# ESSAYS ON OPERATIONAL RISK IN THE BANKING INDUSTRY

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# Essays on Operational Risk in the Banking Industry


## Abstract

This thesis consists of three distinct essays on operational risk in the U.S. banking industry. The first essay investigates whether operational risk events trigger rating agencies, such as S&P, to downgrade credit ratings of affected U.S. banks over the period 1990 to 2014. Our results suggest that disclosed maximum operational loss as a proportion of market value as well as consequent drops in stock market prices have a negative and significant effect on banks' credit ratings through its ratings score, provided by S&P. The findings are robust to severe operational risk events with loss amounts exceeding $10 million. We also find that post-Global Financial Crisis, S&P becomes more accurate in issuing credit ratings following the disclosure of the severity of operational risk events.

The second essay examines analyst forecast revision and accuracy around operational risk event announcements in U.S. banks over the period 1990 to 2016. It also investigates the individual effects of career concerns of banking analysts, competition among analysts and the Global Financial Crisis on analyst forecasting behaviour following the bad news disclosure. Our results suggest that analysts, that were previously optimistic, revise their forecasts significantly downwards, hence, improving their forecast accuracy. On the other hand, we find that competition causes analysts to issue upward-biased forecasts. The results are more pronounced for severe operational risk events with loss amounts exceeding $10 and $35 million.

The third essay examines the impact of operational risk event announcements, which are considered as a new measure of firm performance, on CEO compensation in U.S. banks over the period 1992 to 2016. Our results suggest that the frequency of operational risk events disclosed has a negative and significant impact on banking executives' compensation, mainly in terms of their option-based compensation. We also find that the higher the compensation committee to board size ratio, the more the CEO will be penalised through a reduction in their options following the frequency of operational risk event announcements. The results are more pronounced following the Global Financial Crisis and the Dodd-Frank Act.

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# 1 Introduction

## 1.1 Background and Motivation

Operational risk is defined as "the risk of loss resulting from inadequate or failed internal processes, people and systems, or from external events" (Basel Committee on Banking Supervision, 2006, p.144). The banking industry has been hit by large-scale operational failures such as Allied Irish Bank, Barings Bank, Société Générale amongst others, over the past two decades. Such high-profile operational losses have resulted in bankruptcies, mergers, or significant equity price drops of a large number of highly reputable banks, hence bringing operational risk to the limelight. Operational risk has, thereby, been subject of heated discussions among various stakeholders including risk managers, regulators, analysts, rating agencies and academics in the past several years, especially in the banking industry. The consequent effects of severe operational risk events, as seen through the waves of bank failures during the global financial crisis, can be disastrous on the wider economy.

The Basel Committee of Banking Supervision (BCBS) has acknowledged operational risk as a major source of material bank failures along with other risks including credit, liquidity and market risks. The Basel II Capital Accord requires banks to reserve regulatory capital against operational risk exposure in addition to that reserved against credit and market risk exposures (BCBS, 2006b). However, unlike the other types of risk in the banking industry, operational risk represents a purely idiosyncratic risk that is not affected by contagion effects (Danielsson et al., 2001; Perry and de Fontnouvelle, 2005). As such, any disclosure on banks' operational risk exposure and management corresponds to information that is unique to the disclosing bank. Whilst regulatory requirements imposed comprehensive disclosures for credit and market risks such as the International Financial Reporting Standard No. 7: Financial Instruments: Disclosures (IFRS 7), no such regulatory accounting standard is imposed on operational risk (PricewaterhouseCoopers, 2010).

We focus exclusively on operational risk event announcements due to the idiosyncratic nature of operational risk in banks (Lopez 2002; Chernobai et al., 2011). Hence, bank managers cannot escape their responsibility for operational risk events; for example, by attributing their occurrences to systematic risks. In addition, the vast majority of operational risk events are announced by external parties such as regulators, clients, creditors and other counterparties. Thus, bank managers have little control over the disclosures made in these announcements (Chernobai et al., 2011; Barakat et al., 2019).

Operational risk event announcements are arrivals of unanticipated bad news in the banking industry, which reveal internal control deficiencies, weak corporate governance mechanisms and ineffective risk management practices, thus having a negative impact on expected future cash flows and banks' creditworthiness (Chernobai et al., 2011). Rating agencies point out that operational risk events may very much be likely to cripple a bank, and in such cases, capital is treated as the only line of defence to overcome operational risk losses (Benyon, 2009). Moody's further states that it may downgrade credit ratings of banks with operational risk fragilities (Moody's Investors Service, 2016). Clearly, rating agencies consider operational risk to have a fundamental impact on credit ratings assigned to banks.

In addition, the disclosure of operational risk events may trigger banking analysts to revise their forecasts downwards as this adverse idiosyncratic informational shock, disclosed by the media and hitting financial markets, conveys valuable signals about possible deterioration of expected future cash flows and earnings per share of the affected banks. Moreover, CEOs, who are held accountable for firms' performance, are likely to be penalised for operational risk disclosure through a reduction in their compensation as this bad news can be considered as a negative measure of firms' performance.

Prior literature on operational risk has mainly focused on the stock market reaction following operational risk event announcements (Perry and de Fontnouvelle, 2005; Cummins et al., 2006; Gillet et al., 2010; Fiordelisi et al., 2013). These extant studies provide strong evidence that stock market reacts significantly to operational risk events and quantify the significant drops in stock prices as reputational damage. However, the literature has failed to analyse operational risk from the perspectives of other stakeholders.

Motivated by these facts, this thesis investigates the pricing of operational risk by different stakeholders, including external ones i.e. rating agencies and banking analysts and internal stakeholder i.e. banking executives. Whilst credit ratings drive both the equity and debt markets, analyst forecasts affect only the equity markets (Barakat et al., 2014), As such, the thesis empirically explores the impact of operational risk events on each of the following: credit ratings; analyst forecasts; and CEO compensation. First, the effects on banks' credit ratings of operational risk features. i.e., the frequency of undisclosed and disclosed operational risk events, the severity of the operational loss events and the resulting stock market reactions are investigated. Second, analyst forecast revision and accuracy following operational risk disclosures are analysed. Finally, the effects on CEO compensation in the form of total pay, bonus, stocks and options of the frequency and severity of operational risk events are examined. The findings will eventually enable us to determine any anomalies and mispricing of operational risk by providing evidence of the marginal impact on credit ratings assigned to banks, bias in analyst forecasts and CEO compensation.

A distinctive feature of the thesis is the use of a unique operational loss data source known as the Financial Institutions Risk Scenario Trends (FIRST) database, marketed by Algorithmics Inc, a member of IBM. Algo FIRST is known as the largest and most comprehensive database on operational risk event announcements. We focus on the U.S. banking sector predominantly due to data availability. The vast majority of operational risk data obtained from Algo FIRST is more focused on U.S. banks. In addition, our thesis focuses on the banking sector due to the unique regulatory and supervisory frameworks imposed on banks in comparison to other sectors like insurance, oil/gas, and so on.

The banking industry has been largely hit by the financial crisis, which has led to several bank failures and a number of regulations including the Basel II/III requirements, the Dodd-Frank Act and recent regulations of SIBs/SIFIs. Credit rating agencies, analysts and practitioners seemed unable to understand the risk that banks were exposed to prior the financial crisis. So, this research helps us understand their response to unforeseen risky events, albeit on a much smaller scale than a financial crisis. The analysis of this issue is particularly important given the prominence of the banking sector in modern economics and the spill over of a banking crisis to the real economy. In what follows, more details on the structure of the thesis and a summary of each of the essays are presented.

## 1.2 Structure and Contents of the Thesis

This thesis is composed of the three following empirical papers:

- *When do Operational Risk Events Trigger a Credit Rating Downgrade?*
- *How do Banking Analysts Behave around Unanticipated Bad News? Evidence from Operational Risk Event Announcements*
- *The Impact of Operational Risk Event Announcements on CEO Compensation in the Banking Industry*

### 1.2.1 When do Operational Risk Events Trigger a Credit Rating Downgrade?

Rating agencies assess the probability distribution of firms' future cash flows, i.e., their creditworthiness, and produce credit ratings that are considered as a useful risk measure for investors and firms to facilitate their access to credit markets (Driss et al., 2016). Banks, however, face critical risks including operational risk, which can cause considerable threats to the financial health, growth and reputation of these financial institutions. Operational risk event announcements by banks are indicative of their low quality corporate governance and risk management practices, leading to lower expected future cash flows (Chernobai et al., 2011). This, in turn, will negatively affect banks' creditworthiness and is likely to cause rating agencies to downgrade credit ratings of affected banks.

Rating agencies, mainly S&P, Moody's and Fitch, consider operational risk to be a damaging factor, which affects the efficiency, soundness and reputation of financial institutions (Ferry, 2003). As such, they point out that credit ratings should be adjusted to account for operational risk events (Moody's Investors Service, 2016). As an example, Société Générale suffered a severe operational risk loss event amounting to $7 billion in 2008 due to rogue trading and consequently, the bank faced a downgrade in its credit ratings. Fitch explained that the internal fraud highlighted issues about the effectiveness of the bank's system and gave rise to reputational risk.

Prior studies examine the effect on credit ratings of internal control quality, proxied by firms' disclosure of internal control weaknesses, which however excluded operational risk (Elbannan, 2009; Dhaliwal et al., 2009; Hammersley et al., 2012). They show that firms with weak corporate governance are likely to experience a downgrade in their credit ratings. Whilst Chernobai et al. (2011) document that internal control weaknesses may be related to a greater incidence of losses due to operational risk, extant studies have failed to investigate the impact of operational risk events on credit ratings.

Therefore, in this study, we investigate whether the mind-sets of rating agencies' to downgrade banks' credit ratings are affected by operational risk features, which include the frequency of undisclosed operational risk events from inside information that rating agencies possess prior to event disclosure, the frequency of operational risk events announced, their severity and the resulting stock market reactions. We perform additional analyses to investigate the effects of severe operational risk events with loss amounts exceeding $10 million and the Global Financial Crisis on credit rating changes.

Using a sample of 1,328 operational risk event announcements by publicly traded U.S. banks from 1990 to 2014, extracted from Algo FIRST, and employing random effects panel data regressions, we examine the impact of operational risk event disclosures on affected banks' credit ratings in the following quarter. Our key findings reveal that maximum operational loss disclosed as a proportion of firm's market value as well as adverse stock market reactions to operational risk event announcements during a particular fiscal quarter have a negative and significant impact on S&P credit rating changes in the following quarter. This implies that the severity of operational risk event disclosures conveys crucial information that S&P takes into consideration. We also find strong evidence that, in the case of severe operational losses exceeding $10 million, the results are relatively more pronounced such that the higher the maximum operational loss to market value, the more is S&P credit ratings' downgrade. Moreover, following the Global Financial Crisis, we observe that S&P downgrades credit ratings of firms that have suffered from operational risk events while prior to the crisis period, operational risk disclosures were ignored in firms' assessment.

All in all, the findings of this paper sheds light on the fact that by incorporating operational risk into their overall credit rating assessment, rating agencies will eventually motivate banks to effectively enhance their operational risk management.

### 1.2.2 How do Banking Analysts Behave around Unanticipated Bad News? Evidence from Operational Risk Event Announcements

Banking analysts act as vital information intermediaries by issuing analyst forecasts that reflect their discovery of private information and interpretation of public corporate disclosures based on their expertise and technical know-how (Ivkovic and Jegadeesh, 2004). As new information hits the market, analysts may decide to revise their forecasts, which are used by investors in their trading decisions. Operational risk event announcements are bad news that are disclosed to the public unexpectedly and convey new important information about firms' internal control deficiencies, weak corporate governance and ineffective risk management practices (Chernobai et al., 2011).

Operational risk disclosures are unanticipated news and bank managers usually have limited or no control over the disclosures. Therefore, banking analyst behaviour around operational risk event announcements would expose clearly any potential bias due to unobservable conflicts of interest in banking analyst research activities to extract private benefits from maintaining close relationships with bank managers; for example, due to career concerns (Horton et al. 2017), brokerage business (O'Brien et al. 2005) or competition with other analysts (Huang et al. 2017).

Prior studies have however primarily focused on the impact of earnings announcements, as the only significant corporate public information, on analyst forecasts (Ivkovic and Jegadeesh, 2004; Chen et al., 2010). Rubin et al. (2017) show that a higher number of analysts react and revise their forecasts following anticipated earnings disclosure due to its economic impact compared to unanticipated 8-K reports.

Nonetheless, unanticipated news are still considered to be informative to analysts as they convey relevant information for future earnings. However, they do not comprise of operational risk event disclosures, which are important corporate disclosures also revealing valuable signals about firms' anticipated future cash flows and earnings per share.

While recent studies have found that equity value consequences of operational risk events are economically substantial (Perry and de Fontnouvelle 2005; Cummins et al. 2006; Gillet et al. 2010; Sturm 2013), there is no prior research as to whether these operational risk event announcements lead to equity analysts' revisions of earnings forecasts. Therefore, the objective of this study is to examine operational risk disclosures from the perspective of banking analysts. Since analysts are those who know the firms particularly well, the way they react around operational risk event disclosures reveals the severity of the risky events. However, banking analysts might also not react rationally to very adverse news due to career concerns and severe competition and instead either might choose to ignore or underreact to the arrival of firm-specific news.

Hence, in this study, we investigate analyst forecast revision and accuracy around operational risk event announcements in banks and further examine the individual effects of career concerns of analysts, competition among analysts and the global financial crisis on analyst forecasting behaviour following the bad news disclosure. We utilize a sample of 315 operational risk event first announcements and 299 settlement announcements by publicly traded U.S. banks from 1990 to 2016, extracted from Algo

FIRST and employ an ordinary least squares regression model for each analyst following the firm, which incurred an operational risk event announcement.

Our results shed light on the determinants of optimism bias in banking analyst behaviour upon the arrival of unanticipated news. We find that operational risk event announcements enhance analyst forecast accuracy for optimistic analysts who had issued upward biased forecasts prior to the announcement. This result confirms that operational risk event disclosures are informative to banking analysts and is consistent with operational risk events revealing useful information about internal control deficiencies and improper risk management practices.

On the other hand, we find no evidence that analysts following a potential employer (i.e., a bank which has an analyst research department) bias their behaviour or enhance their forecast accuracy around operational risk disclosure to secure an employment opportunity. We document that stronger competition among banking analysts causes an upward bias in analyst forecast revision around operational risk event announcements. This implies that analysts tend to curry favour with firms through the issuance of optimistic forecasts to gain higher sales and trading commissions. Interestingly, robustness checks show that our results are more pronounced for severe operational losses exceeding $10 and $35 million and the Global Financial Crisis period demonstrates that analysts become more accurate in their forecasting.

All in all, the major contribution of this study is that it demonstrates that operational risk disclosures provide crucial information which reduces the error and bias in analyst forecasts and enhances market discipline. In addition, it calls for banking supervisors to monitor more closely analyst forecasting behaviour that may be subject to conflict of interest and, hence, increase their optimism bias in analyst forecasts.

### 1.2.3 The Impact of Operational Risk Event Announcements on CEO Compensation in the Banking Industry

CEOs are rewarded for managing firms' resources and maximising firm value on behalf of shareholders through CEO compensation. The rapid acceleration of the high level of CEO pay in the banking industry has spurred an intense debate about pay-performance relationship. One of the main concerns is whether pay the CEOs are receiving actually reflect their performance. Some academics argue that large executive pay packages are the result of the managerial power theory, which relates to executives' undue influence on pay-setting processes (i.e., executives earn rents above those required for them to do the job), resulting in a weak pay-performance relationship (Bebchuk and Fried, 2003). In contrast, the optimal contracting perspective argues that large executive pay packages are required to attract, motivate and reward managerial talent (Fryman et al., 2010).

Prior studies have focused on stock market-based as well as accounting-based measures of firm performance to investigate the impact on CEO compensation (Gibbons and Murphy, 1992; Sloan, 1993; Hubbard and Palia, 1994). Most empirical studies have found a small but significant association between firm performance and CEO compensation. We contribute to this literature by employing a new measure of performance, more specifically a negative measure, that is, operational risk, which previous studies have failed to consider. Chernobai et al. (2011) point out that operational risk event announcements reveal serious internal control deficiencies, weak corporate governance mechanisms and poor risk management practices in financial firms. This, hence, reflects bad news about firm performance.

Therefore, in this study, we investigate whether there is a change in ex post CEO compensation, in the form of total pay, bonus, stocks and options, as a consequence of the frequency and severity of operational risk event announcements by banks, especially following the Global Financial Crisis and the Dodd-Frank Act. We also examine whether the compensation committee ratio has an impact on CEO compensation around operational risk disclosures. We use a sample of 1,289 operational risk event first announcements by publicly traded U.S. banks from 1992 to 2016, extracted from Algo FIRST and employ both static (ordinary least squares and fixed effects) and dynamic (generalized methods of moments) regression models.

Our findings reveal that CEOs are penalised through a reduction in their option-based compensation following the frequency of operational risk disclosure in the previous fiscal year. However, we find no evidence that operational loss disclosed and consequent drops in stock prices result in lower CEO compensation. Interestingly, the stronger the corporate governance mechanism in place in terms of compensation committee to board size ratio, the more the CEOs are penalised in the current fiscal year for bad firm performance measured by the frequency of operational risk event announcements in the previous fiscal year. We find evidence that the reduction in CEO option-based compensation following the number of operational risk events disclosed increases after the Global Financial Crisis and even more after the Dodd-Frank Act.

All in all, the findings of this study sheds light on a new measure of negative firm performance in the form of the frequency of operational risk event announcements by banks. It suggests that since CEOs are penalised for the number of operational risk events disclosed, CEOs should ensure a more effective operational risk management is in place within the firms to earn higher rewards. In addition, this study enables bank regulators and practitioners assess whether the different regulations, especially the compensation reforms introduced, have any meaningful impact on CEO compensation practices.

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# 2 When do Operational Risk Events Trigger a Credit Rating Downgrade?

