explore a risky investment project when firms have more cash and high growth opportunities. In column 2 in Table 2.4, we control for the delta and vega of CEOs' compensation and CEO tenure. The coefficients on *ocyear* and *ocyear_postcrisis* are 0.052 and -0.054 respectively. We find that CEOs with higher CEO vega are negatively associated with lower stock return volatility, possibly owing to the endogeneity of vega (Coles et al., 2006; Low, 2009). The results of other control variables are consistent with those in column 1.

We apply the *OC* measure which captures the persistent overconfidence effect in columns 3 and 4. In column 3, the coefficient on *OC* is 0.035 and the coefficient on *OC_postcrisis* is -0.072. This is consistent with the results for the *ocyear* measure. The financial crisis negatively influences the risk-taking of firms which have overconfident CEOs. In column 4, after controlling for CEO delta, CEO vega and CEO tenure, the empirical results remain consistent with the results with the *ocyear* measures.

Table 2.5 OLS for the relative option moneyness measure of overconfidence

	<i>Dependent variable: Idiosyncratic risk:</i>			
	(1)	(2)	(3)	(4)
rt_ocyear	0.085*** (-0.011)	0.068*** (-0.011)		
rt_ocyear_postcrisis	-0.074*** (-0.019)	-0.069*** (-0.019)		
rt_OC			0.049*** (-0.009)	0.042*** (-0.01)
rt_OC_postcrisis			-0.075*** (-0.016)	-0.060*** (-0.016)
Postcrisis	-0.068 (-0.042)	0.032 (-0.043)	-0.063 (-0.042)	0.036 (-0.043)
Log Sales	-0.074*** (-0.005)	-0.047*** (-0.005)	-0.074*** (-0.005)	-0.046*** (-0.005)
Leverage	0.085*** (-0.022)	0.095*** (-0.022)	0.082*** (-0.022)	0.093*** (-0.022)
MB	-0.040*** (-0.004)	-0.025*** (-0.005)	-0.035*** (-0.004)	-0.021*** (-0.005)
ROA	-0.132*** (-0.004)	-0.114*** (-0.004)	-0.131*** (-0.004)	-0.113*** (-0.004)
Stock return	0.009** (-0.004)	0.009*** (-0.004)	0.011*** (-0.004)	0.011*** (-0.004)
PPE	-0.064*** (-0.004)	-0.045*** (-0.004)	-0.065*** (-0.004)	-0.046*** (-0.004)
Cash	0.198*** (-0.025)	0.231*** (-0.025)	0.190*** (-0.025)	0.224*** (-0.025)
Sales growth	0.065*** (-0.013)	0.043*** (-0.013)	0.070*** (-0.013)	0.047*** (-0.013)
Log delta		-0.004 (-0.004)		-0.004 (-0.004)
Log vega		-0.060*** (-0.002)		-0.060*** (-0.002)
Log tenure		0.015*** (-0.004)		0.013*** (-0.004)
Industry fixed effect	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes
Observations	16,144	15,306	16,144	15,306
Adjusted R ²	0.471	0.500	0.471	0.499

Notes: rt_ocyear equals to 1 when the moneyness of CEO's vested option are in the top quintile among all CEOs in that year; otherwise, 0. rt_OC equals to 1 when the moneyness of CEO's vested option are in the top quintile among all CEOs at least twice; otherwise, 0. Postcrisis is a dummy for the year from 2010 and onward. Log sales is the logarithm of sales revenue. Leverage denotes the book value of long-term debt plus the debt in current liabilities divided by total assets. ROA denotes the return on assets, the ratio of operating income before depreciation to book assets. Stock return is the firm's annual stock return during the fiscal year. Sales growth is the percentage increase in sales from year $t-1$ to year t . PPE is the property, plant, and equipment divided by total assets. Cash is the book value of cash and short-term investments divided by book value of assets. Log delta is the dollars change in CEO stock and option portfolio for a 1% change in stock price (in \$1000s). Log vega is the logarithm form of the dollars change in CEO option holdings for a 1% change in stock return volatility (in \$1000s). Log tenure is the logarithm form of the number of years that the CEO has been CEO of the firm. Except the tenure, all independent variables are lagged by one year. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

We report the empirical results applying the relative overconfidence measure *rt_ocyear* in Table 2.5. The control variables are consistent with the absolute option moneyness measures. In column 1, the coefficient on *rt_ocyear* is 0.085, suggesting that the CEOs identified by the *rt_ocyear* measure are positively associated with risk-taking. The term *rt_ocyear_postcrisis* is an interaction term of *rt_ocyear* and *postcrisis*. The coefficient on *rt_ocyear_postcrisis* is -0.074, suggesting that CEO overconfidence after the crisis has a negative impact on firms' risk-taking. These results are consistent with the results with the absolute overconfidence measure: CEO overconfidence has a positive relation to firm risk-taking, while the financial crisis has a negative impact on it. The overall effect of CEOs' overconfidence during the post-crisis period is still positive. As for the control variables, the signs of the coefficients are the same as with the absolute overconfidence measures. In column 2, the main results remain consistent after controlling for CEO delta, CEO vega and CEO tenure. The coefficients on *rt_ocyear* and *rt_ocyear_postcrisis* are 0.068 and -0.069, respectively. In columns 3 and 4, we use the *rt_OC* measure, which captures those CEOs who persistently hold their options at or beyond 100% moneyness twice. In column 3, the coefficient on *rt_OC* is 0.049, suggesting a positive relation between CEO overconfidence and the firm's risk-taking. The interaction term *rt_OC_postcrisis* is -0.075, implying that overconfident CEOs tended to be more cautious after the financial crisis. In column 4, after controlling for CEO delta, CEO vega and CEO tenure, the coefficients on *rt_OC* and *rt_OC_postcrisis* are 0.042 and -0.06, respectively.

Our hypothesis is thus supported by both the relative overconfidence measures and the absolute overconfidence measures. The 2008 financial crisis as a shock had a considerable impact on overconfident CEOs' beliefs. After the crisis, overconfident CEOs adjust their behaviour and become more cautious in term of firms' risk-taking behaviours.

2.4.1 Robustness analysis

To validate the above empirical results, we apply three measures of overconfidence and repeat the OLS regressions to check whether our argument still holds.

Following Campbell et al. (2011), we construct two overconfidence measures based on relative levels of firm investment. Prior studies such as Malmendier and Tate (2005) have demonstrated that CEO overconfidence is associated with firms' investment decision-making both empirically and theoretically.

As pointed by Campbell et al. (2011), the linkage between CEO overconfidence and a firm's investment level suggests that firm investment may contain information about CEO overconfidence. To construct the overconfidence measure based on investment level, we firstly calculate an industry-adjusted investment rate and sort all firms on that rate. The investment rate is defined as capital expenditures divided by beginning-of-year property, plant and equipment. The overconfidence measure *ir_oc2* is defined as a CEO whose firm is in the top quintile of the industry-adjusted investment rate for two years. The two-year requirement is imposed because the investment is not smooth over time. This requirement reduces the risk of identifying firms which by chance bunch investment within a particular year. The empirical results are qualitatively the same when relaxing the two-year requirement. To check the validation of firm investment level, we construct an overconfidence measure *ir_oc* based on a single year of industry-adjusted investment.

The investment-based overconfidence measures are subject to a concern. Different from the option-based overconfidence measure, the investment-based measures do not directly depend on information on managerial compensation and incentives (Campbell et al., 2011). Since a firm's industry-adjusted investment level depends on many factors which may influence the firm risk-taking, we need to interpret the results for the investment-based measure with caution.

Table 2.6 OLS regressions with an investment measure of overconfidence

	<i>Dependent variable: Idiosyncratic risk</i>					
	(1)	(2)	(3)	(4)	(5)	(6)
ir_oc	0.127*** (-0.011)	0.100*** (-0.011)				
ir_oc_postcrisis	-0.066*** (-0.019)	-0.036* (-0.019)				
ir_oc2			0.128*** (-0.021)	0.104*** (-0.021)		
ir_oc2_postcrisis			-0.095** (-0.039)	-0.063* (-0.038)		
ir_rt					0.163*** (-0.017)	0.130*** (-0.017)
ir_rt_postcrisis					-0.091*** (-0.029)	-0.062** (-0.029)
Postcrisis	-0.201*** (-0.027)	-0.112*** (-0.028)	-0.078* (-0.042)	0.023 (-0.043)	-0.202*** (-0.027)	-0.110*** (-0.028)
Log sales	-0.077*** (-0.005)	-0.047*** (-0.005)	-0.073*** (-0.005)	-0.046*** (-0.005)	-0.075*** (-0.005)	-0.046*** (-0.005)
Leverage	0.084*** (-0.022)	0.094*** (-0.022)	0.085*** (-0.022)	0.095*** (-0.022)	0.081*** (-0.022)	0.092*** (-0.022)
MB	-0.039*** (-0.004)	-0.023*** (-0.005)	-0.032*** (-0.004)	-0.018*** (-0.005)	-0.041*** (-0.004)	-0.026*** (-0.005)
ROA	-0.131*** (-0.004)	-0.112*** (-0.004)	-0.130*** (-0.004)	-0.112*** (-0.004)	-0.131*** (-0.004)	-0.112*** (-0.004)
Stock return	0.016*** (-0.004)	0.015*** (-0.004)	0.012*** (-0.004)	0.012*** (-0.004)	0.011*** (-0.004)	0.011*** (-0.004)
PPE	-0.057*** (-0.004)	-0.040*** (-0.004)	-0.066*** (-0.004)	-0.046*** (-0.004)	-0.061*** (-0.004)	-0.043*** (-0.004)
Cash	0.180*** (-0.025)	0.216*** (-0.025)	0.192*** (-0.025)	0.224*** (-0.025)	0.187*** (-0.025)	0.220*** (-0.025)
Sales growth	0.036*** (-0.013)	0.02 (-0.013)	0.073*** (-0.013)	0.049*** (-0.013)	0.051*** (-0.013)	0.031** (-0.013)
Log delta		-0.007* (-0.004)		-0.003 (-0.004)		-0.005 (-0.004)
Log vega		-0.059*** (-0.002)		-0.060*** (-0.002)		-0.060*** (-0.002)
Log tenure		0.019*** (-0.004)		0.016*** (-0.004)		0.017*** (-0.004)
Industry fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Observations	15,626	14,830	16,144	15,306	15,626	14,830
Adjusted R ²	0.469	0.498	0.471	0.499	0.468	0.497

Notes: ir_oc equals to 1 if a CEO whose firm's investment rate, which is defined as capital expenditures divided by beginning-of-year property, plant and equipment, is in the top quintile of the industry-adjusted investment rate; otherwise, 0. ir_oc2 equal to 1 if a CEO whose firm's investment rate, which is defined as capital expenditures divided by beginning-of-year property, plant and equipment, is in the top quintile of the industry-adjusted investment rate for two years; otherwise, 0. ir_rt equals to 1 if the moneyiness of CEO vested option is more than 100% and the industry-adjusted investment ratio of the firm is in the top quintile for that year; otherwise, 0. Other variables are the same as in Table 2.5. *p<0.1; **p<0.05; ***p<0.01

In Table 2.6, we use *ir_oc* as the independent variable and *ir_oc_postcrisis* is the interaction term of overconfidence and post-crisis. In column 1, the coefficient on *ir_oc* is 0.127. This confirms the positive relation between firm risk and CEO overconfidence. The coefficient on the interaction term *ir_oc_postcrisis* is -0.066. This is consistent with the results on the effect of the financial crisis: the risk-inducing effect of overconfidence is weaker during the post-crisis period. In column 2, controlling for CEO delta, CEO vega and CEO tenure, the coefficients on *ir_oc* and *ir_oc_postcrisis* are 0.1 and -0.036. In column 3, we use *ir_oc2* as the overconfidence measure. As Hirshleifer et al. (2012) state that firm investment can be lumpy, we require firm investment to be at the top quintile twice. In column 4, the coefficient on *ir_oc2* is 0.104. The interaction term between overconfidence and post-crisis is *ir_oc2_postcrisis*, which has a coefficient of -0.063.

We construct the final overconfidence measure by combining both CEO option holding behaviour and firm investment level. The overconfidence measure *ir_rt* requires two conditions to be met at the same time. The two conditions are: the vested option is in the moneyness more than 100% and the industry-adjusted investment ratio of the firm is in the top quintile for year *t*. In column 5, the coefficient on *ir_rt* is 0.163 and the coefficient on the interaction term *ir_rt_postcrisis* is -0.091. The overall overconfidence effect during the post-crisis period is positive, as the positive effect dominates the negative effect. As shown in column 6, the empirical results remain qualitatively the same when we incorporate CEO delta, CEO vega and CEO tenure as controls for the executives' individual characteristics.

To further check the robustness of the empirical results, we redo the regressions by replacing the dependent variable with firms' total risk, which is measured by the standard deviation of stock return. The empirical results remain qualitatively the same as for those using idiosyncratic risk. The results are reported in the Table 2.7, Table 2.8 and Table 2.9. We also applied instrumental variable approaches to check the robustness of the empirical results. The results are available on request.

2.5 Conclusions

Prior studies demonstrate that CEO overconfidence has a positive relation to firm risk-taking, since overconfident CEOs tend to overestimate the expected return from investment projects and underestimate the risk. Few studies explore the question of whether overconfident CEOs adjust their beliefs after experiencing a financial crisis. This chapter sheds light on this question by investigating the overconfident CEOs' risk-taking behaviours before and after the 2008 financial crisis. We construct a measure of CEOs' overconfidence based on whether they retain in-the-money vested options. We also construct a relative overconfidence measure based on the cross-sectional ranks of the moneyness of CEOs' retained options. The empirical results show that the overconfident CEOs are positively associated with firms' risk-taking. After the 2008 financial crisis, overconfident CEOs tended to be more cautious in term of risk-taking. These results remain consistent with both absolute moneyness measures and relative moneyness measures. To check the robustness of these results, we apply the firms' investment level as a proxy for CEO overconfidence. We also construct an overconfidence measure considering both CEOs' option-holding behaviours and the firms' investment level. The empirical results are qualitatively the same with these alternative overconfidence measures.

Overall, this chapter shows that the association between firms' risk-taking behaviours and CEO overconfidence is time-varying. Specifically, the association is influenced by a big financial shock such as the 2008 financial crisis. This study contributes to the literature by showing that overconfident CEOs' risk-taking behaviours can be influenced by a financial crisis. Moreover, this chapter suggests that past experience should be considered when analysing CEOs' overconfidence biases.

Table 2.7 OLS regressions based on the option measure of overconfidence

	<i>Dependent variable: Total risk</i>			
	(1)	(2)	(3)	(4)
ocyear	0.074*** (-0.009)	0.057*** (-0.009)		
ocyear_postcrisis	-0.080*** (-0.017)	-0.074*** (-0.017)		
OC			0.045*** (-0.008)	0.034*** (-0.008)
OC_postcrisis			-0.084*** (-0.014)	-0.066*** (-0.014)
Postcrisis	0.062 (-0.04)	0.159*** (-0.04)	0.067* (-0.04)	0.161*** (-0.04)
Log sales	-0.062*** (-0.004)	-0.036*** (-0.004)	-0.061*** (-0.004)	-0.036*** (-0.004)
Leverage	0.041** (-0.02)	0.052** (-0.02)	0.035* (-0.02)	0.048** (-0.02)
MB	-0.028*** (-0.004)	-0.016*** (-0.004)	-0.023*** (-0.004)	-0.013*** (-0.004)
ROA	-0.126*** (-0.004)	-0.107*** (-0.004)	-0.125*** (-0.004)	-0.106*** (-0.004)
Stock return	0.009*** (-0.003)	0.010*** (-0.003)	0.012*** (-0.003)	0.012*** (-0.003)
PPE	-0.054*** (-0.004)	-0.035*** (-0.004)	-0.054*** (-0.004)	-0.035*** (-0.004)
Cash	0.190*** (-0.023)	0.211*** (-0.023)	0.183*** (-0.023)	0.205*** (-0.023)
Sales growth	0.062*** (-0.012)	0.036*** (-0.012)	0.069*** (-0.012)	0.041*** (-0.012)
Log delta		0.004 (-0.003)		0.005 (-0.003)
Log vega		-0.064*** (-0.002)		-0.065*** (-0.002)
Log tenure		0.018*** (-0.004)		0.017*** (-0.004)
Industry fixed effect	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes
Observations	16,144	15,306	16,144	15,306
Adjusted R ²	0.484	0.518	0.483	0.518

Notes: The variables are defined as the same as in Table 2.4. Except log tenure, all independent variables are lagged by one year. p<0.1; **p<0.05; ***p<0.01

Table 2.8 OLS for the relative moneyness measure of overconfidence

	<i>Dependent variable: Total risk</i>			
	(1)	(2)	(3)	(4)
rt_ocyear	0.094*** (-0.01)	0.072*** (-0.01)		
rt_ocyear_postcrisis	-0.097*** (-0.018)	-0.090*** (-0.017)		
rt_OC			0.056*** (-0.009)	0.042*** (-0.009)
rt_OC_postcrisis			-0.093*** (-0.015)	-0.077*** (-0.014)
Postcrisis	0.053 (-0.039)	0.150*** (-0.04)	0.06 (-0.039)	0.156*** (-0.04)
Log sales	-0.062*** (-0.004)	-0.036*** (-0.004)	-0.062*** (-0.004)	-0.036*** (-0.004)
Leverage	0.040* (-0.02)	0.051** (-0.02)	0.037* (-0.02)	0.048** (-0.02)
MB	-0.030*** (-0.004)	-0.017*** (-0.004)	-0.024*** (-0.004)	-0.013*** (-0.004)
ROA	-0.126*** (-0.004)	-0.107*** (-0.004)	-0.125*** (-0.004)	-0.106*** (-0.004)
Stock return	0.009*** (-0.003)	0.010*** (-0.003)	0.012*** (-0.003)	0.012*** (-0.003)
PPE	-0.053*** (-0.004)	-0.035*** (-0.004)	-0.055*** (-0.004)	-0.035*** (-0.004)
Cash	0.190*** (-0.023)	0.211*** (-0.023)	0.181*** (-0.023)	0.204*** (-0.023)
Sales growth	0.062*** (-0.012)	0.036*** (-0.012)	0.068*** (-0.012)	0.041*** (-0.012)
Log delta		0.004 (-0.003)		0.004 (-0.003)
Log vega		-0.064*** (-0.002)		-0.064*** (-0.002)
Log tenure		0.018*** (-0.004)		0.017*** (-0.004)
Industry fixed effect	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes
Observations	16,144	15,306	16,144	15,306
Adjusted R ²	0.484	0.519	0.483	0.518

Notes: The variables are defined as the same as in Table 2.5. Except log tenure, all independent variables are lagged by one year. p<0.1; **p<0.05; ***p<0.01*

Table 2.9 OLS regressions for the investment measure of overconfidence

	<i>Dependent variable: Total risk</i>					
	(1)	(2)	(3)	(4)	(5)	(6)
ir_oc	0.126*** (-0.01)	0.094*** (-0.01)				
ir_oc_postcrisis	-0.103*** (-0.018)	-0.069*** (-0.017)				
ir_oc2_dummy			0.121*** (-0.02)	0.092*** (-0.02)		
ir_oc2_postcrisis			-0.110*** (-0.036)	-0.075** (-0.035)		
inter_ir_rt					0.172*** (-0.016)	0.131*** (-0.016)
inter_ir_rt_postcrisis					-0.134*** (-0.027)	-0.102*** (-0.027)
Postcrisis	-0.086*** (-0.026)	0.001 (-0.026)	0.04 (-0.039)	0.138*** (-0.04)	-0.092*** (-0.025)	-0.002 (-0.026)
Log sales	-0.065*** (-0.004)	-0.037*** (-0.004)	-0.061*** (-0.004)	-0.035*** (-0.004)	-0.063*** (-0.004)	-0.036*** (-0.004)
Leverage	0.034* (-0.021)	0.046** (-0.021)	0.039* (-0.02)	0.050** (-0.02)	0.032 (-0.021)	0.045** (-0.021)
MB	-0.028*** (-0.004)	-0.015*** (-0.004)	-0.021*** (-0.004)	-0.011*** (-0.004)	-0.030*** (-0.004)	-0.018*** (-0.004)
ROA	-0.124*** (-0.004)	-0.105*** (-0.004)	-0.124*** (-0.004)	-0.106*** (-0.004)	-0.124*** (-0.004)	-0.105*** (-0.004)
Stock return	0.016*** (-0.003)	0.015*** (-0.003)	0.013*** (-0.003)	0.013*** (-0.003)	0.012*** (-0.003)	0.012*** (-0.003)
PPE	-0.048*** (-0.004)	-0.030*** (-0.004)	-0.055*** (-0.004)	-0.036*** (-0.004)	-0.051*** (-0.004)	-0.033*** (-0.004)
Cash	0.168*** (-0.023)	0.194*** (-0.024)	0.184*** (-0.023)	0.205*** (-0.023)	0.175*** (-0.023)	0.198*** (-0.024)
Sales growth	0.037*** (-0.012)	0.017 (-0.012)	0.071*** (-0.012)	0.042*** (-0.012)	0.049*** (-0.012)	0.025** (-0.012)
Log delta		0.002 (-0.003)		0.005 (-0.003)		0.003 (-0.003)
Log vega		-0.064*** (-0.002)		-0.065*** (-0.002)		-0.064*** (-0.002)
Log tenure		0.021*** (-0.004)		0.019*** (-0.004)		0.020*** (-0.004)
Industry fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Observations	15,626	14,830	16,144	15,306	15,626	14,830
Adjusted R ²	0.481	0.516	0.483	0.518	0.480	0.515

Notes: The variables are defined as the same as in Table 2.6. Except the tenure, all independent variables are lagged by one year. p<0.1; **p<0.05; ***p<0.01**

APPENDIX 2.A

We derive CEO stock option delta and vega using the Black and Scholes (1973) option pricing model as modified by Merton (1973). The Black–Scholes model requires the following variables to estimate the delta and vega values for CEOs' stock options.

CEO delta is the dollar change in wealth associated with a 1% change in the firm's stock price (in \$1000s).

CEO vega is the dollar change in wealth associated with a 1% change in the standard deviation of the firm's returns (in \$1000s).

d = natural logarithm of the expected dividend yield over the life of the option;

S_t = stock price at time t (Execucomp variable PRCCF);

σ = expected stock return volatility over the life of the option: annualised standard deviation of stock return estimated over the 60 months prior to the

beginning of the fiscal period which equals $\sqrt{\frac{\sum_{t=-60}^{-1} (r_t - \bar{r})^2}{59}} * \sqrt{12}$, where $r = \ln\left(\frac{S_t}{S_{t-1}}\right)$.

N = cumulative probability function for the normal distribution;

N' = normal density function;

X = strike price of executive option;

$$Z = \left[\ln\left(\frac{S}{X}\right) + T\left(r - d + \frac{\sigma^2}{2}\right) \right] / \sigma T^{(1/2)} ;$$

$$\text{Delta} = \frac{\partial V}{\partial S} = e^{-dt} N(Z) * (S/100) ;$$

$$\text{Vega} = \frac{\partial V}{\partial \sigma} = e^{-dt} N'(Z) S T^{(1/2)} * (0.01) .$$

Following Coles et al.'s (2013) approach, we calculate the delta and vega values of CEOs' compensation with data from the Execucomp database. The Financial Accounting Standards Board (FASB) FAS 123R imposed an accounting change for equity-based compensation that occurred during the study's sampling period. Due this change of format, the Execucomp reporting regimes are different in the fiscal years 1992 to 2006. Post-2006, the new

reporting format is imposed. Thus the Execucomp database contains different data variables pre-2006 and post-2006. Therefore, we calculate delta and vega values for the different reporting regimes.

We apply the Core and Guay's (2002) approximation approach to compute delta and vega for the CEOs' option portfolio. Under the pre-2006 reporting format, the requirement for current year's option grants and previously granted options are different. For the current year's options grants, the tranche-level details are reported, such as the exercise price, the maturity of each tranche of options, the exercise price and the number of options. As for previously granted options, only the data about the intrinsic value and number are available for the vested and unvested executive option portfolio. Following Core and Guay (2002) and Coles et al. (2013), we compute the three different portfolios separately. The three kinds of options portfolios are the vested options, the unvested options from previously granted awards and options granted in the current year. The incentives of these three option portfolios compromise the CEOs' total option-linked incentives.

The risk-free rate is taken to be the 1-year Treasury bill rate, obtained from the Federal Reserve website. The dividend yield is the variable DIVYIELD in the Execucomp database. DIVYIELD is not available for the samples after 2006. Pre-2006, Execucomp provide a variable ((BS_VOLATILITY)) as an estimation of stock volatility. We use the variable BS_VOLATILITY as the stock volatility used in the Black–Scholes formula.

For the options awarded in the current year, we can estimate the incentives of executive options straight with the variables in Execucomp database, as it gives both the exercise price (EXPRIC) and the number of options granted for the current year (NUMSECUR). The maturity of the options equals the expiration date (EXDATE) minus the current date. The aggregate number of all tranches equals the variable OPTION_AWARDS_NUM.

The maturity of vested options is assumed to be the maturity of unvested options minus three. We estimate the average exercise price based on the

realisable value of vested options (OPTS_VESTED_VAL) and the number of options (OPTS_VESTED_NUM).

$$\text{Estimated Exercise Price} = PRCCF - \frac{OPTS_VESTED_VAL}{OPTS_VESTED_NUM}$$

Information about the intrinsic value of previously granted unvested options is not directly available. We need to estimate this as the reported intrinsic value of all unvested options (OPTS_UNVESTED_VAL) minus the total intrinsic value of the options granted in the current year. The calculation can be expressed as follows:

$$\begin{aligned} & OPTS_UNVESTED_VAL_PREVIOUS \\ &= OPTS_UNVESTED_VAL \\ & - \sum [(PRCCF - EXPRIC) * NUMSECUR] \end{aligned}$$

With a similar logic, we estimate the number of previously granted unvested options as the total number of options granted in the current year (OPTS_UNEX_UNEXER_NUM) minus the number of unvested options (OPTION_AWARDS_NUM).

$$\begin{aligned} & OPTS_UNVESTED_NUM_PREVIOUS \\ &= OPTS_UNEX_UNEXER_NUM - OPTION_AWARDS_NUM \end{aligned}$$

With the estimated intrinsic value and number of previously-granted unvested options, we can estimate the average exercise price of each tranche of options. The average exercise price of each option is computed as the stock price in that year minus the average intrinsic value of each option:

$$\begin{aligned} & EXERCISE_PRICE_UNVESTED_PREVIOUS \\ &= PRCCF - \frac{OPTS_UNVESTED_VAL_PREVIOUS}{OPTS_UNVESTED_NUM_PREVIOUS} \end{aligned}$$

We obtain the estimations of the delta and vega for the three option portfolios. We can aggregate the overall delta and vega for the executive incentives. The

overall delta is the sum of the delta of options granted in the current year, the delta of the vested options, the delta of previously granted unvested options, and the delta of the stock shares owned by the CEO. The total vega is the sum of the vega of options granted in the current year, the vega of the vested options, and the vega of previously granted unvested options. The vega of the stock share portfolio is excluded, following the assumption in Guay (1999) whereby the vega of the stock share portfolio is taken to be zero.

APPENDIX 2.B

Table 2.10 Absolute option moneyness measure of overconfidence across years

Year	mean	ocyear	observations	mean	OC	observations
1992	21.23%	31	146	17.12%	25	146
1993	30.78%	157	510	22.16%	113	510
1994	25.10%	185	737	24.97%	184	737
1995	26.96%	210	779	28.50%	222	779
1996	31.73%	270	851	32.55%	277	851
1997	37.71%	339	899	37.60%	338	899
1998	33.37%	320	959	40.77%	391	959
1999	34.84%	355	1019	41.41%	422	1019
2000	33.50%	343	1024	41.70%	427	1024
2001	25.88%	251	970	39.69%	385	970
2002	14.20%	137	965	36.48%	352	965
2003	25.66%	251	978	40.08%	392	978
2004	26.60%	257	966	40.68%	393	966
2005	27.87%	245	879	43.57%	383	879
2006	32.51%	341	1049	43.47%	456	1049
2007	29.96%	352	1175	41.79%	491	1175
2008	11.84%	137	1157	38.29%	443	1157
2009	14.12%	160	1133	36.54%	414	1133
2010	18.56%	206	1110	37.57%	417	1110
2011	19.30%	205	1062	39.45%	419	1062
2012	20.72%	208	1004	38.05%	382	1004
2013	33.77%	312	924	42.42%	392	924
2014	32.95%	286	868	38.13%	331	868

Table 2.11 Relative option moneyness measure of overconfidence across years

Year	mean	rt ocyear	observations	mean	rt OC	observations
1992	20.55%	30	146	11.64%	17	146
1993	20.00%	102	510	13.53%	69	510
1994	20.08%	148	737	17.64%	130	737
1995	20.03%	156	779	19.90%	155	779
1996	20.09%	171	851	22.56%	192	851
1997	20.02%	180	899	23.69%	213	899
1998	20.02%	192	959	26.07%	250	959
1999	20.02%	204	1019	26.01%	265	1019
2000	20.02%	205	1024	27.44%	281	1024
2001	20.00%	194	970	28.45%	276	970
2002	20.00%	193	965	29.43%	284	965
2003	20.04%	196	978	32.21%	315	978
2004	20.08%	194	966	31.88%	308	966
2005	20.02%	176	879	33.33%	293	879
2006	20.02%	210	1049	32.60%	342	1049
2007	20.00%	235	1175	33.45%	393	1175
2008	20.05%	232	1157	33.88%	392	1157
2009	20.04%	227	1133	33.01%	374	1133
2010	20.00%	222	1110	34.59%	384	1110
2011	20.06%	213	1062	36.35%	386	1062
2012	20.02%	201	1004	34.56%	347	1004
2013	20.02%	185	924	34.42%	318	924
2014	20.05%	174	868	30.07%	261	868

Table 2.12 Investment-based measures of overconfidence across years

Year	mean	ir oc	observations	mean	ir oc2	observations	mean	ir rt	observations
1992	20.16%	25	146	0.00%	0	146	6.45%	8	146
1993	20.18%	90	510	1.18%	6	510	4.71%	21	510
1994	20.00%	130	737	2.31%	17	737	4.46%	29	737
1995	20.12%	138	779	3.21%	25	779	3.94%	27	779
1996	20.05%	151	851	4.82%	41	851	3.85%	29	851
1997	20.00%	159	899	3.78%	34	899	4.15%	33	899
1998	20.00%	170	959	4.69%	45	959	3.76%	32	959
1999	20.09%	181	1019	3.93%	40	1019	3.33%	30	1019
2000	20.00%	179	1024	4.59%	47	1024	3.69%	33	1024
2001	20.02%	171	970	4.23%	41	970	3.28%	28	970
2002	20.05%	170	965	4.15%	40	965	3.77%	32	965
2003	20.09%	172	978	4.09%	40	978	3.15%	27	978
2004	20.10%	166	966	4.55%	44	966	4.84%	40	966
2005	20.05%	153	879	4.21%	37	879	3.80%	29	879
2006	20.04%	185	1049	3.72%	39	1049	4.44%	41	1049
2007	20.06%	206	1175	3.49%	41	1175	4.58%	47	1175
2008	20.08%	203	1157	4.24%	49	1157	4.25%	43	1157
2009	20.00%	200	1133	4.06%	46	1133	3.60%	36	1133
2010	20.02%	188	1110	4.14%	46	1110	4.05%	38	1110
2011	20.00%	185	1062	4.61%	49	1062	3.68%	34	1062
2012	20.02%	178	1004	5.08%	51	1004	3.71%	33	1004
2013	20.02%	164	924	4.11%	38	924	4.64%	38	924
2014	20.11%	153	868	10.14%	88	868	4.20%	32	868

Table 2.13 Correlation matrix of variables

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)
1. Idiosyncratic risk	-																		
2. ocyear	0.08	-																	
3. OC	0.03	0.6	-																
4. rt_ocyyear	0.05	0.78	0.52	-															
5. rt_OC	0.01	0.53	0.79	0.62	-														
6. ir_oc	0.12	0.21	0.2	0.22	0.22	-													
7. ir_oc2	0.05	0.02	0.08	0.02	0.08	0.41	-												
8. ir_rt	0.07	0.47	0.31	0.58	0.37	0.56	0.13	-											
9. Log sales	-0.47	-0.08	-0.06	-0.09	-0.07	-0.15	-0.03	-0.09	-										
10. Leverage	-0.06	-0.11	-0.09	-0.11	-0.11	-0.15	-0.05	-0.12	0.25	-									
11. MB	0.06	0.39	0.26	0.37	0.26	0.23	0.02	0.31	-0.17	-0.19	-								
12. ROA	-0.29	0.18	0.13	0.16	0.12	0.07	-0.02	0.1	0.25	-0.12	0.2	-							
13. Return	-0.03	0.17	0.05	0.15	0.04	-0.03	-0.07	0.06	-0.05	-0.03	0.2	0.09	-						
14. Log PPE	-0.44	-0.13	-0.11	-0.13	-0.11	-0.22	-0.04	-0.15	0.86	0.32	-0.2	0.16	-0.05	-					
15. Cash	0.19	0.11	0.13	0.13	0.15	0.18	0.04	0.15	-0.45	-0.38	0.37	-0.1	0.09	-0.47	-				
16. Sale growth	0.07	0.23	0.15	0.2	0.14	0.27	0.03	0.24	-0.06	-0.03	0.25	0.15	0.09	-0.1	0.06	-			
17. Log delta	-0.32	0.18	0.26	0.17	0.25	0.08	0.03	0.11	0.47	0	0.29	0.26	0.08	0.39	0.06	0.08	-		
18. Log vega	-0.57	-0.06	0.01	-0.04	0.03	-0.1	-0.03	-0.06	0.5	0.09	-0.01	0.23	0.09	0.47	-0.14	-0.08	0.53	-	
19. Log tenure	0.01	0.11	0.33	0.11	0.3	0.08	0.03	0.09	-0.08	-0.03	0.03	0.06	-0.01	-0.08	0.05	0.07	0.23	0.07	-

CHAPTER 3. CEO vega and default risk in the banking industry

3.1 Introduction

The financial sector in the US was criticised for excessive risk-taking during the 2008 financial crisis. There are a number of reasons for financial institutions to take excessive risks. The financial industry and academia agree that managerial pay incentives are closely related to firms' risk-taking (IMF, 2014). Among different elements of CEO remuneration packages, equity-based compensation is highly relevant to CEOs' risk-taking behaviours and is widely used to mitigate the agency problem. Two measures of the incentive provided by equity-based compensation for a CEO to take greater risks in running the firm are typically recognised as CEO delta and CEO vega. CEO delta is the sensitivity of CEO wealth to stock price, and a high value indicates greater incentive for CEOs to increase the value of firms. CEO vega is the sensitivity of CEO wealth to stock price volatility, and a high value indicates greater incentive for risk-averse CEOs to take more risk. Empirical studies show that remuneration packages that produce a high CEO vega can mitigate the risk-related agency problem by motivating CEOs to take risky investment projects (Guay, 1999; Rajgopal and Shevlin, 2002; Coles et al., 2006).

The benefits of utilising equity-based compensation have been well addressed in prior studies. However, few studies explore whether utilising equity-based compensation has a value-destroying effect on firms by increasing firms' default risk. This chapter attempts to shed light on the connection between the incentives of CEO equity-based compensation and default risk. Instead of using stock price volatility to proxy for firm risk, we apply the default risk to measure the downside risk of firms. Default risk, denoting the likelihood that a leveraged firm cannot fulfil its debt obligations, is a more comprehensive measure of a bank's risk as it incorporates information from both investing and financing activities (Garlappi et al., 2008). Few studies specifically investigate the connection between CEO vega and default risk in the banking industry. This chapter explores the association between default risk and incentives of CEOs equity-based compensation in the US banking industry. We focus on the banking industry for several reasons. Firstly, the agency problem is more severe in banks. Banks as a financial intermediary have private information about debtors. Thus, banks' day-to-day business is opaque to shareholders. This opacity implies that monitoring the CEOs of banks is difficult or costly.

Furthermore, the main business in the banking industry is to take short-term loans and provide long-term loans. Taking short-term profitable projects could expose banks to long-term risk. In this sense, moral hazard is highly relevant in the banking industry. Finally, banks are typically highly leveraged. On the one hand, the leverage is a productive factor for banks. On the other hand, high leverage drives banks close to default, compared with firms in other industries. Thus, default risk plays a more important role in the banking industry. Overall, due to these characteristics of banks, the association between vega and default risk in the banking industry are more marked compared to those in other industries.

Moreover, the association between CEO vega and default risk could be affected by the risk-shifting problem. The risk-shifting problem suggests that when firms are financially distressed, shareholders have little to lose compared with bondholders (Jensen and Meckling, 1976). The downside risk is borne mostly by bondholders. Therefore, shareholders tend to motivate managers to take excessive risk. Empirical studies such as Brander and Poitevin (1992), Ertugrul and Hegde (2008) and Li et al. (2017) show that equity-based compensation schemes are influenced by risk-shifting behaviours. John and John (1993) suggest that in high-leverage firms, pay-to-performance sensitivity tends to decrease, as debtholders have stronger incentives to monitor managers when firms have high leverage ratios. Kim et al. (2017) demonstrate that leverage dampens the relationship between managerial risk-taking and equity-based incentives. Unlike Kim et al. (2017), this chapter explicitly focuses on default risk in the banking industry. We classify banks as either high-leverage or low-leverage firms to investigate the association between CEO vega and default risk in high-leverage banks and low-leverage banks.

We also investigate how a high-impact regulatory policy in the banking industry influences the relationship between CEO vega and default risk. DeYoung et al. (2013) show that the Gramm-Leach-Bliley Financial Modernization Act of 1999 (GLB Act) has had a significant impact on banking industry in the US. Specifically, it has allowed banks to fully compete in insurance underwriting, securities brokerage and investment banking. Thus, we explore the association between CEO vega and default risk before and after the

GLB Act was launched by incorporating a dummy variable which identifies the periods before and after the implementation of the GLB Act.

The empirical results show that CEO vega is positively associated with default risk after controlling for other elements of a compensation package, such as salary and bonus. We do not observe a significant association between default risk and CEO delta. These results suggest that CEO vega (i.e. convexity of CEO compensation) is significantly associated with default risk in the banking industry. The results are consistent with the results of DeYoung et al. (2013). Unlike DeYoung et al. (2013), who focus on stock volatility, we focus on the default risk, which incorporates both accounting information and stock market prices. Moreover, we analyse the association between CEO vega and default risk in high-leverage banks and low-leverage banks. We find that the association between CEO vega and default risk is statistically significant in low-leverage banks but not in high-leverage banks. We also find that the association between CEO vega and default risk differs between the pre-GLB and the post-GLB periods. CEO vega has a significant association with default risk only during the post-GLB period.

This chapter has implications for both academia and practitioners. Firstly, it contributes to the literature on the ability of equity-based compensation to promote risk-taking behaviour. Our results suggest that though equity-based compensation can mitigate the agency problem, the benefits could be at the cost of an increase in default risk. Moreover, this research has implications for corporate governance practice. The empirical results imply that the risk-inducing effect of CEO vega could become weaker due to risk-shifting between shareholders and bondholders. From the bondholders' perspective, it is necessary to incorporate debtholders' views into the process of designing executive compensation.

The rest of the chapter is organised as follows. In Section 3.2, we review the related literature and present the hypotheses. In Section 3.3, we describe the data and methodology. In Section 3.4, we analyse the empirical results. Section 3.5 sets out the conclusions.

3.2 Literature review

3.2.1 Agency problem and compensation incentives

According to the classic agency theory, there are conflicts of interests between shareholders and day-to-day managers (Jensen and Meckling, 1976). On the one hand, if managers have, at most, partial ownership of firms, and especially if they have none, they may not always act in the best interests of shareholders. On the other hand, as managers' personal wealth and human capital depend on the value of their firms, they are generally risk-averse. Without an extra incentive for risk-taking, managers are reluctant to implement risky investment projects. That suggests that managers could pass up some investment opportunities even though they have an expected positive net present value.

The agency problem can be mitigated through monitoring or properly designed compensation. Monitoring is costly and even ineffective in certain scenarios. For instance, it is difficult for shareholders to monitor managers in the banking industry as information on debtors, for instance, is not usually available to shareholders. Another way of mitigating the agency problem is to align managers' interests with those of shareholders with well-designed compensation schemes. The pay schemes for CEOs are particularly important, as CEOs play an essential role in the decision-making over corporate policies.

To mitigate agency problems, CEO compensation needs to meet two requirements at the same time. For the moral hazard problem of managers, pay schemes need to motivate managers to act in shareholders' interests. For the under-investment problem, compensation schemes need to motivate risk-averse managers to invest in risky projects which potentially have positive net present value. Equity-based compensation can provide an incentive for CEOs to align the interests of shareholders and with those of debtholders. For instance, Knopf et al. (2002) show that, where an incentive is provided in the form of CEO option compensation, CEO delta denotes the sensitivity of CEOs' wealth to stock price. High-delta compensation schemes motivate CEOs to increase the value of their firms as their wealth will increase along with the firm's equity increase.

CEO compensation also needs to mitigate CEOs' risk-aversion. Shareholders and managers have different risk preferences, as their abilities in risk diversification differ. Shareholders can diversify their risk by investing in other firms. In contrast, managers cannot short-sell their own firms' stocks. Additionally, managers' human capital also depends on the value of their own firms. Therefore, managers are overly exposed to their own firm's risk. Due to managers' risk exposure, they tend to be risk-averse if there are no extra incentives. Due to managerial risk aversion, managers are reluctant to implement innovative projects which are potentially value-adding (the under-investment problem). Research on agency theory also suggests that managers' risk aversion is an essential aspect of the agency problem (Jensen and Meckling, 1976; Huagen and Senbet, 1981; Smith and Stulz, 1985).

To mitigate the under-investment issue, managerial compensation packages need to motivate managers to take risk. Studies show that offering CEOs convex payments such as stock options can motivate them to implement risky projects. As the value of stock options cannot be negative, CEOs can benefit from an increase in stock price in good times but bear only limited losses in bad times. The convexity of CEOs' compensation can be measured by the value of CEO vega, which denotes the sensitivity of CEOs' wealth to stock price volatility. Empirical studies show that high-vega compensation schemes are associated with high risk-taking by firms. For instance, Smith and Stulz (1985) demonstrate that a positive-vega pay element, such as stock options, can motivate CEOs to take more risk. Guay (1999) finds that CEO vega is positively associated with a firm's risk-taking behaviour. Coles et al. (2006) argue that high-vega compensation schemes motivate CEOs to invest in innovative projects and to implement more aggressive leverage policies. These studies imply that high-vega compensation can be viewed as a risk-taking incentive for CEOs, by influencing their investment and financing decisions.

Although high-vega CEO compensation can mitigate the agency problem, it could have detrimental effects. Indeed, a natural question arises: can the risk-taking incentives go too far, and lead to excessive risk-taking? Recent empirical studies provide support for this. For instance, some studies show that high-vega compensation has a positive relation with firms' misreporting

behaviours. Bergstresser and Philippon (2006) show that CEOs whose compensation is closely tied to the value of stock and option holdings are more likely to manipulate reported earnings. Armstrong and Vashishtha (2012) find strong evidence for the positive relation between CEO vega and misreporting. Additionally, high-vega CEO compensation is found to be associated with exploration risk in the oil and gas industry. Rajgopal and Shevlin (2002) show that high-vega managerial compensation is associated with higher exploration risk and less hedging against oil and gas prices. These studies at least imply that the well-known advantage of high-vega CEO compensation is not cost-free, in that it can have a value-destroying effect on firms.

This chapter is related to the work by Vallascas and Hagendorff (2013) which explores the association between default risk and CEO bonus schemes. The authors find that CEOs' cash bonuses are negatively associated with bank default risk. Their results at least imply that CEO compensation should be considered when making policy relating to default risk. The existing empirical evidence illustrates that high-vega managerial compensation can mitigate the risk-related agency problem. However, the benefit is at the cost of excessive risk-taking, which may jeopardise a bank. Thus, the first hypothesis is proposed as follows:

Hypothesis 1: CEO vega is positively associated with the default risk of banks.

3.2.2 The risk-shifting problem

The association between CEO vega and default risk could be influenced by the risk-shifting problem. Jensen and Meckling (1976) present the risk-shifting problem as managers tending to take excessive risk when firms are financially distressed. The problem can be briefly set out as follows. In ordinary times, debtholders have claims for their debts, which are fixed amounts according to the lending contracts. Shareholders have claims for the value of equities, which, theoretically, has no upper bound. The value of equity is close to zero if the firm is about to default. If firms perform well, the firm risk stemming from innovative projects and aggressive borrowing policy is mostly borne by

shareholders. In contrast, debtholders have priority claims over shareholders and bear less firm risk than shareholders.

However, this relation does not hold when firms do not perform well, especially when firms are about to default. When firms are close to default, shareholders' claims become little compared with those of debtholders. In this scenario, debtholders have the most value of firms. Shareholders can then potentially benefit from a new project at little marginal cost because their claims of firms are small anyway. As a result, shareholders tend to implement new risky projects. Under this circumstance, the firm risk is 'shifted' from shareholders to debtholders.

Prior studies on risk-shifting focus on the conflict of interest between shareholders and debtholders. It is notable that conflicts of interest also exist between shareholders and CEOs. When firms are doing well, CEOs can benefit from increases in the value of equities. However, when firms are close to default, CEOs and shareholders are differently exposed to potential losses. Shareholders' losses are limited to the decreased value of their equities. In contrast, CEOs' potential losses are more than the decreased value of their equities, in that their personal human capital will decrease if their firms default.

Empirical studies provide support for this argument. For instance, Williamson (1988) shows that CEOs' human capital has more value due to employment continuity especially when human capital is specific to firms. Fox and Marcus (1992) find that CEOs' human capital – their skills, experience, ability and relationships – is more highly valued in some firms than in others. John and John (1993) show that managers tend to benefit more from be in charge of firms if their firms are in solvent states. These studies imply that the CEOs' utility varies according to firms' financial states. For firms in a good financial state, the cost of insolvency is very little. As CEOs' human capital depends on the solvency of firms, the cost of insolvency becomes considerable when firms are about to default. Thus, CEOs' interests are more aligned with those of shareholders when the firm is in a good financial state and more aligned with those of creditors when it is in a bad financial state. Thus, we expect that CEOs' utility function has a hybrid feature of both shareholders and creditors

(bondholders) and CEOs' risk-taking behaviour should vary in different financial states.

Prior studies on CEO vega generally assume that the relationship between incentive (in the form of pay) and risk-taking is independent of context. For instance, Knopf et al. (2002) and DeYoung et al. (2013) show that CEO vega is positively associated with firms' risk-taking and they treat the association between CEO vega and default risk as a state-independent association. Other studies argue that the relationship is influenced by the financial state of the firm. For instance, Brockman et al. (2010) show that short-maturity debt lessens the association between vega and bond yields. The authors argue that short-term debt mitigates the agency costs of debt because creditors implement more monitoring when firms have more short-term debt. Kim et al. (2017) show that leverage has an attenuating impact on the relationship between incentives and risk-taking. Both studies imply that the association between CEO vega and default risk tends to be weaker when firms approach default. We expect that the association between CEO vega and default risk is dependent on the firms' financial states, which are proxied here by leverage ratios. Therefore, we propose the following hypothesis:

Hypothesis 2: The association between CEO vega and default risk is weaker in banks which have high leverage ratios.

3.2.3 Differences in the association between CEO vega and default in the pre- and post-GLB periods

DeYoung et al. (2013) state that the GLB Act has had a significant impact on banking industry in the US. Specifically, it allowed banks to fully compete in insurance underwriting, securities brokerage and investment banking (IMF, 2014). In the post-GLB period, the traditional commercial banks have therefore had broader investment opportunities and bank boards have offered CEOs incentives to explore the new growth opportunities in these non-traditional markets (DeYoung et al., 2013). In this sense, we expect the association between CEO vega and default risk to be significant during the post-GLB period. We propose the last hypothesis as follows:

Hypothesis 3: CEO vega has significantly different degrees of association with default risk in the pre-GLB and post-GLB periods.

3.3 Data and methodology

Following DeYoung et al. (2013), we start with the observations of commercial banks in the US. We extract observations on CEO compensation by commercial banking companies (Standard Industrial Classification SIC 6020) in the Execucomp database. Our sample starts from 1994, which is the earliest year for which we have complete observations. The sample ends in 2005 to avoid contamination from the financial crisis of 2008, which could materially change CEOs' sensitivity to risk (DeYoung et al., 2013). The accounting data are collected from the Compustat database. We merge the dataset from Execucomp and Compustat and keep only the observations covered in both databases. Following Bharath and Shumway (2008) and Brogaard et al. (2017), we winsorise all variables at the 1% and 99% level to mitigate the influence of outliers. These percentages for winsorising are chosen to both mitigate the influence of outliers and maximise the sample size. We end up with 94 banks with 497 observations. The sample size is relatively small due to the limited number of commercial banks in our samples. To mitigate the concern of small sample size, we check robustness of the results with different measures of risk such as idiosyncratic risk and total risk. Moreover, in the GMM estimations, we also apply the small-sample GMM model which is specific for the small sample size.

Table 3.1 shows the detailed definitions of variables. The descriptive statistics are stated in Table 3.2. DTD refers to the mean of distance-to-default of banks. DTD ranges from -2.28 to 26.191. The mean of DTD is 5.97. Since variables such as CEO vega, CEO delta, salary and bonus are highly skewed, we incorporate the logarithm form of these variables in the regressions. The mean of CEO delta is 1245.01 and the mean of CEO vega is 616.21. These results are consistent with the results in Bharath and Shumway (2008) and Brogaard et al. (2017).

Table.3.1 Definitions of variables

DTD	Distant To Default (DTD) refers to how many standard deviation banks are away from the default point, which is the breakeven when the value of assets equal to debt.
Delta	The dollar changes in CEO stock and option portfolio for a 1% change in stock price (in \$1000s).
Vega	The dollar changes in CEO option holdings for a 1% change in stock return volatility (in \$1000s).
SALARY	The dollar value of the base salary (cash and non-cash) earned by the named executive officer during the fiscal year, measured by Execucomp variable SALARY (1000s).
BONUS	The dollar value of a bonus (cash and non-cash) earned by the named executive officer during the fiscal year, measured by Execucomp variable BONUS (in 1000s).
OTHCOMP	The dollar value of all other compensation earned by the named executive officer during the fiscal year, measured by Execucomp variable OTHCOMP (in 1000s).
Leverage	The book value of long-term debt plus the debt in current liabilities divided by total assets. Calculated as variables in Compustat database $(dlc + dlta) / at$.
MB	The market value of the firm divided by book value of assets. Calculated as variables $(prcc_f * csho + lt) / at$ in Compustat database.
Age	The number of years of CEO's age.
ROA	Return on assets, the ratio of operating income before depreciation to book assets. Calculated as Compustat variables ni / at .
Size	The value of total assets, measured by Compustat variable at (in millions of dollars).