## 2.1 Abstract

Operational risk event announcements reveal new adverse private information on internal control deficiencies within firm-level corporate governance and risk management practices, which could subsequently result in a reputational loss for the firm. The purpose of this study is to examine whether operational risk events motivate rating agencies to revise the credit ratings of the affected firm downwards. Most importantly, we investigate whether the mind-sets of rating agencies to change the credit ratings of banks are affected by either or both the frequency of undisclosed operational risk events (i.e., inside information that they possess regarding operational risk events prior to their announcement) and disclosed operational risk events and the resulting stock market reactions (i.e., external data). To achieve this aim, we use proprietary data on the frequency, severity and announcement of operational risk events, incurred by publicly traded U.S. banks during the period 1990 to 2014, extracted from the Algo FIRST database. We find clear evidence that maximum operational loss to market value causes a downgrade in S&P's ratings score of firms that have suffered from operational risk events. Interestingly, we find that S&P reacts to stock market reactions to operational risk event disclosures by revising the affected firms' credit ratings downwards. Robustness check shows that this result is relatively more pronounced for severe operational losses exceeding $10 million. In addition, following the Global Financial Crisis, S&P tends to issue more accurate and informative credit ratings unlike the pre-crisis period.

## 2.2 Introduction

Bank credit ratings are determined by rating agencies' assessment of the probability distribution of future cash flows to bondholders (Ashbaugh-Skaife et al., 2006). They represent a forward-looking assessment of the ability and willingness of the bank to meet its financial obligations in full and on time (Standard & Poor's, 2002). As such, they are considered as an important signal to stakeholders about the bank's creditworthiness (Basel Committee on Banking Supervision, 2000).

On the other hand, banks are exposed to a multiplicity of risks, including operational risk, which can cause considerable threats to the financial health, growth, as well as reputation of these institutions. Operational risk event announcements are arrivals of unexpected bad news in the financial industry. Banks incurring these operational risk events may suffer from substantial operational losses. Additionally, such operational risk events signal to the market the inherent flaws in internal control systems, corporate governance quality and risk management effectiveness, that may have future adverse implications (Chernobai et al., 2011). As a consequence of operational risk events, the expected cash flows of banks are perceived to be lower, and in cases where liquidity problems arise, their likelihood of default tends to increase.

An example is the 'London Whale' case, where Fitch Ratings downgraded JPMorgan Chase's credit rating one day after the public announcement that one of banking giant's trading units had suffered an operational loss amounting to $2 billion. Although Fitch claimed the financial impact on JPMorgan as "manageable", it also highlighted that the magnitude and the "ongoing nature" of the trading activity that led to the loss implied a lack of liquidity at the lender. Thus, Fitch downgraded JPMorgan's long-term issuer default rating to A+ from AA- and lowered its short-term rating from F1+ to F1. Interestingly, it also placed the New York company under review for possible more downgrades in the future (Sherter, 2012).

Moreover, operational risk concerns can prevent rating agencies from upgrading the credit ratings of a firm even if the latter is enjoying increasing profitability. In its 2004 opinion of Citigroup's ratings, Moody's explained that "like several competitors, Citigroup has attracted significant litigation exposure and regulatory scrutiny out of the collapse of the technology stock bubble and its role with failed firms such as Enron". Litigation concern centred on Enron was considered as the biggest challenge and was known to be the main reason why Citigroup's creditworthiness was not upgraded to AAA from AAA- since 2001 (Risk.Net, 2005).

Therefore, with the three major credit rating agencies, Standard & Poor's (S&P), Moody's and Fitch Ratings, focusing on the role of operational risk in the rating of banks, it is clear that operational risk should have a meaningful impact on credit ratings. Arguably, by incorporating operational risk into their overall credit rating assessment, the rating agencies eventually motivate banks to effectively enhance their operational risk management.

As reputational risk also emerges for a company following an operational risk event, rating agencies estimate the consequent impact on income and expected future cash flow. A tainted reputation can substantially affect an institution's bottom line and, eventually, its ability to borrow capital in the future, hence, making rating agencies very concerned. Randy Nornes, executive VP of Aon Risk Solutions in Chicago, said "reputational distress within an organization increases uncertainty, prompting rating agencies to issue warnings or actions more quickly" (Tsikoudakis, 2012). Fitch voiced its concern about the Basel II operational risk definition, which excludes reputational risk, strongly stating that "in our view, this is a major source of risk for some institutions and should be addressed either in the operational risk regime or separately" (Keefe, 2001). Hence, it is clear that rating agencies believe that reputational risk should also be taken into account when making rating decisions.

Prior academic studies in the finance literature have focused on providing evidence of the impact of operational losses on reputational risk of financial institutions by investigating the stock market reactions to operational loss event announcements (Perry and de Fontnouvelle, 2005; Cummins et al., 2006; Gillet et al., 2010; Fiordelisi et al., 2013)[1]. They have shown significant drops in stock prices following the first press announcement of operational losses, implying reputational damage caused by operational risk event announcements. However, studies have failed to investigate the impact of operational risk event disclosures on credit ratings as well as whether reputational risk has an effect on the credit ratings assigned to banks.

On the other hand, extant literature on credit ratings has explored the impact of firms' disclosure of internal control weaknesses (ICWs), as a proxy for internal control quality, on credit ratings (Dhaliwal et al., 2009; Elbannan, 2009; Crabtree and Maher, 2012; Hammersley et al., 2012). However, they have not considered operational losses, which is a consequence of a weak internal control environment (Chernobai et al., 2011). As

[1] The terms 'operational risk events', 'operational risk loss' and 'operational losses' are used interchangeably in this study.

such, this is the first study to provide empirical evidence of the direct impact of operational risk and resulting reputational risk on credit ratings. We aim to systematically determine whether operational risk events affect credit ratings before or after their disclosure.

Using a sample of publicly listed U.S. banks from 1990 to 2014, this study seeks to make four contributions to the literature. First, it examines the impact on credit ratings of the announcement of operational risk events at their first press cutting date and their loss amount disclosed. Since operational losses, especially those of a significant amount, are indicative of poor internal systems and affect future cash flows (Chernobai et al., 2011), rating agencies are motivated to revise banks' credit ratings. However, if rating agencies do not revise the credit ratings of banks, which have incurred an operational risk event, it might imply that the rating agencies trust that the banks would be able to overcome the consequences of the operational risk events and remedy their causes. In other words, they might believe that the future expected cash flows of these banks would not suffer due to their good creditworthiness.

Second, we examine whether stock market reactions following operational risk event announcements have a significant impact on credit ratings. Whilst extant studies provide evidence that the stock market reacts significantly to operational risk events (Perry and de Fontnouvelle, 2005; Cummins et al., 2006; Gillet et al., 2010; Fiordelisi et al., 2013), this is the first study to analyse the impact of stock market reactions to these operational risk events on credit ratings.

Third, we examine whether reputational loss incurred by banks, that suffered the operational loss, cause rating agencies to review their credit ratings as a damaged reputation might cause serious threat to their going concern value. Whilst prior studies have shown that operational risk generates reputational risk (Perry and de Fontnouvelle, 2005; Cummins et al., 2006; Gillet et al., 2010; Fiordelisi et al., 2013; Sturm, 2013a), this is the first study to analyse the impact of reputational risk caused by operational risk event announcements on banks' credit ratings.

Finally, we investigate whether private data regarding the operational risk events obtained from discussions with bank managers (i.e., internal data) matter to rating agencies in making credit ratings decisions. Meetings and discussions with company management are usually part of the rating process, which normally help rating analysts to better assess the management capability, the different risks the company are facing and their risk appetite.  Following material announcements by the company or significant industry events, meetings and dialogue with management is more frequent (U.S. Securities and Exchange Commission, 2002).

If credit ratings are adjusted before operational risk event announcements, it implies that the rating agencies have access to private information. In this case, we use frequency in terms of detection date (which means the number of events that ended but were not announced) as a proxy for undisclosed private data. Operational loss amounts, their market reactions and the reputational impact, are used as proxies for announcement. While undisclosed frequency of operational risk events is associated with the discovery role of rating analysts, their announcements are associated with the interpretation role (Rubin et al., 2017). Lastly, we extend our analysis by investigating whether severe losses exceeding $10 million matter to rating agencies.

A distinctive feature of this empirical study is the use of an operational loss data source that identifies actual operational loss events (Chernobai et al., 2011) instead of having to manually search through publicly available sources to develop a sample of U.S. banks that announced operational risk events, in which case, omission of some important events is highly likely to be possible. Our sample is derived from the Financial Institutions Risk Scenario Trends (FIRST) database, marketed by Algorithmics Inc., a member of IBM. Previously, the data have been used in studies by Cummins et al. (2006), De Fontnouvelle et al. (2006), Dahen and Dionne (2010), Gillet et al. (2010), Chernobai et al. (2011), Barakat et al. (2014).

Our results reveal that the severity of operational risk event announcements, in the form of maximum operational loss to market value, causes S&P to downgrade credit ratings of affected firms. We also find strong evidence that S&P reacts to drops in stock prices following operational risk event disclosures by revising firms' credit ratings downwards. In a robustness test, we extend our analysis by investigating the effect of severe operational losses exceeding $10 million on credit ratings and we find clear evidence that the downgrade in affected firms' credit ratings is slightly higher following disclosed maximum loss to market value. In another robustness test, we explore the effect of the Global Financial Crisis on the impact of operational risk events on credit ratings. We observe that, in the pre-crisis period, S&P was optimistically biased in their credit assessment and, interestingly, following the Global Financial Crisis, S&P becomes more accurate and, as expected, downgrades the credit ratings of firms that have suffered from operational risk events as they signal internal control deficiencies and ineffective risk management practices within the firms.

The remainder of the paper is organised as follows. Section 2.3 provides a background and reviews the literature on credit ratings, operational risk and reputational risk. Section 2.4 develops our research hypotheses. Section 2.5 describes the variables used, clarifies data sources, the sample selection procedure and explains our empirical model. Section 2.6 presents our empirical findings and, lastly, Section 2.7 concludes.

## 2.3 Literature Review

### 2.3.1 Credit Ratings

#### 2.3.1.1 Overview of Credit Ratings

A firm's credit rating reflects a rating agency's opinion of the firm's overall creditworthiness and its capacity to satisfy its financial obligations (Standard & Poor's, 2002). As Crabtree and Maher (2012) point out, "credit ratings provide a succinct representation of analysts' perceptions of default risk associated with a firm's outstanding debt". Firm credit rating is determined by rating agencies' assessment of the firm's cash flow vulnerability, that is, the likelihood that the firm will be able to meet its contractual financial commitments on a timely basis, and in full, as a going concern.

Credit ratings are mostly provided by three main rating agencies namely: Standard & Poor's (S&P), Moody's Investor Services (Moody's) and Fitch IBCA (Fitch), although there are others. While each rating agency adopts a distinct rating scale, there is equivalence across the rating scales that enables comparability such that, for example, AA+ rating from S&P is equivalent to Aa1 rating from Moody's, and AA+ from Fitch. This equivalence is well understood by market participants. A change in a firm's credit rating signals an improvement or deterioration of fundamental credit quality.

In addition to credit ratings, rating agencies also announce outlooks. As explained by Micu et al. (2004, p.56), outlooks "reflect rating agencies' prognosis – positive, negative or stable – regarding the likely direction of an issuer's credit quality over the medium term, usually over a 12- to 18- month horizon. They are typically modified when a change in an issuer's risk profile has been observed but it is not yet regarded as permanent enough to warrant a new credit rating. Moreover, a change in outlook does not always lead to a change in rating".

In our empirical study, we follow Ashbaugh-Skaife et al. (2006) by using S&P's long-term issuer credit rating, which is a forward-looking opinion focusing on the obligor's capacity and willingness to meet its financial commitments as they fall due. It does not apply to any specific financial obligation, as it does not take into account the nature and provisions of the obligation, its standing in bankruptcy or liquidation, statutory preferences, or the legality and enforceability of the obligation (S&P Global Ratings, 2016).

#### 2.3.1.2 Prior Literature on Credit Ratings

Rating agencies play a crucial informational and valuation role in the capital market by assessing and publishing their opinions of firms' creditworthiness in the form of credit ratings (Elbannan, 2009). The latter is widely used in financing and investment decision-making, which has consequently fuelled extensive research on rating determinants. Rating agencies assign credit ratings based on public information about borrowers' operating and financial conditions, private information derived from discussions with borrowers about the management, planning and strategy of the company as well as their subjective judgements.

More importantly, accounting information is extensively used by rating agencies in the fundamental analysis of developing and benchmarking profitability, and leverage ratios for assigning ratings to bonds issues (Elbannan, 2009). Bissoondoyal-Bheenick and Treepongkaruna (2011) employ an ordered probit model and find that firm-level factors, including operating performance, asset quality, capital adequacy and liquidity risk, are important determinants of banks' credit ratings across different rating agencies. They also document that market risk as well as country-level variables, like gross domestic product and inflation, are insignificant factors to explain banks' credit ratings.

Furthermore, according to Crabtree and Maher (2012, p.888), "any additional information relating to the integrity and veracity of the firm's financial statements would be important in establishing the level of confidence analysts place in the reported numbers". They further explain that internal control assessment, which is a requirement of Sarbanes–Oxley Act (SOX), can reveal further information in relation to various aspects of the firm's control effectiveness, thereby having direct implications on the reported financial statements. As Moody's Investors Services (2004) highlights, "negative reports regarding a firm's internal control processes can provide a more grievous signal concerning the firm's ability to control its operations". Doyle et al.

(2007) show that companies with internal control weaknesses, often attributed to broader deficiencies in company-level controls, have lower quality financial statements. Therefore, it can be argued that SOX-mandated information concerning a firm's internal control effectiveness should be associated with the firm's credit ratings.

Extant studies use the firm's disclosure of internal control weaknesses (ICWs), as a proxy for internal control quality, to investigate the impact on firms' credit ratings (Elbannan, 2009; Dhaliwal et al., 2009; Hammersley et al., 2012). Elbannan (2009) investigates whether a firm's credit rating is linked to the quality of internal control over financial reporting. He empirically shows that "firms with low internal control quality are more likely to have lower credit ratings, speculative-grade rating, lower cash flows from operating activities" and higher income variability compared to firms with high-quality controls. Hammersley et al. (2012) show that firms that failed to remediate previously-disclosed material weaknesses in their internal control systems experience poorer credit ratings. Therefore, we argue that since operational risk events are key indicators of weak internal control systems in place (Chernobai et al., 2011), they are likely to have a negative impact on firms' credit ratings.

In addition, several studies examine the effect of corporate governance on firms' credit ratings (Sengupta, 1998; Bhojraj and Sengupta, 2003; Ashbaugh-Skaife et al., 2006). Ashbaugh-Skaife et al. (2006) analyse whether firms with strong corporate governance are assigned higher credit ratings in contrast to firms with weak corporate governance. Their findings reveal that a hypothetical firm, which acquires desirable governance characteristics from a bondholder's viewpoint, approximately doubles its likelihood of receiving an investment-grade credit rating. As such, better governance can translate into significant savings on the cost of debt for firms. We can therefore argue that since operational risk, which relates to an internal control deficiency, is also viewed as an indicator of a weak corporate governance structure (Chernobai et al., 2011), this could lead to a credit rating downgrade.

Other studies on the same stream of research investigate whether bank loan spread increases with a firm's disclosure of ICWs. Costello and Wittenberg-Moerman (2011) find that when a firm experiences an ICW, lenders tend to substitute financial-ratio-based performance pricing provisions with provisions based on credit ratings. All in all, previous literature has shown that disclosure of a firm's ICWs provides additional information to credit analysts, which then motivates these analysts to revise the firm's credit ratings downwards. Moreover, rating agencies have stated that details on firm internal control deficiencies reveal useful information and can be a crucial determinant of credit ratings (Moody's Investor Service, 2004; Fitch, 2004).

However, previous studies have not considered operational loss and examine its direct impact on credit ratings despite the fact that these internal control weaknesses may be related to a greater incidence of losses due to operational risk (Chernobai et al., 2011). Jayan Dhru, the managing director and head of North American Financial Institutions Group at S&P in New York, revealed that "historically, serious losses in trading operations have been traced to a series of weaknesses around issues related to policies, infrastructure and methodologies" (Standard & Poor's, 2005). Kim Olson, managing director in Fitch Ratings' credit policy group, said that they are "digging deep into the history of operational risk losses in financial institutions by taking a more careful and considerable eye to their internal control environment and asking for both their qualitative and quantitative methods in the management of operational risk by also analysing how they collect their data" (Fitch Ratings, 2004).

Therefore, it can be argued that information about operational risk events should provide direct insight to rating agencies in regard to the quality of the internal control system and the reliability of the firm's audited financial statements, including the firm's default risk. However, to our knowledge, there are no prior studies that have analysed the direct effect of operational risk events and their loss amounts on banks' credit ratings, despite the fact that prior literature clearly argues that actual operational losses can be considered as a consequence of a weak internal control environment (Chernobai et al., 2011). Shedding light on this association should be useful to market participants, external financiers and, more importantly, to banking institutions in order to assist management in implementing a more effective risk management system.

## 2.3.2 Operational Risk

### 2.3.2.1 Overview of Operational Risk

While operational risk is, by itself, not a new concept for banks, it has nevertheless not received the same amount of attention as credit risk and market risk until recent years. Operational risk occurs in the banking industry on a daily basis and it affects the soundness and operating efficiency of all banking activities and all business lines. Growing investors' risk appetites, coupled with fundamental changes in the global financial market, increasing globalisation and deregulation, as well as corporate restructuring had a significant impact on the magnitude and nature of operational risk confronting banks (Helbok and Wagner, 2006).

According to the recent study by Scope (2016), operational risk is considered to be paramount for banks, especially those with large asset-management, private-banking or custody services, for which credit or funding risks are less prominent. Such banks would be likely to look at the operational risk of specific material transactions such as acquisitions or divestitures. Moreover, technology reliability and cybersecurity are two very important issues that are highly relevant for most banks and are viewed as part of operational risk. Weaknesses, accidents or fraud can cause significant problems for banks as the banking industry is increasingly IT-based and IT-driven in trading, retail as well as wholesale banking. Cyber threats, which consist of cyber-attacks, cyber espionage and cyber fraud, expose banks to both on-going operational risk losses and the potential for catastrophic events that can destroy their reputation.