Table 3.2 Summary statistics

	Mean	SD	Min	Q 0.25	Median	Q 0.75	Max	Range	Skew	Kurtosis
DTD	5.97	3.83	-2.28	3.27	5.65	8.20	26.19	28.47	0.77	1.40
Delta	1245.01	6268.64	0.30	99.13	270.49	834.25	209952.87	209952.57	26.42	855.49
Vega	616.21	2499.01	0.00	38.25	121.62	412.95	74873.34	74873.34	19.54	538.56
SALARY	753.67	381.78	0.00	525.00	709.67	910.65	5600.00	5600.00	3.63	27.38
BONUS	639.58	1351.73	0.00	0.00	181.70	640.10	14500.00	14500.00	4.51	26.85
OTHCOMP	178.71	562.19	0.00	33.39	75.88	175.88	12223.89	12223.89	13.94	248.52
ROA	0.03	0.02	-0.06	0.02	0.03	0.04	0.26	0.32	3.60	39.45
Size	9.84	1.44	6.83	8.74	9.55	10.73	14.76	7.93	0.89	0.60
Leverage	0.16	0.09	0.01	0.09	0.15	0.22	0.71	0.70	0.99	2.08
MB	1.98	1.19	0.13	1.29	1.75	2.41	18.07	17.94	4.30	39.33
Age	56.56	6.25	32.00	53.00	57.00	61.00	81.00	49.00	-0.03	0.99

Notes: Distant To Default (DTD) refers to how many standard deviation banks are away from the default point, which is the breakeven when the value of assets equal to debt. Delta is the dollar changes in CEO stock and option portfolio for a 1% change in stock price (in \$1000s). Vega is the dollar changes in CEO option holdings for a 1% change in stock return volatility (in \$1000s). SALARY is the dollar value of the base salary (cash and non-cash) earned by the named executive officer during the fiscal year. BONUS is the dollar value of a bonus (cash and non-cash) earned by the named executive officer during the fiscal year. OTHCOMP is the dollar value of all other compensation earned by the named executive officer during the fiscal year. ROA refers to the ratio of operating income before depreciation to book assets. Size refers to the total value of total assets. Leverage refers to the book value of long-term debt plus the debt in current liabilities divided by total assets. MB refers to the market value of the firm divided by book value of assets. Age is the number of years of CEO's age.

3.3.1 Measurement of default risk

Default risk denotes the likelihood that a leveraged firm is not able to fulfil its debt obligations by paying the contractual interest or principal (Garlappi et al., 2008). Default risk is essential in both academic research and financial practice, for instance in asset pricing (Garlappi et al., 2008), forecasting (Bharath and Shumway, 2008) and managerial compensation (Hagendorff and Vallasas, 2011; Vallasas and Hagendorff, 2013). The advantage of default risk is that it incorporates both accounting information and information from the stock market. In contrast, the stock return volatility measures the variation in the secondary market and can be affected by macro-factors such as interest rate and the monetary policies. The distance-to-default model also has practical applications in the financial industry, such as Moody's Kealhofer, McQuown, and Vasicek (KMV) proprietary model (Bharath and Shumway, 2008). Gropp et al. (2006) show that distance-to-default has greater predictive power for bank default than other indicators.

This chapter applies the Bharath and Shumway (2008) distance-to-default as the measure of default risk. Bharath and Shumway's model, also known as expected default frequency (EDF), is a simplified version of Merton's (1974) distance-to-default model. The idea of Merton's (1974) approach is that equity can be viewed as a call option of the total assets and the strike price of the call option is the liability of the firm. Given that the discount rate equals the risk-free rate, the probability of default is the probability that total liabilities exceed total assets. Bharath and Shumway (2008) and Brogaard et al. (2017) suggest that the EDF estimation performs well at forecasting distress and even slightly outperforms other estimations. Unlike Vassalou and Xing's (2004) default likelihood index model, for instance, EDF forgoes the iterative estimation procedure and estimates the default risk based on several assumptions about input parameters. Bharath and Shumway (2008) show that the iterative procedure is not sufficient because the usefulness of the distance-to-default measure is due to the functional form suggested by the Merton model.

Following Bharath and Shumway (2008) and Brogaard et al. (2017), we make several assumptions about the distance-to-default estimation. Firstly, we assume that the market value of each firm's debt is approximated by the face value of that debt:

$$D = F, \quad (3.1)$$

where D denotes the market value of the firm's debt and F denotes its face value.

We assume that the risk of debt is associated with the equity risk. Thus, the volatility of each firm's debt can be estimated as:

$$\sigma_D = 0.05 + 0.25 * \sigma_E, \quad (3.2)$$

where σ_D denotes the volatility of debt and σ_E denotes the volatility of equity.

Bharath and Shumway (2008) suggest that the 5% (the term 0.05) in equation (3.2) represents term structure volatility. The term 0.25 states the relation between volatility of debts and volatility of stocks. The total volatility of a firm can be estimated as the weighted average of the volatility from debts and equity, which can be written as:

$$\begin{aligned} \sigma_V &= \frac{E}{E + F} * \sigma_E + \frac{F}{E + F} * \sigma_D \\ &= \frac{E}{E + F} * \sigma_E + \frac{F}{E + F} * (0.05 + 0.25 * \sigma_E) \end{aligned} \quad (3.3)$$

where σ_V denotes the total volatility of the firm and E is the value of equity.

We assume that the expected return on the firm's assets are equal to the firm's stock return over the prior year:

$$\mu = r_{i,t-1}, \quad (3.4)$$

where μ is the expected return on the firm's assets and $r_{i,t-1}$ is the firm's stock return over the previous year.

Therefore, the distance-to-default is calculated by:

$$DTD = \frac{\ln \left[\frac{E + F}{F} \right] + (\mu - 0.5\sigma_V^2)T}{\sigma_V \sqrt{T}} \quad (3.5)$$

where T is the time-to-maturity.

3.3.2 Measurement of managerial incentives

We derive CEO vega and CEO delta based on Black and Scholes (1973) option pricing model as modified by Merton (1973). CEO delta is calculated as the dollar change in wealth associated with one percent change in the stock price. Guay (1999) estimates CEO vega by measuring the convexity contributed by a stock option as the dollars change for a one-percent change in the standard deviation of stock returns. The convexity of the stock option compensations can be estimated using Black-Scholes formula as modified to account for dividend payouts by Merton (1973). The detailed calculation procedures for CEO vega and CEO delta are stated in the Appendix 3.B.

3.3.3 Other compensation elements

Besides CEO vega and delta, we also include other elements of compensations as control variables. Balachandran et al. (2010) show that CEO compensation is typically composed of salary, non-equity-based compensation, equity-based compensation and other compensation. The different elements of a compensation package vary in the degree of incentive they provide to invest in risky projects. The salary component is a guaranteed cash payment, since it is paid regardless of the firm's performance, and so does not provide much incentive for executive managers to take risk. The non-equity-based component includes the annual bonus and a payment according to the company's long-term incentive plan (Balachandran et al., 2010). Non-equity-based compensation is usually paid annually based on predetermined agreements which require CEOs to achieve certain accounting goals. Other compensation refers to pension, healthcare benefits, perquisites and other post-retirement benefits (Balachandran et al., 2010). We include different elements of compensation to control for their different degrees of incentive.

3.4 Empirical design and results

We construct the relationship between CEOs' remuneration and bank default risk in a dynamic model, which is consistent with Vallascas and Hagendorff (2013). The authors assume that for each bank the distance-to-default converges to an optimal (though unobservable) level over time. We assume that the observed changes in banks' distance-to-default can be thought of a function of two drivers. One is discretionary adjustment and the other is an exogenous shock. Over time, exogenous shocks drive the observed default risk away from the optimal level, and so banks need to adjust the discretionary component to achieve the optimal level.

$$DTD_{i,t} - DTD_{i,t-1} = \gamma(DTD_{i,t}^* - DTD_{i,t-1}) + \mu_{i,t} \quad (3.6)$$

γ is the speed of adjustment of the distance-to-default towards the optimal level by banks. The value of γ ranges between 0 and 1. If $\gamma = 0$, then there is no adjustment for the discretionary component since the difference between actual risk and the observed risk in the previous period is just an exogenous shock. If $\gamma = 1$, then we assume that the adjustment of actual risk to the target level will take place instantaneously. In reality, the adjustments of banks would be costly. Moreover, it is infeasible that it takes place contemporaneously. Therefore, γ ranges between 0 and 1, suggesting partial adjustment of default risk by banks in reality.

The optimal, unobservable level of distance-to-default for banks is denoted $DTD_{i,t}^*$. The target level of distance-to-default DTD can be written as a function of CEO vega, a vector of bank characteristics X and an unobservable bank attribute $e_{i,t}$:

$$DTD_{i,t}^* = \alpha Vega_{i,t-1} + \beta X_{i,t-1} + e_{i,t} \quad (3.7)$$

The independent variables are lagged one period to allow the incentives in year $t-1$ to generate risk-taking in year t . We substitute the equation (3.7) into

equation (3.6). The observed level of distance-to-default at a given time t can be expressed as follows:

$$DTD_{i,t} = (1 - \gamma)DTD_{i,t-1} + \gamma(\alpha Vega_{i,t-1} + \beta X_{i,t-1} + e_{i,t}) + \varphi_{i,t} \quad (3.8)$$

3.4.1 An endogeneity issue and GMM regression

The simple OLS regression of the distance-to-default on the independent variables could be subject to an endogeneity problem. Balachandran et al. (2010) argue that the endogeneity error is present because the unobservable quality of management and governance influences both default risk and CEO compensation. As we cannot find an exogenous variable as the instrumental variable, we need to use a predetermined internal instrumental variable. We use the Generalized Method of Moments (GMM) estimator proposed by Arellano and Bover (1995) and Blundell and Bond (1998). Specifically, we use the system-GMM model, which uses both original levels and the lags of independent variables as instrumental variables. There is an argument that suggests a reverse causality between distance-to-default and CEO vega: bank CEOs who tend to pursue more risky strategies are more likely to encourage the board to offer risk-inducing compensation. Our GMM model rules out this alternative explanation. The system-GMM estimator can address the issue of endogeneity in the association between distance-to-default and CEO compensation incentive.

Compared with the difference-GMM estimator, the system-GMM estimator has two advantages: first, it allows us to include the time-invariant variables in the models; and second, it exhibits higher levels of both consistency and efficiency if the variables used as instruments are properly chosen (Vallascas and Hagendorff, 2013).

The validity of the GMM estimators depends on two assumptions. First, the system-GMM estimator requires that stationary error terms do not exhibit serial correlation. Second, the system-GMM estimator requires that the post-instrumentation residuals are stationary. This assumption implies that the

differenced error term should not exhibit second-order serial correlation in the first difference residual. We apply the Hansen J test of over-identifying restrictions to validate the second assumption. A statistically insignificant value of J implies that the instrument set is valid. We use the statistics developed by Arellano and Bond (1991) to test for the presence of second-order serial correlation in the first residual. An insignificant $m2$ statistic suggests that the differenced error term is not second-order serially correlated.

We incorporate other variables in the model as control variables. Firstly, we include the book leverage ratio, which is defined as the ratio of market value to total assets, to control for the impact of leverage. Secondly, we control for the size effect. In our model, we use LnAsset , the log transformation of total assets, to proxy for the size of firms. On the one hand, large firms may benefit from diversification across different countries, including better access to more investment opportunities and more funding (Dermine and Schoenmaker, 2010). On the other hand, due to the too-big-to-fail effect, large firms have better protection and a better safety net (Benston et al., 1995). As a result, the too-big-to-fail effect can encourage risk-shifting incentives and lead to a higher risk level. We expect that size has contrasting effects on distance-to-default.

Following DeYoung et al. (2013), we include the log transformation of the market-to-book ratio, LnMB , to control for the investment opportunity of firms. We expect that LnMB has a positive coefficient. We also control for CEO age, although we use the log transformation of age. Young CEOs are subject to more regulatory scrutiny than older CEOs because older CEOs are more likely to have an established track record. Therefore, older CEOs are more likely to be risk-taking than younger CEOs. All the control variables are observed at year $t-1$.

3.4.2 Multivariate results

As discussed in Section 3.2.1, theory predicts that CEO vega has a positive association with default risk. This implies that CEO vega can motivate CEOs to implement more risk-taking policies. Moreover, we expect the association between CEO vega and default risk is weakened by an increase in the leverage

ratio. Since the potential losses due to solvency would dominate the impact of CEO vega, the association between CEO vega and default risk should be weaker in high-leverage banks.

We report the empirical results in this section. Roodman (2009) points out that a properly identified system-GMM estimator for the lagged dependent variable should lie between the OLS estimators and the fixed effect estimator. We present both the OLS estimators and fixed effect estimators to show the validity of the system-GMM estimator in Table 3.3. Column 1 presents the OLS regression with year fixed effects. Column 2 shows the fixed effects model in which we control for the year fixed effects and firm fixed effects. Column 3 shows the one-step system-GMM. When estimating the system-GMM model, we assume that the CEO vega, CEO delta, leverage ratio and ROA are endogenous with respect to distance-to-default. This assumption is consistent with the results in Vallascas and Hagendorff (2013). Coles et al. (2006) show that firms' financial policies, investment and executive managerial compensation are likely to be jointly determined. Thus, we treat CEO incentives, including CEO vega and CEO delta, as endogenous. We include the lagged two-period distance-to-default, CEO vega, CEO delta, leverage ratio and ROA as instrumental variables.

As for leverage ratio, Jokipii and Milne (2011) show that banks adjust the level of risk and the equity ratio simultaneously. This suggests that there is a bi-directional relationship between distance-to-default and leverage. ROA can be viewed as a proxy for profitability. The profitability of banks could represent both the risk and the return at the same time because banks increase profitability through more aggressive financial policies, which also implies more aggressive risk-taking. CEO age will not be affected by the level of the bank's default risk. We include the year fixed effects and CEO age as the exogenous variables as neither changes with to default risk.

The estimated results in Table 3.3 support our argument. The coefficient on lag distance-to-default has a positive sign. This suggests that the level of default risk in the previous year is positively associated with that in the current year. This implies that banks cannot adjust the risk level instantaneously and the

prior financial policies also have an impact on the current state. CEO vega has a negative effect on the distance-to-default. Hypothesis 1 is supported: the sensitivity of CEO wealth to stock return volatility, that is, CEO vega, is positively associated with default risk (i.e. is negatively associated with distance-to-default).

The coefficient on book leverage ratio has a negative sign, which implies that the book leverage ratio is positively associated with a bank's default risk. The results confirm our argument that the level of debt significantly affects the default risk of banks. A higher level of leverage drives banks closer to default (i.e. a smaller distance-to-default).

ROA shows a negative association with the distance-to-default. ROA can be interpreted as the profitability of banks. The profitability of banks has two different effects. While higher profitability may imply that banks are potentially aggressive in providing loans, if they are too aggressive, then losses might appear in the following year. We observe that the coefficient on lag distance-to-default in the OLS model is 0.528 and the coefficient on lag distance-to-default in the fixed effects model is 0.282. The coefficient on lag distance-to-default in the system-GMM model is 0.477, which lies between upper bound of 0.528 and lower bound of 0.282. This implies that our system-GMM model is properly specified. In column 3 of Table 3.3, the p value of $m1$ is $6.01e-05$, which implies the presence of first-order correlation of residuals. The p value of $m2$ is 0.311, which suggests that the residuals do not show second-order correlation. These results confirm that the model is properly specified. The Hansen J test has a p value of 0.952, which is insignificant and so suggests that our model is not over-identified.

To check the validity of the association between CEO vega and distance-to-default, we incorporate in the model other elements of CEO compensation, such as salary and bonuses. The empirical results are reported in Table 3.4. The effect of CEO vega on distance-to-default remains negative, implying a positive association between CEO vega and default risk. The coefficients on CEO vega is -0.308, which is statistically significant at the 0.05 level. We do not observe a statistically significant effect of salary. We interpret this as

meaning that the salary payments are relatively fixed and do not change in respect of default risk. We did not observe a significant effect of bonus payment either. With the system-GMM estimator the coefficient on the lag term of distance-to-default is 0.513, which lies in between the OLS value of 0.521 and the fixed effect value of 0.265. These results suggest that the system-GMM model is rightly specified. In column 3 of Table 3.4, the p value of $m2$ is 0.3, suggesting the absence of second-order correlation of residuals. The p value of $m1$ is $5.93e-05$, implying the presence of first-order correlation of residuals. The results of $m1$ and $m2$ confirm that the GMM model is properly specified. The Hansen J test has a p value of 0.966, which is insignificant and so suggests that the system-GMM model is not over-identified. Overall, the association between CEO vega and default risk remains statistically significant after controlling for the impact of CEO salary payment, the bonus payment and other forms of compensation.

To check the robustness of the results, we also control for the state fixed effects. The results are presented in Table 3.10 and Table 3.11 in Appendix 3.A. The main results remain qualitatively the same.

Table 3.3 Regression without controls for other components of CEO compensation packages

Variables	(1) OLS	(2) Fixed effects	(3) GMM
DTD_{t-1}	0.528*** (0.0834)	0.282*** (0.0992)	0.477*** (0.120)
$LnVega_{t-1}$	-0.301** (0.130)	-0.470* (0.281)	-0.666* (0.383)
$LnDelta_{t-1}$	0.156 (0.153)	0.245 (0.396)	0.400 (0.471)
$Leverage_{t-1}$	-9.523*** (1.531)	-5.222** (2.187)	-11.69*** (3.571)
$LnMB_{t-1}$	0.325 (0.387)	-1.204* (0.694)	0.160 (0.777)
$LnAge_{t-1}$	0.785 (0.930)	1.944** (0.835)	1.680 (1.780)
$LnROA_{t-1}$	-7.049 (6.434)	6.084 (10.62)	-15.52* (8.801)
$LnSize_{t-1}$	0.169 (0.104)	-1.824*** (0.509)	0.346 (0.341)
<i>Constant</i>	-2.938 (3.922)	20.76*** (5.723)	2.767 (5.502)
Observations	497	497	496
R-squared	0.684	0.599	
Number of PERMNO		94	94
m1(p)			6.01e-05
m2(p)			0.311
Hansen(p)			0.952

Notes: Model 1 is the OLS regression with year dummy. Model 2 is the fixed effect model. We control for the firm fixed effect. Model 3 is the one-step system-GMM. We use the two-period lag of LnVega, LnDelta, Leverage and ROA as instrumental variables. We include the year dummy and CEOs' age as exogenous variables. DTD is the distance-to-default. LnVega is the log of vega. Vega is the dollar change in CEO option holdings for a 1% change in stock return volatility (in \$1000). LnDelta is the log of delta. Delta is the dollar change in CEO stock and option portfolio for a 1% change in stock price (in \$1000). Leverage is the book leverage ratio. LnMB is the log transformation of market to book ratio. LnAge is the log of CEOs' age. LnROA is the log of return on assets. LnSize is the log transformation of total assets. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 3.4 Regressions with controls for other components of CEO
compensation packages

Variables	(1) OLS	(2) Fixed effects	(3) GMM
DTD_{t-1}	0.521*** (0.0860)	0.265** (0.103)	0.513*** (0.108)
$LnVega_{t-1}$	-0.308** (0.127)	-0.449 (0.282)	-0.651* (0.363)
$LnDelta_{t-1}$	0.136 (0.148)	0.163 (0.407)	0.359 (0.434)
$LnSalary_{t-1}$	0.188 (0.422)	-0.564 (0.610)	0.610 (0.521)
$LnBonus_{t-1}$	0.0809 (0.0512)	0.0669 (0.0473)	0.0239 (0.0533)
$LnOTHCOMP_{t-1}$	-0.0112 (0.0689)	0.185 (0.135)	0.0286 (0.0811)
$Leverage_{t-1}$	-9.737*** (1.580)	-5.299** (2.242)	-10.34*** (3.403)
$LnMB_{t-1}$	0.235 (0.399)	-1.198* (0.691)	0.0490 (0.760)
$LnAge_{t-1}$	0.639 (1.020)	1.915* (1.054)	0.711 (1.255)
$LnROA_{t-1}$	-7.655 (6.673)	5.170 (11.10)	-13.60* (7.592)
$LnSize_{t-1}$	0.104 (0.136)	-1.692*** (0.495)	0.167 (0.251)
<i>Constant</i>	-2.988 (3.934)	22.56*** (5.831)	-4.142 (5.320)
Observations	496	496	496
R-squared	0.684	0.597	
Number of PERMNO		94	94
m1(p)			5.93e-05
m2(p)			0.300
Hansen(p)			0.966

Notes: Model 1 is the OLS regression with year dummy. Model 2 is the fixed effect model. We control for the firm fixed effect. Model 3 is the one-step system-GMM. We include the year dummy and CEOs' age as the exogenous variables. We use two-period lag of the rest independent variables as instrument variables. DTD is the distance-to-default. LnVega is the log of vega. Vega is the dollar change in CEO option holdings for one-percent change in stock return volatility (in \$1000). LnDelta is the log of delta. Delta is the dollar change in CEO stock and option portfolio for a 1% change in stock price (in \$1000). LnMB is the log transformation of the market to book ratio. LnBonus is the log of CEO cash bonus payment. LnSalary is the log of CEOs' salary. LnOTHCOMP is the log of CEOs other compensation payment, include pensions and other benefits. Leverage is the book leverage ratio. LnMB is the log transformation of market to book ratio. LnAge is the log of CEOs' age. LnROA is the log of return on assets. LnSize is the log transformation of total assets. Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table 3.5 Regressions with an interaction term between high leverage and vega

Variables	(1) OLS	(2) Fixed effects	(3) GMM
DTD_{t-1}	0.530*** (0.0845)	0.294*** (0.0997)	0.518*** (0.106)
$LnVega_{t-1}$	-0.354*** (0.129)	-0.477* (0.268)	-0.880*** (0.298)
$HIGH*LnVega_{t-1}$	0.0656 (0.0546)	0.00520 (0.0526)	0.0679 (0.101)
$HIGH$	-0.681*** (0.234)	-0.604** (0.264)	-1.649*** (0.417)
$LnDelta_{t-1}$	0.168 (0.150)	0.213 (0.393)	0.241 (0.368)
$Leverage_{t-1}$	-8.380*** (2.022)	-3.689 (2.796)	-4.931 (4.138)
$LnMB_{t-1}$	0.315 (0.387)	-1.200* (0.707)	0.331 (0.584)
$LnAge_{t-1}$	0.692 (0.929)	1.788** (0.847)	1.614 (1.243)
$LnROA_{t-1}$	-7.005 (6.419)	6.356 (10.89)	-7.063 (5.880)
$LnSize_{t-1}$	0.198* (0.115)	-1.684*** (0.521)	0.525** (0.203)
<i>Constant</i>	2.233 (4.037)	19.90*** (5.615)	-2.384 (5.124)
Observations	497	497	497
R-squared	0.688	0.602	
Number of PERMNO	94	94	94
m1(p)			4.62e-05
m2(p)			0.366
Hansen(p)			1

Notes: DTD is the distance-to-default. HIGH equals 1 if the leverage ratio is higher than the median in a given year. Otherwise, HIGH equals 0. Vega is the log of vega. Vega is the dollar change in CEO option holdings for a 1% change in stock return volatility (in \$1000). LnDelta is the log of delta. Delta is the dollar change in CEO stock and option portfolio for a 1% change in stock price (in \$1000). Leverage is the book leverage ratio. LnMB is the log transformation of market to book ratio. LnAge is the log of CEOs' age. LnROA is the log of return on assets. LnSize is the log transformation of total assets. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 3.6 Regressions with an interaction term and other components of CEO compensation packages

Variables	(1) OLS	(2) Fixed effects	(3) GMM
DTD_{t-1}	0.522*** (0.0870)	0.276*** (0.104)	0.496*** (0.0875)
$LnVega_{t-1}$	-0.361*** (0.126)	-0.451* (0.271)	-0.870*** (0.264)
$HIGH*LnVega_{t-1}$	0.0639 (0.0546)	0.000290 (0.0522)	0.0681 (0.0876)
$HIGH$	-0.679*** (0.233)	-0.608** (0.261)	-1.319*** (0.401)
$LnDelta_{t-1}$	0.149 (0.146)	0.135 (0.405)	0.261 (0.295)
$LnSalary_{t-1}$	0.180 (0.413)	-0.618 (0.615)	0.454 (0.660)
$LnBonus_{t-1}$	0.0784 (0.0496)	0.0757 (0.0484)	0.0540 (0.0886)
$LnOTHCOMP_{t-1}$	-0.00952 (0.0680)	0.187 (0.139)	0.0308 (0.0811)
$Leverage_{t-1}$	-8.570*** (2.067)	-3.675 (2.738)	-7.773** (3.394)
$LnMB_{t-1}$	0.230 (0.400)	-1.199* (0.703)	0.189 (0.562)
$LnAge_{t-1}$	0.550 (1.016)	1.786* (1.054)	1.200 (1.251)
$LnROA_{t-1}$	-7.612 (6.650)	5.385 (11.38)	-8.547 (6.479)
$LnSize_{t-1}$	0.136 (0.142)	-1.565*** (0.509)	0.432 (0.275)
<i>Constant</i>	2.136 (4.039)	21.98*** (5.769)	-2.770 (4.872)
Observations	496	496	496
R-squared	0.685	0.597	
Number of PERMNO	94	94	94
m1(p)			5.37e-06
m2(p)			0.300
Hansen(p)			1

Notes: DTD is the distance-to-default. HIGH equals 1 if the leverage ratio is higher than the median in a given year. Otherwise, HIGH equals 0. Vega is the log of vega. Vega is the dollar change in CEO option holdings for a 1% change in stock return volatility (in \$1000). LnDelta is the log of delta. Delta is the dollar change in CEO stock and option portfolio for a 1% change in stock price (in \$1000). LnSalary is the log of CEOs' salary. LnBonus is the log of CEOs' cash bonus payment. LnOTHCOMP is the log of other compensations. Leverage is the book leverage ratio. LnMB is the log transformation of market to book ratio. LnAge is the log of CEOs' age. LnROA is the log of return on assets. LnSize is the log transformation of total assets. Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

3.4.3 CEO vega in high-leverage firms and low-leverage firms

In light of the risk-shifting issue discussed in Section 3.2.2, we explore how banks' leverage ratios influence the association between CEO vega and default risk. Specifically, we expect that the leverage ratio has an attenuating impact on the association between CEO vega and default risk.

To test the association between CEO vega and default risk in high-leverage and low-leverage banks, we introduce a dummy variable, *HIGH*. *HIGH* equals 1 if the leverage ratio is below the median in a given year. Otherwise, *HIGH* equals 0. We include the interaction term *HIGH*LnVega* in regressions. The empirical results are shown in Table 3.5. The coefficient on *HIGH*LnVega* is not statistically significant. In contrast, the coefficient on *LnVega* is negative and statistically significant at the 0.05 level. The *p* values of *m1* and *m2* are 4.62e-05 and 0.366 respectively. The *p* value of the Hansen *J* test is 1. The coefficient on CEO vega is 0.518 in the system-GMM model. The system estimator lies within the interval of the OLS estimator (0.530) and the fixed effect estimator (0.294), which suggests that the system-GMM model is properly specified. The coefficient on CEO vega is -0.88, which is statistically significant at the 0.01 level. In contrast, the coefficient on *HIGH*LnVega* is statistically insignificant. Therefore, hypothesis 2 is accepted, as these results support our argument that if banks have high leverage ratios, CEOs with high-vega pay packages are less likely to increase default risk.

We include other elements of compensation, such as salary and cash bonuses, in the model in Table 3.6. The main results remain qualitatively the same.

3.4.4 Pre- and post-GLB periods

We expect the association between CEO vega and default risk are different during the pre- and post-GLB periods. Specifically, we expect to observe a stronger association between CEO vega and default risk after the GLB Act (1999) because the banks have more channels to increase risk.

To disentangle the risk-inducing effect of CEO vega during the pre- and post-

GLB periods, we introduce a dummy variable, *Post_GLB*, to identify the post-GLB period. *Post_GLB* equals 1 for the year 2000 and after. *Post_GLB* equals 0 for all earlier years. We include an interaction term, *Post_GLB*LnVega*, in the regressions. The term *Post_GLB*LnVega* captures the impact of CEO vega on distance-to-default during the post-GLB period. The term *LnVega* captures the effect of CEO vega on distance-to-default during the pre-GLB period. The estimations based on OLS, fixed effect, one-step GMM models are reported in Table 3.7. In column 3 of Table 3.7, the coefficients on the interaction term *Post_GLB*LnVega* are negative and statistically significant.

These results suggest that the difference in the effect of CEO vega is statistically significant between the pre-GLB and post-GLB periods. In contrast, the coefficient on the term *LnVega* is not statistically significant. The *p* value of the Hansen *J* test is 0.997, suggesting our model is not over-identified. The *p* value for *m1* and *m2* are 3.37e-05 and 0.125, suggesting the GMM model is properly specified. The coefficient on lag distance-to-default is 0.514, which lies between the values given using the OLS estimator (0.525) and the fixed effect estimator (0.282). Therefore, hypothesis 3 is accepted. These results confirm our expectation that CEO vega has a significant association between CEO vega and default risk when the banks have more opportunities, such as more investment channels. In contrast, when banks have fewer opportunities to implement aggressive business policies, the effect of CEO vega on distance-to-default become insignificant. These results are consistent with the results of DeYoung et al. (2013).

We include other elements of CEO compensation packages, such as salary and cash bonus, in regressions in Table 3.8. The *p* value of *m1* is 4.37e-06 and the *p* value of *m2* is 0.136. The *p* value of the Hansen *J* test is 1. The coefficient on CEO vega in the GMM model is 0.508, which lies within the upper bound of the OLS estimator (0.516) and the lower bound of the fixed effects estimator (0.257). These results confirm the validity of the system-GMM model. We find that the main results remain qualitatively the same after controlling for other elements of the compensation package.

3.5 Conclusions

Equity-based compensation has an incentive for CEOs to be risk-taking: CEO

vega measures the incentive that motivate them to undertake risky investments. Prior studies such as Coles et al. (2006) suggest that both CEO delta and CEO vega benefit firms by mitigating the agency conflicts between shareholders and managers. However, few studies explore whether the benefits from such incentives are at the cost of an increase in the probability of the firm's default. This chapter sheds light on the (potentially) value-destroying effects of these incentives. Moreover, the risk-inducing effect of CEO vega could be influenced by firms' financial states. This chapter explicitly explores the varying association of CEO vega on default risk in US banks. The relation between CEO vega and default risk is estimated by the distance-to-default measure proposed by Bharath and Shumway (2008). We find that CEO vega is positively associated with default risk. After controlling for particular elements of CEO compensation, the results are qualitatively the same. These results imply that CEO compensation packages significantly influence default risk in the banking industry. We also find that CEO vega has a significant association with default risk during the post-GLB period. Additionally, we explore how risk-shifting affects the relation between CEO vega and default risk. We classify the banks into high-leverage and low-leverage banks. We find the association between CEO vega and default risk is stronger in high-leverage banks. This chapter contributes to the literature on the side-effects of equity-based compensation. It also contributes to the literature on the state-dependent effect of managerial compensation incentives (i.e. for firms in different financial states). This chapter also has implications for practitioners. For instance, it could be beneficial to take the debtholders' view into consideration when designing executive compensation packages in high-leverage banks.

Table 3.7 Pre- and post-GLB (1999)

Variables	(1) OLS	(2) Fixed effects	(3) GMM
DTD_{t-1}	0.525*** (0.0852)	0.282*** (0.0997)	0.514*** (0.109)
$LnVega_{t-1}$	-0.110 (0.135)	-0.301 (0.256)	-0.279 (0.300)
$Post_GLB * LnVega_{t-1}$	-0.428*** (0.156)	-0.725*** (0.191)	-0.973*** (0.356)
$Post_GLB$	7.193*** (0.904)	9.006*** (1.297)	1.177 (5.415)
$LnDelta_{t-1}$	0.203 (0.154)	0.553 (0.401)	0.341 (0.421)
$Leverage_{t-1}$	-9.926*** (1.598)	-5.525** (2.323)	-10.45*** (3.470)
$LnMB_{t-1}$	0.392 (0.391)	-1.397** (0.686)	0.365 (0.597)
$LnAge_{t-1}$	0.601 (0.944)	1.552* (0.880)	1.438 (1.299)
$LnROA_{t-1}$	-9.221 (6.137)	6.031 (11.09)	-11.98** (5.463)
$LnSize_{t-1}$	0.202* (0.106)	-1.753*** (0.513)	0.444** (0.223)
<i>Constant</i>	-3.640 (3.949)	13.96** (5.361)	0 (0)
Observations	497	497	497
R-squared	0.689	0.616	
Number of PERMNO	94	94	94
m1(p)			3.37e-05
m2(p)			0.125
Hansen(p)			0.996

Notes: DTD is the distance-to-default. Post_GLB equals 1 for the year 2000 and after. Pre_GLB equals 0 for all other years. LnVega is the log of vega. Vega is the dollar change in CEO option holdings for a 1% change in stock return volatility (in \$1000). LnDelta is the log of delta. Delta is the dollar change in CEO stock and option portfolio for a 1% change in stock price (in \$1000). Leverage is the book leverage ratio. LnMB is the log transformation of market to book ratio. LnAge is the log of CEOs' age. LnROA is the log of return on assets. LnSize is the log transformation of total assets. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 3.8 Pre- and post-GLB with other elements of CEO compensation package

Variables	(1) OLS	(2) Fixed effect	(3) GMM
<i>DTD_{t-1}</i>	0.516*** (0.0875)	0.257** (0.103)	0.508*** (0.0881)
<i>LnVega_{t-1}</i>	-0.115 (0.132)	-0.234 (0.258)	-0.362 (0.265)
<i>Post_GLB*LnVega_{t-1}</i>	-0.430*** (0.156)	-0.777*** (0.185)	-0.868*** (0.300)
<i>Post_GLB</i>	7.158*** (0.894)	9.481*** (1.235)	9.836*** (1.771)
<i>LnDelta_{t-1}</i>	0.184 (0.150)	0.489 (0.409)	0.305 (0.320)
<i>LnSalary_{t-1}</i>	0.164 (0.420)	-1.146* (0.590)	0.461 (0.664)
<i>LnBonus_{t-1}</i>	0.0801 (0.0496)	0.0766 (0.0487)	0.0108 (0.0934)
<i>LnOTHCOMP_{t-1}</i>	-0.0135 (0.0669)	0.182 (0.132)	0.0147 (0.0758)
<i>Leverage_{t-1}</i>	-10.17*** (1.650)	-5.765** (2.368)	-11.79*** (2.809)
<i>LnMB_{t-1}</i>	0.312 (0.403)	-1.345* (0.686)	0.620 (0.579)
<i>LnAge_{t-1}</i>	0.469 (1.038)	1.950* (1.129)	1.281 (1.213)
<i>LnROA_{t-1}</i>	-9.768 (6.363)	5.455 (11.63)	-10.31 (6.453)
<i>LnSize_{t-1}</i>	0.143 (0.137)	-1.575*** (0.498)	0.403 (0.275)
<i>Constant</i>	-3.648 (3.955)	16.92*** (5.542)	-10.71** (4.950)
Observations	496	496	496
R-squared	0.690	0.616	
Number of PERMNO	94	94	94
m1(p)			4.37e-06
m2(p)			0.136
Hansen(p)			1

Notes: DTD is the distance-to-default. Post_GLB equals 1 for the year 2000 and after. Pre_GLB equals 0 for all other years. LnVega is the log of vega. Vega is the dollar change in CEO option holdings for a 1% change in stock return volatility (in \$1000). LnDelta is the log of delta. Delta is the dollar change in CEO stock and option portfolio for a 1% change in stock price (in \$1000). LnSalary is the log of CEOs' salary. LnBonus is the log of CEOs' cash bonus payment. LnOTHCOMP is the log of other compensations. Leverage is the book leverage ratio. LnMB is the log transformation of market to book ratio. LnAge is the log of CEOs' age. LnROA is the log of return on assets. LnSize is the log transformation of total assets. Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

APPENDIX 3.A

Table 3.9 Frequency of observations, by year

Fiscal year	Frequency	Percentage	Cumulative percentage
1994	20	4.03	4.03
1995	30	6.05	10.08
1996	43	8.67	18.75
1997	43	8.67	27.42
1998	40	8.06	35.48
1999	46	9.27	44.76
2000	44	8.87	53.63
2001	43	8.67	62.3
2002	49	9.88	72.18
2003	53	10.69	82.86
2004	43	8.67	91.53
2005	42	8.47	100
Total	496	100	100

Table 3.10 Regression without controls for other components of compensation
and state fixed effect

Variables	(1) OLS	(2) Fixed effects	(3) GMM
DTD_{t-1}	0.503*** (0.0909)	0.308*** (0.104)	0.435*** (0.149)
$LnVega_{t-1}$	-0.542*** (0.189)	-0.464* (0.276)	-0.855* (0.446)
$LnDelta_{t-1}$	0.345 (0.227)	0.220 (0.393)	0.761 (0.548)
$Leverage_{t-1}$	-9.338*** (1.666)	-5.142** (2.330)	-11.25** (4.834)
$LnMB_{t-1}$	0.371 (0.462)	-1.363* (0.778)	0.140 (1.140)
$LnAge_{t-1}$	0.430 (1.150)	2.080** (0.865)	0.578 (2.213)
$LnROA_{t-1}$	-4.079 (7.766)	-10.18 (12.03)	-24.89 (18.55)
$LnSize_{t-1}$	0.198* (0.118)	-1.683*** (0.536)	0.139 (0.314)
<i>Constant</i>	3.313 (4.716)	19.20*** (5.865)	4.669 (9.116)
Observations	492	492	492
R-squared	0.704	0.604	
Number of PERMNO	93	93	93
m1(p)			0.000123
m2(p)			0.307
Hansen(p)			0.987

Notes: Model 1 is the OLS regression with year dummy. Model 2 is the fixed effect model. We control for the firm fixed effect. Model 3 is the one-step system-GMM. We use the two-period lag of LnVega, LnDelta, Leverage and ROA as instrumental variables. We include the year dummy and CEOs' age as exogenous variables. DTD is the distance-to-default. LnVega is the log of vega. Vega is the dollar change in CEO option holdings for a 1% change in stock return volatility (in \$1000). LnDelta is the log of delta. Delta is the dollar change in CEO stock and option portfolio for a 1% change in stock price (in \$1000). Leverage is the book leverage ratio. LnMB is the log transformation of market to book ratio. LnAge is the log of CEOs' age. LnROA is the log of return on assets. LnSize is the log transformation of total assets. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 3.11 Regressions with controls for other components of compensation
with state effect

Variables	(1) OLS	(2) Fixed effects	(3) GMM
<i>DTD_{t-1}</i>	0.498*** (0.0940)	0.290*** (0.107)	0.438*** (0.105)
<i>LnVega_{t-1}</i>	-0.509*** (0.192)	-0.460* (0.274)	-0.774** (0.376)
<i>LnDelta_{t-1}</i>	0.292 (0.226)	0.142 (0.403)	0.400 (0.378)
<i>LnSalary_{t-1}</i>	0.303 (0.476)	-0.532 (0.607)	0.763 (0.846)
<i>LnBonus_{t-1}</i>	0.0802 (0.0541)	0.0908* (0.0479)	0.0418 (0.124)
<i>LnOTHCOMP_{t-1}</i>	-0.0243 (0.0772)	0.177 (0.140)	-0.0366 (0.0870)
<i>Leverage_{t-1}</i>	-9.351*** (1.733)	-5.291** (2.408)	-10.48*** (3.038)
<i>LnMB_{t-1}</i>	0.219 (0.479)	-1.439* (0.772)	0.287 (0.787)
<i>LnAge_{t-1}</i>	0.327 (1.246)	2.098* (1.106)	0.160 (1.721)
<i>LnROA_{t-1}</i>	-5.810 (8.521)	-13.68 (11.88)	-4.387 (18.59)
<i>LnSize_{t-1}</i>	0.0997 (0.163)	-1.559*** (0.529)	0.0392 (0.361)
<i>Constant</i>	2.650 (4.686)	20.81*** (6.026)	2.541 (6.923)
Observations	491	491	491
R-squared	0.705	0.603	
Number of PERMNO	94	94	94
m1(p)			1.39e-05
m2(p)			0.388
Hansen(p)			1

Notes: Model 1 is the OLS regression with year dummy. Model 2 is the fixed effect model. We control for the firm fixed effect. Model 3 is the one-step system-GMM. We include the year dummy and CEOs' age as the exogenous variables. We use two-period lag of the rest independent variables as instrument variables. DTD is the distance-to-default. LnVega is the log of vega. Vega is the dollar change in CEO option holdings for one-percent change in stock return volatility (in \$1000). LnDelta is the log of delta. Delta is the dollar change in CEO stock and option portfolio for a 1% change in stock price (in \$1000). LnMB is the log transformation of the market to book ratio. LnBonus is the log of CEO cash bonus payment. LnSalary is the log of CEOs' salary. LnOTHCOMP is the log of CEOs other compensation payment, include pensions and other benefits. Leverage is the book leverage ratio. LnMB is the log transformation of market to book ratio. LnAge is the log of CEOs' age. LnROA is the log of return on assets. LnSize is the log transformation of total assets. Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

APPENDIX 3.B

We derive CEO stock option delta and vega using Black and Scholes (1973) option pricing model as modified by Merton (1973). The Black–Scholes model requires the following variables to estimate the delta and vega values for CEOs' stock options.

CEO delta is the dollar change in wealth associated with a 1% change in the firm's stock price (in \$1000s).

CEO vega is the dollar change in wealth associated with a 1% change in the standard deviation of the firm's returns (in \$1000s).

d = natural logarithm of the expected dividend yield over the life of the option;

S_t = stock price at time t (Execucomp variable PRCCF)

σ = expected stock return volatility over the life of the option: annualised standard deviation of stock return estimated over the 60 months prior to the

beginning of the fiscal period, which equals $\sqrt{\frac{\sum_{t=-60}^{-1} (r_t - \bar{r})^2}{59}} * \sqrt{12}$, where $r = \ln\left(\frac{S_t}{S_{t-1}}\right)$.

N = cumulative probability function for the normal distribution;

N' = normal density function;

X = strike price of executive option;

$Z = \left[\ln\left(\frac{S}{X}\right) + T\left(r - d + \frac{\sigma^2}{2}\right) \right] / \sigma T^{(1/2)}$;

$\Delta = \frac{\partial V}{\partial S} = e^{-dt} N(Z) * (S/100)$;

$\text{Vega} = \frac{\partial V}{\partial \sigma} = e^{-dt} N'(Z) S T^{(1/2)} * (0.01)$.

Following Coles et al.'s (2013) approach, we calculate the delta and vega value of CEOs' compensation based on the Execucomp database. The Financial Accounting Standards Board (FASB) FAS 123R imposed an accounting change for equity-based compensation, because of which the Execucomp reporting regimes are different in the fiscal years 1992 to 2006. Post-2006, the new reporting format is imposed. The Execucomp database contains different

data variables pre-2006 and post-2006. Therefore, we calculate delta and vega values under different reporting regimes.

Pre-2006, we apply the Core and Guay's (2002) approximation approach to compute the delta and vega values of CEOs' option portfolios. Under the reporting format of pre-2006, the requirement for current year's option granted and previously granted options are different. For current year's options granted, the tranche-level detailed information is reported, such as the exercise price, the maturity of each tranche of options, the exercise price and the number of options granted. As for previously granted options, only the data about the intrinsic value and number are available for the vested and unvested executive option portfolio. Following Core and Guay's (2002) and Coles et al. (2013), we compute the three different portfolios separately. The three kinds of options portfolios are the vested options, the unvested options from previously granted awards, and option granted in the current year. The incentives of these three option portfolios compromise the CEOs' total option-linked incentives.

The risk-free rate is the 1-year Treasury bill rate obtained from Federal Reserve website. The dividend yield is the variable DIVYIELD in the Execucomp database. DIVYIELD is not available for the samples after 2006 as Execucomp changed the reporting format. Pre-2006, Execucomp provided a variable ((BS_VOLATILITY)) as an estimation of stock volatility. We use the variable BS_VOLATILITY as the stock volatility in the Black–Scholes formula.

For the options awarded in the current year, we can estimate the incentives of executive options with the variables in the Execucomp database, as the Execucomp database contains the exercise price (EXPRIC) and the number of options granted for the current year (NUMSECUR). The maturity of the options equals the expiration date (EXDATE) minus the current date. The aggregate number of all tranches equals the variable OPTION_AWARDS_NUM.

The maturity of vested options is assumed to be the maturity of unvested options minus three. We estimate the average exercise price based on the

realisable value of vested options (OPTS_VESTED_VAL) and the number of options (OPTS_VESTED_NUM).

$$\text{Estimated Exercise Price} = PRCCF - \frac{OPTS_VESTED_VAL}{OPTS_VESTED_NUM}$$

Information about the intrinsic value of previously granted unvested options is not directly available. We therefore need to estimate the intrinsic value of the options as the reported intrinsic value of all unvested options (OPTS_UNVESTED_VAL) minus the total intrinsic value of the option granted in the current year. The calculation can be expressed as follows:

$$\begin{aligned} & OPTS_UNVESTED_VAL_PREVIOUS \\ &= OPTS_UNVESTED_VAL \\ &- \sum [(PRCCF - EXPRIC) * NUMSECUR] \end{aligned}$$

With a similar logic, we estimate the number of previously granted unvested options as the total number of options granted in the current year (OPTS_UNEX_UNEXER_NUM) minus the number of unvested options (OPTION_AWARDS_NUM).

$$\begin{aligned} & OPTS_UNVESTED_NUM_PREVIOUS \\ &= OPTS_UNEX_UNEXER_NUM - OPTION_AWARDS_NUM \end{aligned}$$

With the estimated intrinsic value and number of previously granted unvested options, we can estimate the average exercise price of each tranche of options. The average exercise price of each option is computed as the stock price in that year minus the average intrinsic value of each option.

$$\begin{aligned} & EXERCISE_PRICE_UNVESTED_PREVIOUS \\ &= PRCCF - \frac{OPTS_UNVESTED_VAL_PREVIOUS}{OPTS_UNVESTED_NUM_PREVIOUS} \end{aligned}$$

We obtain the estimations of the delta and vega for the three option portfolios. We can aggregate the overall delta and vega for the executive incentives. The

overall delta is the sum of the delta of options granted in the current year, the delta of the vested options, the delta of previously granted unvested options and the delta of the stock shares owned by the CEO. The total vega is the sum of the vega of options granted in the current year, the vega of the vested options and the vega of previously granted unvested options. The vega of the stock share portfolio is excluded, as the assumption in Guay (1999) is that the vega of the stock share portfolio is zero.

Post-2006, we compute incentives as of fiscal year-end based on these data. Execucomp provides a detailed record for each tranche of options – the vested options, the unvested options and the unearned options (OPTS_UNEX_EXER, OPTS_UNEX_UNEXER, OPTS_UNEX_UNEARN). The exercise price is EXPRIC and expiration date is EXDATE. Following Coles et al. (2013), we do not include unearned options. The unearned options are the unearned awards for which the future vesting is conditional on achieving stock price or accounting targets (Coles et al., 2013). The data for these variables are not available in the Execucomp database. Omitting them leads to an underestimation of both delta and vega. We plug the input variables into the Black–Scholes option formula and can estimate delta and vega for each option tranche. The delta of stock share portfolios is simply computed as the 1% change of the value of the stock share portfolio. We use the variable SHROWN_EXCL_OPTIONS, which is the total number of restricted and unrestricted shares. The total delta of the executive portfolio is the sum of the delta of the vested option, the delta of unvested options and the delta of stock share portfolios. The total vega of CEOs’ portfolios is the sum of the vega of vested options and the vega of unvested options.

CHAPTER 4. The overlapping-hours phenomenon and price jumps: the case of ADRs

4.1 Introduction

Jumps –extreme, unexpected increases or decreases– in prices within a short period attract great interest from academia and financial practitioners. For instance, jumps in stock prices are important in determining risk management (Duffie and Pan, 2001), risk premium (Pan, 2002) and asset allocation (Jarrow and Rosenfeld, 1984). With the significant progress of both parametric and non-parametric techniques in this field, the existence of jumps and their contributions to stock price variation have been widely confirmed by empirical studies (Huang and Tauchen, 2005; Bollerslev et al., 2008; Tauchen and Zhou, 2011). Separating jump variation from the continuous price sample variability can significantly improve the forecasting accuracy of realised volatility (Andersen et al., 2007).

Jumps can occur after news announcement but also in the absence of news announcement. For instance, Eraker et al. (2003) show that the US macroeconomic announcements coincide with statistically significant price jumps. Barndorff-Nielsen and Shephard (2006) find that most statistically identified jumps in stock indexes are associated with government macroeconomic announcements. Bollerslev et al. (2008) show that economic news like large changes in federal interest rates or oil prices are related to jumps in the stock market. Besides macroeconomic news, firm-specific news also affects the incidence of price jumps. For example, Bollerslev et al. (2008) demonstrates that firm-specific news is positively associated with price jumps at the individual stock level. Evans (2011) indicates that unexpected firm-specific news such as the death of CEOs and lawsuits coincide with negative price jumps.

However, neither macroeconomic news or firm-specific news can fully explain the drivers behind jumps. A few recent studies argue that price jumps in security markets are also associated with market liquidity. Market liquidity, an essential concern in the stock market, refers to the ease which assets can be purchased or sold without causing significant price changes. It is associated with severe incidents in the financial market. A well-known example is the ‘Flash Crash’ in the US stock market on 6 May 2010. The Dow Jones

Industrial Average dropped by over 1,000 points in just 15 minutes, before recovering to approximately 70% of the previous value. A distinguishing feature of the Flash Crash is that it happened in the absence of major negative news about economic fundamentals. Christoffersen et al. (2016) suggest that the such crashes in the stock market are driven by market illiquidity.

Recent empirical studies also provide supportive evidence for the association between price jumps and market liquidity. For instance, Jiang et al. (2011) show that after controlling for the effect of information shocks, liquidity shocks in bid–ask spreads and market depth still have significant predictive power for price jumps. Evans (2011) finds a similar association between price jumps and liquidity in the US futures market. The author shows that market liquidity, in terms of trading volume and number of trading ticks, has a positive association with price jumps. Gilder et al. (2014) analyse the liquidity of 30 Dow Jones stocks around the incidence of price jumps and show that variables measuring liquidity, i.e. bid–ask spreads and the number of trades, are the drivers behind jumps.

There are a number of cross-listed stocks traded on the exchanges around the world. According to the Annual Statistics Guide of the World Federation of Stock Exchanges (WFE) in 2016, over 2,400 firms around the world are listed as foreign firms on 56 major stock exchanges. One way for firms to cross-list their stocks on two stock exchanges is by issuing depositary receipts. A survey by JP Morgan (2003) shows that the American depositary receipts (ADRs) and their underlying stocks are viewed as substitutes. Gagnon and Karolyi (2010) suggest that ADRs, traded simultaneously in different markets, allow arbitrageurs to explore price deviations across countries. Depositary receipts and the underlying stocks can be traded in domestic and overseas markets in different time-zones. For instance, the US stock exchanges apply Eastern Standard Time (EST), which is five hours behind Greenwich Mean Time (GMT), which the UK stock exchange applies. During the last two trading hours of the UK stock exchange, the US stock market is also open.¹ As a result, the cross-listed stocks have overlapping hours when both stock markets are

¹ The overlapping hours vary in different date due the daylight-saving time. The detailed discussion is presented in Section 4.4.3.

open and non-overlapping hours when only one market is open, as we focus on two stock markets (the UK and the US stock markets).