Roger Ferguson, vice chairman of the board of governors of the Federal Reserve System from 2001 to 2006, at a hearing before the Committee on Banking, Housing, and Urban Affairs of the United States Senate in 2003 said: "In an increasingly technologically driven banking system, operational risks have become an even larger share of total risk. Frankly, at some banks, they are probably the dominant risk" (Chernobai et al., 2008, p.3).

The Basel Committee on Banking Supervision (BCBS) defines operational risk as "the risk of loss resulting from inadequate or failed internal processes, people and systems or from external events. This definition includes legal risk, but excludes strategic and reputational risk" (BCBS, 2006, p.144). Operational risk is considered as a firm-specific non-systematic risk. As the Bank of International Settlements (BIS) puts it, "Unlike market and perhaps credit risk; the [operational] risk factors are largely internal to the bank" (BIS, 1998). According to the Basel II, operational risk events are classified according to event type, which include the seven event types as given below:

i) Internal fraud: Losses due to acts of a type intended to defraud, misappropriate property or circumvent regulations, the law or company policy, excluding diversity/ discrimination events, which involves at least one internal party. For example, in November 1995, Daiwa Bank was indicted on charges of conspiring to conceal trading losses incurred by its bond trader and was subsequently fined $340 million, the largest criminal fine ever at the time.

i) External fraud: Losses due to acts of a type intended to defraud, misappropriate property or circumvent the law, by a third party.

ii) Employment Practices and Workplace Safety: Losses arising from acts inconsistent with employment, health or safety laws or agreements, from payment of personal injury claims, or from diversity/discrimination events.

iii) Clients, Products and Business Practices: Losses arising from an unintentional or negligent failure to meet a professional obligation to specific clients (including fiduciary and suitability requirements), or from the nature or design of a product.

iv) Damage to Physical Assets: Losses arising from loss or damage to physical assets from natural disaster or other events.

v) Business Disruption and System Failures: Losses arising from disruption of business or systems failures.

vi) Execution, Delivery and Process Management: Losses from failed transaction processing or process management, from relations with trade counterparties and vendors.

Generally, most of the operational losses that are usually encountered are frequent and do not result in major damage. For instance, losses due to employee errors, equipment failures, IT disruptions and minor fraud cases. However, regulators and risk management experts are much more concerned with the less frequent and high-impact loss events such as rogue trading scandals and the terrorist attacks in the U.S. in September 2001, which are rather unpredictable. Such events are referred to as black swan events, i.e., rare events but ones which can have disastrous effects on the financial market by causing major losses in excess of billions of dollars and can even threaten the survival of the affected firms.

The global financial system has been shaken by a vast number of highly publicized operational losses over the last 20 years, causing severe financial instability. Over 100 operational losses exceeding $100 million in value each and several others exceeding $1 billion have affected financial firms globally since the end of 1980s. Berger et al. (2012) have observed that U.S. commercial banks have collapsed during the financial crisis mainly due to loan losses, liquidity problems, and fraud occurrences. Internal and external fraud are both considered by BCBS to be operational risk events (BCBS, 2006). Further characteristics of notable operational losses have been analysed in depth by Chernobai et al. (2007), Chernobai and Yildirim (2008) and Chernobai et al. (2011).

The large-scale operational losses have led to many cases of bankruptcies, mergers or substantial price declines of a large number of highly reputable financial institutions. Some prominent examples of operational losses include Barings Bank in 1995 losing $1.4 billion from rogue trading in its branch in Singapore leading to the failure of the whole institution (Stonham, 1996; Ross, 1997), Allied Irish Bank (AIB) in 2002 losing $750 million in rogue trading (Dunne and Helliar, 2002), the colossal losses from the September 11, 2001, terrorist attacks and, more recently, Deutsche Bank, which was fined in excess of $2.5 billion for its role in a scam to fix rates such as the London Interbank Offered Rate (Reuters, 2015).

As a consequence of these high-profile scandals, academics, professionals, credit rating agencies and regulators (e.g. BCBS, 1998, 2001, 2006; Cummins et al., 2006; Helbok and Wagner, 2006; Chernobai et al., 2011) have recently started paying more attention to operational risk exposure and its management practices in financial institutions. It has been identified as an increasingly important source of risk for large, internationally active banks (Cummins et al., 2006) and an important factor for banks' performance and stability, and one which banks maintain substantial capital reserves against (Abdymomunov et al., 2019).

The Basel Committee, in response to these events, published the New Capital Accord or Basel II to encourage better risk management by internationally active banks (BCBS, 2006). Basel II, for the first time, requires banks to incorporate an explicit capital charge for operational risk into their regulatory capital requirements. The Basel II Accord provides guidelines for the calculation options of economic operational risk capital for banks, which are the Standard Approach, the Basic Indicator Approach and the

Advanced Measurement Approach (AMA). It incentivizes banks in the U.S. to adopt the advanced measurement approach (AMA), which uses internal risk measurement systems to determine the operational risk capital charge. AMA encourages self-surveillance of the banks, such that the latter become better aware of the risks they face and thereby take action against them.

#### 2.3.2.2 Operational Risk and Credit Ratings

The major rating agencies have published several reports discussing operational risk management and analysing the implications of operational risk for the assignment of corporate financial ratings (Moody's Investors Service, 2004). Moody's explains that the capital markets activities are highly exposed to operational risks because of the following reasons: Firstly, it is common for individuals to carry out transactions involving very large nominal amounts. As these people are often remunerated based on their trading performance, there is a high temptation to conceal losses or even generate artificial gains. Moody's further argues that regardless of how sophisticated a bank's systems and controls are, individuals' intent on fraud will often find a way to circumvent them as shown by remarkable similarity of some large fraudulent incidents over the past twenty years or more. Similarly, because transactions are typically of significant size, errors of an unintentional nature (rather than fraud) have larger consequences relative to the associated revenue in retail banking (Moody's Investors Service, 2016).

As an example, the second-largest French bank, also one of the largest banks in Europe, Société Générale, suffered a major operational risk event in 2008 amounting to €4.9 billion ($7 billion) as a result of rogue trades by a Paris-based trader, who concealed his positions through "a scheme of elaborate fictitious transactions". Consequently, Fitch said that “the fraud raised questions about the effectiveness of the bank’s systems and created reputational risk for the bank” and therefore, it cut SocGen’s rating one notch to AA-.

Moody’s reveals that rating agencies have begun to appreciate the underlying operational risk behind many of the securities they evaluate such as asset-backed securities, namely Residential Mortgage Backed Securities (RMBS), Commercial Mortgage Backed Securities (CMBS), Collaterized Loan Obligations (CLO) and Collaterized Debt Obligations (CDO) amongst others (Wheeler, 2011). As they are heavily dependent on successful transfer and underlying servicing processes, any related operational processes failure is likely to result in a quick drop in the value of the securities. Consequently, Moody’s believes that all its 200 asset-backed securities with senior ratings need to be adjusted to account for the operational risk guidelines.

In a Fitch report, 'Regulatory Capital Ratios: A Case Study’, Fitch Ratings points out “the danger that the relative share of capital for operational risk could increase given the high incidence of fraud, hasty mergers of financial institutions, unwinding of complex financial instruments (causing litigation in some cases), settlement failures and rapid changes in key personnel and staffing levels. It also recognises the fact that an operational risk loss event is much more likely to cripple a company than a market or credit risk event, and that capital is only the last line of defence against operational risk losses” (Benyon, 2009).

Moody's states that it may assign lower credit ratings to banks with exposed operational risk fragilities, depending on the extent and nature of the issues (Moody's Investors Service, 2016). A concrete example of rating agencies' application of operational risk in their credit ratings decisions is the case where Fitch has upgraded one Italian bank's subsidiary for improvements in their organizational structure, which shows the agency is serious about the use of operational risk management as an element in the ratings assessment process (Benyon, 2009).

All in all, operational risk event announcements convey a negative signal about poor managerial control or integrity and damages the reputation of the firm. Customers may switch to competitors, causing a downward revision of the firm's expected future cash flows. As Moody's.RiskNews.net describes, "since operational risk will affect credit ratings, share prices and organisation reputation, analysts will increasingly include it in their assessment of the management, the strategy and the expected long-term performance of the business" (Ferry, 2003).

Furthermore, Kim Olson, a managing director in Fitch Ratings' credit policy group, highlighted the fact that the significance of operational risk in the credit ratings of financial institutions is increasing with the regulatory focus on it, especially the guidance of Basel II (Risk.Net, 2005). Clearly, rating agencies consider operational risk in the banking industry to have a fundamental impact on credit ratings assigned to these financial institutions.

#### 2.3.2.3 Prior Literature on Operational Risk

While analytical work in the area of operational risk has significantly advanced at some financial institutions over the years, academic literature on that topic remains sparse because of a lack of data. To date, academic work on operational risk has concentrated in the area of Pillar 1 of the Capital Accord dealing with the quantification of regulatory risk capital. More recently, Chernobai et al. (2011) have developed an econometric framework and use publicly reported operational loss data from 1980 to 2005 to investigate the effects of internal factors on the incidence of operational risk losses in U.S. financial institutions. Their results hold uniformly across different operational event types, consistent with the theory that lack of internal control is the common root cause of various operational risk events.

Another steam of literature investigates the effect of operational loss events on effective spreads and the price impact of trades, on bonds, as well as on credit default swaps (CDS). Plunus et al. (2012) examine the bond market response to the announcement of 71 operational loss events that occurred between 1994 and 2006 across 41 U.S. firms. Their findings show significant negative bond market reactions to operational loss disclosures around the first press release date. Moreover, they find that debtholders' response is more averse to operational losses of the event type “Clients, Products and Business Practices”. Sturm (2013b) documents the impact of operational risk event announcements on CDS in European banks. He finds that CDS spreads rise only around the settlement dates and when the relative operational loss size is higher, and argues that these findings indicate that some features and timings of operational risk event announcements lead to a rise in a bank's default risk. Therefore, we argue that operational risk events have been analysed from the perspective of debtholders but not from an analyst point of view, which is what this study aims at investigating by considering rating analysts' reactions to firms' credit ratings.

Furthermore, using a sample of 331 operational loss events from 1995 to 2009, Barakat et al. (2014) observe that an operational loss announcement increases information asymmetry (which they measure by effective spreads and the price impact of trades) across U.S. financial firms around the first press cutting date and find that the impact is more pronounced for events caused by internal fraud. Their results also reveal that the stronger the corporate governance in financial institutions and the closer to the settlement date, the lower is the level of information asymmetry. Our study will help us understand whether ratings agencies are able to make an informed decisions about revising the affected firms' credit ratings despite increased information asymmetry at first announcements or rather they have private information from meetings with firms' management on which they can act upon.

Other studies have focused on the equity market reaction to operational risk announcements (Perry and de Fontnouvelle, 2005; Cummins et al., 2006; Gillet et al., 2010; Fiordelisi et al., 2013; Sturm, 2013a) and show that such public news leads to severe drops in stock prices, more particularly in the event of internal fraud. Whilst these studies have examined operational risk from the perspective of market investors, our study aims to understand credit rating agencies point of view i.e. whether they care about these disclosures by adjusting the credit ratings of affected firms to reflect this bad news.

Few studies have observed a strong link between the quality of internal controls and risk variables (Beneish et al., 2008; Hammersley et al., 2008; Ashbaugh-Shaife et al., 2009; Dhaliwali et al., 2011). Although these studies have not specifically focused on operational risk, their findings suggest that the results could also be relevant to operational risk in general. According to Chernobai et al. (2011), operational risk loss amounts convey negative implications about a firm's expected future cash flows. Hence, we argue that this should motivate rating agencies to revise downward a firm's credit rating due to increased risk of whether the firm will survive and have cash flows to service existing debts as well as take on new financial obligations.

While, in practice, rating agencies have placed great emphasis on the importance of operational risk on credit ratings (Moody's Investor Service, 2004; Fitch, 2004), previous studies have not addressed the direct impact of operational risk on credit ratings. As such, this study is going to systematically explore the effect of operational risk on credit ratings. We also examine whether high-scale operational risk events (exceeding $10 million) matter to rating agencies.

## 2.3.3 Reputational Risk

### 2.3.3.1 Overview of Reputational Risk

Corporate reputation has long been recognized as a major source of competitive advantage and as a value-creating resource, which enables firms to maintain a consistent or even boost their market performance (Deephouse, 2000). Since a big proportion of the market value comes from hard-to-assess intangible assets such as brand equity, intellectual capital and goodwill, firms are vulnerable to anything that can damage their reputation.

In particular, banking is an industry that relies hugely on the trust and confidence of their customers. Unlike tangible goods, trust is not related to a specific product or service but to the entire bank (Hirt-Schlotmann et al., 2015). In an industry as competitive as financial services, a tarnished reputation can be catastrophic. Equity markets tend to react consequently to the reputational damage. This underpins the reason why banks place so much emphasis on the issue of trust and reputational risk.

Reputational risk is defined by the Board of Governors of the Federal Reserve System (2004) as "the potential that negative publicity regarding an institution's business practices, whether true or not, will cause a decline in the customer base, costly litigation, or revenue reductions". As per BCBS (2009, p.19), it is "the risk arising from negative perception on the part of customers, counterparties, shareholders, investors, debt-holders, market analysts, other relevant parties or regulators that can adversely affect a bank's ability to maintain existing, or establish new business relationships and continued access to sources of funding". Walter (2008) explains reputational risk in the banking and financial services context as the possibility of loss in the going-concern value of the financial institution – the risk-adjusted value of expected future earnings.

In general, reputational risk refers to any risk that has the potential to damage the estimate of an institution from the point of view of third parties. Oftentimes, the harm to a firm's reputation is considered as intangible and may surface gradually. However, there is strong evidence that equity markets immediately react to the reputational consequences of some operational events (Perry and de Fontnouvelle, 2005).

### 2.3.3.2 Reputational Risk and Credit Ratings

The recent financial crisis demonstrated, more than ever before, the fundamental importance of reputational risk for banks. Banks suffering from a damaging reputation can lead to equity market distrust, hence, negatively impacting a bank's capacity to raise debt and equity. As Scope (2016) highlights, "a bank's reputational and public image can be hurt by its retail operations, wholesale activities, private banking and asset management. In retail and commercial banking, examples include mis-selling, excessive charging of customers and cross-selling strategies, burdening customers with unnecessary products through bundling. In wholesale markets, examples include the interest-rate-benchmark mismanagement or deliberate manipulation, rogue-trader events, excessive remuneration practices and so on". Lastly, in private banking and asset management, there might be cases of inappropriate tax advice or money laundering practices on behalf of clients.

All the above have a disastrous effect on the respective banks' reputations. As the global financial crisis years brought the banking industry even more into the public limelight, any such reputational events can have an extended impact on the affected banks and on the banking industry as a whole. Therefore, it can be argued that rating agencies must have a closer look at reputational risk when assigning credit rating to banks. As Scope (2016) further points out, "even if reputational risk is likely to be a 'soft' part of the rating analysis, it is nonetheless essential for assessing public trust in the bank".

### 2.3.3.3 Prior Literature on Reputational Risk

Reputational risk is categorized as a more elusive risk type in comparison to credit, market and operational risk, due to the difficulty in quantifying its effects. However, over the last decade, a growing amount of financial literature has attempted to measure reputational risk for listed companies by analysing stock market reactions to operational loss events, which was deemed to be the most important source for reputational risk (Ruspantini and Sordi, 2011).

Perry and de Fontnouvelle (2005, p.5) explain in a simple model, “a firm’s stock price equals to the present discounted expected value of the cash flows it will generate. Any reputational risk event will undermine the present or future expected cash flows and subsequently, reduces the equity value of the affected firm. For instance, an operational loss announcement may be characterised as a consequence of a weak internal control environment. As such, shareholders are likely to sell their stocks if they believe future losses are forthcoming”. Therefore, it can be assumed that reputational risk can be indirectly measured by estimating the impact of an operational loss announcement on a firm’s equity value.

Such an approach has been adopted by Perry and de Fontnouvelle (2005), Cummins et al. (2006), Gillet et al. (2010), Fiordelisi et al. (2013) and Sturm (2013a). These studies have shown consistent evidence of large drops in the market values of loss firms, which even exceed the operational loss amount, following an operational risk event announcement. They interpret this difference as reputational damage or reputational loss. As such, they argue that operational risk event announcements are usually found to generate statistically significant reputational risk.

In addition, several prior studies have examined whether the impact of operational risk events on banks' reputations differ according to the types of operational risk events (Perry and de Fontnouvelle, 2005; Cummins et al., 2006; Gillet et al., 2010; Fiordelisi et al., 2013). While Gillet et al. (2010) show that the loss in firms' market value is greater than the announced loss amounts (interpreted as evidence of reputational damage) in cases of internal fraud, Fiordelisi et al. (2013) provide evidence that external fraud has the greatest impact on firms' reputation. In terms of business lines, only Fiordelisi et al. (2013) investigate which business line is most exposed to reputational risk and they find "trading and sales" business lines to be the case.

Overall, there remains a limited number of studies dealing with reputational risk in the financial industry, with most of them based on the U.S. financial industry and small-sized samples. Our study focuses on U.S. banks exclusively. As Fiordelisi et al. (2013, p.1359) state, "although reputational risk is crucial in all types of businesses, it assumes special importance in the banking sector due to asymmetric information, the qualitative asset transformation made by banks and the supply of payment and risk management services create systemic risk". However, to date, previous literature has not examined whether reputational risk has an impact on the credit rating of banks, which is what this paper is also going to analyse. It further contributes to the literature by investigating whether the association of reputational risk and credit ratings differs in terms of severe operational risk events with losses exceeding $10 million.