Empirical studies show that overlapping trading hours affect the intraday trading pattern of cross-listed stocks. The trading activities and liquidity pattern during the overlapping hours are significantly different from the rest of day; this is known as the overlapping-hours phenomenon. Werner and Kleidon (1996) first observed the overlapping-hours phenomenon, by investigating the intraday trading pattern of cross-listed stocks traded on the UK and US stock exchanges. The authors found that the overlapping hours were characterised as decreased bid–ask spreads and high trading volume compared with the non-overlapping hours. Moulton and Wei (2009) also find that the overlapping hours lead to better market liquidity provision, characterised as higher trading volume, number of transactions and market depth, and lower bid–ask spreads. The overlapping-hours phenomenon is in fact observed in stock markets worldwide. Halling et al. (2013) show that overlapping hours are positively associated with trading volume shocks based on cross-listed stocks from 24 countries.

Few studies investigate the incidence of price jumps in the context of cross-listed stocks. This study attempts to shed light on incidence of price jumps in cross-listed stocks trading, and takes a further step in exploring the association between the overlapping-hours phenomenon and price jumps. It contributes to the literature in three respects. First, we find that ADRs show very different intraday liquidity patterns during the overlapping times when compared with those during non-overlapping hours. For ADRs, the average transaction size is found to be larger during overlapping hours than during non-overlapping hours, suggesting more intensive trading of ADRs. Moreover, the market depth increases during overlapping hours due to increased liquidity.

Secondly, we are the first to investigate the influence of the overlapping-hours phenomenon on the occurrence of intraday jumps in cross-listed stocks. Jiang et al. (2011) and Evans (2011) identify that market liquidity is associated with jump variation in the Treasury bill and the US futures markets but they do not focus on individual stocks. Gilder et al. (2014) show that liquidity shocks, as

measured using the effective bid–ask spreads and the number of trades, are the key drivers behind jumps in stock prices. We find that ADRs have much fewer price jumps during overlapping hours than their matched group sample, implying less discontinuous movement. This suggests that the overlapping hours reduce the number of price jumps because of an increase in market liquidity.

Finally, we investigate the effect of varying overlapping hours on market liquidity. Menkveld (2008), Moulton and Wei (2009) and Halling et al. (2013) assume that the common trading hours of the domestic and the overseas markets are constant over time. Little attention has been paid to the fact that the calendars of daylight-saving time are different in the UK and the US. This leads to different overlapping hours during different times of year. To the best of our knowledge, we are the first to investigate the effects of the varying overlapping hours caused by the daylight-saving time on ADRs. Indeed, we find the overlapping-hours phenomenon is sensitive to this change in overlapping hours. The finding suggests that the overlapping-hours phenomenon is driven by the common trading hours of two stock markets rather than by an isolated trading pattern.

This study also has some implications for policymakers of emerging economies who plan to raise capital in overseas markets. For instance, China and the UK plan to connect the Shanghai Stock Exchange and London Stock Exchange, which means more cross-listed securities will be traded on both stock exchanges. As the overlapping-hours phenomenon significantly affects the intraday liquidity of depository receipts, common trading hours become an important factor for policymakers to consider before issuing depository receipts.

This rest of the chapter is organised as follows. In Section 4.2, we review the literature on the overlapping-hours phenomenon and price jumps and present the hypotheses. In Section 4.3, the data and methodology are discussed. In Section 4.4, we analyse the empirical results. The conclusions are presented in Section 4.5.

4.2 Literature review

4.2.1 The overlapping-hours phenomenon

As the financial markets integrate globally, more firms choose to cross-list, that is, to list their stocks on different stock exchanges. For instance, Pagano et al. (2002) document that the number of firms which choose to list their stocks on foreign exchanges increased significantly from the late 1990s. They show that this trend is particularly significant in the US stock market. The number of non-US listings in the 1990s had increased fourfold, to 467 firms, by the end of 2002, and these cross-listed stocks accounted for 10.2% of trading volume on the NYSE in 2003.² There are even more non-US firms on the NASDAQ. The proportion of cross-listed stocks, by trading volume, has grown strongly since 2003 in the US market and also have a growing presence in European stock exchanges. For instance, non-domestic stocks make up about 50% share in Amsterdam, Brussels, Frankfurt and Switzerland (Pagano et al., 2001).

An important driver behind multimarket trading is the substitution effect of the cross-listed stocks in the domestic market and the cross-listed market. A survey by JP Morgan (2003) shows that US investors view the home-market stocks and cross-listed stocks of the same firms as close substitutes. The substitutes of trading across markets can be seen as the ‘traditional vehicle for international diversification’ (Moulton and Wei, 2009). This study focuses on American depositary receipts (ADRs), which is a major way for non-US companies to list their securities on the US market. ADRs were introduced by JP Morgan in 1927 and are most commonly used by US investors to diversify their assets internationally. ADRs are issued in US dollars by depositary banks such as the Bank of New York, Citibank and JP Morgan. Depositary banks immobilise underlying home securities through a custodian in the home market and issue ADRs, which represent claims on the immobilised home stocks. The depositary banks are responsible for currency conversion and pay the dividends in US dollars. Since ADRs and their underlying stocks are usually traded in different exchanges located in different time zones, this feature leads to a special pattern for cross-listed stocks: the presence of overlapping hours (i.e.

² See the on-line NYSE factbook (<http://www.nysedata.com>)

when both domestic and overseas markets are open) and non-overlapping hours (when only one market is open). When both markets are open, the cross-listed are quoted simultaneously on the different stock exchanges. Due to the unique character of overlapping hours, the trading activities for cross-listed stocks are different during overlapping and non-overlapping hours.

Werner and Kleidon (1996) observe the overlapping-hours phenomenon by analysing the intraday pattern of British cross-listed stocks traded on the UK and the US markets in 1991. The authors find that the overlapping hours of the two stock markets are characterised by higher trading volumes. Moreover, they document that the bid–ask spreads on the UK stock market tend to decrease during the overlapping hours. Werner and Kleidon propose two reasons for the higher trading volumes during the overlapping hours. Firstly, the more informative stock prices are preferred by both liquidity traders and informed traders. Secondly, arbitrage activities from two markets lead to the trading concentration during overlapping hours. The second explanation is supported by the fast growth of multimarket trading in the last two decades. O’Hara and Ye (2011) find that multimarket trading is expanding rapidly in both the US and the European stock markets. Halling et al. (2013), Pukthuanthong and Roll (2009) and Bekaert et al. (2011) similarly find there has been increasing multimarket trading in emerging markets since the late 1990s. In this study, we focus on the observable features of the overlapping-hours phenomenon rather than entangling the two reasons for the overlapping-hours phenomenon.

Empirical studies show that market liquidity differs between overlapping hours and non-overlapping hours. For instance, Moulton and Wei (2009) find that overlapping trading hours are characterised by higher trading volumes, larger numbers of transactions, greater market depth and lower bid–ask spreads. Halling et al. (2013), in a study of 361 companies from 24 countries, find that trading volume shocks in two stock markets have a stronger association if the two markets have longer overlapping trading times. In this study, we first explore the intraday patterns of market liquidity for ADRs with high-frequency data.

4.2.2 Market liquidity

In this session, we review relevant literature on different measures for market liquidity: bid-ask spreads, trading activities and market depth.

Bid–ask spread

As noted by O’Hara and Ye (2011), stock markets with lower transaction costs as measured by bid–ask spreads can be viewed as having higher market liquidity. According to the literature on the overlapping-hours phenomenon, the greater competition arising from intensive trading during overlapping hours should reduce the bid–ask spread. Thus, we propose the following hypothesis about the quoted bid–ask spread, the effective bid–ask spread, the realised bid–ask spread and the price impact:

Hypothesis 1: The bid–ask spreads of ADRs are smaller during overlapping hours than during non-overlapping hours.

Trading activities

Another important feature of overlapping hours is increased trading volume. Werner and Kleidon (1996) find that the increased trading volume is caused by new information being incorporated in the price. Menkveld (2008) confirms that trading volume is higher during overlapping hours. The author explains that ‘liquidity traders’ can split orders across markets and suggests that arbitrage and order-splitting across two markets are the reasons for increased volume during overlapping hours. Moulton and Wei (2009) confirm that the trading volume of cross-listed stocks is higher during overlapping trading hours and suggest this is caused by arbitrage trading, order splitting and heightened information flow. In the present chapter, we measure trading activities in three respects: trading volume in dollars, the number of transactions and the average transaction size. We expect the number of transactions and trading volume of ADRs to be larger during overlapping hours than during non-overlapping hours. Moreover, we also expect the average size of transactions in ADRs to be larger during overlapping hours because potential arbitrage opportunities are more likely to be exploited by institutional

and informed traders, who typically place larger orders than individual investors. Thus, we propose the hypotheses about trading activities as follows:

Hypothesis 2a: The trading volume of ADRs is higher during overlapping hours than during non-overlapping hours.

Hypothesis 2b: The average number of transactions of ADRs is higher during overlapping hours than during non-overlapping hours.

Hypothesis 2c: The average transaction size of ADRs is higher during overlapping hours than during non-overlapping hours.

Market depth

Besides trading activities, we also want to explore how overlapping hours affect the quoting activity. We analyse the quote data to examine the intraday pattern of both market depth and market depth imbalance. Market depth is defined as the sum of all orders from both bid and ask sides. When sufficient liquidity exists in the market, market depth should be high, that is, sufficient orders from the buy and sell sides should be available on the order book. As pairs trading increases the quoting activities during overlapping hours, we expect the market depth of ADRs to be higher during overlapping hours than during non-overlapping hours:

Hypothesis 3: The market depth of ADRs is higher during overlapping hours than during non-overlapping hours.

Many studies on the overlapping-hours phenomenon use simple standard deviation as a measure of price volatility. Werner and Kleidon (1996) find higher volatility during overlapping hours than during non-overlapping hours. Moulton and Wei (2009) find that both cross-listed and locally traded stocks have higher volatility during overlapping hours, though the difference is not statistically significant.

4.2.3 Price jumps

Instead of measuring stock price volatility, as in studies such as Werner and Kleidon (1996) and Moulton and Wei (2009), we focus on price jumps of ADRs for two reasons. Firstly, price jumps play an important role in asset pricing and risk management, which have attracted much attention in recent research. Todorov (2010) states that investors demand a premium for bearing the randomness of future variance, namely the variance risk. The variance risk has two critical parts: a well-known stochastic volatility, which is the continuous change of return; and jumps, which are extreme discontinuous shocks to asset returns. Unanticipated market jumps are associated with investors' fears of extreme events, which have different characteristics from the well-known stochastic volatility. Bollerslev et al. (2014) suggest that jump tail risk has a distinguished risk characteristic which is poorly described by the traditional stock volatility models. Cremers et al. (2015) find that both aggregate jumps and volatility risk help explain variance in the expected returns of the cross-section of stocks. The authors also argue that both aggregate jumps and volatility risk can be measured separately and are economically important. With the development of econometric methods and the availability of high-frequency data, a number of studies, such as Barndorff-Nielsen and Shephard (2006), Andersen et al. (2007), Lee and Mykland (2008), Aït-Sahalia and Jacod (2009) and Christensen et al. (2010), have developed new methods to detect the jump components of return volatility.

The second reason for focusing on price jumps in this study is that market liquidity is one of the key drivers behind the occurrence of jumps. Market liquidity during overlapping hours tends to be higher than during non-overlapping hours, and this is likely to influence the occurrence of price jumps. Early studies on price jumps argue that macroeconomic news or firm-specific news can partially explain the incidence of most price jumps. Eraker et al. (2003) find that statistically significant jumps coincide with the US macroeconomic news announcements. Huang and Tauchen (2005), Barndorff-Nielsen and Shephard (2006) and Andersen et al. (2007) all find an association between significant jumps in aggregate stock indexes and the macroeconomic news. Bollerslev et al. (2008) state that other *ex-post* identifiable broad-based economic news such as federal interest rate changes, oil price changes and security concerns also influence the financial market systematically. As noted

by Bollerslev et al. (2008) and Evans (2011), individual stock price jumps are influenced not only by macroeconomic news but also by unexpected information at the firm level, such as the death of CEOs and lawsuits.

However, neither macroeconomic news nor unexpected firm-level information can fully explain jumps in stock prices. Researchers have started to pay attention to the connection between price jumps and market liquidity. Jiang et al. (2011) compare the importance of variation in market liquidity and macroeconomic news in explaining jumps in the US Treasury bond market. The authors find that jumps usually occur around macroeconomic news announcement, but news announcements have limited power in explaining price jumps. In contrast, liquidity shocks such as changes in bid–ask spreads and market depth have significant predictive power for jumps even after controlling for information shocks (Jiang et al., 2011). Evans (2011) distinguishes the news-related jump variation from other jump variation by studying the US futures market. The author finds that market liquidity variables such as trading volume and the number of ticks are significantly associated with jump variation in the futures markets. Jiang et al. (2011) and Evans (2011) agree that market liquidity is associated with the presence of jump variation but they do not focus on individual stocks. Gilder et al. (2014) investigate the dynamics of the liquidity of 30 Dow Jones stocks around jumps. They believe that liquidity shocks in the effective bid–ask spreads and the number of trades are the key drivers for jumps. However, they do not find any specific intraday pattern for the jumps.

We are the first to investigate the connection between price jumps and liquidity dynamics of cross-listed stocks in the UK and the US stock markets. The overlapping-hours phenomenon suggests that the effective bid–ask spreads tend to narrow during overlapping hours, due to increased market liquidity. It is reasonable to expect that such improved market liquidity also reduces the incidence of price jumps during overlapping hours. Thus, we propose the following hypothesis:

Hypothesis 4: During overlapping hours, ADRs tend to have fewer price jumps than non-cross-listed stocks.

4.3 Data and methodology

4.3.1 Data and matched pairs

We focus on the cross-listed stocks traded on the US and the UK stock markets. There are mainly three reasons for our market selection. First, both the UK and the US stock markets have open trading environments where investors can access the markets freely. Second, the UK has the largest number of ADRs in the US market among all the European countries and has no regulatory constraints preventing cross-border arbitrage in ADRs. Third, active trading of ADRs in the UK and the US markets suggests that the ADRs in the two markets are more likely to be used as substitutes.

We construct our samples from the Thomson Reuters Datastream database. We select the ADRs which were actively traded in both the US and the UK stock exchanges from July 2005 to January 2009. Since we are interested in exchange-based stocks, we exclude Level I ADRs, which are issued over the counter, and only retain Level II and III ADRs. We also exclude firms which do not have intraday transaction data. These procedures result in a sample of nine ADRs (Tickers for ADRs are ‘BP’, ‘GSK’, ‘TOT’, ‘HBC’, ‘DEO’, ‘AZN’, ‘BHP’, ‘TEF’ and ‘UL’).

To investigate intraday trading patterns of cross-listed stocks, we conduct a matched-pairs analysis using a non-cross-listed benchmark for each cross-listed stock. This method is widely used in studies comparing differences in market liquidity such as Moulton and Wei (2009), O’Hara and Ye (2011), Battalio and Schultz (2011) and Collin-Dufresne and Fos (2015). We apply the daily stock price data from Centre for Research in Securities Prices (CRSP) database to select the matched pairs. Following Davies and Kim (2009), we use the average daily stock close price and market capitalisation as the key variables to match our pair stocks. Davis and Kim (2009) compare the test power of one-to-one matched-samples estimation with other methods based on extensive simulation results. The authors find that the optimal practice is to match stocks one-to-one based on market capitalisation and stock price, as this gives fairly good results, despite using fewer market characteristics than comparable tests. Adding additional market characteristics can increase the test

power slightly, but this is offset by the problem raised when the additional characteristics are not independent of stock listing states.

Using the sample of cross-listed stocks, we look for a non-cross-listed firm best-matched by the daily closing prices and the market capitalisation in the US market, which minimises the value of the matching error given by:

$$D_{i,j} = \left| \frac{MCAP_i}{MACP_j} - 1 \right| + \left| \frac{PRC_i}{PRC_j} - 1 \right|, i \neq j \quad (4.17)$$

where $MCAP$ is the market capitalisation of the stock, which is defined as stock price times outstanding shares; PRC is the stock price. The matched results are shown in Table 4.1. We also use trading volume as a third variable for pairs matching. The matched results are similar. Finally, we have nine pairs of ADRs and non-cross-listed stocks.

We calculate the intraday measures based on the dataset from Tick Data over the same time period. The intraday samples include both the quote and trade data for stocks traded on NYSE, NASDAQ and AMEX, including variables such as trading time, bid–ask quotes and trading volume. We select the sample period 5 July 2005 to 30 January 2009. As our raw intraday data is recorded tick by tick, we can aggregate the tick data into different time intervals. We use 5-minute interval in this study, as this a good balance between revealing sufficient information and including too much noisy information (Andersen et al., 2010). We also conduct the same analysis with 1-minute, 2-minute and 10-minute intervals as robustness checks.

4.3.2 Jump process

This section briefly reviews the theoretical framework of the jump diffusion model. According to Bollerslev et al. (2008) and Andersen et al. (2010), the logarithmic price process can be expressed as a continuous-time jump diffusion in differential equation form:

$$dp(t) = \mu(t)dt + \sigma(t)dW(t) + \kappa(t)dq(t), 0 \leq t \leq T \quad (4.1)$$

where $p(t)$ denotes the i th logarithmic asset price at time t , $\mu(t)$ is a continuous and locally bounded variation process, the stochastic volatility process $\sigma(t) > 0$ is a cadlag, $W(t)$ denotes a standard Brownian motion and $q(t)$ is a counting process with possible time-varying intensity $\lambda(t)$. Thus, $[dq(t) = 1] = \lambda(t)dt$, where $\kappa(t) \equiv p(t) - p(t-)$ refers to the size of corresponding discrete jumps in the logarithmic price process.

Following the convention that one time unit corresponds to a trading day, the continuous log prices record on trading day t can be expressed as $\{p_t(t-1+s)\}_{s \in [0,1]}$ where the integer values $t = 1, 2, 3, \dots$ coincide with the end of the day. S denotes the time range from market open to market close on trading day t . In practice, the price process can be recorded at only a finite number of discrete points in time. Let Δ denotes the time interval. The j th within-day return is then defined as:

$$r_{i,t,j} \equiv p_i(t-1+j\Delta) - p_i(t-1+(j-1)\Delta) \quad (4.2)$$

where $j = 1, 2, \dots, \frac{1}{\Delta}$, so a trading day consists of $\frac{1}{\Delta}$ returns in total.

To detect the price jump component, the first step is to construct realised volatility, to capture both continuous movements and discontinuous movements of prices. The *realised volatility* or *realised variance* is defined by the summation of the corresponding Δ intraday squared returns:

$$RV_{t+1}(\Delta) \equiv \sum_{j=1}^{1/\Delta} r_{t+j\Delta,\Delta}^2 \quad (4.3)$$

providing a natural measure of the daily *ex-post* variation.

According to the theory of quadratic variation, Andersen and Bollerslev (1998) suggest that realised variation converges uniformly in probability to the

incremental of the quadratic variation process as the sampling frequency of the underlying returns increases. For $\Delta \rightarrow 0$, realised variation can be expressed as:

$$RV_{t+1}(\Delta) \rightarrow \int_t^{t+1} \sigma^2(s)ds + \sum_{t < s \leq t+1} \kappa^2(s) \quad (4.4)$$

In the absence of jumps, the term $\sum_{t < s \leq t+1} \kappa^2(s)$ equals zero and the realised variation consistently estimates the integrated volatility which provides the corresponding standardisation factor for the daily returns. However, the realised variation incorporates both the integrated variance stemming from the continuous sample path and the squared jumps stemming from the jump process. Thus, it is crucial to find a robust estimation for integrated variance with the presence of a jump process.

Barndorff-Nielsen (2004) and Barndorff-Nielsen and Shephard (2006) present the separate non-parametric identification of the continuous part and the jump part through the use of new asymptotic results for $\Delta \rightarrow 0$. They state that realised power variation can provide a consistent estimation for an integrated variance with the presence of jumps. The standardised realised power variation is defined as:

$$BV_{t+1} \equiv \mu_1^{-2} \sum_{j=2}^{\frac{1}{\Delta}} |r_{t,j}| |r_{t,j-1}|, t \equiv 1, \dots, T \quad (4.5)$$

where $\mu_r = E|u|^r = 2^{r/2} \frac{\Gamma(\frac{1}{2}(r+1))}{\Gamma(\frac{1}{2})}$, $\Gamma(\cdot)$ denotes gamma function, for $r > 0$, $u \sim N(0,1)$. Hence $\mu_1^{-2} = (E|u|) = \frac{\pi}{2}$.

Boudt et al. (2011) suggest that even in the presence of jumps, the probability limit of realised bipower variation can be expressed as:

$$\text{plim}_{\Delta \rightarrow 0} BV_t = IV_t = \int_{t-1}^t \sigma^2(s)ds, t = 1, \dots, T \quad (4.6)$$

BV_t consistently estimates the integrated variance for the price process irrespective of whether jumps are present or not. For $\Delta \rightarrow 0$, there is at most one jump between two adjacent intervals. As a result, to consistently detect the jump component in total return variation, the two estimations can be compared: RV_t and BV_t .

4.3.3 The Lee and Mykland (2008) jump test

Tests to detect price jumps have been developed by Barndorff-Nielsen and Shephard (2006), Andersen et al. (2007) and Lee and Mykland (2008). We employ the Lee and Mykland (LM) test in this research because it can detect the exact time of a jump which occurs within one trading day as well as the number of jumps. The main idea behind the LM test is straightforward: in the absence of jumps, the instantaneous returns are due to Brownian motion. Standardised returns that are too large to be plausibly caused by standard Brownian motion are caused by a jump. Lee and Mykland (2008) propose the following test statistic for jump i at time t :

$$J_{t,i} \equiv \frac{|r_{t,i}|}{\sigma(t_i)} \quad (4.7)$$

where $r_{t,i}$ is the log return of price and $\sigma(t_i)$ is the estimate of instantaneous volatility.

Lee and Mykland (2008) state that the window range, K , should be large enough to minimise the effect of jumps on estimating instantaneous volatility but smaller than the total number of observations. The authors recommend that for returns sampled at intervals of 60, 30, 15 and 5 minutes, the values of K should be 78, 110, 156 and 270 respectively. Lee and Mykland (2008) propose that to reject the null hypothesis of no price jumps, $J_{t,i}$ should meet the following standard:

$$J_{t,i} > G^{-1}(1 - \alpha)S_n + C_n \quad (4.8)$$

where $G^{-1}(1 - \alpha)$ is the $1 - \alpha$ quantile function of the standard Gumbel function, G has a cumulative distribution function $P(G \leq x) = \exp(-e^{-x})$, $C_n = \sqrt{2\log n} - \frac{\log(\pi) + \log(\log(n))}{2\sqrt{2\log n}}$ and $S_n = \frac{1}{\sqrt{2\log n}}$, where n is the total number of observations. If the significance level is $\alpha > 0.1$, we reject the null hypothesis of no jump if $J_{t,i} > S_n\beta^* + C_n$ with β^* such that $\exp(-\exp(\beta^*)) = 1 - \alpha$, that is, $\beta^* = -\log(-\log(1 - \alpha))$. This is expected to detect no more than α spurious jumps in a given sample of n observations.

4.3.4 Periodicity issues

The Lee and Mykland (2008) test is based on a rolling window of observations to estimate the local volatility. The window size should not be so large that it cannot capture time-varying volatility. A small window size will confront the intraday periodicity, which denotes that volatility has a certain periodicity within a trading day. Failure to adjust for intraday periodicity leads to over-detection when volatility is high and under-detection when volatility is low (Boudt et al., 2011). Boudt et al. (2011) and Boudt et al. (2012) indicate that robust intraday volatility can be estimated as the product of average daily volatility and an intraday periodicity factor. We follow Boudt et al.'s (2011) method and use a periodicity estimation factor to adjust for intraday periodicity. The authors suggest that the Shortest Half scale estimator (ShortH estimator) has the smallest maximum bias. The ShortH estimator is defined as:

$$ShortH_i = 0.741 \cdot \min\{\bar{r}_{(h_i),i} - \bar{r}_{(1),i}, \dots, \bar{r}_{(n_i),i} - \bar{r}_{(n_i+h_i+1),i}\} \quad (4.9)$$

The ShortH estimator for the periodicity factor can be expressed as:

$$\hat{f}_i^{ShortH_i} = \frac{ShortH_i}{\sqrt{\left\lfloor \frac{1}{\lambda/\Delta} \right\rfloor \sum_{j \in N_i} ShortH_j^2}} \quad (4.10)$$

ShortH is robust to jumps but has relatively low power. Thus, Boudt et al. (2011) suggest using the weighted standard deviation:

$$\hat{f}_i^{WSD} = \frac{WSD_i}{\sqrt{\left\lfloor \frac{1}{\lambda/\Delta} \right\rfloor \sum_{j \in N_i} WSD_j^2}} \quad (4.11)$$

where

$$WSD_j = \sqrt{1.081 \times \frac{\sum_{l=j}^{n_j} w_{l,j} \bar{r}_{l,j}^2}{\sum_{l=1}^{n_j} w_{l,j}}} \quad (4.12)$$

where $w_{l,j} = w(\bar{r}_{l,j}/\hat{f}_i^{ShortH})$. The weights function, $w(y)$, equals 1 when $y^2 \leq 6.635$; and equals 0 otherwise.

$$\begin{cases} 1 & ((\bar{r}_{l,j}/\hat{f}_i^{ShortH})^2 \leq 6.635 \\ 0 & otherwise \end{cases} \quad (4.13)$$

The threshold 6.635 refers to the 99% quantile of the χ^2 distribution with one degree of freedom.

Finally, we apply the periodicity factor in the statistic for the jump test. Therefore, we have a modified estimation:

$$FiltJ_{t,i} \equiv \frac{|r_{t,i}|}{\sigma(t_i)f_{t,i}} \quad (4.14)$$

where $\sigma(t_i)$ is estimated as the square root of realised bipower variation over observations preceding $r_{t,i}$ and $f_{t,i}$ is an intraday periodicity factor, with Boudt et al.'s (2011) modified estimator. Finally, the statistic for jump can expressed as:

$$Jump_{t,i} \equiv r_{t,i} \cdot J(FiltJ_{t,i} - G^{-1}(1 - \alpha)S_n - C_n) \quad (4.15)$$

where C_n and S_n are as defined in Equation (4.8). $I(\cdot)$ is the indicator function for a positive argument and equals 1 if a jump is detected, and 0 otherwise:

$$I = \begin{cases} 1, & FiltJ_{t,i} - G^{-1}(1 - \alpha)S_n - C_n > 0 \\ 0, & FiltJ_{t,i} - G^{-1}(1 - \alpha)S_n - C_n \leq 0 \end{cases} \quad (4.16)$$

4.3.5 Data-cleaning procedures

Data cleaning is an essential issue for studies using high-frequency data (Hansen and Lunde, 2006; Brownlees and Gallo, 2006). Errors are found in the records of trading systems such as NYSE and NASDAQ (Falkenberry, 2002). In this study, we follow the cleaning procedures in Barndorff-Nielsen et al. (2009) on both the trade data and the quote data samples.

With the trade data we first eliminate entries with corrected trades, that is, where the correction indicator does not equal zero ($CORR \neq 0$). Second, as we focus on normal trading hours in the US market, we delete entries with a time outside the window when the US exchange is open, and keep the entries within a time range from 9:30 am to 4:00 pm. Third, we drop price observations with zero or negative value, which are likely to be caused by errors. Fourth, we delete entries with abnormal sale condition: trades where column ‘COND’ has a letter code other than ‘E’ or ‘F’. Fifth, since multiple transactions may occur during one time stamp, we replace multiple transactions by the median price to obtain a unique price for each time stamp. Finally, as the trading price should be within the range between the ask price and the bid price, we exclude the trading prices that are above the ask price plus the bid–ask spread or below the bid price minus the bid–ask spread.

With the quote data, we first delete the bid or ask quotes which are zero or negative. Second, to exclude the extreme bid or ask entries, we eliminate the observations which have a spread larger than 50 times the median spread during that trading day. Third, we need to remove the outliers, but, as stated by Falkenberry (2002), there is a risk of ‘over-scrubbing’ the data. Simply removing extreme values risks removing large price jumps, which are key to

this research. Therefore, we apply the alternative procedures in the ‘high-frequency package’ of R software. We calculate three different medians: a rolling centred median that excludes the observations under consideration; a rolling median of the following window observations; and a rolling median of the previous window observations. Then, we choose the value closest to the mid-quote from the three median options. Finally, we delete entries for which the mid-quote deviates by more than 10 times the median absolute deviations from the selected median value. Fourth, when there are multiple quotes at the same time stamp, we merge the multiple bid or ask observations with their corresponding median value.

4.3.6 Measures for market conditions

Prior studies widely apply bid–ask spreads to measure market liquidity (Cai et al., 2004; Bennett and Wei, 2006; Hasbrouck, 2009; O’Hara and Ye, 2011). Specifically, we apply the quoted bid–ask spreads and the effective bid–ask spreads to measure the transaction cost in this study. We normalise the bid–ask spreads to make the variables comparable with prior studies.

The quoted bid–ask spread is defined as the difference between the best bid quote and the best ask quote, divided by the midpoint quote:

$$Quoted\ Spread = \frac{Ask_{i,t} - Bid_{i,t}}{M_{i,t}} \quad (4.18)$$

where $Ask_{i,t}$ denotes the best ask price, $Bid_{i,t}$ denotes the best bid price and $M_{i,t}$ is the midpoint quote of stock i at the time of the transaction t .

The effective bid–ask spread is defined as:

$$Effecitve\ Spread = \frac{2I_{i,t}(R_{i,t} - M_{i,t})}{P_{i,t}} \quad (4.19)$$

where $I_{i,t}$ is an indicator variable that equals one for customer-initiated buys and minus one for customer-initiated sells (Bessembinder, 2003); transactions occurring at midpoint are classified using the ‘tick test’ method (Lee and Ready, 1991). $P_{i,t}$ is the transaction price. $M_{i,t}$ is the midpoint quote of stock i at the time t of the transaction.

The average size of transaction (ATS) is defined as:

$$ATS = \frac{Value\ Traded_{i,t}}{NT_{i,t}} \quad (4.20)$$

where $Value\ Traded_{i,t}$ is the dollar value of trading volume at time t for stock i , and $NT_{i,t}$ denotes the number of transactions occurring at time t for stock i .

4.4 Empirical results

Since we are interested in how overlapping hours influence intraday trading of the matched pairs (cross-listed and non-cross-listed) of stocks, we aggregate our measures into an intraday pattern and compare the average value of market measures during overlapping hours with those during non-overlapping hours. We analyse five aspects of the intraday market: the transaction cost, trading volume, average transaction size, market depth and price jump intensity.

Summary statistics are presented in Table 4.2. The median of trading volume for ADRs is 624,446 thousand dollars. The median of trading volume for matched stocks is 649,137 thousand dollars. Thus the trading volumes of ADRs and of matched stocks are of similar magnitude. The median of effective spread and quoted spread for ADRs are 5.85 and 11.66 basis points respectively. Those for non-cross-listed stocks are 7.87 and 14.23 basis points respectively. Since we conduct difference-in-difference (DiD) tests which check the relative changes of variables, we do not have to require the market liquidity variables for ADRs and matched stocks to be exactly the same. The number of transactions, the average transaction size and market depth are also of the same magnitude.

To demonstrate the overlapping-hours phenomenon, we calculate the mean for each variable, i.e. bid–ask spread, trading volume, number of transactions, average transaction size and market depth, for each 5-minute time interval and plot them in intraday graphs in Figures 4.1 to 4.7. We also conduct the DiD test to check whether the differences between the matched pairs are statistically significant. The DiD test can be expressed as:

$$Y_{ist} = \alpha + \gamma C_s + \lambda L_t + \beta(C_s \times L_t) + \varepsilon_{ist} \quad (4.21)$$

where C_s is a dummy for the control group, L_t is a time period dummy, s denotes state (cross-listed stocks (CL) or non-cross-listed stocks (NCL)) and t denotes period (overlapping hours (OL) or non-overlapping hours (NOL)). Y_{ist} denotes the liquidity measure at time t . The treatment effect can be estimated as:

$$\begin{aligned} \beta = & [E(Y_{ist}|s = CL, t = OL) - E(Y_{ist}|s = CL, t = NOL)] \\ & - [E(Y_{ist}|s = NCL, t = OL) - E(Y_{ist}|s = NCL, t = NOL)] \end{aligned} \quad (4.22)$$

As we apply the DiD test, the liquidity measures of ADRs and matched stocks do not have to be exactly the same. An important assumption of the DiD test is the parallel trend assumption. As illustrated in Figures 4.1 to 4.7, the intraday patterns of ADRs and matched stocks are similar, with common trends, suggesting the validation of the parallel trend assumption.

All the graphs and the DiD test results indicate that the measures relating to ADRs during overlapping hours are different from those during non-overlapping hours. The results for the bid–ask spread, trading volume, average size of transactions and market depth are also consistent with our expectation that overlapping hours significantly improve market liquidity for ADRs.

4.4.1 Market liquidity

To investigate the effect of overlapping-hours on trading cost, we use quoted bid–ask spread and effective bid–ask spreads to proxy for trading costs. As shown in Figures 4.1 and 4.2, both effective and quoted spreads of ADRs are

significantly different during overlapping hours and non-overlapping hours. These results are consistent with Moulton and Wei (2009): the overlapping hours are characterised by lower bid–ask spreads. The lower effective and quoted spreads imply lower trading costs during overlapping hours of the UK and the US stock markets compared non-overlapping hours.

The findings above imply that that intensive intraday arbitrage trading reduces the trading cost during overlapping hours. Lower transaction costs can lead to higher profit margins, which could also be a reason for intraday trading. It is notable that there is a spike at the end of overlapping hours, at around 11:30 am US Eastern Standard Time (ETS), which is the closing time of the UK market. A similar pattern is also observed in the quoted bid–ask spread graphs in Figure 4.1.

The observed spike in the bid–ask spreads around the closing time of the UK market supports our expectation that intensive arbitrage takes place during the overlapping hours. A possible arbitrage activity is pairs trading. The idea behind pairs trading is straightforward: a cross-listed stock and its corresponding stock in the home market generate similar cash flows. According to the Law of One Price, the prices of the paired stocks tend to converge (Grossman and Stiglitz, 1980). When the price divergence of the paired stocks is large enough to cover the transaction cost (including bid–ask spreads, commission fees and conversion fees) and a profit margin, an arbitrager will take a short position in the winner stock and a long position in the loser stock, betting that the prices of the two stocks will converge. The intraday pairs trading arbitrageurs of ADRs need to set positions when both domestic and overseas markets are open. When one of the stock exchanges is closing, the intraday arbitrageurs will close their positions to avoid overnight risk. Since many intraday arbitrageurs leave at the close of the UK market, the US stock market experiences a temporary ‘vacuum’ period during which there is a drop in market liquidity. Limited competition among market players drives up the average bid–ask spread. Along with intraday arbitrageurs leaving the ADR market, the average bid–ask spread decreases to a normal level and remains stable during the rest of the trading day. A similar pattern is observed in the graphs of effective bid–ask spreads in Figure 4.2. The average effective

bid–ask spreads are smaller during overlapping hours than those during non-overlapping hours.

We also investigate the actual trading intensity through three measures: the trading volume in dollars, the average number of trades and the average transaction size. The average trading volumes for ADRs are plotted in Figure 4.3. The well-known U-shape of the curve is consistent with prior studies; the trading volume is larger at both the opening and the closing time of the US stock market, and smaller in the middle. The trading volume is considerably higher during overlapping hours than during non-overlapping hours. The DiD test results in Table 4.3 suggest that the average difference in the trading volume, which is \$448,260.98 every five minutes, is statistically significant. This provides evidence for our argument that intensive intraday arbitrage of ADRs exists during overlapping hours.

Furthermore, we decompose the trading volume into the number of trades (NT) and the average trade size (ATS). As Figure 4.4 shows, the number of trades is considerably higher during overlapping hours than during non-overlapping hours. Table 4.3 shows that the overlapping hours lead to 3.3 more transactions every five minutes on average for ADRs during overlapping hours than during non-overlapping hours.

As shown in Figure 4.5, the average size of transactions does not exhibit a similar U-shaped pattern which is observed in graphs showing the trading volume and the number of trades. For non-cross-listed stocks, the average size of transactions remains stable throughout the day. The ADRs' ATS during overlapping hours are \$8,283.22 larger than those during non-overlapping hours. The trade size of ADRs drops around the closing time of the UK market and remains stable during the rest of the day.

The results of the average trade size strongly support our statement that intraday arbitrage is the key driver of the overlapping-hours phenomenon. First, the ADRs' increased trade size during overlapping hours suggests that trading is more intensive than during the non-overlapping hours. Second, although it is hard to explicitly identify who places the orders, large orders are more likely to

come from institutional investors. Menkveld (2008) suggests that institutional investors tend to split large orders to reduce market impact. Individual investors, however, are not motivated to aggregate small orders into bigger ones. The sudden shift in trade size implies that orders could be driven by different motivations. Our research provides a possible explanation for the increased trade size. ADRs are widely used by institutional investors who have advantages in both information and trading costs over individual investors. The arbitrage opportunities offered by ADRs during overlapping hours are more likely to be exploited by institutional investors because converting ADRs is less costly for them.

Beside measures for actual trading, we also use market depth and market depth imbalance to investigate how overlapping hours affect ADRs quotes. The intraday patterns for market depth and market depth imbalance are shown in Figure 4.6 and Figure 4.7 respectively. The results show that market depth of ADRs is higher during overlapping hours than during non-overlapping hours. The ‘deeper’ market suggests that there are more selling and buying orders during a given time, which make it easier for market orders to be executed. The deeper market during overlapping hours implies better market liquidity, which is consistent with our observations from bid–ask spread and actual trading measures, above. The overlapping hours do not have an impact on overall market depth. The quoting activities are more intensive during overlapping hours and drop to a normal level after the close of the UK market. Overall, the results on market depth support our argument that increased intraday arbitrage leads to more quoting activities. We also hypothesise that market depth is associated with price-discontinuous movements, i.e. price jumps. If the market is sufficiently deep, it would be difficult to detect price jumps, as there might be selling and buying orders at each price and the stock price would move continuously.

4.4.2 Price jumps

We apply the Lee and Mykland jump test to detect price jumps in this study. We aggregate the total number of jumps during the whole sample period and

plot average number of jumps for both the sample group and the matched group. Figure 4.8 shows that ADRs have many fewer negative price jumps during overlapping hours than during non-overlapping hours. Moreover, the total number of price jumps for ADRs is considerably smaller during overlapping hours than during non-overlapping hours, as shown in Figure 4.9. The price jumps for ADRs are concentrated in the first 15 minutes of trading. The DiD test results for jump numbers are shown in Table 4.8. For ADRs, the average total number of price jumps during overlapping hours is 0.1884 less than the average for the matched group. The number of negative price jumps during overlapping hours is 0.1028 less. The number of positive price jumps during overlapping hours is 0.085 less. All of the differences are statistically significant at 0.01 level. The intensity of price jumps supports our hypothesis that ADRs are more liquid during overlapping hours and the improved market liquidity reduces the incidence of price jumps.

The results of price jumps are consistent with Grossman and Stiglitz's (1980) argument that profit opportunities for pairs trading can be viewed as a reward to arbitragers for enforcing the 'Law of One Price'. Overall, the intensity of stock price jumps is consistent with the pairs trading literature. The common trading hours between the US and the UK markets improve the liquidity of ADRs and simultaneously reduce the price movements of ADRs.

4.4.3 Robustness analysis

We conduct two analyses to check the robustness of our results. One is based on the daylight-saving-time effect and the other is based on the different length of overlapping hours. The first robustness analysis is motivated by Halling et al. (2013), who state that the number of overlapping trading hours is positively associated with multimarket trading in two markets. There could be an alternative explanation for the uncommon trading pattern that we found during the overlapping hours: such pattern could be routine in the US market and irrelevant to the common trading hours between the US and UK stock markets. This possibility has been largely ignored in past studies, but we test it by using the varying overlapping hours in the US and UK as a natural experiment.

The daylight-saving time is observed in both the US and the UK. The dates for daylight-saving time differ, however. In the US, the daylight-saving period starts on the second Sunday in March and ends on the first Sunday in November. In contrast, in the UK the daylight-saving period starts on the last Sunday in March and ends on the last Sunday in October. This difference leads to an annual variation in the overlapping hours. For instance, as Table 4.9 shows, in 2007, from March 11th to March 25th, the UK and US stock markets had three overlapping hours but from October 28th to November 4th there was only one overlapping hour. On the rest of dates, the UK and the US markets had two overlapping hours.

If the uncommon pattern of ADR trading is caused by trading habits of the US traders rather than being a result of overlapping hours, the pattern should remain consistent throughout the year. We construct a subsample by including only the observations in the trading days with three overlapping hours. We reproduce similar plots and perform the DiD analysis on the subsample. As Figures 4.10 and 4.11 show, the quoted bid–ask spreads and effective bid–ask spreads for ADRs is smaller during 9:30pm to 12:30am EST than during the rest of the day. It is notable that the cut-off point of the shifts is 12:30am EST rather than 11:30am EST. It is worth noting that 12:30am EST is the closing time of the UK market in the subsample. The results of the DiD test are shown in Table 4.4. The effective bid–ask spread and quoted bid–ask spread are 1.48 and 3.34 respectively less during overlapping hours for ADRs. The average traded value is also higher during overlapping hours for ADRs. The average number of transactions and average size of transactions are 6 and 6,298.59 more during overlapping hours for ADRs. The market depth is also deeper for ADRs during overlapping hours. All of the differences in the variables are statistically significant at 0.01 level. These different measures of trading activities suggest that the market liquidity is better for ADRs during overlapping hours. These results imply that the uncommon patterns of ADR trading are not a fixed routine in the US markets but vary following the overlapping hours between the UK and US stock markets. Furthermore, the intraday patterns in trading volume, numbers of transactions, average

transaction size and market depth, which are shown in Figures 4.12, 4.13, 4.14, 4.15 and 4.16, respectively, confirm the robustness of our results.

Our second robustness analysis compares the different length of the overlapping hours with the non-overlapping hours. We hypothesise that if the uncommon patterns are inconsistent, the DiD test results should be statistically insignificant. We choose 1 hour 45 minutes, 1 hour 30 minutes and 1 hour as the overlapping hours and conduct the DiD tests. Tables 4.5, 4.6 and 4.7 show that market liquidity is better during overlapping hours for ADRs. These demonstrate that the DiD test results are qualitatively the same when we use different lengths of overlapping hours. Overall, the overlapping-hours phenomenon of ADRs is sensitive to the shift in daylight-saving time. The overlapping-hours phenomenon remains statistically significant when applying the different lengths of overlapping time.

4.5 Conclusions

This chapter investigates the uncommon intraday patterns of market liquidity for ADRs during overlapping hours. Moreover, we investigate how the market liquidity patterns influence the incidence of price jumps. Motivated by the literature on the overlapping-hours phenomenon, we used a number of liquidity measures, including bid–ask spreads, trading volume, number of trades, average transaction size and market depth, to check intraday trading patterns in cross-listed stocks in the US stock market. We find that ADRs’ intraday liquidity is significantly affected by the overlapping hours. The trading volume, the number of transactions, trade size and market depth are statistically significantly larger during overlapping hours than during non-overlapping hours. The bid–ask spreads are smaller during overlapping hours.

As ADRs have different market liquidity during overlapping and non-overlapping hours, we also analyse the incidence of price jumps, which are influenced by market liquidity. We employ the Lee and Mykland (2008) jump test to detect price jumps and observe that the number of jumps is significantly smaller during overlapping hours. As fewer price jumps imply less jump risk,

our study suggests that ADRs are attractive to institutional investors because of their liquidity and lower jump risk.

To check the robustness of our results, we investigate the daylight-saving time effect on the overlapping-hours phenomenon. We find that the overlapping-hours phenomenon is sensitive to the varying number of overlapping hours caused by different dates for daylight-saving time in the US and the UK. Moreover, we conduct similar analyses with different lengths of overlapping hours. Both of the analyses confirm the robustness of the empirical results.

This study attempts to shed light on the explanations for the overlapping-hours phenomenon of stocks traded in multiple markets. We are first to explore the connection between intraday jumps and the overlapping-hours phenomenon. Our study contributes to the rapidly growing research on the relationship between price jumps and market liquidity. Finally, this study has implications for companies which plan to list their stocks on overseas stock exchanges. The trading time of stock exchanges should be considered a key factor for countries which plan to promote new depositary receipts issued in overseas markets. For instance, China plans to raise overseas capital by issuing depositary receipts in European markets. The common trading hours of stock exchanges should be considered because overlapping hours influence both the market liquidity and the incidence of price jumps of the depositary receipts.

Table 4.1 ADRs and matched stocks based on market capital and stock prices

Group	Company name	Price	Volume in shares	Market capital	Trading volume in USD	Outstanding share
Cross-listed	B P PLC	62.08	4714.49	61787.11	278.76	987.15
Matched	UNITED TECHNOLOGIES CORP	65.26	4781.54	60064.91	297.69	943.30
Cross-listed	GLAXOSMITHKLINE PLC	47.13	1693.20	19515.47	78.27	413.14
Matched	KELLOGG CO	48.20	1826.12	19009.55	87.92	394.71
Cross-listed	TOTAL S A	82.88	1845.93	12262.05	134.28	162.58
Matched	VORNADO REALTY TRUST	85.87	1974.72	12754.64	139.88	149.77
Cross-listed	H S B C HOLDINGS PLC	76.21	1425.63	8406.06	91.39	110.86
Matched	WYNN RESORTS LTD	74.71	2285.78	7991.86	162.81	107.26
Cross-listed	DIAGEO PLC	68.11	614.58	7847.36	40.94	114.21
Matched	V F CORP	68.07	800.79	7539.95	54.30	110.76
Cross-listed	ASTRAZENECA PLC	46.96	1343.89	6746.86	62.36	141.55
Matched	COVENTRY HEALTH CARE INC	46.30	1601.15	6672.52	63.26	146.68
Cross-listed	B H P BILLITON LTD	50.03	3643.71	6113.93	196.30	121.15
Matched	WHOLE FOODS MARKET INC	54.09	2800.09	5846.84	114.48	125.99
Cross-listed	TELEFONICA S A	64.96	331.62	4610.02	22.75	71.05
Matched	HARMAN INTL INDS INC NEW	70.02	938.99	4569.58	56.70	64.24
Cross-listed	UNILEVER PLC	31.24	776.41	3082.17	22.25	104.23
Matched	AMERICAN FINANCIAL GROUP	31.36	556.30	3066.41	15.61	101.02

Table 4.2 Summary statistics

	PES	PQS	Value traded	NT	ATS	Depth	DI
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
ADRs							
Min.	1.37	1.97	17113	1.78	4514	11.65	0.91
1st Qu.	4.00	7.01	253387	12.54	17693	534.84	1.77
Median	5.85	11.66	624446	23.33	25923	1586.7	2.43
Mean	7.87	15.64	1170782	31.91	29472	4658.98	2.92
Mean-Median	2.02	3.975	546336	8.575	3549	3072.28	0.48
3rd Qu.	8.95	19.69	1465521	42.15	36869	4811.43	3.50
Max.	98.35	140.66	17978072	229.56	480115	196303.96	32.62
Matched stocks							
Min.	1.30	1.46	20905	2.95	2781	23.38	0.74
1st Qu.	4.89	8.15	335367	21.04	14267	428.12	1.38
Median	7.87	14.23	649137	31.92	20734	1008.86	1.57
Mean	10.52	19.52	1056360	39.04	22729	2389.34	1.72
Mean-Median	2.643	5.298	407223	7.12	1995	1380.48	0.15
3rd Qu.	12.82	25.52	1274189	49.19	28928	2524.66	1.85
Max.	146.77	279.33	37744448	259.36	201767	124344.56	20.79

Notes: *PES* is the five-minute volume-weighted proportional effective bid–ask spread. *PQS* is the five-minute volume-weighted proportional quoted bid–ask spread. Value traded is the trading volume over five minutes. *NT* is the total number of transactions over five minutes. *ATS* is the average size of one transaction over five minutes. *Depth* is the sum of bid depth and ask depth. *DI* is the market depth imbalance. All statistics are calculated over the 9 ADRs and 9 non-cross-listed firms included in the sample covering the period July 2005 to January 2009.

Table 4.3 ADRs DID tests with 2 hours overlapping

Measures	Group	Overlap	Non-overlap	Overlap–non-overlap
PES	ADRs	7.32	8.43	-1.11***
	Matched	11.87	9.16	2.71***
	Difference	-4.56	-0.74	-3.82***
PQS	ADRs	14.78	16.50	-1.72***
	Matched	21.92	17.13	4.79***
	Difference	-7.14	-0.63	-6.50***
Value traded	ADRs	1642710.82	698852.63	943858.18***
	Matched	1304158.35	808561.15	495597.20***
	Difference	338552.47	-109708.51	448260.98***
NT	ADRs	39.64	24.18	15.46***
	Matched	45.10	32.97	12.13***
	Difference	-5.46	-8.80	3.33***
ATS	ADRs	35249.37	23693.62	11555.75***
	Matched	24364.86	21092.33	3272.53***
	Difference	10884.51	2601.29	8283.22***
Depth	ADRs	7151.35	2166.61	4984.74***
	Matched	2874.31	1904.37	969.94***
	Difference	4277.03	262.23	4014.80***
DI	ADRs	3.42	2.41	1.01***
	Matched	1.73	1.70	0.03
	Difference	1.69	0.71	0.98***

Notes: *PES* is the five-minute volume-weighted proportional effective bid–ask spread. *PQS* is the five-minute volume-weighted proportional quoted bid–ask spread. *Value traded* is the trading volume over five minutes. *NT* is the total number of transactions over five minutes. *ATS* is the average size of one transaction over five minutes. *Depth* is the sum of bid depth and ask depth. *DI* is the market depth imbalance. All statistics are calculated over the 9 ADRs and 9 non-cross-listed firms included in the sample covering the period July 2005 to January 2009. Differences that are significant at 1%, 5%, 10% levels are designated by ***, **, and *, respectively.

Table 4.4 ADRs DID tests with 3 hours overlapping

Measures	Group	Overlap	Non-overlap	Overlap-non-overlap
PES	ADRs	6.05	5.74	0.31***
	Matched	9.17	7.38	1.79***
	Difference	-3.12	-1.64	-1.48***
PQS	ADRs	10.55	10.28	0.27***
	Matched	15.85	12.24	3.61***
	Difference	-5.31	-1.97	-3.34***
Value traded	ADRs	1598421.64	848199.81	750221.83***
	Matched	1276247.72	1004621.92	271625.80***
	Difference	322173.92	-156422.10	478596.03***
NT	ADRs	43.97	32.22	11.74***
	Matched	50.24	44.50	5.74***
	Difference	-6.28	-12.28	6.00***
ATS	ADRs	29960.45	22263.04	7697.41***
	Matched	20828.12	19429.30	1398.82***
	Difference	9132.32	2833.73	6298.59***
Depth	ADRs	8980.62	3772.84	5207.78***
	Matched	3804.43	3510.41	294.01***
	Difference	5176.19	262.43	4913.76***
DI	ADRs	2.71	1.85	0.86***
	Matched	1.56	1.53	0.03
	Difference	1.15	0.33	0.82***

Notes: *PES* is the five-minute volume-weighted proportional effective bid–ask spread. *PQS* is the five-minute volume-weighted proportional quoted bid–ask spread. *Value traded* is the trading volume over five minutes. *NT* is the total number of transactions over five minutes. *ATS* is the average size of one transaction over five minutes. *Depth* is the sum of bid depth and ask depth. *DI* is the market depth imbalance. All statistics are calculated over the 9 ADRs and 9 non-cross-listed firms included in the sample covering the July 2005 to January 2009. Differences that are significant at 1%, 5%, 10% levels are designated by ***, **, and *, respectively.