## 2.4 Hypotheses Development

The discussion of the prior literature suggests three main hypotheses regarding the impact of operational risk and reputational risk on credit ratings. The first hypothesis tests whether the frequency and the severity of disclosed operational risk events in a fiscal quarter have a significant impact on credit ratings in the next quarter. In this study, frequency is measured as the number of operational risk events that have been disclosed and severity is measured in the following ways: the operational loss amount, market reaction to operational risk event announcements, and reputational loss. Therefore, the first hypothesis is partitioned into four sub-hypotheses. The first sub-hypothesis tests whether the number of operational risk event announcements for each bank in a fiscal quarter motivate credit analysts to revise credit ratings of banks in the following quarter. Arguably, an increase in the number of operational risk event announcements disclosed is expected to result in a downgrade in credit ratings. Thus, the following sub-hypothesis is formulated as follows:

$H_{1a}$*: The number of operational risk event announcements have an adverse impact on banks' credit ratings.*

The second sub-hypothesis focuses on the operational loss amount disclosed at the first announcement date. If the loss amount is disclosed, this is likely to signal important information to credit analysts. Cummins et al. (2006) argue that the loss might indicate poor managerial controls or other management defects. A high operational loss amount disclosed might adversely cause the market to revise downward a firm's expected future cash flows and creditworthiness. The vulnerability of the firm's future cash flows is the primary area of interest of risk to debt holders as this determines the firm's ability to service its existing debt and its capacity to take on and service new debt (Merton, 1995). As such, a decline in future operating cash flows due to operational risk loss amount incurred is expected to result in a downgrade in credit ratings. Accordingly, the following sub-hypothesis is proposed:

$H_{1b}$ *The operational loss amount disclosed has a negative impact on banks' credit ratings.*

The third sub-hypothesis is concerned with the stock market reactions to operational risk event announcements. Previous empirical studies have investigated whether the announcements of information on operational loss events contain relevant information for the stock market at all (Perry and de Fontnouvelle, 2005; Cummins et al., 2006; Gillet et al., 2010; Fiordelisi et al., 2013; Sturm, 2013a). These studies have shown that the announcement of information about a loss due to operational risk conveys relevant and unexpected information to the stock market such that it affects the value of the firm. They all show that these announcements have a significant negative impact on the stock price of the financial institution which incurred the loss. Therefore, we predict that the stock market reactions, measured by the cumulative abnormal returns, are likely to cause rating agencies to revise their credit ratings downwards.

$H_{1c}$ *Stock market reaction to operational risk event announcements has a negative effect on banks' credit ratings.*

Walter (2008) argues that operational risk event announcements may not only inflict direct financial losses on a firm, but they may also have an indirect impact on the firm via reputational risk. Perry and de Fontnouvelle (2005) explain that an operational risk event may damage a firm's reputation if the loss amount is considered as an indicator of weak internal controls. Extant studies in this area measured reputational loss as any decline in a firm's market value that exceeds the announced operational risk loss amount (Perry and de Fontnouvelle, 2005; Cummins et al., 2006; Gillet et al., 2010; Fiordelisi et al., 2013; Sturm, 2013a). These studies examine the reputational impact of operational risk announcements on stock market reactions and show that the market, indeed, reacts significantly to these loss announcements.

Consequently, the negative effects of reputational risk can result in losses for a company in terms of loss of current or future potential customers, current business partners revising their terms and conditions of cooperation, other costly events like regulatory investigation, lawsuits and so on (Sturm, 2013a). This might cause a change in the expectations about future cash flows of the firm. Arguably, we predict that the decrease in market value associated with reputational loss is likely to lead to a downgrade in banks' credit ratings.

$H_{1d}$*: Reputational loss has an adverse effect on banks' credit ratings.*

Credit ratings are based on both public information about borrowers' operating and financial conditions as well as private information obtained through confidential discussions with borrowers. Rating agencies such as Moody's, S&P and Fitch have privileged access to information about borrowers and devote considerable resources to analysing such information (U.S. Securities and Exchange Commission, 2002). Sometimes they obtain this information, including operational risk events, from the banks' management team well before it is made publicly available.

This hypothesis differs from $H_{1a}$ as it investigates pre-operational risk event disclosure while $H_{1a}$ examines post operational risk event disclosure effect on credit ratings. In order to test $H_2$, we use the dates the operational risk event actually started and ended to determine whether rating agencies react to these loss events throughout the duration of the events following private information obtained by the affected firm's management. In contrast, for $H_{1a}$, we use operational risk event first announcement date i.e. the first press cutting date the event was announced to the public. As operational risk events reveal poor internal control weaknesses in firms (Chernobai et al., 2011), we expect ratings agencies to react to these internal data about operational risk incurred by banks by downgrading their credit ratings. Our second hypothesis is formulated as follows:

$H_2$*: The number of operational risk events that have been detected in banks have a negative impact on their credit ratings.*

Our third hypothesis deals with the relative size of operational losses. While $H_{1b}$ tests the effect of operational loss amount (with no restriction on the size of the loss) on credit ratings assigned to firms, we follow Sturm (2013a) by investigating whether the relative size of operational losses exceeding $10 million have a greater impact on credit ratings downgrade following operational risk disclosure through $H_3$.

If operational risk adversely affects credit ratings, we would intuitively expect larger losses to cause even more severe impact on credit ratings. However, Sturm (2013a) points out that the market participants do not account perfectly for the relative size of operational losses. More specifically, they find that for relatively small losses the market value exceeds loss amount while for relatively large losses the market value is lower than the operational loss amount.

While the market overestimates negative consequences of relatively small losses and underestimates the consequences of relatively large losses, we expect the reverse impact of operational losses on credit ratings. Since rating agencies adjust ratings of firms depending on their creditworthiness, large operational losses are expected to affect firms' expected future cash flows more compared to relatively small losses. Hence, we predict that the impact of operational risk losses exceeding $10 million is likely to have a significant impact on credit ratings.

$H_3$*: The impact of operational risk events on banks' credit ratings differ depending on the relative size of the loss (exceeding $10 million).*

## 2.5 Data and Methodology

### 2.5.1 Data and Sample Selection

The empirical analysis is performed by utilizing a sample of operational risk events announced in the media from 1990 to 2014, which is obtained from IBM Algo FIRST, an operational risk database marketed by IBM. This resource provides detailed descriptions of more than 15,000 operational risk events that occurred in financial and non-financial industries globally. It supplies a range of information, including the name of the company and its group, geographical location of the event, event type, date of the loss occurrence, settlement date, loss amount, as well as a complete explanation of the loss event. In the context of our study, the criteria used to filter this data collection are as follows:

- The organization geography is restricted only to the United States.
- The company that suffered the loss belongs to the banking sector only; all other financial services have been excluded.
- Basel event types that do not fall under the seven Basel II operational risk event type categories have been excluded.
- All companies that are not publicly quoted in the U.S. are excluded.

After the first screening, our sample comprises of 1,556 operational risk events. Then, the following criteria for loss announcements were created in order to be included in our final analysis:

- The first announcement date is known.
- The start date and the end date of the operational risk event are both known.
- A precise loss amount or exposure was announced on the first announcement date or on the settlement date.

We have removed 2015 and 2016 operational risk events from our sample as a more conservative approach due to the fact that there could be some running operational risk events that could be undetected or not announced yet. For e.g. an internal fraud event started on 25$^{th}$ November 2015 and ended on 20$^{th}$ January 2016 but the date the operational risk event was first disclosed to the public was on 3$^{rd}$ February 2017. Since our initial dataset comprises of operational risk events from 1990 to 2016, it might include events that happened (i.e. started and ended) during 2015 and 2016 but whose first announcement dates have not yet been announced to the public before end of 2016. As such, we removed these 2015 and 2016 risky events to ensure that each operational risk event in our sample has a corresponding start date, end date and first announcement date.

For each event, the start date, end date, first announcement date as well as the nominal loss amount reported by the news have been double-checked manually through the LexisNexis news database for consistency and corrected if necessary. For the first announcement date, the date of the very first news article in the press mentioning the loss was used, even if the actual loss amount announcement appeared several days later. If the announcement of an operational loss event occurred on a weekend, then the announcement date chosen was the next trading day. The extent of information related to the loss event released on this date ranges from simply the announcement of a lawsuit or investigation without the loss amount to a complete descriptive report of the loss event, including the loss amount. In the cases where the loss amount at the first announcement date is not found, the settlement loss amount is instead used as all the loss amounts are normally known at the settlement date (Gillet et al., 2010).

We finally organize our data as a cross-sectional time-series panel, where the panel represents individual banks and is unbalanced due to unequal lengths of time the banks are represented within our sample. Balance sheet data are obtained from Compustat in Wharton Research Data Services (WRDS). We include only firms with two-digit Standard Industrial Classification (SIC) codes of 60 (depository institutions), 61 (non-depository institutions), 62 (security and commodity brokers) and 67 (other investment offices). Market values of equity are extracted from the Center for Research in Security Prices (CRSP).

Credit ratings for U.S. banks from 1990 to 2014 are downloaded from Bloomberg. We use the long-term local issuer credit ratings complied by Standard & Poor's, which are widely used as an assessment of default risk (Ashbaugh-Skaife et al., 2006; Elbannan, 2009). The ratings range from AAA (highest rating) to D (lowest rating- debt in payment default). We consider credit rating changes on a quarterly basis from 1990Q1 to 2014Q4. The ratings downloaded include outlooks (with *+ or *-). We ignore the outlooks and considered those credit ratings with outlooks as being stable, i.e., with no credit rating change. The sample selection is guided by data availability.

Due to the strictness of these criteria, our final sample is composed of 1,328 operational risk events from large and medium-sized U.S. banks. Table 2.2 summarizes information on the composition of our final sample. For the purpose of our analysis, the multiple ratings are converted into numerical scale as provided in Table 2.3. More specifically, higher ratings are represented by higher values, following Ashbaugh-Skaife et al. (2006) and Elbannan (2009). We further extend our analysis by using a sub-sample of severe operational loss amounts (exceeding $10 million).

### 2.5.2 Variables Definitions

In order to investigate the impact of operational risk and reputational risk on credit rating changes, we use credit rating changes on a quarterly basis from 1990 Quarter 2 to 2014 Quarter 4 as our dependent variable. The quarterly change in domestic long-term issuer credit ratings by S&P is determined by the difference between the current rating and the previous rating. According to Table 2.3, ratings range from AAA (highest rating) to D (lowest rating). A positive change implies a credit rating upgrade; a negative change means a credit rating downgrade and zero change means the credit rating is stable.

In terms of our explanatory variables, we use different proxies for operational risk and these include the number of events disclosed at each first announcement date, the corresponding maximum and average of all operational loss amounts disclosed at each operational first announcement date, the maximum and average of the operational loss to market capitalization, the stock market reactions to operational risk events, and the frequency of private data obtained prior to announcement. The reputational impact of operational risk events, more precisely reputational loss, is used as a proxy for reputational risk.

Operational loss announcements and the market reactions following these announcements, including the reputational impact are considered as external data. In contrast, frequencies in terms of the start date and end date of the operational risk event are considered as internal data, which credit analysts know prior to the first announcements of the operational risk events. Both internal and external data will be tested separately in different models to evaluate whether credit analysts react to external data and/or internal data in terms of revising the credit ratings. Variables used in our empirical study are described in Table 2.1.

Following the literature on operational risk (Perry and de Fontnouvelle, 2005; Gillet et al., 2010; Sturm, 2013a; Fiordelisi et al., 2013), we compute the direct stock market reaction to operational risk event announcements using the cumulative abnormal stock return (*CAR*). As explained by Perry and de Fontnouvelle (2005) and Sturm (2013a), CAR is estimated using an event study methodology, which aggregates abnormal returns over time over an event window for each stock. In line with prior studies, the following formula is employed:

$$CAR_{i[-5,5]} = \sum_{t=-5}^{5} AR_{i,t} \text{ , where } AR_{i,t} = R_{i,t} - (\widehat{\alpha_i} + \widehat{\beta_i} R_{m,t}) \qquad (1)$$

($\alpha_i$: idiosyncratic risk element of stock $i$; $\beta_i$: is its beta coefficient)

For the purpose of our study, we choose an event window of one week, i.e., five trading days before the first press cutting date and five days after the first press cutting date (-5, +5), assuming that any possible information leakage will have an impact on stock prices starting five trading days prior to the first announcement date and ending five trading days after the first announcement date. Prior studies on operational risk (Perry and de Fontnouvelle, 2005; Gillet et al., 2010; Sturm, 2013a) have used longer event windows including (-10, +10) and (-20, +20). We use the event window (-5, +5) to avoid any overlap of operational risk event announcements with other regulatory disclosures. On the other hand, the event window (-3, +3) would be a very short period for credit rating agencies to respond. We obtain CAR for each operational risk event at their first announcement date through Event Study by WRDS.

Following the literature on reputational risk (Gillet et al., 2010; Sturm, 2013a; Fiordelisi et al., 2013), we capture the reputational impact from operational risk loss events

(*RCAR*) using the loss-adjusted CAR, which is computed by adding CAR with operational loss (i.e., nominal operational loss amount divided by market capitalization of the company). Reputational loss arises when RCAR is greater or equal to zero.

Drawing from prior studies on credit ratings (Elbannan, 2009; Bissoondoyal-Bheenick and Treepongkaruna, 2011), we control for several firm-level accounting-based proxies. This include: firm size, proxied by the natural logarithm of total deflated assets (*Log Total Assets*); profitability, using the return on assets (*Return on Assets*); leverage, measured by the total debt to total assets (*leverage*); growth of the loss firm, proxied using the ratio of market value of equity to its book value (*Market to Book Ratio*); cash reserves of the firm, using the ratio of cash and short-term investments to total assets (*CSTI to Total Assets*) and capital adequacy, measured by the total equity to total assets (*Capital Adequacy*). In addition, we control for the market-based performance of the firm using the annual standard deviation of daily stock returns (*Stock Return Volatility*). Finally, in line with Barakat et al. (2019), we control for changes in business cycle using the natural logarithm of the GDP per capita (*Log GDP per Capita*).

### 2.5.3 Descriptive Statistics

Descriptive statistics for all the variables employed in this study are presented in Table 2.4. We find that, on average, the credit rating score of firms in our sample reduces by 0.02 on a quarterly basis. In terms of operational risk event variables, the mean number of events announced on a quarterly basis is 0.28 and the maximum loss disclosed is $41 million on average. Interestingly, we observe that the stock market reacts negatively by an average 0.25% drop in prices around operational risk event announcements. This result initially suggests that operational risk event announcements might inject some private information into the equity markets, thereby causing a drop in affected firms' stock prices.

### 2.5.4 Empirical Model

In order to test our research hypotheses, we estimate random effects regressions to account for auto correlations and unobserved effects inherent in the panel structure of our sample. A test for individual heterogeneity-regressors correlation has been carried out using the Hausman test and based on the results showing significant evidence of no correlation, the random effect panel data regressions have been used. We employ the following panel regression model:

$$\begin{aligned} Credit\ Rating\ Change_{i,t} &= \beta_0 + \beta_1\ Oprisk\ characteristics_{i,t-1} + \beta_2\ Log\ Total\ Assets_{i,t-1} \\ &+ \beta_3\ Return\ on\ Assets_{i,t-1} + \beta_4\ Leverage_{i,t-1} \\ &+ \beta_5\ Market\ to\ Book\ Ratio_{i,t-1} + \beta_6\ CSTI\ to\ Total\ Assets_{i,t-1} \\ &+ \beta_7\ Capital\ Adequacy_{i,t-1} + \beta_8\ Stock\ Return\ Volatility_{i,t-1} \\ &+ \beta_9\ Log\ GDP\ per\ Capita_{i,t-1} + \delta year_t + \lambda firm_t + e_i \qquad (2) \end{aligned}$$

Where $i$ refers to a specific bank and $t$ is the fiscal quarter. $year_t$ captures the year fixed-effects and $firm_t$ captures the firm fixed-effects. Operational risk announcement characteristics include the severity (i.e., loss amount, loss to market value, stock market reaction and reputational impact) and the frequency of operational risk events. We regress credit rating change in the current quarter on each of the operational risk characteristics as well as all relevant control variables in the previous quarter. By using lag of all explanatory and control variables (as denoted by the subscript $t-1$), we eliminate endogeneity concerns due to simultaneity of the cause and effect. Definitions of the dependent and independent variables are provided in Table 2.1.

## 2.6 Empirical Results

Models 1 to 10 show the results of the impact of operational risk events disclosed, i.e., external data, on credit rating change. This includes the frequency of operational risk event announcements (Model 1) and the severity, which is measured using operational loss amount disclosed, loss as a proportion of market value, stock market reactions and the reputational loss (Models 2 to 10). Models 11 and 12 report the results of the impact of operational risk events that have been detected by S&P prior their disclosure, i.e., internal data, on credit rating change.

### 2.6.1 Frequency and Severity of Operational Risk Event Announcements

Table 2.5 presents the results of our main multivariate regressions. We do not find evidence supporting the first sub-hypothesis, $H_{1a}$, that a rise in the frequency of operational risk event announcements causes S&P to revise affected firms' credit ratings in the following quarter. In contrast, our results reveal statistical evidence that the severity of operational risk event announcements causes a credit rating downgrade in the next quarter. As per Table 2.5, Model 4, maximum loss to market value leads to a 0.03% downgrade in the firms' credit ratings through its ratings score by S&P in the following quarter at 5% significance level. This suggests that the higher the operational loss as a proportion of the firm's market value, the more will S&P react to the disclosure by downgrading the affected firm's credit ratings. However, we observe that maximum loss disclosure alone has no economically significant impact on firms' credit ratings in the next quarter at 1% significance level. Whilst Cummins et al. (2006) argue that operational loss amount reveals poor managerial controls and cause downward revision of the loss firm's future cash flows and creditworthiness, our results reveal that only when the loss amount is measured relative to the firm's market value, credit ratings agencies react by downgrading the firm's credit ratings.

In terms of our third sub-hypothesis, $H_{1c}$, we document that drops in stock prices following operational risk event announcements cause a 0.01% downgrade in firms' ratings score by S&P in the following quarter at 5% significance level (Table 2.5, Model 6). This implies that operational risk event disclosures reveal bad signals about firms' performance and internal control weaknesses, as reflected in negative stock market reactions, thereby, causing S&P to revise the credit ratings of the affected firms downwards (Perry and de Fontnouvelle, 2005; Cummins et al., 2006; Gillet et al., 2010; Fiordelisi et al., 2013). This supports our sub-hypothesis $H_{1c}$.

Additionally, we observe that the reputational stock market impact of operational risk event announcements causes a 0.01% downgrade in firms' ratings score in the next quarter (Table 2.5, Model 6). This suggests that the greater the drops in the stock prices due to the reputational impact on firms following operational risk event disclosures, the more will S&P react by downgrading the affected firms' credit ratings (Perry and de Fontnouvelle, 2005; Cummins et al., 2006; Gillet et al., 2010; Fiordelisi et al., 2013;

Sturm, 2013a). However, our findings do not lend support to the premise that reputational losses cause credit rating deteriorations.

In terms of our second hypothesis, $H_2$, we find no statistical evidence that the number of operational risk events detected prior to their disclosure has a significant impact on S&P credit ratings deteriorations (Table 2.5, Models 11-12). As such, privileged access to private information, i.e., internal data, obtained by S&P from firms which have incurred operational risk events, are not reflected in credit ratings until they are disclosed to the public. This finding suggests that S&P tends to ignore this private information obtained from loss firms' management although they reveal important indicators about firms' internal control deficiencies (Chernobai et al., 2011). We argue that this might be due to close relationship established between the rating agency and firms' management, thereby introducing conflicts of interest. However, when the bad news is made public, S&P then acts rationally to meet stakeholders' expectations. With respect to our firm-level control variables, *Return on Assets* is positively associated with credit ratings change at 1% significance level under all models, which implies that an increase in firms' profitability will cause a credit rating upgrade.

Overall, our findings reveal that the disclosure of an operational risk event, in the form of its severity, which is measured by the operational loss as a proportion of firm market value and stock market reaction following the risky event, triggers S&P to downgrade the affected firm's credit rating in the following quarter. We argue that this is due to the fact that the operational risk event announcements signal bad news about firms' internal control weaknesses, poor corporate governance and ineffective risk management practices (Chernobai et al., 2011). Furthermore, the loss amount to market value provides more information to S&P about the severity of the operational risk events, hence, enabling them to make a more informative decision while revising firms' credit ratings. However, it is worth acknowledging that the coefficient of our explanatory variables on S&P credit ratings are not substantial and we argue that this is because operational risk is still not considered to be one of the primary drivers of credit ratings.

### 2.6.2 Robustness Test: Severe Operational Risk Events

We perform additional analyses to investigate the impact of severe operational risk events, defined as losses that exceed $10 million, on credit rating change. The result is presented in Table 2.6.

We find clear evidence that, consistent with our main multivariate results, the severity of operational risk event announcements with loss amounts exceeding $10 million matters to S&P. In addition, the impact of the operational loss to market value on S&P credit ratings is slightly more pronounced, as reflected by a 0.04% downgrade in affected firms' credit ratings through its ratings score in the next quarter at 5% significance level (Table 2.6, Model 4). This implies that the greater the operational loss to a firm's market value, the more negative is the impact on credit ratings in the following quarter. We also observe that drops in stock prices following severe operational risk event disclosures cause a 0.01% downgrade in affected firms' ratings score at 10% significance level (Table 2.6, Model 6), thus supporting our third hypothesis, $H_3$. Moreover, in line with our main results, we find that the reputational impact of stock market reactions triggers S&P to downgrade credit ratings of firms which have suffered operational risk events exceeding $10 million.

Interestingly, we find some evidence that internal data, in the form of operational risk events that were known by S&P and were then disclosed to the public, is positively associated with a credit rating change. An increase in the number of operational risk events detected prior announcement causes S&P to revise the affected firms' ratings score upward by 0.07% at 10% significance level. This may suggest that when S&P has access to private data, obtained by firms suffering from operational risk events, through meetings with banks' managers, they tend to issue optimistically biased ratings. We argue that this may be due to their relationship with firms, which consequently raise questions about the integrity of their decision to revise affected firms' credit ratings upwards following operational risk event announcements.

### 2.6.3 Robustness Test: Pre- and Post-Global Financial Crisis Subsamples

As another robustness check, we estimate Equation (2) for the pre-Global Financial Crisis and post-Global Financial Crisis periods to investigate if S&P responds differently to operational risk event announcements before and after the crisis period. The results for the pre- and post-Global Financial Crisis are presented in Tables 2.7 and 2.8, respectively.

We document that in the pre-Global Financial Crisis period, S&P issued biased credit ratings. This is evidenced by a 0.08% upgrade in affected firms' credit ratings through its ratings score at 1% significance level despite the disclosure of maximum operational loss as a proportion of firms' market values (Table 2.7, Model 4). Clearly, the severity of operational risk event announcements, which reveals serious internal control weaknesses within firms (Chernobai et al., 2011), did not trigger S&P to revise credit ratings of firms suffering from these risky events prior to the crisis period. Interestingly, our results show that post-crisis period, an increase in operational loss to firms' market values causes the S&P to downgrade the affected firms' ratings score by 0.04% at 1% significance level (Table 2.8, Model 4). This suggests that the Global Financial Crisis disciplines ratings agencies like S&P to provide more accurate and informative credit ratings. However, the stock market reactions to operational risk event announcements on credit ratings were indifferent pre- and post-Global Financial Crisis.

## 2.7 Conclusion

Credit ratings are built on a keen analysis of a firm's creditworthiness, including its risk management capabilities, hence, demonstrating good quality operational risk management practices contributes to more favourable credit ratings. However, operational risk event announcements raise concerns about the risk controls of the firm and, thus, give rise to doubts about its overall reputation and future creditworthiness. This study investigates when operational risk events trigger a credit rating downgrade, i.e., when the frequency or severity of the risk events are disclosed or, rather, prior to the disclosure when internal data are shared with rating agencies by firms.

Our key findings show that the maximum operational loss amount disclosed as a proportion of a firm's market value and more adverse stock market reactions to operational risk event announcements during a particular fiscal quarter have a negative impact on credit ratings, provided by S&P, in the following quarter. However, our results do not lend support to the premise that internal data causes credit rating deteriorations. Interestingly, we find that severe operational risk events with loss amounts exceeding $10 million cause a slightly greater downgrade in credit ratings following disclosed maximum operational loss to market value. In addition, the effect of the Global Financial Crisis causes S&P to become more accurate in their credit assessment following operational risk event announcements.

Overall, our paper contributes to the literature on credit ratings and operational risk by providing empirical evidence that the severity of operational risk events, in the form of maximum loss to a firm's market value and the stock market reactions, convey vital information that rating agencies like S&P take into consideration when determining the creditworthiness of banks. The findings of this study help firms' management better understand the extent to which their current credit rating level is impacted by the announcement of unanticipated bad news in the form of the operational risk events. As such, this encourages firms to effectively manage operational risk to avoid incurring any operational risk losses due to the repercussions on the firms' credit rating. In addition, the results enable the loss firms' management to effectively plan further post-announcement actions such as organising press releases to help restore the reputation of the affected firms and reassure the stakeholders especially in terms of their future creditworthiness so that they do not face a credit rating downgrade.

The main limitation of this study is that our sample is focused only on U.S. banks due to data availability constraint, hence the findings cannot be generalised. More adjustments might be required for non-banking or even non-financial institutions due to different institutional, legal, and regulatory settings in place. However, future research could be done to examine whether operational risk event announcements by other financial and non-financial firms and the consequent reputational impact cause the rating agencies to react by downgrading the credit ratings of the affected firms. Moreover, future studies could investigate the impact of operational risk events on the outlooks provided by credit rating agencies. Additionally, the reaction of other rating agencies such as Moody's and Fitch following operational risk event announcements might be explored, provided necessary data is available, to determine any similarity or difference in how they treat such risky events in their credit ratings decisions.

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# APPENDIX A

## Table 2.1 Description of Variables

This table provides the definitions and the sources of the variables used in this study.

| Variable | Definition | Data Source |
|---|---|---|
| **Dependent Variable** | | |
| *Credit Rating Change* | Difference between the current quarter rating and the last quarter rating. A positive change implies an upgrade; a negative change implies a downgrade and no change means stable credit ratings. | Bloomberg |
| **Event-Level Variables** | | |
| *Oprisk Frequency* | Number of operational risk events whose first announcement dates fell in the quarter prior to the current rating quarter. | Algo FIRST, LexisNexis |
| *Maximum Loss* | Maximum deflated loss amount of all operational risk events whose first announcement dates fell one quarter prior to the current rating quarter. | Algo FIRST, LexisNexis |
| *Average Loss* | Average deflated loss amount of all operational risk events whose first announcement dates fell one quarter prior to the current rating quarter. | Algo FIRST, LexisNexis |
| *Maximum Loss to MVE* | Maximum loss to market value of all operational risk events whose first announcement dates fell one quarter prior to the current rating quarter. Measurement units: percent | Algo FIRST, LexisNexis |
| *Average Loss to MVE* | Average loss to market value of all operational risk events whose first announcement dates fell one quarter prior to the current rating quarter. Measurement units: percent | Algo FIRST, LexisNexis |
| *Minimum CAR* | Minimum cumulative abnormal returns (CAR) of all operational risk events whose first announcement dates fell one quarter prior to the current rating quarter. Measurement units: percent | Algo FIRST, LexisNexis, WRDS |
| *Average CAR* | Average cumulative abnormal returns of all operational risk events whose first announcement dates fell one quarter prior to the current rating quarter. Measurement units: percent | Algo FIRST, LexisNexis, WRDS |
| *Minimum RCAR* | Minimum adjusted cumulative abnormal returns of all operational risk events whose first announcement dates fell one quarter prior to the current rating quarter. Measurement units: percent | Algo FIRST, LexisNexis, WRDS |
| *Average RCAR* | Average adjusted cumulative abnormal returns of all operational risk events whose first announcement dates fell one quarter prior to the current rating quarter. Measurement units: percent | Algo FIRST, LexisNexis, WRDS |
| *Reputational Loss* | 1 if the adjusted cumulative abnormal returns in the quarter prior to the current rating quarter is negative; 0 otherwise. | Algo FIRST, LexisNexis, WRDS |

| | | |
|---|---|---|
| *Oprisk Detected Not Announced* | Number of operational risk events that have been detected one quarter prior to the current rating but whose first announcement dates fell in the current rating quarter. | Algo FIRST, LexisNexis |
| *Oprisk Detected Announced* | Number of operational risk events that have been detected and whose first announcement dates fell one quarter prior to the current rating. | Algo FIRST, LexisNexis |
| **Firm-Level Control Variables** | | |
| *Log Total Assets* | Natural logarithm of the total deflated assets of the quarter prior to the current rating quarter. Measurement units: *ln* (USD) | CRSP, Compustat |
| *Return on Assets* | Income before extraordinary items scaled by total assets of the quarter prior to the current rating quarter. Measurement units: percent | CRSP, Compustat |
| *Leverage* | Sum of short-term debt and long-term debt scaled by total assets of the quarter prior to the current rating quarter. Measurement units: percent | CRSP, Compustat |
| *Market to Book Ratio* | Ratio of market value of equity to book equity of the quarter prior to the current rating quarter. Measurement units: percent | CRSP, Compustat |
| *CSTI to Total Assets* | Ratio of cash and short-term investment to total assets of the quarter prior to the current rating quarter. Measurement units: percent | CRSP, Compustat |
| *Capital Adequacy* | Ratio of total equity to total assets of the quarter prior to the current rating quarter. Measurement units: percent | CRSP, Compustat |
| *Stock Return Volatility* | Standard deviation of the daily equal weighted returns (including distributions) of the quarter prior to the current rating quarter. Measurement units: percent | CRSP |
| **Macro-economic Variable** | | |
| *Log GDP per Capita* | Natural logarithm of the quarterly Real Gross Domestic Product (GDP) per capita of the quarter prior to the current rating quarter. Measurement units: *ln* (USD) | FRED Economic Data |

**Table 2.2 Sample Selection Procedure**

This table details the screening procedure of data on operational risk event announcements from U.S. banks for the period 1990-2014.

| Data Screening Description | Number of Operational Event Announcements |
|---|---|
| 1. Algo FIRST Database | 1,556 |
| – Events with no event description information | (62) |
| – Events whose duration could not be determined | (65) |
| – Events that occurred in listed subsidiaries are non-bank firms (two-digit SIC other than 60, 61, 62 and 67) | (1) |
| – Events from firms that are not publicly listed | (53) |
| – Events from banks whose credit ratings are not available in Bloomberg | (47) |
| 2. Final sample | 1,328 |

**Table 2.3 Credit Rating Classification**

This table reports the transformation of credit rating letters assigned by S&P into numeric values.

| S&P Credit Rating | Rating Score |
|---|---|
| AAA | 23 |
| AA+ | 22 |
| AA | 21 |
| AA- | 20 |
| A+ | 19 |
| A | 18 |
| A- | 17 |
| BBB+ | 16 |
| BBB | 15 |
| BBB- | 14 |
| BB+ | 13 |
| BB | 12 |
| BB- | 11 |
| B+ | 10 |
| B | 9 |
| B- | 8 |
| CCC+ | 7 |
| CCC | 6 |
| CCC- | 5 |
| CC | 4 |
| C | 3 |
| SD | 2 |
| D | 1 |

# Table 2.4 Sample Descriptive Statistics

This table reports the descriptive statistics for our variables. All variable definitions are as reported in Table 2.1.

| Variables | N | Min | 1p | 5p | 25p | 50p | Mean | SD | 75p | 95p | 99p | Max |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Dependent Variable | | | | | | | | | | | | |
| *Credit Rating Change* | 3,805 | -14 | -1 | 0 | 0 | 0 | -0.02 | 0.48 | 0 | 0 | 1 | 10 |
| Event-Level Variables | | | | | | | | | | | | |
| *Oprisk Frequency* | 3,805 | 0 | 0 | 0 | 0 | 0 | 0.28 | 0.82 | 0 | 2 | 4 | 9 |
| *Maximum Loss (in millions)* | 3,805 | 0 | 0 | 0 | 0 | 0 | 41 | 527 | 0 | 24.7 | 654 | 16,400 |
| *Average Loss (in millions)* | 3,805 | 0 | 0 | 0 | 0 | 0 | 0.57 | 5.35 | 0 | 0.77 | 12.8 | 151 |
| *Maximum Loss to MVE* | 3,805 | 0 | 0 | 0 | 0 | 0 | 0.07 | 0.63 | 0 | 0.09 | 1.87 | 22.65 |
| *Average Loss to MVE* | 3,805 | 0 | 0 | 0 | 0 | 0 | 0.01 | 0.09 | 0 | 0.00 | 0.09 | 4.81 |
| *Minimum CAR* | 3,805 | -27.68 | -9.79 | -3.11 | 0 | 0 | -0.25 | 2.39 | 0 | 0.46 | 5.53 | 22.43 |
| *Average CAR* | 3,805 | -24.79 | -7.90 | -1.90 | 0 | 0 | -0.06 | 2.17 | 0 | 1.27 | 6.02 | 43.17 |
| *Minimum RCAR* | 3,805 | -27.68 | -9.79 | -2.94 | 0 | 0 | -0.22 | 2.38 | 0 | 0.59 | 6.13 | 22.43 |
| *Average RCAR* | 3,805 | -24.79 | -6.82 | -1.72 | 0 | 0 | -0.02 | 2.17 | 0 | 1.45 | 6.59 | 43.22 |
| *Reputational Loss* | 3,805 | 0 | 0 | 0 | 0 | 0 | 0.10 | 0.30 | 0 | 1 | 1 | 1 |
| *Oprisk Detected Not Announced* | 3,805 | 0 | 0 | 0 | 0 | 0 | 0.26 | 0.90 | 0 | 2 | 4 | 17 |
| *Oprisk Detected Announced* | 3,805 | 0 | 0 | 0 | 0 | 0 | 0.06 | 0.30 | 0 | 1 | 1 | 5 |
| Firm-Level Variables | | | | | | | | | | | | |
| *Log Total Assets* | 3,805 | 20.63 | 21.53 | 22.19 | 23.20 | 24.13 | 24.38 | 1.57 | 25.44 | 27.46 | 28.34 | 28.56 |
| *Return on Assets* | 3,805 | -4.71 | -0.70 | -0.05 | 0.21 | 0.29 | 0.28 | 0.29 | 0.37 | 0.63 | 1.01 | 2.71 |
| *Leverage* | 3,805 | 0.05 | 4.09 | 6.08 | 12.83 | 19.19 | 22.33 | 15.01 | 25.97 | 60.96 | 71.66 | 82.22 |
| *Market to Book Ratio* | 3,805 | 9.38 | 40.58 | 70.42 | 126.88 | 178.87 | 200.72 | 118.09 | 239.56 | 412.67 | 633.56 | 1453.89 |
| *CSTI to Total Assets* | 3,805 | 0.06 | 1.18 | 1.91 | 3.59 | 6.34 | 10.51 | 10.14 | 14.27 | 31.31 | 48.10 | 64.50 |
| *Capital Adequacy* | 3,805 | 2.39 | 3.13 | 4.64 | 7.29 | 8.57 | 8.96 | 2.91 | 10.35 | 13.82 | 18.90 | 27.50 |
| *Stock Return Volatility* | 3,805 | 0.25 | 0.28 | 0.34 | 0.53 | 0.69 | 0.83 | 0.5 | 0.97 | 1.78 | 3.77 | 3.77 |
| Macroeconomic-Level Variable | | | | | | | | | | | | |
| *Log GDP per Capita* | 3,805 | 10.47 | 10.47 | 10.49 | 10.63 | 10.74 | 10.70 | 0.11 | 10.79 | 10.81 | 10.83 | 10.83 |

# Table 2.5 Estimation Results for Credit Rating Change

This table reports the random-effects panel data regression results for *Credit Rating Change* on a quarterly basis following operational risk event announcements from U.S. publicly listed banks for the period 1990 to 2014. *t-statistics* are reported in parentheses. *, ** and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively (two-tailed). All variable definitions are reported in Table 2.1.