Table 4.5 ADRs DID tests with 1 hour 45 minutes overlapping

Measures	Group	Overlap	Non-overlap	Overlap-non-overlap
PES	ADRs	7.45	8.47	-1.02***
	Matched	12.54	9.20	3.34***
	Difference	-5.09	-0.72	-4.36***
PQS	ADRs	15.06	16.58	-1.52***
	Matched	23.32	17.21	6.12***
	Difference	-8.26	-0.63	-7.63***
Value traded	ADRs	1631328.98	701046.76	930282.22***
	Matched	1299039.76	808103.90	490935.86***
	Difference	332289.22	-107057.14	439346.36***
NT	ADRs	39.34	24.19	15.16***
	Matched	44.96	32.87	12.09***
	Difference	-5.62	-8.68	3.06***
ATS	ADRs	35752.22	23757.36	11994.87***
	Matched	24625.05	21135.78	3489.27***
	Difference	11127.17	2621.57	8505.60***
Depth	ADRs	7087.17	2167.07	4920.10***
	Matched	2861.57	1888.45	973.11***
	Difference	4225.60	278.62	3946.99***
DI	ADRs	3.42	2.39	1.03***
	Matched	1.73	1.71	0.03
	Difference	1.69	0.69	1.00***

Notes: *PES* is the five-minute volume-weighted proportional effective bid-ask spread. *PQS* is the five-minute volume-weighted proportional quoted bid-ask spread. *Value traded* is the trading volume over five minutes. *NT* is the total number of transactions over five minutes. *ATS* is the average size of one transaction over five minutes. *Depth* is the sum of bid depth and ask depth. *DI* is the market depth imbalance. All statistics are calculated over the 9 ADRs and 9 non-cross-listed firms included in the sample covering the period July 2005 to January 2009. Differences that are significant at 1%, 5%, 10% levels are designated by ***, **, and *, respectively.

Table 4.6 ADRs DID tests with 1 hour 30 minutes overlapping hours

Measures	Group	Overlap	Non-overlap	Overlap–non-overlap
PES	ADRs	7.13	8.51	-1.38***
	Matched	10.45	9.22	1.24***
	Difference	-3.33	-0.71	-2.62***
PQS	ADRs	14.29	16.66	-2.37***
	Matched	19.30	17.23	2.07***
	Difference	-5.01	-0.57	-4.44***
Value traded	ADRs	1513532.64	713144.99	800387.65***
	Matched	1167285.18	814002.77	353282.41***
	Difference	346247.46	-100857.78	447105.24***
NT	ADRs	1513532.64	713144.99	800387.65***
	Matched	1167285.18	814002.77	353282.41***
	Difference	346247.46	-100857.78	447105.24***
ATS	ADRs	32039.10	23950.48	8088.62***
	Matched	22720.34	21183.90	1536.44***
	Difference	9318.76	2766.59	6552.18***
Depth	ADRs	6719.18	2191.51	4527.67***
	Matched	2680.24	1896.80	783.44***
	Difference	4038.95	294.71	3744.24***
DI	ADRs	3.29	2.38	0.91***
	Matched	1.71	1.70	0.01
	Difference	1.57	0.68	0.90***

Notes: *PES* is the five-minute volume-weighted proportional effective bid–ask spread. *PQS* is the five-minute volume-weighted proportional quoted bid–ask spread. *Value traded* is the trading volume over five minutes. *NT* is the total number of transactions over five minutes. *ATS* is the average size of one transaction over five minutes. *Depth* is the sum of bid depth and ask depth. *DI* is the market depth imbalance. All statistics are calculated over the 9 ADRs and 9 non-cross-listed firms included in the sample covering the period July 2005 to January 2009. Differences that are significant at 1%, 5%, 10% levels are designated by ***, **, and *, respectively.

Table 4.7 ADRs DID tests with 1 hour overlapping hour

Measures	Group	Overlap	Non-overlap	Overlap–non-overlap
PES	ADRs	7.14	8.64	-1.50***
	Matched	9.86	9.29	0.57***
	Difference	-2.72	-0.65	-2.07***
PQS	ADRs	14.28	16.92	-2.64***
	Matched	18.19	17.34	0.85***
	Difference	-3.91	-0.42	-3.49***
Value traded	ADRs	1448876.75	747232.97	701643.78***
	Matched	1075806.70	839681.34	236125.36***
	Difference	373070.05	-92448.37	465518.42***
NT	ADRs	37.40	25.00	12.40***
	Matched	40.83	33.72	7.12***
	Difference	-3.44	-8.72	5.28***
ATS	ADRs	31688.20	24453.28	7234.93***
	Matched	22378.33	21353.54	1024.79***
	Difference	9309.87	3099.74	6210.14***
Depth	ADRs	6378.74	2260.15	4118.59***
	Matched	2446.84	1934.06	512.79***
	Difference	3931.90	326.10	3605.80***
DI	ADRs	3.25	2.35	0.90***
	Matched	1.70	1.70	0.00
	Difference	1.55	0.65	0.90***

Notes: *PES* is the five-minute volume-weighted proportional effective bid–ask spread. *PQS* is the five-minute volume-weighted proportional quoted bid–ask spread. *Value traded* is the trading volume over five minutes. *NT* is the total number of transactions over five minutes. *ATS* is the average size of one transaction over five minutes. *Depth* is the sum of bid depth and ask depth. *DI* is the market depth imbalance. All statistics are calculated over the 9 ADRs and 9 non-cross-listed firms included in the sample covering the period July 2005 to January 2009. Differences that are significant at 1%, 5%, 10% levels are designated by ***, **, and *, respectively.

Table 4.8 Number of price jumps for ADRs and matched stocks

Measures		Group	Overlap	Non-overlap	Difference
Total number of jumps		ADRs	0.2045	0.0046	0.1999***
	0.90	Matched stocks	0.4130	0.0247	0.3883***
	Level	Difference	-0.2085	-0.0201	-0.1884***
Measures		Group	Overlap	Non-overlap	Difference
Number of positive jumps		ADRs	0.1028	0.0021	0.1007***
	0.90	Matched stocks	0.1977	0.0114	0.1863***
	Level	Difference	-0.0949	-0.0093	-0.0857***
Measures		Group	Overlap	Non-overlap	Difference
Number of negative jumps		ADRs	0.1017	0.0025	0.0992***
	0.90	Matched stocks	0.2153	0.0133	0.2020***
	Level	Difference	-0.1136	-0.0108	-0.1028***

Differences that are significant at the 1%, 5% and 10% levels are designated by ***, ** and *, respectively.

Table 4.9 Daylight-saving dates in the UK and the US and number of hours of overlapping trading on the stock markets

Year	3 overlapping hours	1 overlapping hour	2 overlapping hours
2006	None	March 26 to April 2	the rest of dates
2007	March 11 th to March 25 th	October 28 to November 4	the rest of dates
2008	March 9 th to March 30 th	October 26 th to November 2 nd	the rest of dates

Figure 4.1 Quoted bid-ask spread, 2 h overlapping

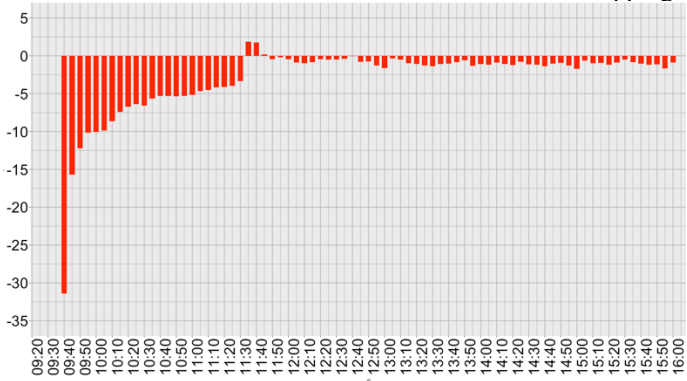
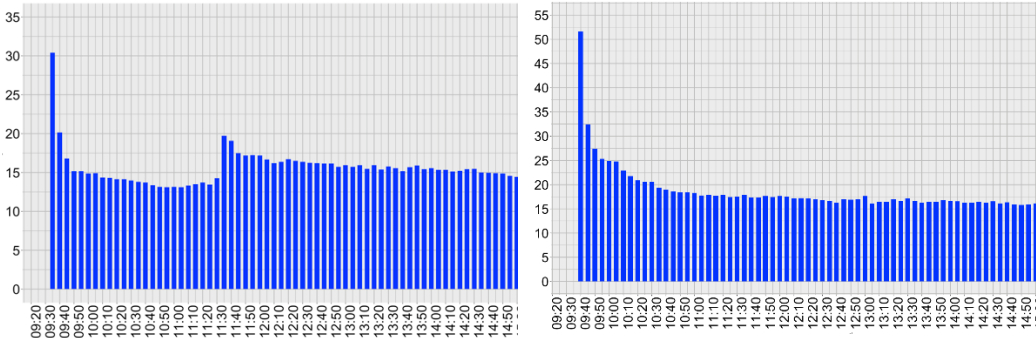


Figure 4.2 Effective bid–ask spread, 2 h overlapping

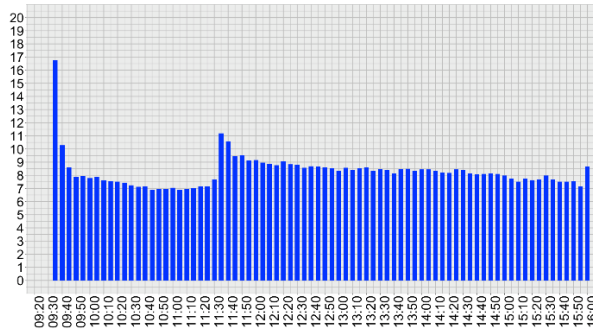


Figure 4.2(a) ADRs pes 2h overlapping

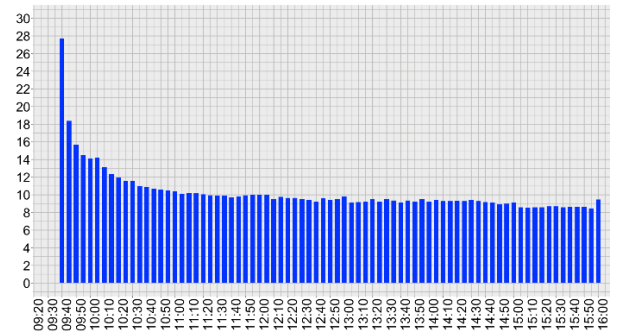


Figure 4.2(b) Matched stocks pes 2h overlapping

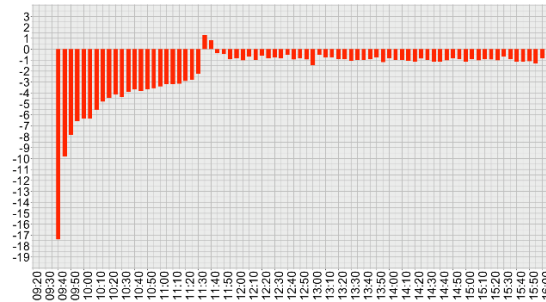


Figure 4.2(c) ADRs-Matched stocks pes 2h overlapping

Figure 4.3 Value traded, 2 h overlapping

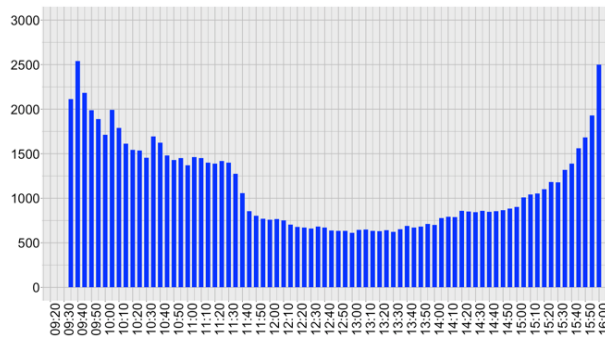


Figure 4.3(a) ADRs value traded 2h overlapping

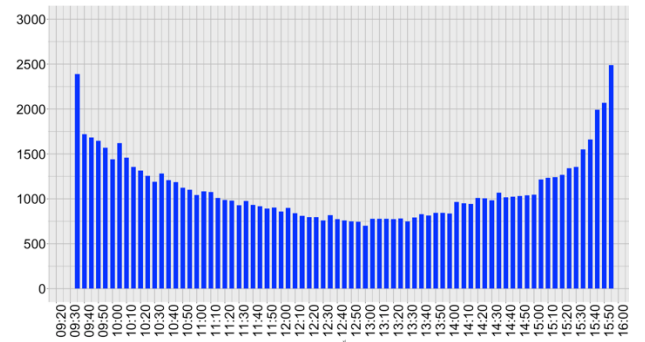


Figure 4.3(b) Matched value traded 2h overlapping

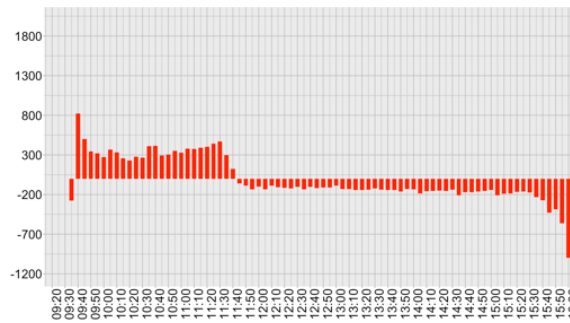


Figure 4.3(c) ADRs-Matched stocks value traded 2h overlapping

Figure 4.4 Number of transactions, 2 h overlapping

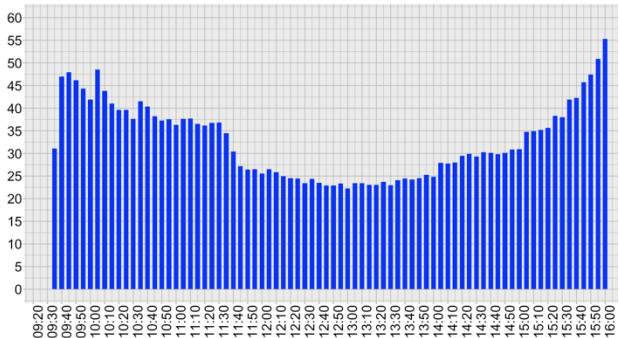


Figure 4.4(a) ADRs number of trade 2h overlapping

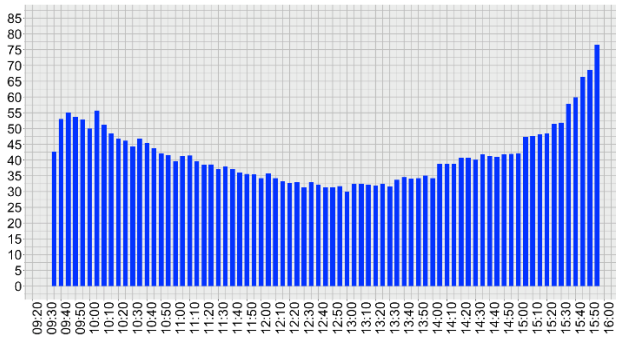


Figure 4.4(b) Matched number of trade 2h overlapping

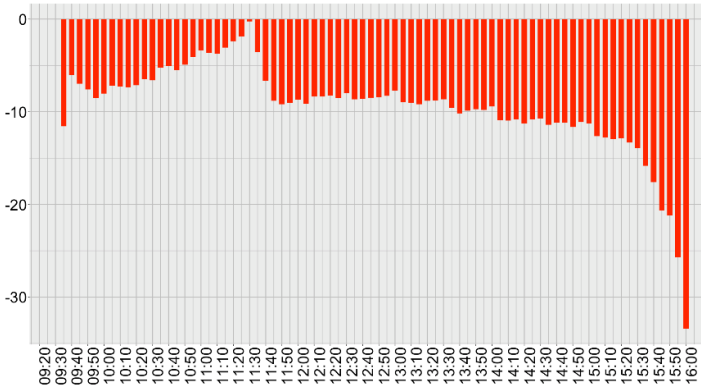


Figure 4.4(c) ADRs-Matched stocks number of trade 2h overlapping

Figure 4.5 Average size of trades, 2 h overlapping

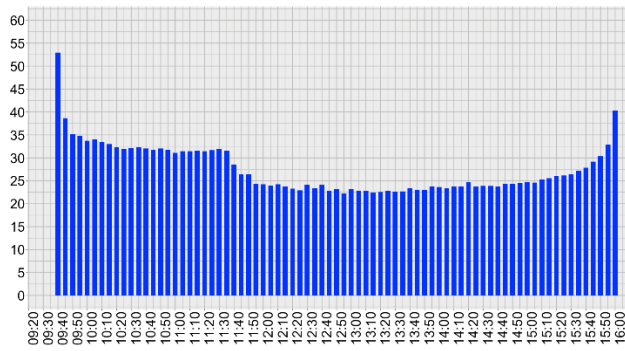


Figure 4.5(a) ADRs ATS 2h overlapping

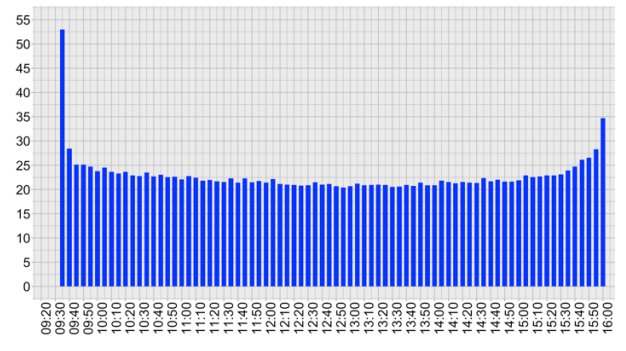


Figure 4.5(b) Matched stocks ATS 2h overlapping

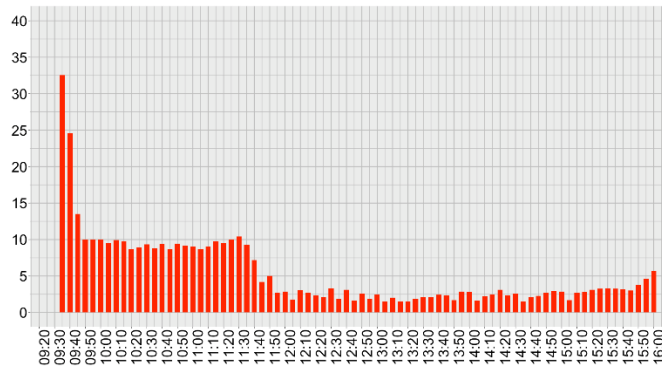


Figure 4.5(c) ADRs-Matched stocks ATS 2h overlapping

Figure 4.6 Market depth, 2 h overlapping

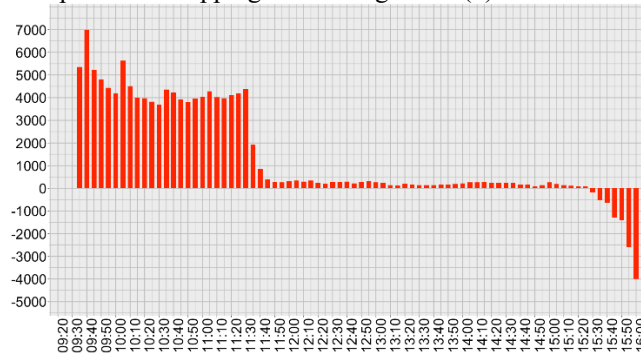
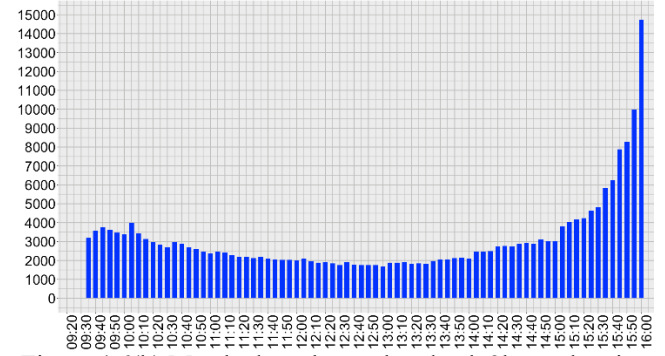
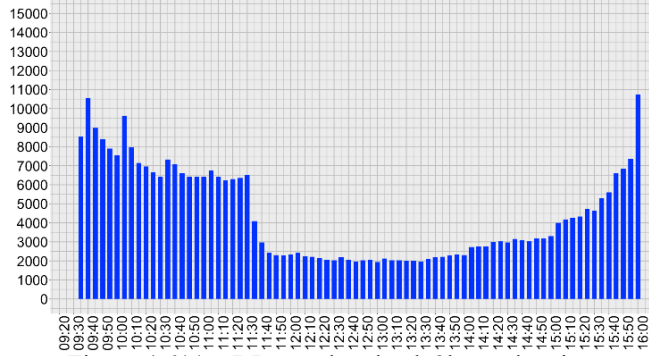