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Event-Level Variables | | | | | | | | | | | | |
| *Oprisk Frequency* | -0.0100 | | | | | | | | | | | |
| | (-0.79) | | | | | | | | | | | |
| *Maximum Loss* | | -0.0000** | | | | | | | | | | |
| | | (-1.97) | | | | | | | | | | |
| *Average Loss* | | | -0.0000*** | | | | | | | | | |
| | | | (-5.05) | | | | | | | | | |
| *Maximum Loss to MVE* | | | | -0.0295** | | | | | | | | |
| | | | | (-2.31) | | | | | | | | |
| *Average Loss to MVE* | | | | | 0.0491 | | | | | | | |
| | | | | | (0.57) | | | | | | | |
| *Minimum CAR* | | | | | | 0.0077** | | | | | | |
| | | | | | | (2.31) | | | | | | |
| *Average CAR* | | | | | | | 0.0037 | | | | | |
| | | | | | | | (1.05) | | | | | |
| *Minimum RCAR* | | | | | | | | 0.0079** | | | | |
| | | | | | | | | (2.36) | | | | |
| *Average RCAR* | | | | | | | | | 0.0032 | | | |
| | | | | | | | | | (0.90) | | | |
| *Reputational Loss* | | | | | | | | | | -0.0172 | | |
| | | | | | | | | | | (-0.57) | | |
| *Oprisk Detected Not Announced* | | | | | | | | | | | 0.0096 | |
| | | | | | | | | | | | (0.91) | |
| *Oprisk Detected Announced* | | | | | | | | | | | | 0.0113 |
| | | | | | | | | | | | | (0.40) |
| Firm-Level Variables | | | | | | | | | | | | |
| *Log Total Assets* | -0.0150 | -0.0157 | -0.0114 | -0.0171 | -0.0181 | -0.0158 | -0.0185 | -0.0156 | -0.0185 | -0.0171 | -0.0215 | -0.0194 |
| | (-0.59) | (-0.62) | (-0.45) | (-0.68) | (-0.72) | (-0.63) | (-0.74) | (-0.62) | (-0.74) | (-0.68) | (-0.85) | (-0.77) |
| *Return on Assets* | 0.2891*** | 0.2896*** | 0.2881*** | 0.2887*** | 0.2902*** | 0.2910*** | 0.2898*** | 0.2913*** | 0.2898*** | 0.2892*** | 0.2899*** | 0.2898*** |
| | (8.49) | (8.51) | (8.49) | (8.48) | (8.52) | (8.55) | (8.51) | (8.56) | (8.51) | (8.49) | (8.51) | (8.51) |
| *Leverage* | 0.0000 | 0.0001 | 0.0004 | 0.0002 | -0.0000 | 0.0001 | -0.0000 | 0.0001 | -0.0000 | -0.0000 | -0.0001 | 0.0000 |
| | (0.02) | (0.09) | (0.26) | (0.12) | (-0.02) | (0.04) | (-0.00) | (0.04) | (-0.01) | (-0.01) | (-0.05) | (0.00) |
| *Market to Book Ratio* | 0.0001 | 0.0001 | 0.0001 | 0.0001 | 0.0001 | 0.0001 | 0.0001 | 0.0001 | 0.0001 | 0.0001 | 0.0001 | 0.0001 |
| | (0.91) | (0.92) | (0.97) | (0.88) | (0.87) | (0.83) | (0.84) | (0.84) | (0.85) | (0.87) | (0.80) | (0.85) |
| *CSTI to Total Assets* | 0.0019 | 0.0019 | 0.0019 | 0.0019 | 0.0019 | 0.0018 | 0.0018 | 0.0018 | 0.0018 | 0.0019 | 0.0019 | 0.0018 |
| | (1.17) | (1.17) | (1.16) | (1.16) | (1.15) | (1.12) | (1.11) | (1.13) | (1.11) | (1.14) | (1.15) | (1.11) |
| *Capital Adequacy* | 0.0062 | 0.0062 | 0.0062 | 0.0060 | 0.0061 | 0.0057 | 0.0059 | 0.0058 | 0.0059 | 0.0061 | 0.0060 | 0.0060 |
| | (1.06) | (1.05) | (1.07) | (1.03) | (1.04) | (0.98) | (1.01) | (0.99) | (1.01) | (1.04) | (1.03) | (1.02) |
| *Stock Return Volatility* | -0.0206 | -0.0172 | -0.0119 | -0.0153 | -0.0210 | -0.0223 | -0.0220 | -0.0228 | -0.0221 | -0.0212 | -0.0227 | -0.0210 |
| | (-0.81) | (-0.68) | (-0.47) | (-0.60) | (-0.83) | (-0.88) | (-0.87) | (-0.90) | (-0.87) | (-0.84) | (-0.90) | (-0.83) |
| *Log GDP per Capita* | -0.9344 | -0.9194 | -0.8528 | -0.9045 | -0.9688 | -0.9264 | -0.9475 | -0.9313 | -0.9511 | -0.9414 | -0.9093 | -0.9678 |
| | (-0.87) | (-0.86) | (-0.80) | (-0.85) | (-0.91) | (-0.87) | (-0.89) | (-0.87) | (-0.89) | (-0.88) | (-0.85) | (-0.91) |
| Constant | 9.7790 | 9.6317 | 8.8278 | 9.5058 | 10.2090 | 9.7157 | 9.9979 | 9.7634 | 10.0359 | 9.9007 | 9.6629 | 10.2268 |
| | (0.88) | (0.86) | (0.79) | (0.85) | (0.91) | (0.87) | (0.90) | (0.87) | (0.90) | (0.89) | (0.86) | (0.92) |
| Firm F.E | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Year F.E | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Number of Observations | 3,805 | 3,805 | 3,805 | 3,805 | 3,805 | 3,805 | 3,805 | 3,805 | 3,805 | 3,805 | 3,805 | 3,805 |
| Within $R^2$ | 0.0512 | 0.0520 | 0.0575 | 0.0524 | 0.0511 | 0.0524 | 0.0513 | 0.0524 | 0.0512 | 0.0511 | 0.0512 | 0.0510 |

# Table 2.6 Robustness Test: Estimation Results for Severe Operational Losses exceeding $10 Million

This table reports the random-effects panel data regression results for *Credit Rating Change* on a quarterly basis following severe operational risk event announcements exceeding $10 million from U.S. publicly listed banks for the period 1990 to 2014. *t-statistics* are reported in parentheses. *, ** and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively (two-tailed). All variable definitions are reported in Table 2.1.

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Event-Level Variables | | | | | | | | | | | | |
| *Oprisk Frequency* | -0.0228 | | | | | | | | | | | |
| | (-0.97) | | | | | | | | | | | |
| *Maximum Loss* | | -0.0000 | | | | | | | | | | |
| | | (-1.55) | | | | | | | | | | |
| *Average Loss* | | | -0.0000*** | | | | | | | | | |
| | | | (-5.25) | | | | | | | | | |
| *Maximum Loss to MVE* | | | | -0.0372** | | | | | | | | |
| | | | | (-2.51) | | | | | | | | |
| *Average Loss to MVE* | | | | | -0.7016 | | | | | | | |
| | | | | | (-1.45) | | | | | | | |
| *Minimum CAR* | | | | | | 0.0110* | | | | | | |
| | | | | | | (1.91) | | | | | | |
| *Average CAR* | | | | | | | 0.0049 | | | | | |
| | | | | | | | (0.75) | | | | | |
| *Minimum RCAR* | | | | | | | | 0.0105* | | | | |
| | | | | | | | | (1.84) | | | | |
| *Average RCAR* | | | | | | | | | 0.0024 | | | |
| | | | | | | | | | (0.36) | | | |
| *Reputational Loss* | | | | | | | | | | -0.0209 | | |
| | | | | | | | | | | (-0.28) | | |
| *Oprisk Detected Not Announced* | | | | | | | | | | | 0.0245 | |
| | | | | | | | | | | | (1.45) | |
| *Oprisk Detected Announced* | | | | | | | | | | | | 0.0712* |
| | | | | | | | | | | | | (1.74) |
| Firm-Level Variables | | | | | | | | | | | | |
| *Log Total Assets* | -0.0074 | -0.0223 | 0.0117 | -0.0315 | -0.0359 | -0.0323 | -0.0319 | -0.0324 | -0.0309 | -0.0332 | -0.0290 | -0.0183 |
| | (-0.05) | (-0.14) | (0.08) | (-0.20) | (-0.23) | (-0.20) | (-0.20) | (-0.20) | (-0.19) | (-0.21) | (-0.18) | (-0.12) |
| *Return on Assets* | 0.5831*** | 0.5909*** | 0.5616*** | 0.5935*** | 0.5433*** | 0.5409*** | 0.5686*** | 0.5459*** | 0.5718*** | 0.5743*** | 0.6196*** | 0.5697*** |
| | (3.01) | (3.06) | (3.09) | (3.11) | (2.80) | (2.80) | (2.94) | (2.83) | (2.95) | (2.96) | (3.17) | (2.96) |
| *Leverage* | 0.0097 | 0.0102 | 0.0094 | 0.0102 | 0.0096 | 0.0097 | 0.0102 | 0.0098 | 0.0102 | 0.0100 | 0.0087 | 0.0110 |
| | (1.41) | (1.49) | (1.46) | (1.51) | (1.40) | (1.42) | (1.48) | (1.43) | (1.48) | (1.45) | (1.25) | (1.60) |
| *Market to Book Ratio* | -0.0010 | -0.0010 | -0.0013 | -0.0012 | -0.0013 | -0.0012 | -0.0011 | -0.0012 | -0.0010 | -0.0010 | -0.0012 | -0.0011 |
| | (-0.85) | (-0.88) | (-1.25) | (-1.09) | (-1.11) | (-1.09) | (-0.96) | (-1.04) | (-0.90) | (-0.88) | (-1.10) | (-0.95) |
| *CSTI to Total Assets* | 0.0032 | 0.0016 | -0.0024 | 0.0010 | 0.0008 | 0.0026 | 0.0025 | 0.0028 | 0.0027 | 0.0028 | 0.0049 | 0.0017 |
| | (0.36) | (0.17) | (-0.29) | (0.11) | (0.09) | (0.29) | (0.28) | (0.31) | (0.30) | (0.32) | (0.54) | (0.19) |
| *Capital Adequacy* | 0.0054 | 0.0046 | 0.0010 | 0.0050 | 0.0072 | 0.0005 | 0.0057 | 0.0011 | 0.0066 | 0.0054 | 0.0101 | 0.0122 |
| | (0.14) | (0.12) | (0.03) | (0.13) | (0.18) | (0.01) | (0.15) | (0.03) | (0.17) | (0.14) | (0.26) | (0.31) |
| *Stock Return Volatility* | -0.1374* | -0.1133 | -0.0568 | -0.0873 | -0.1263* | -0.1521** | -0.1487* | -0.1543** | -0.1457* | -0.1429* | -0.1767** | -0.1429* |
| | (-1.82) | (-1.47) | (-0.78) | (-1.13) | (-1.66) | (-2.02) | (-1.95) | (-2.05) | (-1.90) | (-1.88) | (-2.23) | (-1.90) |
| *Log GDP per Capita* | 6.2635 | 6.4044 | 7.6162* | 6.5886 | 5.9245 | 5.7197 | 5.8701 | 5.6830 | 5.8438 | 5.9711 | 6.5750 | 5.6620 |
| | (1.36) | (1.39) | (1.76) | (1.45) | (1.29) | (1.25) | (1.27) | (1.24) | (1.27) | (1.29) | (1.42) | (1.24) |
| Constant | -65.8109 | -66.9890 | -80.5354* | -68.7153 | -61.4579 | -59.3807 | -61.0587 | -59.0130 | -60.8471 | -62.1117 | -68.5057 | -59.3795 |
| | (-1.36) | (-1.39) | (-1.77) | (-1.44) | (-1.28) | (-1.24) | (-1.27) | (-1.23) | (-1.26) | (-1.28) | (-1.42) | (-1.24) |
| Firm F.E | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Year F.E | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Number of Observations | 272 | 272 | 272 | 272 | 272 | 272 | 272 | 272 | 272 | 272 | 272 | 272 |
| Within $R^2$ | 0.2942 | 0.2992 | 0.3763 | 0.3125 | 0.2982 | 0.3035 | 0.2928 | 0.3026 | 0.2913 | 0.2911 | 0.2982 | 0.3014 |

## Table 2.7 Robustness Test: Estimation Results for the Subsample of Announcements Prior to the Global Financial Crisis

This table reports the random-effects panel data regression results for *Credit Rating Change* on a quarterly basis following operational risk event announcements prior the Global Financial Crisis from U.S. publicly listed banks for the period 1990 to 2014. *t-statistics* are reported in parentheses. *, ** and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively (two-tailed). All variable definitions are reported in Table 2.1.

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Event-Level Variables | | | | | | | | | | | | |
| *Oprisk Frequency* | -0.0054 | | | | | | | | | | | |
| | (-0.37) | | | | | | | | | | | |
| *Maximum Loss* | | 0.0000*** | | | | | | | | | | |
| | | (2.78) | | | | | | | | | | |
| *Average Loss* | | | 0.0000*** | | | | | | | | | |
| | | | (2.84) | | | | | | | | | |
| *Maximum Loss to MVE* | | | | 0.0784*** | | | | | | | | |
| | | | | (2.85) | | | | | | | | |
| *Average Loss to MVE* | | | | | 0.0879 | | | | | | | |
| | | | | | (1.31) | | | | | | | |
| *Minimum CAR* | | | | | | 0.0047 | | | | | | |
| | | | | | | (1.00) | | | | | | |
| *Average CAR* | | | | | | | 0.0056 | | | | | |
| | | | | | | | (1.16) | | | | | |
| *Minimum RCAR* | | | | | | | | 0.0059 | | | | |
| | | | | | | | | (1.26) | | | | |
| *Average RCAR* | | | | | | | | | 0.0074 | | | |
| | | | | | | | | | (1.54) | | | |
| *Reputational Loss* | | | | | | | | | | -0.0440 | | |
| | | | | | | | | | | (-1.46) | | |
| *Oprisk Detected Not Announced* | | | | | | | | | | | -0.0044 | |
| | | | | | | | | | | | (-0.34) | |
| *Oprisk Detected Announced* | | | | | | | | | | | | -0.0578* |
| | | | | | | | | | | | | (-1.92) |
| Firm-Level Variables | | | | | | | | | | | | |
| *Log Total Assets* | 0.0503** | 0.0482** | 0.0490** | 0.0504** | 0.0507** | 0.0497** | 0.0495** | 0.0499** | 0.0495** | 0.0515** | 0.0501** | 0.0515** |
| | (2.20) | (2.12) | (2.16) | (2.22) | (2.23) | (2.19) | (2.17) | (2.19) | (2.18) | (2.26) | (2.19) | (2.26) |
| *Return on Assets* | 0.3345*** | 0.3380*** | 0.3422*** | 0.3432*** | 0.3398*** | 0.3354*** | 0.3360*** | 0.3361*** | 0.3371*** | 0.3338*** | 0.3348*** | 0.3322*** |
| | (7.12) | (7.21) | (7.29) | (7.31) | (7.22) | (7.15) | (7.16) | (7.16) | (7.18) | (7.11) | (7.13) | (7.08) |
| *Leverage* | -0.0026** | -0.0025** | -0.0025** | -0.0025** | -0.0026** | -0.0025** | -0.0025** | -0.0025** | -0.0025** | -0.0026** | -0.0025** | -0.0026** |
| | (-2.07) | (-1.99) | (-2.03) | (-2.06) | (-2.08) | (-2.06) | (-2.05) | (-2.07) | (-2.05) | (-2.13) | (-2.05) | (-2.13) |
| *Market to Book Ratio* | 0.0001 | 0.0001 | 0.0001 | 0.0001 | 0.0001 | 0.0001 | 0.0001 | 0.0001 | 0.0001 | 0.0001 | 0.0001 | 0.0001 |
| | (0.74) | (0.70) | (0.70) | (0.74) | (0.73) | (0.73) | (0.73) | (0.73) | (0.73) | (0.73) | (0.74) | (0.81) |
| *CSTI to Total Assets* | -0.0005 | -0.0005 | -0.0005 | -0.0004 | -0.0004 | -0.0006 | -0.0006 | -0.0006 | -0.0006 | -0.0006 | -0.0005 | -0.0004 |
| | (-0.34) | (-0.33) | (-0.30) | (-0.23) | (-0.27) | (-0.38) | (-0.38) | (-0.38) | (-0.39) | (-0.35) | (-0.33) | (-0.27) |
| *Capital Adequacy* | 0.0098* | 0.0096* | 0.0096* | 0.0099* | 0.0100* | 0.0098* | 0.0098* | 0.0098* | 0.0098* | 0.0099* | 0.0098* | 0.0103* |
| | (1.72) | (1.68) | (1.69) | (1.73) | (1.75) | (1.72) | (1.72) | (1.71) | (1.72) | (1.73) | (1.72) | (1.80) |
| *Stock Return Volatility* | -0.0219 | -0.0192 | -0.0192 | -0.0202 | -0.0213 | -0.0212 | -0.0212 | -0.0211 | -0.0210 | -0.0218 | -0.0216 | -0.0219 |
| | (-0.91) | (-0.80) | (-0.80) | (-0.84) | (-0.88) | (-0.88) | (-0.88) | (-0.87) | (-0.87) | (-0.90) | (-0.90) | (-0.91) |
| *Log GDP per Capita* | -0.2208 | -0.2225 | -0.2360 | -0.2368 | -0.2348 | -0.2237 | -0.2248 | -0.2248 | -0.2263 | -0.2147 | -0.2220 | -0.2216 |
| | (-1.23) | (-1.24) | (-1.32) | (-1.32) | (-1.31) | (-1.25) | (-1.25) | (-1.25) | (-1.26) | (-1.20) | (-1.24) | (-1.23) |
| Constant | 1.1873 | 1.2507 | 1.3755 | 1.3526 | 1.3258 | 1.2316 | 1.2480 | 1.2394 | 1.2630 | 1.0978 | 1.2050 | 1.1674 |
| | (0.81) | (0.86) | (0.94) | (0.93) | (0.91) | (0.84) | (0.86) | (0.85) | (0.87) | (0.75) | (0.82) | (0.80) |
| Firm F.E | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Number of Observations | 2,549 | 2,549 | 2,549 | 2,549 | 2,549 | 2,549 | 2,549 | 2,549 | 2,549 | 2,549 | 2,549 | 2,549 |
| Within $R^2$ | 0.0524 | 0.0557 | 0.0558 | 0.0556 | 0.0531 | 0.0528 | 0.0529 | 0.0530 | 0.0533 | 0.0531 | 0.0524 | 0.0535 |

## Table 2.8 Robustness Test: Estimation Results for the Subsample of Announcements During and After the Global Financial Crisis

This table reports the random-effects panel data regression results for *Credit Rating Change* on a quarterly basis following operational risk event announcements during and post Global Financial Crisis from U.S. publicly listed banks for the period 1990 to 2014. *t-statistics* are reported in parentheses. *, ** and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively (two-tailed). All variable definitions are reported in Table 2.1.