Figure 4.7 Depth imbalance, 2 h overlapping

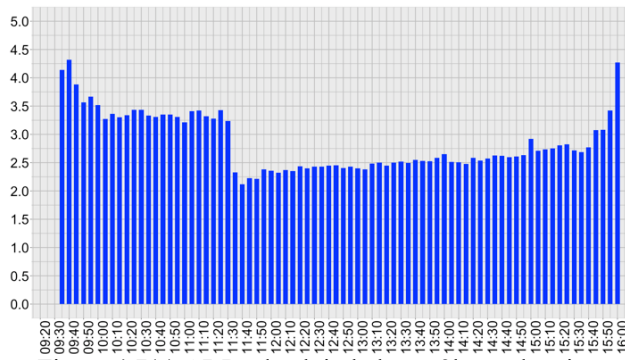


Figure 4.7(a) ADRs depth imbalance 2h overlapping

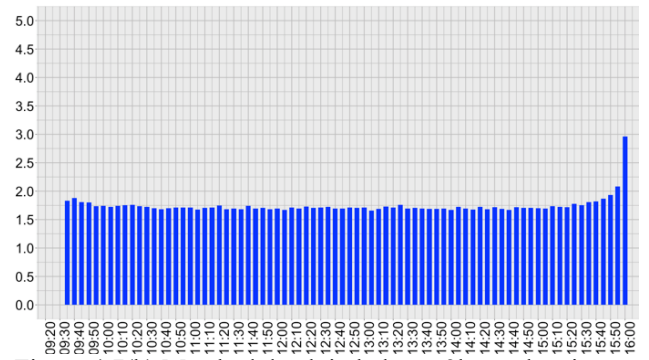


Figure 4.7(b) Matched depth imbalance 2h overlapping

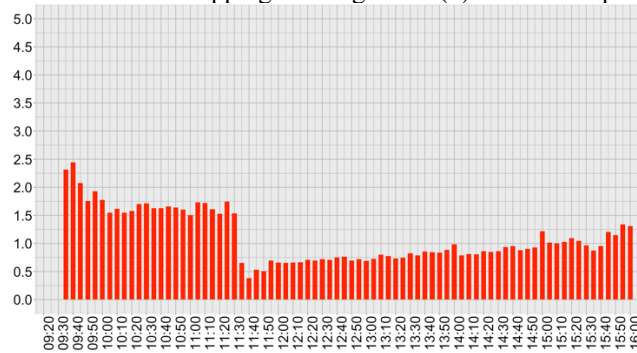


Figure 4.7(c) ADRs-Matched stocks depth imbalance 2h overlapping

Figure 4.8 Number of negative jumps

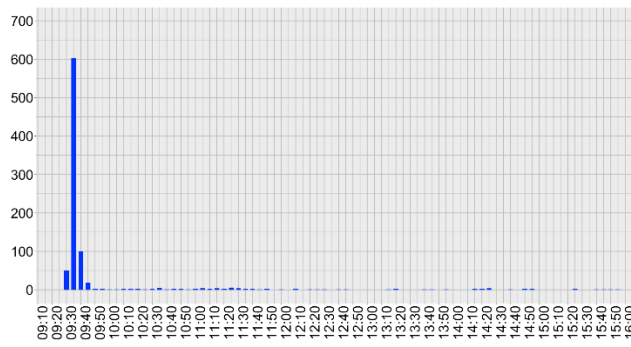


Figure 4.8(a) ADRs number of negative jumps

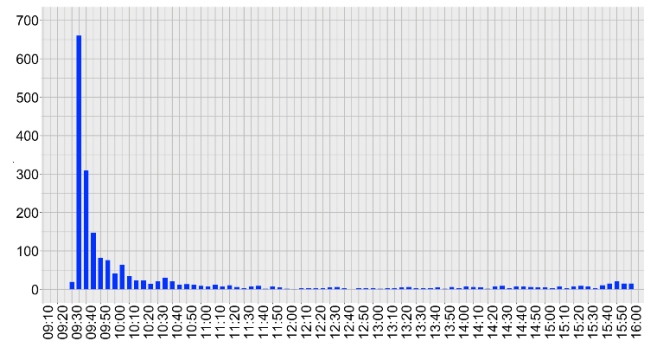


Figure 4.8(b) Matched stocks number of negative jumps

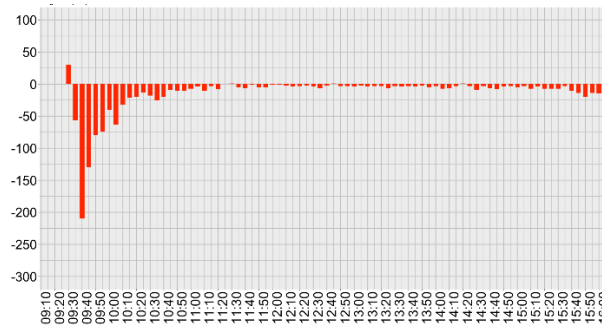


Figure 4.8(c) ADRs-Matched stocks number of negative jumps

Figure 4.9 Total number of jumps

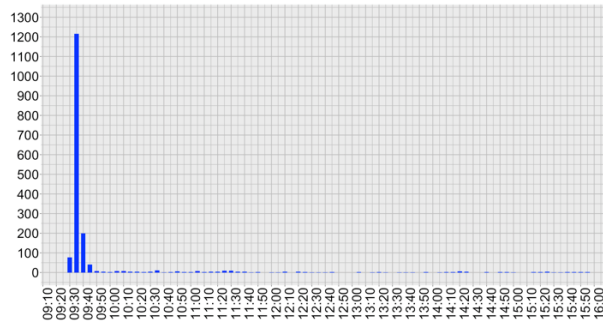


Figure 4.9(a) ADRs total number of jumps

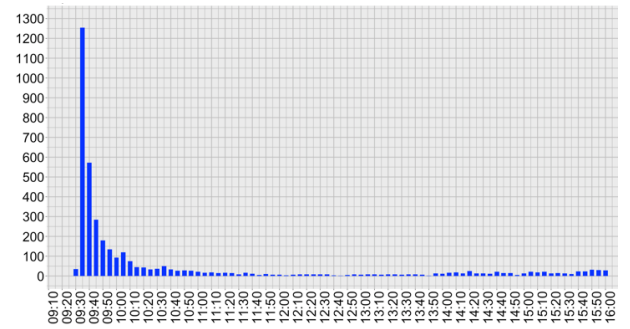


Figure 4.9(b) Matched stocks total number of jumps

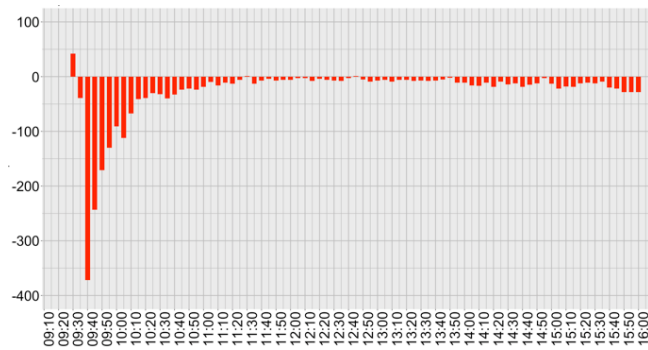


Figure 4.9(c) ADRs-Matched stocks total number of jumps

Figure 4.10 Quoted bid–ask spreads, 3 h overlapping

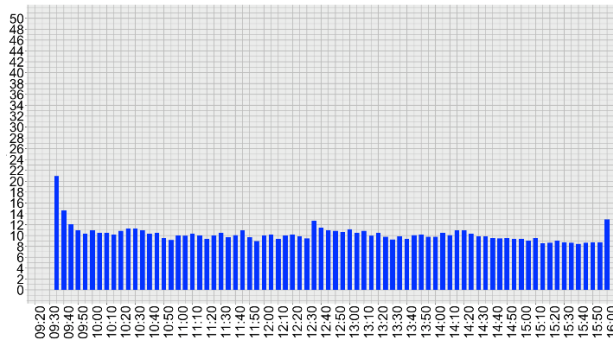


Figure 4.10(a) ADRs PQS 3h overlapping

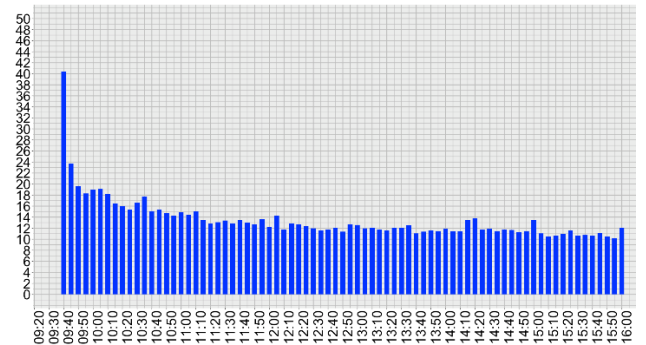


Figure 4.10(b) Matched stocks PQS 3h overlapping

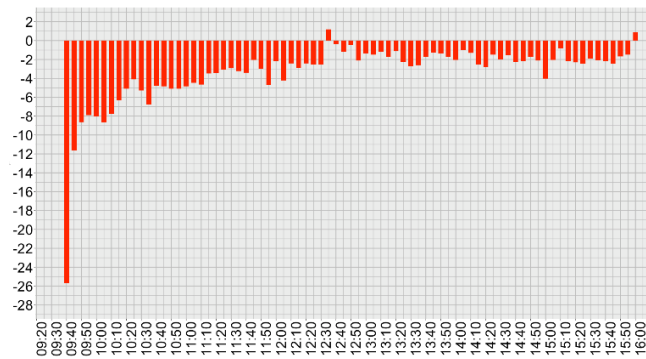


Figure 4.10(c) ADRs-Matched stocks PQS 3h overlapping

Figure 4.11 Effective bid–ask spreads, 3 h overlapping

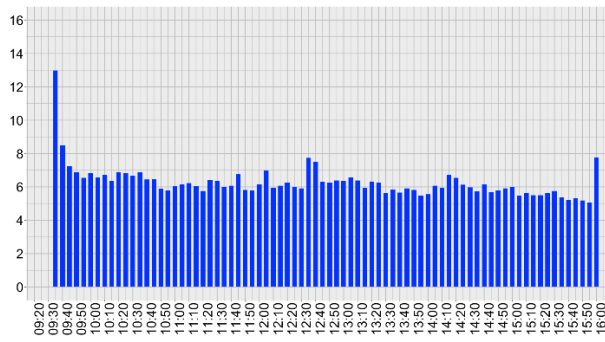


Figure 4.11(a) ADRs PES 3h overlapping

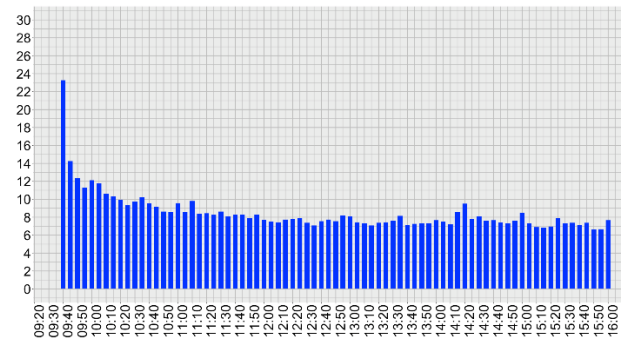


Figure 4.11(b) Matched stocks PES 3h overlapping

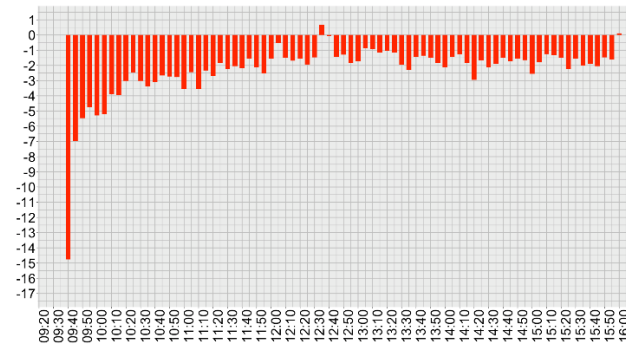


Figure 4.11(c) ADRs-Matched stocks PES 3h overlapping

Figure 4.12 Value traded, 3 h overlapping

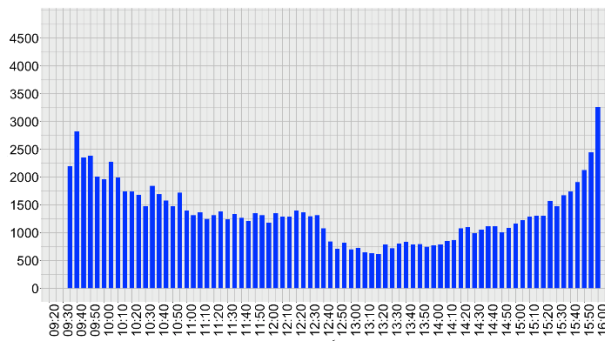


Figure 4.12(a) ADRs value traded 3h overlapping

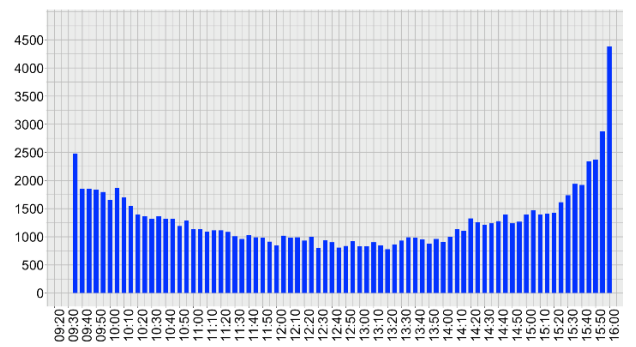


Figure 4.12(b) Matched stocks value traded 3h overlapping

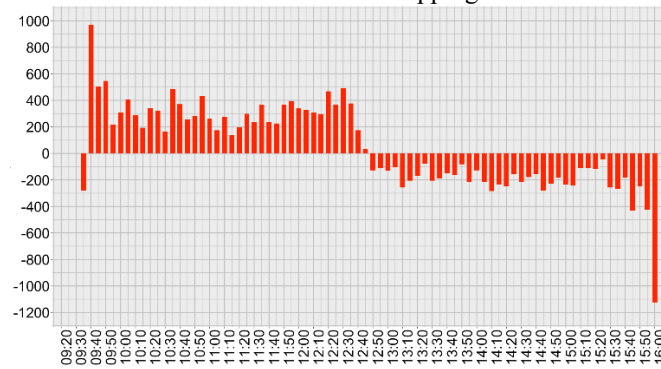


Figure 4.12(c) ADRs-Matched stocks value traded 3h overlapping

Figure 4.13 Number of transactions, 3 h overlapping

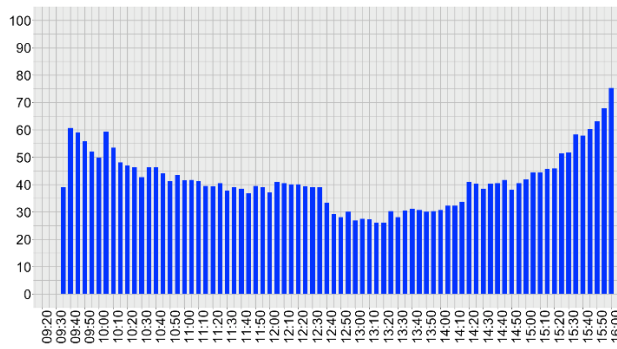


Figure 4.13(a) ADRs number of trade 3h overlapping

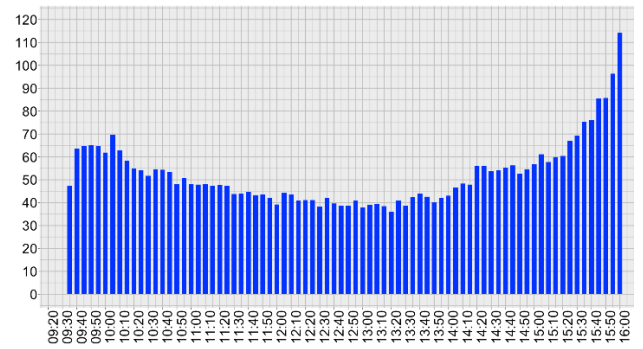


Figure 4.13(b) Matched stocks number of trade 3h overlapping

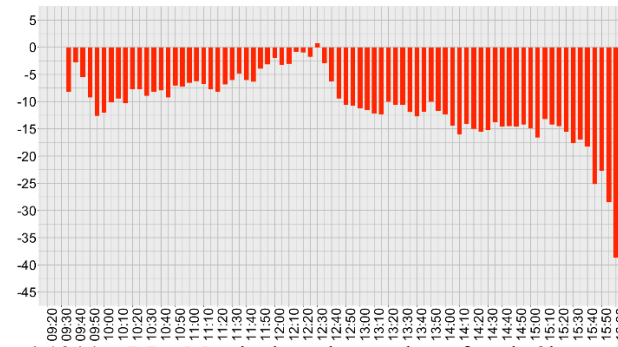


Figure 4.13(c) ADRs-Matched stocks number of trade 3h overlapping

Figure 4.14 Average size of transactions, 3 h overlapping

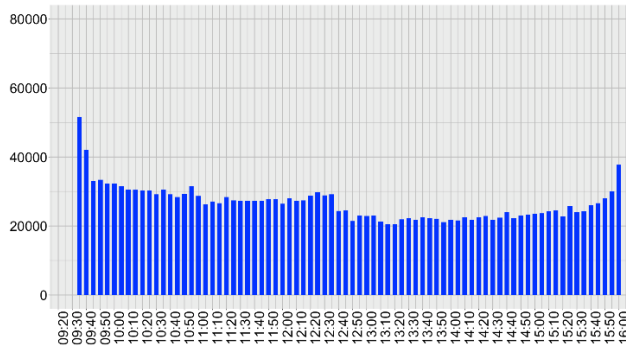


Figure 4.14(a) ADRs ATS 3h overlapping

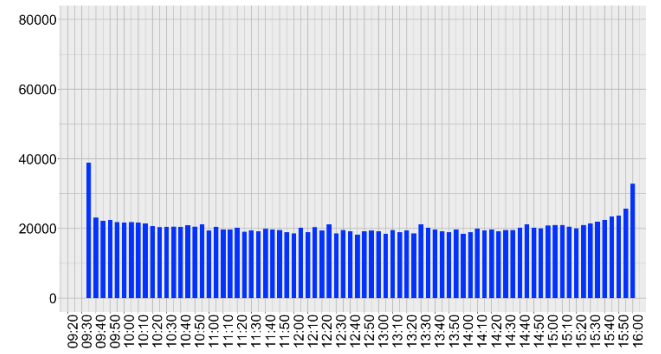


Figure 4.14(b) Matched stocks ATS 3h overlapping

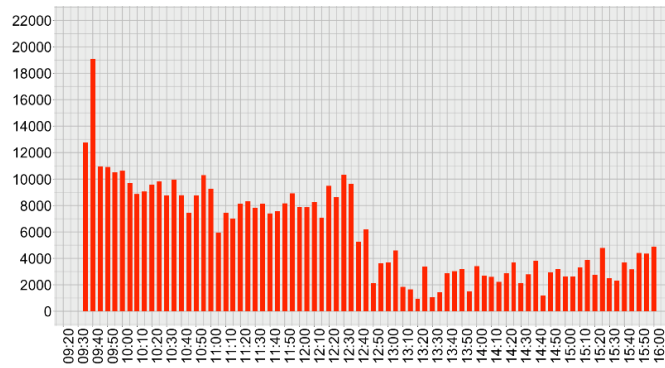


Figure 4.14(c) ADRs-Matched stocks ATS 3h overlapping

Figure 4.15 Depth imbalance, 3 h overlapping

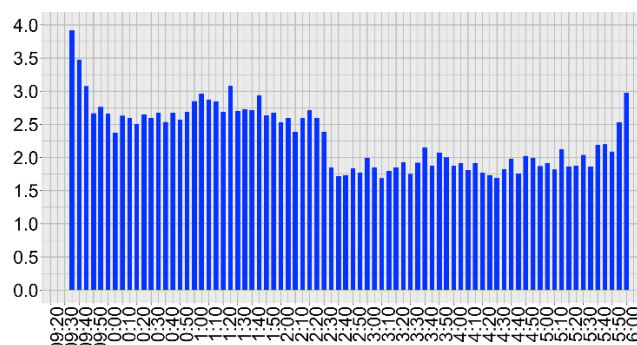


Figure 4.15(a) ADRs depth imbalance 3h overlapping

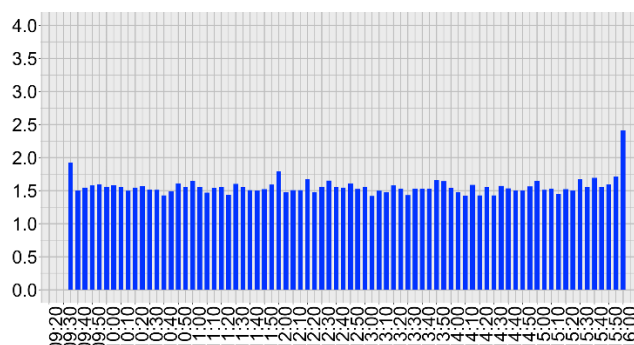


Figure 4.15(b) Matched depth imbalance 3h overlapping

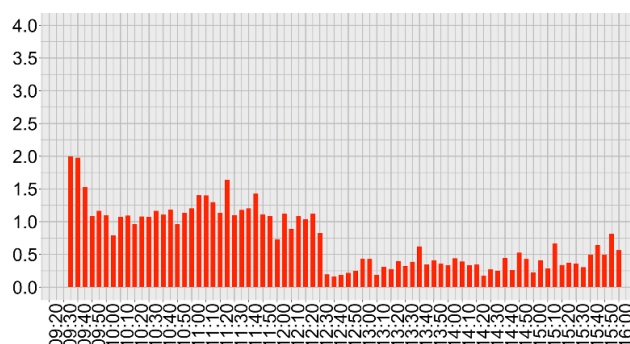


Figure 4.15(c) ADRs-Matched stocks depth imbalance 3h overlapping

Figure 4.16 Market depth, 3h overlapping

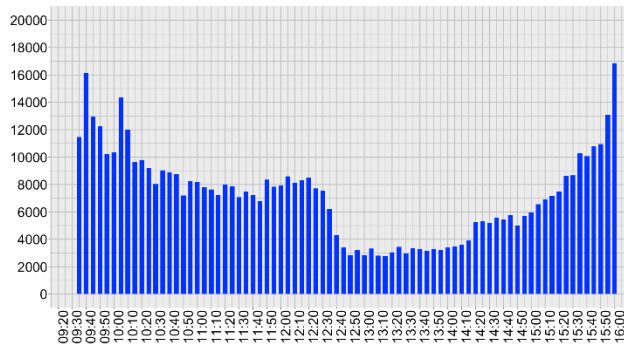


Figure 4.16(a) ADRs market depth 3h overlapping

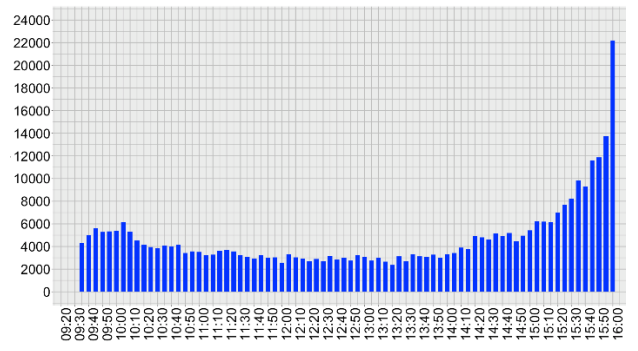


Figure 4.16(b) Matched stocks market depth 3h overlapping

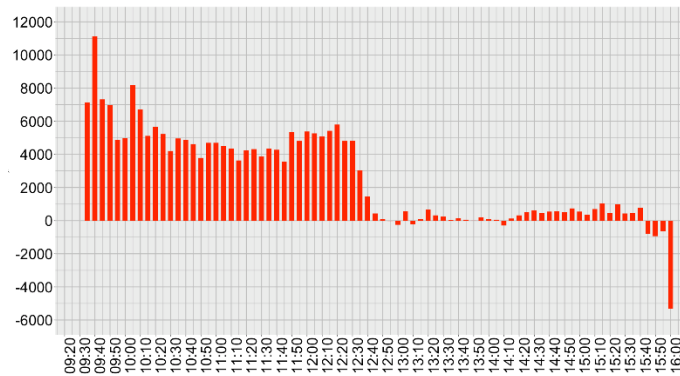


Figure 4.16(c) ADRs-Matched stocks market depth 3h overlapping

CHAPTER 5. Conclusions

This thesis examines three different but related areas of research on financial risk beyond the conventional framework of the efficient market hypothesis. The first empirical chapter examines the association between CEO overconfidence and firms' risk-taking after the experience of a severe financial shock. According to the literature on the availability heuristic, the impact of overconfidence could be changed by high-impact events such as a financial crisis. We utilise the 2008 financial crisis as a high-impact event to explore the risk-inducing effect of CEO overconfidence during the pre- and post-crisis periods. This may be useful to draw inferences on managerial traits and their implications on firms' risk-taking behaviours.

The second empirical chapter considers the incentives for risk-taking behaviour provided by managerial compensation packages and their association with default risk in the banking industry. It investigates the association between CEO vega and default risk on default risk in the US banks. Although the pay package with high vega value can motivate CEOs to implement risky projects, CEO vega could also increase the default risk of banks. The effect of offering executive managers risk-related incentives is influenced by the financial conditions of firms. This may be important to evaluate the impact of the compensation packages on CEOs' risk-taking behaviours.

The third empirical chapter examines the association between jumps in stock prices and market liquidity in the context of cross-listed stocks. It investigates the intraday patterns of market liquidity and price jumps for cross-listed stocks during overlapping hours. This chapter is useful to draw inferences on price jumps and their association with market liquidity in the context of cross-listed stocks.

The main findings and related implications from this work can be summarised as follows. In the first empirical chapter, we find that CEO overconfidence is positively associated with firms' risk. Moreover, we find that during the post-crisis period, the association between CEO overconfidence and firms' risk-taking becomes weaker. The results are robust to the use of different measures of CEO overconfidence. This chapter contributes to the literature on the impact of managerial traits on firms' behaviour. We also propose a new measure of

CEO overconfidence, which is used in the robustness analysis. We find that the association between CEO overconfidence and firms' risk-taking is state-dependent, which means that it can be influenced by the CEOs' past experiences. This chapter also enriches the literature on the availability heuristic. The empirical research suggests that high-impact events could change individuals' beliefs and views about the future. This has an implication for corporate governance practices: executive managers' past experience should be considered when assessing the impact of managerial traits.

In the second empirical chapter, we find that CEO vega is positively correlated with the default risk of banks. Since banks typically have higher leverage ratios than other types of firm, making banks closer to the threshold of default, we also investigate the association between CEO vega and default risk in different financial states. We find that the positive association between CEO vega and default risk is mitigated by high leverage ratios. This chapter contributes to the literature on the association managerial pay packages and default risk. This chapter has several implications. First, although convex managerial compensation packages can induce risk-taking, these effects could be at the cost of increased default risk. Second, the association between CEO vega and default risk is related to the firms' financial states. This implies that the incentives provided by managerial compensation packages are state-dependent. This result has a practical implication: the current financial states of firms should be considered when designing managerial pay schemes. In high-leverage banks, the association between CEO vega and default risk tends to be weaker.

In the third empirical chapter, we investigate the intraday market liquidity of ADRs during overlapping hours. We find that the market is more liquid during overlapping hours than during the rest of the trading day. Moreover, we find that the improved market liquidity is associated with fewer price jumps. We find that the overlapping-hours phenomenon is sensitive to the varying overlapping hours caused by different dates for daylight-saving time. This chapter also has practical implications for those countries that intend to issue depositary receipts in overseas markets. For example, the government of China has a plan to link the Shanghai Stock Exchange with the London Stock

Exchange (Bloomberg, 2018). A new two-way depositary receipt programme will make the China A-shares more accessible to international investors as well as overseas securities more accessible to Chinese investors. The time zones of stock exchanges become a key factor to consider for policymakers.

What are the possible limitations to this work? For the first empirical chapter, the overconfidence measure is limited to CEOs who have information on their options holdings. For those CEOs do not have this information, their overconfidence cannot be identified. This means the options measure of overconfidence cannot be applied to non-listed firms or to emerging markets where the data is not available. For the second empirical chapter, a concern is that our inferences on US banks may not apply in developing countries, as different countries have different regulations for the banking industry. Additionally, the key incentives in emerging countries could be in other forms, which cannot be proxied by conventional compensation schemes, which include options and stocks. For instance, in Chinese state-owned companies, one essential incentive for CEOs is to be promoted, which typically is related to political power. In these cases, CEO vega does not affect firms' risk-taking as much as the incentives of being promoted. For the third empirical chapter, a potential concern is that the overlapping-hours phenomenon does not necessarily exist in all stock markets, as this depends on geographical distance. The inferences based on the overlapping hours may not apply in those markets which do not have overlapping trading hours.

How can future research build on this thesis? For the first empirical study, a potential direction of research is utilising other direct measures for CEO overconfidence, for instance using a personal psychological survey. A more direct measure like this would be helpful. It would also be interesting to investigate other members of the executive team, such as the chief finance officers and the chairs of the board. For the second empirical study, a potential direction is to take account of debtholders' influence on CEOs' behaviours. Debtholders' risk exposure increases when banks are close to default. However, debtholders' impact on the board may not proportionally increase. It would therefore be worth exploring how debtholders influence CEOs' behaviours when banks are close to default. Additionally, the debtholders' impact on

behaviours of other executive managers, such as CFOs or board members, could also be a direction for further research. For the third empirical study, a possible direction is to explore the association between price jumps and market liquidity in other markets, such as futures markets, bond markets and commodity markets. For instance, the bond market is typically less liquid than the stock markets. Less market liquidity could lead to more price jumps. The price jumps could play a more important role in these less-liquid markets.

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