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Event-Level Variables | | | | | | | | | | | | |
| *Oprisk Frequency* | -0.0131 | | | | | | | | | | | |
| | (-0.51) | | | | | | | | | | | |
| *Maximum Loss* | | -0.0000 | | | | | | | | | | |
| | | (-1.57) | | | | | | | | | | |
| *Average Loss* | | | -0.0000*** | | | | | | | | | |
| | | | (-3.81) | | | | | | | | | |
| *Maximum Loss to MVE* | | | | -0.0359* | | | | | | | | |
| | | | | (-1.86) | | | | | | | | |
| *Average Loss to MVE* | | | | | -0.0470 | | | | | | | |
| | | | | | (-0.18) | | | | | | | |
| *Minimum CAR* | | | | | | 0.0080 | | | | | | |
| | | | | | | (1.45) | | | | | | |
| *Average CAR* | | | | | | | 0.0021 | | | | | |
| | | | | | | | (0.36) | | | | | |
| *Minimum RCAR* | | | | | | | | 0.0081 | | | | |
| | | | | | | | | (1.45) | | | | |
| *Average RCAR* | | | | | | | | | 0.0010 | | | |
| | | | | | | | | | (0.17) | | | |
| *Reputational Loss* | | | | | | | | | | -0.0236 | | |
| | | | | | | | | | | (-0.37) | | |
| *Oprisk Detected Not Announced* | | | | | | | | | | | 0.0174 | |
| | | | | | | | | | | | (0.91) | |
| *Oprisk Detected Announced* | | | | | | | | | | | | 0.0534 |
| | | | | | | | | | | | | (1.02) |
| Firm-Level Variables | | | | | | | | | | | | |
| *Log Total Assets* | -0.1416 | -0.1476 | -0.1421 | -0.1504 | -0.1494 | -0.1437 | -0.1488 | -0.1436 | -0.1488 | -0.1474 | -0.1521 | -0.1529 |
| | (-1.20) | (-1.27) | (-1.23) | (-1.29) | (-1.28) | (-1.23) | (-1.28) | (-1.23) | (-1.28) | (-1.26) | (-1.30) | (-1.31) |
| *Return on Assets* | 0.2345*** | 0.2364*** | 0.2388*** | 0.2378*** | 0.2338*** | 0.2370*** | 0.2342*** | 0.2368*** | 0.2340*** | 0.2338*** | 0.2372*** | 0.2361*** |
| | (3.84) | (3.88) | (3.94) | (3.90) | (3.83) | (3.88) | (3.84) | (3.88) | (3.83) | (3.83) | (3.88) | (3.87) |
| *Leverage* | -0.0013 | -0.0015 | -0.0014 | -0.0014 | -0.0013 | -0.0010 | -0.0012 | -0.0010 | -0.0012 | -0.0013 | -0.0014 | -0.0013 |
| | (-0.26) | (-0.30) | (-0.29) | (-0.28) | (-0.25) | (-0.21) | (-0.24) | (-0.21) | (-0.25) | (-0.26) | (-0.29) | (-0.27) |
| *Market to Book Ratio* | 0.0014** | 0.0014** | 0.0012** | 0.0013** | 0.0014** | 0.0014** | 0.0014** | 0.0014** | 0.0014** | 0.0014** | 0.0014** | 0.0014** |
| | (2.32) | (2.24) | (2.03) | (2.16) | (2.32) | (2.23) | (2.31) | (2.24) | (2.32) | (2.33) | (2.28) | (2.35) |
| *CSTI to Total Assets* | 0.0192*** | 0.0191*** | 0.0191*** | 0.0192*** | 0.0191*** | 0.0187*** | 0.0190*** | 0.0187*** | 0.0190*** | 0.0191*** | 0.0196*** | 0.0188*** |
| | (3.42) | (3.40) | (3.41) | (3.41) | (3.39) | (3.33) | (3.37) | (3.33) | (3.38) | (3.39) | (3.47) | (3.33) |
| *Capital Adequacy* | 0.0195 | 0.0190 | 0.0175 | 0.0185 | 0.0194 | 0.0185 | 0.0193 | 0.0186 | 0.0194 | 0.0193 | 0.0202 | 0.0192 |
| | (1.26) | (1.23) | (1.14) | (1.20) | (1.25) | (1.19) | (1.25) | (1.20) | (1.25) | (1.25) | (1.30) | (1.24) |
| *Stock Return Volatility* | -0.0547 | -0.0516 | -0.0492 | -0.0498 | -0.0550 | -0.0566 | -0.0560 | -0.0569 | -0.0555 | -0.0556 | -0.0590 | -0.0571 |
| | (-1.49) | (-1.41) | (-1.35) | (-1.36) | (-1.50) | (-1.55) | (-1.52) | (-1.55) | (-1.51) | (-1.51) | (-1.60) | (-1.56) |
| *Log GDP per Capita* | 0.0798 | 0.2132 | 0.2810 | 0.2425 | 0.1209 | 0.0449 | 0.1152 | 0.0413 | 0.1180 | 0.0936 | 0.1596 | 0.1277 |
| | (0.06) | (0.16) | (0.21) | (0.18) | (0.09) | (0.03) | (0.09) | (0.03) | (0.09) | (0.07) | (0.12) | (0.09) |
| Constant | 2.1361 | 0.8470 | 0.0110 | 0.6048 | 1.8763 | 2.5777 | 1.9266 | 2.6136 | 1.8933 | 2.1288 | 1.5207 | 1.8883 |
| | (0.15) | (0.06) | (0.00) | (0.04) | (0.13) | (0.18) | (0.14) | (0.19) | (0.13) | (0.15) | (0.11) | (0.13) |
| Firm F.E | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Number of Observations | 1,256 | 1,256 | 1,256 | 1,256 | 1,256 | 1,256 | 1,256 | 1,256 | 1,256 | 1,256 | 1,256 | 1,256 |
| Within $R^2$ | 0.0575 | 0.0598 | 0.0700 | 0.0608 | 0.0573 | 0.0584 | 0.0573 | 0.0584 | 0.0573 | 0.0573 | 0.0579 | 0.0582 |

# 3 How do Banking Analysts Behave around Unanticipated Bad News? Evidence from Operational Risk Event Announcements

## 3.1 Abstract

We study analyst forecast revision and accuracy around operational risk announcements in U.S. banks from 1990 to 2016. We find operational risk disclosures to be informative for banking analysts. Analysts who were previously optimistic revise their forecasts downwards around such disclosures, thereby improving forecast accuracy. This result is more pronounced for large operational risk events with losses in excess of $10 and $35 million. We find no evidence that banking analysts inflate forecast accuracy to secure an employment opportunity. In contrast with prior literature, we find evidence of competition among banking analysts and upward-biased forecasts, suggesting that analysts seek to use optimistic forecasts to curry favour and attract businesses to their brokerage house around the time of operational risk disclosures.

## 3.2 Introduction

Equity analysts play a crucial role in the capital market by contributing to the reduction of information asymmetries between firms' managers and outside investors. The primary role of analysts consists of discovering information and using their specialized market expertise and technical know-how in interpreting corporate disclosures and converting them into forecasts and recommendations reports that can be useful to investors in making investment decisions (Rubin and Segal, 2016; Rubin et al., 2017).

As new information is discovered, equity analysts may decide to revise their earnings forecasts, which are then translated into a key basis of information for investors in their on-going trading decision-making (Huang and Zhang, 2011).

Some news items are anticipated while others are not. Examples of anticipated news include earnings announcements that are disclosed in the form of quarterly (10-Q) and annual (10-K) financial reports. Empirically, such news has been shown to affect analyst forecasts (Ivkovic and Jegadeesh, 2004; Chen et al., 2010). Examples of unanticipated news include items included in 8-K reports (Rubin et al., 2017).[2] Other examples are sudden disruptions in supply chains due to natural disasters, terrorism, and other adverse unexpected events. We study a special type of unanticipated news item - announcements of operational risk events.

Operational risk is defined as "the risk of loss resulting from inadequate or failed internal processes, people or systems, or from external events" (BCBS, 2001, p.2). Operational risk has been at the root of many large-scale losses suffered by financial institutions globally. Examples include a $7.2 billion trading loss at Société Générale in 2008, Bernard Madoff's $50 billion Ponzi Scheme in 2008, and a $25 billion fine over improper mortgage loan servicing and foreclosure fraud in 2012 jointly imposed on the five largest U.S. banks: Bank of America Corporation, JP Morgan Chase & Co., Wells Fargo & Co., Citigroup Inc., and Ally Financial Inc. There is lack of regulatory disclosure requirements for operational risk: for example, it is not mandated to be included in 8-K filings.[3] From an accounting perspective, operational risk is a loss to a

[2] An exception is Item 2.02

[3] However, banks are required to disclose their operational losses on an aggregate basis in their Y-14Q filings.

bank. Operational risk events also signal internal control weaknesses, poor corporate governance, and risk management ineffectiveness (Chernobai et al., 2011).

Recent research has examined the root causes of operational risk in U.S. financial firms by examining firm-specific characteristics, such as bank size, age, growth opportunities, financial distress, along with macro-economic factors, such as GDP growth (Chernobai et al., 2011). These factors directly drive cash flows, earnings per share and other fundamentals. Recent studies provide consistent evidence of a significant negative equity market reaction to operational risk event announcements, once they occur, especially for internal fraud events (Perry and de Fontnouvelle, 2005; Cummins et al., 2006; Gillet et al., 2010; Sturm, 2013). As such, operational risk event announcements are important corporate disclosures conveying valuable signals about firms' anticipated future cash flows and earnings per share. While, arguably, equity value consequences of operational risk events are economically substantial, there is no prior research as to whether materialized operational losses lead to equity analysts' revisions of earnings forecasts.

Our objective is to examine operational risk event announcements from the perspective of equity analysts. To the best of our knowledge, this is the first study to analyse whether operational risk event announcements are incorporated in forecast revisions. Since operational risk events can have material consequences on a firm's future earnings, we anticipate that analysts would revise their earnings forecasts downwards following announcements of such events. Such revisions are more likely to take place around those announcements that entail immediate financial burden to the firm from the accounting perspective. Because operational risk events are unanticipated news, we expect such revisions to be issued sooner than the timing of a typical earnings forecast made by a particular analyst. We find that operational risk disclosures are informative and that analysts subsequently revise their earnings forecasts downward. We distinguish between operational risk first press-cutting date (first announcement) and its settlement announcement, and we find that the downward revisions are stronger around the first announcement than around the settlement announcement.

We employ a sample of 315 operational risk events' first announcements and 299 settlement announcements in U.S. banks, followed by a total of 534 analysts, from 1990 to 2016. We examine analyst forecast revision and error change (i.e., accuracy) around a reaction window of (−5, +5) of the operational risk event announcement. A comparison between the pre-announcement window (−5, −1) and the post-announcement window (0, +5) enables us to determine whether it is the leakage of private information and/or the event disclosure that cause analysts to revise their forecasts.

A large number of extant studies find that analyst forecasts are influenced by conflicts of interest. This is comprised of investors' desire for analysts to be objective by issuing accurate forecasts versus analysts' need to curry favour with firms whose earnings they are forecasting through the issuance of optimistic forecasts (Schipper, 1991; Lim, 2001; Hong and Kubik, 2003; Cowen et al., 2006). Upward biased forecasts enable analysts to help their brokerage house attract investment banking business and, hence, gain sales and trading commissions.

Banking analysts can also be optimistically biased because of career concerns: analysts may view banks, whose earnings they are forecasting, as future potential employers if the latter has a sell-side equity department (Horton et al., 2017). As such, they are incentivized to satisfy those clients. Horton et al. (2017) find that banking analysts issue forecasts that are relatively more optimistic for employers in the beginning of the year while by the end of the year the forecasts are relatively more pessimistic. This results in a more pronounced walk-down to beatable earnings for employers. Horton et al. (2017) argue that this bias effectively leads to favourable career outcomes. Motivated by these findings, we study whether career concerns affect analysts' earnings forecast revision and accuracy around operational risk event announcements. We find that career concerns have no statistically significant impact on analyst forecast revision and accuracy around operational risk disclosures.

We also attempt to analyse the effect of competition, measured by the number of analysts following the firm, on analyst forecast accuracy around operational risk disclosures. Competition between analysts is known to reduce bias in stock recommendations (Hong and Kacperczyk, 2010) and forecasting errors (Lys and Soo, 1995; Alford and Berger, 1999). Our paper builds on past literature by asking whether competition among analysts rationalizes an analyst's forecast, or whether the competition biases their forecast in order to attract investment banking business and to gain sales for their brokerage house through issuance of optimistic forecasts, hence distinguishing themself from other analysts. We find strong evidence of the latter effect: more intense analyst competition increases positive bias and, as a result, increases the forecast error.

In a robustness test, we extend our analysis by zooming in on severe losses – those exceeding \$10 and \$35 million. As anticipated, we find that operational risk disclosures are most informative and that downward forecast revisions following operational risk announcement are most pronounced for events with large operational losses.

In another robustness test, we explore the exogenous shocks of the Global Settlement of 2003 and the Global Financial Crisis and examine whether they have any impact on analysts' behaviour around unanticipated news. We find that only the Global Financial Crisis period has an economically meaningful impact as it motivates analysts to issue more accurate forecasts following operational risk disclosures, especially in the case of highly severe operational risk events. This result confirms the favourable effects of more stringent scrutiny of operational risk exposure in the banking industry on analyst behaviour upon the arrival of unanticipated news during the crisis period.

This paper helps derive a new measure of the severity of operational risk events. Earlier studies have used two measures of the severity: the dollar amount of the loss (Chernobai et al., 2011) and the reputational loss measured by the drop in the market value that is in excess of the operational loss itself (Perry and de Fontnouvelle, 2005; Cummins et al., 2006; Gillet et al., 2010; Sturm, 2013). Equity analysts are those who know the firm particularly well. Therefore, a significant downward forecast revision around an operational risk event announcement signals the severity of such event. In sum, our study provides empirical evidence that operational risk disclosures enhance the accuracy of the predictions of banking analysts and contribute to the informed decisions of investors.

This study also contributes to the broader literature on the discovery and interpretation skills of equity analysts. Extant literature argues that forecast revisions that follow corporate announcements are indicative of the interpretation skill of the analyst, but only if the corporate announcement is unanticipated (Ivkovic and Jegadeesh, 2004; Chen et al., 2010; Livnat and Zhang, 2012; Rubin et al., 2017). This is due to the fact that a forecast revision that takes place as a consequence of anticipated corporate news, such as earnings announcements (10-Ks, 10-Qs and Item 2.02 in 8-Ks), is potentially affected by the analyst's ability to predict the news. Therefore, an analyst's reaction to anticipated news is likely to be affected by both the discovery and interpretation skills of the analyst. In light of this literature, the first announcements of unanticipated operational risk events should be linked to the interpretation skills of analysts.[4]

Overall, the findings of this paper demonstrate that operational risk disclosures provide new information, which reduce the error and bias in analyst forecasts, and enable market discipline. However, being a non-regulatory disclosure, not every operational risk event incurred by a firm is disclosed to stakeholders. Therefore, in terms of the policy implications, our empirical results favour public disclosures of operational risk. Market participants should not have to wait until operational risk events are disclosed by the media. Hence, regulators could choose to either ask banks to disclose these operational loss data forms that are sent to them on their websites/annual reports, or regulators themselves report these operational risk events to the market. In other words, there should be a regulatory requirement to publicly disclose aggregate or detailed information on operational risk events incurred by banks.

[4] Operational risk settlement announcements usually arrive some time after the first announcement and are hence expected. This is because there is usually a wealth of information publicly disclosed at the market or privately discovered by analysts between the first announcement and settlement announcement of the operational risk event. Thus, the settlement announcements should be linked to both the discovery and interpretation skills of the analyst.

Furthermore, the results call for banking supervisors to monitor more closely analyst activities that may represent a conflict of interest and, hence, amplify the optimism bias in analyst forecasts. More specifically, analysts who are facing a strong competition are more likely to provide optimistic and inaccurate forecasts around unanticipated news, possibly to attract investment-banking business. Hence, banking supervisors should exert harder efforts to make sure that the regulations imposed to mitigate the overlapping of the analyst research and brokerage business lines are complied with properly in the daily activities of brokerage houses.

The remainder of the paper is organised as follows. Section 3.3 reviews the literature and develops our hypotheses. Section 3.4 defines the variables used, clarifies our data sources and explains our empirical model. Section 3.5 presents our empirical findings along with robustness tests in Section 3.6. Section 3.7 concludes.

## 3.3 Literature and Hypotheses Development

### 3.3.1 Overview of Prior Studies

Under the rational expectations hypothesis, which postulates that market participants have rational expectations that are updated when new information is released, an equity analyst will act rationally by taking into account all available information when making forecasts and aiming to maximize forecast accuracy (Muth, 1961; Givoly, 1985). The accuracy of equity analysts' earnings forecasts has been used as a measure to evaluate the uncertainty and information transparency of the firms and industries that analysts' research.

Prior studies on analyst forecasts have mainly focused on earnings announcements as the only significant corporate public information causing analysts to revise their forecasts (Ivkovic and Jegadeesh, 2004; Chen et al., 2010). Rubin et al. (2017) further argue that a greater number of analysts react and make revisions following anticipated earnings news (70%) than unanticipated 8-K reports (14%). They explain this difference by the economic impact of news such that anticipated news is considered to generate greater market reaction than unanticipated news. However, despite the lesser market reaction, the forecasts issued following unanticipated 8-Ks have been found to be informative for analysts, conveying relevant information for future earnings. Additionally, Rubin et al. (2017) find that revisions following unanticipated 8-K reports are associated with smaller forecast error.

Unlike 8-K reports, that may consist of both good and bad unanticipated news, while operational risk event announcements are also unanticipated, they only constitute bad news. Rubin et al. (2017) did not disentangle the effects of good and bad news to determine which drives their results, so literature distinguishing between the two is scarce. Chernobai et al. (2011) document that operational risk events reveal serious internal control weaknesses, resulting from improper business practices, poor governance and excessive risk-taking of executives in financial firms. As such, this adverse idiosyncratic informational shock, disclosed by the media and hitting financial markets, is likely to deteriorate the expected future cash flows of the affected firm.

This adverse financial impact extends beyond the cash flows: recent empirical studies provide strong consistent evidence of a negative equity value impact of operational risk event announcements. For instance, Perry and de Fontnouvelle (2005), Cummins et al. (2006), Gillet et al. (2010), Sturm (2013), and Barakat et al. (2018) find that operational risk event announcements spur severe drops in market prices, which even cause adverse reputational effects beyond the nominal operational risk loss amount. Leakage of private information may cause a significant drop in market values even in the days leading up to the actual announcement date. Cummins et al. (2006) examine the impact of material leakage of information prior to operational risk event announcements on stock market reaction and find that informed traders that possess superior knowledge about internal operations tend to start trading on the private information several days prior to the announcement. When this happens, equity analysts should react by revising their forecasts downwards and correcting any prior optimistic beliefs.

### 3.3.2 Hypotheses Development

The characteristics of operational risk events disclosed at the first announcement shed light on the level of information asymmetry (Barakat et al., 2014). If stakeholders believe that vital information, such as the operational loss amount incurred, is left undisclosed in the announcement, this might translate into greater information asymmetry. The operational loss amount is one measure of the severity of an operational risk event. Gillet et al. (2010) find that there is a stronger negative equity market reaction to operational risk event announcements when the loss amount is not disclosed. Their finding is in line with Hirschey et al. (2005) who show that the magnitude of the negative impact reflects the degree to which firms attempt to hide or minimize the extent of their operational losses. Therefore, operational risk event announcements with a loss amount disclosed should be more informative to analysts.

Each operational risk event in our sample has a first announcement date with a corresponding settlement date and a known settlement loss amount. However, operational risk loss amounts at the first announcements are not known for some events, thus adding to information asymmetry. In such cases, the unanticipated news could cause some confusion in the market and analysts might decide either to ignore the news announcements due to difficulty to interpret them in light of limited information, to revise upwards, or to revise downwards. This confusion may cause an increase in the forecast error. Settlement announcements, on the other hand, normally comprise of more detailed and certain information about operational risk events including the dollar amount of the loss and, typically, they signal that a resolution has been achieved, bringing the event to a closure. This is supported by the empirical study of Barakat et al. (2014) which find evidence of significant increased information asymmetry around operational risk first announcements but decreased information asymmetry around the settlement announcements. Building on their finding, our study takes a step further by analysing whether the decreased information asymmetry in the form of operational risk loss amount disclosure is truly informative to banking analysts causing them to revise their forecasts downwards and improve their accuracy.

When the operational loss amount is disclosed at the settlement announcement, there will be a bigger surprise given that the loss amount was unknown at the first announcement and we would, hence, intuitively expect a downward forecast revision and a reduction in forecast error. In contrast, if the operational loss amount is disclosed at first announcement, there would be a smaller surprise at the settlement announcement. We therefore argue that operational loss amount injects valuable information into the market and causes the analyst to provide downwards revision, associated with a reduction in her forecast error. Therefore, our first hypothesis is formulated as follows:

$H_1$ : *Operational risk loss amount disclosure increases banking analysts' earnings forecast accuracy.*

Extant literature documents that analyst forecasts are highly influenced by conflicts of interest (Schipper, 1991; Lim, 2001; Hong and Kubik, 2003; Jackson, 2005). A large number of studies finds evidence of excessive optimism of sell-side analysts' earnings forecasts because of the pressure to generate trading commissions, underwriting activities in investment banking business and career concerns (Lin and McNicolas, 1998; Hong and Kubik, 2003; Chan et al., 2007; Horton et al., 2017). Lim (2001) argues that analysts who intentionally bias their forecasts upwards can still be considered rational when forecasts are issued for firms where an uncertain information environment prevails and firm management is seen as a vital source of information. In doing so, analysts aim at gaining close relations with the management of the forecasted firms in order to benefit from obtaining continued access to private information and, hence, to enhance their forecast accuracy.

We argue that equity analysts who are not positively biased are less likely to revise their forecasts around operational risk event announcements. Such pessimistic analysts might already know about the internal control weaknesses from their prior discovery of private information (e.g. through their connections with firms' managers). The operational risk event announcement, therefore, does not come as a surprise to them and hence it does not trigger a forecast revision. In contrast, if an analyst is maintaining an excessively upward biased forecast, the new unanticipated piece of bad news is expected to cause the analyst to revise their forecast downwards, thus improving its rationality based on the rational expectations hypothesis. Supported by the findings of Chernobai et al. (2011), which document that operational risk events reveal serious internal control weaknesses, we argue that irrationally optimistic analysts revise their forecasts downwards following these operational risk event announcements. Therefore, our second hypothesis is formulated as follows:

$H_2$ : *Operational risk event announcements reduce earnings forecast bias and enhance earnings forecast accuracy of irrationally optimistic banking analysts.*

Analysts work in an environment where their actions and performances have a significant impact on their future career prospects. For example, a famous large-cap tech analyst at Merrill Lynch was fired due to bad calls on a key tech stock, which resulted in an erosion of his influence among his buy-side clients, as reported by the Wall Street Journal (Hong and Kubik, 2003). Nocera and Kover (1997) explain how analysts strive to be influential among their buy-side clients in order to gain the attention of a top-tier brokerage house if they are not already employed at one. This argument is supported by Hong and Kubik (2003) who show that, controlling for accuracy, analysts who provide optimistic earnings forecasts relative to the consensus tend to experience favourable job separations and be employed by a higher-status brokerage house. They also provide evidence that analysts with relatively poor forecast performance, i.e., less accurate forecasts, are more likely to lead to movements down the brokerage house hierarchy. Therefore, it can be argued that analysts' career concerns depend on their relative forecast accuracy and optimism bias.

A more recent stream of literature observes a gradual movement from optimism to pessimism in analyst forecasts, referred to as a walk-down to beatable earnings (Richardson et al., 2004; Cowen et al., 2006; Ke and Yu, 2006; Horton et al., 2017). Horton et al. (2017) explain that banking analysts provide forecasts for firms with sell-side equity departments, that might be a future potential employer and, hence, they are motivated to satisfy those clients. More precisely, using a sample period from 1999 to 2006, they find that if an analyst is forecasting for a potential employer, the analyst is likely to provide an upward revision and be relatively more positively biased (i.e., optimistic) in the beginning of the year while at the end of the year the analyst will tend to issue forecasts that are relatively more pessimistic. This pessimism gives the employer the opportunity to beat the analyst's earnings expectations and, thereby, to enjoy a higher overall return. These analysts with such optimism-to-pessimism patterns are less likely to be fired by their employers and, instead, experience favourable job separations and move to a higher status brokerage house than those not providing such patterns (Ke and Yu, 2006; Horton et al., 2017). Therefore, we argue that an analyst's behaviour around operational risk event announcements will be influenced by their career concerns. Our third hypothesis is, thus, formulated as follows:

$H_3$ : *Career concerns affect banking analysts' earnings forecast revision and accuracy around operational risk event announcements.*

Prior research also investigates the impact of competition on analyst forecast revision and accuracy (Lys and Soo, 1995; Alford and Berger, 1999; Hong and Kacperczyk, 2010; Huang et al., 2017). Based on the 'competition view' of Huang et al. (2017), which emphasizes that greater analyst coverage intensifies competition among analysts, we consider the number of analysts following the firm (i.e., analyst coverage) as an indicator of the level of competition among analysts.

In line with the rational expectations hypothesis, competition motivates analysts to act rationally by considering all available information when making forecasts and striving to maximize forecast accuracy. Extant literature argues that a higher number of analysts following a firm would lead to a lower forecast error (Lys and Soo, 1995; Alford and Berger, 1999). This argument is supported by Hong and Kacperczyk (2010) who find that competition reduces the optimistic bias in analysts' forecasts. In a competitive environment, assuming that consumers of their forecasts demand accuracy, Hong et al., (2000) argue that inexperienced analysts with more career concerns than experienced analysts would tend to display a herding behaviour. Their forecasts follow the consensus in order to minimize their chances of under-performing and losing their jobs.

At the same time, competition may also encourage analysts to be overoptimistic in their forecasts as they might feel the pressure to distinguish themselves from other analysts, especially in the eyes of potential employers. Extant literature argues that there are several reasons why an optimistic bias is embedded in analyst forecasts. These reasons include: to please the firm's management in exchange for private firm-specific information (Das et al., 1998; Lim, 2001; Barber et al., 2006; Chan et al., 2007); to cater to or attract investment banking businesses (Michaely and Womack, 1999; Dechow et al., 2000; O’Brien et al., 2005); and to stimulate greater trading volume for their brokerage firms to benefit from greater commission revenue (Jackson, 2005). Therefore, higher analyst coverage could strengthen the level of competition and cause an analyst to become optimistic around adverse media news in order to distinguish themselves from competitors (i.e., other analysts). As such, the effect of competition on analyst forecast revision and accuracy around unanticipated bad news is an empirical question and leads us to our fourth hypothesis:

$H_4$ : *Competition with other analysts affects banking analysts’ earnings forecast revision and accuracy around operational risk event announcements.*

Extant literature has examined the impact of major exogenous financial shocks or regulatory changes on analysts’ forecasts. One such regulation is Regulation Fair Disclosure (Reg FD) of 2000. Reg FD prohibits firms from selectively providing information to analysts before disclosing it to the public. The regulation was imposed with the aim to prevent those with informational advantage to enjoy a profit at the expense of others (Eng et al., 2014). Prior studies find that analysts have, consequently, had a lower tendency to issue optimistic forecasts and recommendations (Herrmann et al., 2008; Hovakimian and Saenyasiri, 2010).

Another regulation is the Global Settlement, implemented on 28 April 2003, and is considered as an exogenous shock to career concerns (Horton et al., 2017). It aims at restoring the integrity of research, which was compromised due to prior pressure on analysts to attract investment banking businesses. This enforcement agreement created a “Chinese Wall” between investment banking divisions of brokerage houses and banks' research divisions, thus boosting competition in the sell-side analyst labour market. The Global Settlement has effectively altered the focus of analysts, who are henceforth reluctant to become excessively optimistic for future potential employers. This is mainly because they do not want to disappoint investors who consume their forecasts, and risk dismissal (Horton et al., 2017). This implies that analysts are more interested in keeping their current job rather than looking to be employed by another investment bank. Hence, our fifth hypothesis is formulated as follows:

$H_5$ : *Operational risk event announcements lead to an improvement in banking analysts' earnings forecast accuracy following the* Global Settlement.

The Global Financial Crisis provides the most recent setting that allows us to empirically examine the quality and accuracy of analyst forecasts in a different market environment. Operational risk factors, including the lack of controls on the decisions to underwrite subprime mortgages, have played a major role in fuelling the Global Financial Crisis (Jobst, 2010). There has, consequently, been an increased focus from regulators and investors on analysts' conflicts of interest. Analysts have since started paying more attention to incorporate newly released operational risk event information into their forecast revisions during and following the Global Financial Crisis. Since the crisis, by paying more attention to the informational contents of operational risk event announcements, analysts are now more likely to revise their forecasts downward and to interpret the information more accurately. Therefore, our final hypothesis is formulated as follows:

*$H_6$ : Operational risk event announcements lead to an improvement in banking analysts' earnings forecast accuracy during and following the Global Financial Crisis.*

## 3.4 Data and Methodology

### 3.4.1 Data and Sample Selection

Operational risk event announcements data are collected from the Financial Institutions Risk Scenario Trends (FIRST) database, marketed by Algorithmics Inc., a member of IBM. FIRST's primary goal is to assist financial institutions in identifying, understanding, and managing their operational risk. The database includes information ranging from the name of the firm in which the event took place to a detailed narrative of the event. The data are collected from public sources, such as the media, SEC press releases, and court orders. From this database, we use information on the operational risk events' first announcement dates, settlement dates, loss amounts and event types. We manually double-checked each field for accuracy through the LexisNexis business news database.

For the purpose of this study, we restrict our sample to operational risk event announcements in publicly traded U.S. banks. Each event in our sample has a first announcement date with a corresponding settlement date and a known settlement loss amount. Our initial operational risk events sample comprises 923 event announcements from 95 large and medium-sized publicly traded U.S. banks from 1990 to 2016. Table 3.2 summarizes our full sample selection procedure.

Because our focus is on operational risk event announcements and their impact on analyst forecasts, we restrict our sample to those operational risk event announcements that do not overlap with any other confounding announcements. We use an event window of five trading days prior to five trading days after the operational risk event announcement (−5, +5). Potentially confounding announcements include any quarterly and annual earnings announcements (10-Qs and 10-Ks, respectively), reported in I/B/E/S as the 'announce date of the actual' of the next quarter (FPI = 6) and next year (FPI = 1), and material corporate announcements (Form 8-Ks), filed with the SEC's Electronic Data Gathering, Analysis and Retrieval online system (EDGAR). These earnings and other non-earnings announcements are likely to cause analysts to revise their forecasts (Rubin et al., 2017). Our final operational risk events sample consists of 315 first announcements and 299 settlement announcements during the period 1990–2016. Table 3.3 provides the composition of the final operational risk event announcements sample after removing events that overlap with 8-Ks, 10-Qs, and 10-Ks announcements within the event window (−5, +5).

We merge analysts' EPS estimates data from I/B/E/S with operational risk data from our final sample using a firm identifier and the announcement date of the operational risk event within a window (−5, +5), around first press cutting and settlement dates, respectively. We believe that five trading days prior the first announcement date is reasonable to account for any rumours and leakage of information. The extension to five trading days following the first announcement date is justified by the fact that analysts may need time to process the information before they revise their forecasts.[5]

[5] Since our sample also includes operational risk events with no loss amount disclosed at first announcements, we expect a slowness on the part of analysts to respond. Extant literature on operational risk uses longer event windows including (-10, +10) and (-20, +20). However, we use only (-5, +5) to avoid losing too many observations due to the overlap of operational risk event announcements with other announcements such as 10-Qs, 10-Ks, and 8-Ks.

We further disentangle the disclosure effects by comparing the pre-announcement period (−5, −1) with the post-announcement period (0, +5). Operational risk events are excluded in banks where the number of analysts following is missing or is less than three. After merging the analyst forecasts and operational risk data, we have 13,417 observations at the analyst level.

Following Horton et al. (2017), we identify all banks with investment arms in our sample. This identification starts with the Standard Industrial Classification (SIC) two-digit codes 60–62 and we also use the information disclosed in banks' annual reports (10-K filings) from SEC Edgar and Bloomberg categorization of investment services to confirm our identification. Banks with sell-side equity departments are thereby classified as 'employers' and those with no sell-side equity departments as 'non-employers.' The additional firm-specific financial data are obtained from Compustat and daily share prices are extracted from the Center for Research in Security Prices (CRSP).

### 3.4.2 Measures of Analyst Forecast Quality

We employ two measures of analyst forecast quality. Following Rubin et al. (2017), the first measure, *Analyst Forecast Revision*, is defined as the difference between current forecast and previous forecast of analyst $i$ for firm $j$, standardized by the share price on day −6. This standardization ensures that we exclude any impact on the firm's share price caused by the leakage of private information in the trading week preceding the announcement date. In a nutshell, we aim to examine by how much an analyst will change their EPS estimation for a firm during the reaction window (−5, +5) around the firm's operational risk event announcement. Analyst forecast revision is computed as follows:

$$Analyst\ Forecast\ Revision_{ij} = \frac{Current\ EPS_{ij} - Previous\ EPS_{ij}}{Share\ Price_{ij}(-6)} \qquad (3)$$

In line with Rubin et al. (2017), our second measure is *Analyst Forecast Error*. Forecast error helps to evaluate the accuracy of an analyst forecast, allowing an equity analyst to identify and learn from their mistakes in order to improve their forecasts in the future. An analyst forecast error is measured as the absolute difference between forecast EPS and actual EPS of analyst *i* for firm *j*, standardized by the share price on day −6. Both under-estimation and over-estimation of forecasts are considered as errors in determining the analyst forecast accuracy. The absolute forecast error penalises any variation of analyst forecast from the actual figure, irrespective of the direction of deviation. Analyst forecast error is computed as follows:

$$Analyst\ Forecast\ Error_{ij} = \frac{\left|Forecast\ EPS_{ij} - Actual\ EPS_{ij}\right|}{Share\ Price\ _{ij}(-6)} \qquad (4)$$

We then compute *Analyst Forecast Error Change* as the difference between the current forecast error, i.e., during the reaction window (−5, +5), and the preceding forecast error, i.e., on day −6, of the same analyst *i* for firm *j*, as shown below:

$$\begin{aligned} &Analyst\ Forecast\ Error\ Change_{ij} \\ &\qquad = Analyst\ Forecast\ Error\ _{ij}(reaction\ window) \\ &\qquad - Analyst\ Forecast\ Error_{ij}(-6) \qquad (5) \end{aligned}$$

A reduction in analyst absolute forecast error signifies a more accurate forecast, while an increase in absolute value indicates lower accuracy. Since the time that elapses from one forecast to another varies both over time (across an analyst's forecasts) and cross-sectional, we make necessary adjustments so that analyst forecast revision and forecast error change are measured on equal terms (Rubin et al., 2017).[6] As such, we utilize an annualized measure by dividing analyst *i*'s forecast revision and forecast error change by the number of days that have elapsed since this analyst's previous forecast and multiply the result by 365.

### 3.4.3 Independent Variables

In this section, we present the independent variables that are related to our hypotheses (Section 3.3.2). These variables are divided into three groups: event-level variables, analyst-level variables and firm-level variables.

From the FIRST database, we use several event-level variables related to the characteristics of the operational risk event announcement. The first, *Unknown Loss Amount Dum*, is a dummy variable that captures whether the operational loss amount is unknown on the first announcement date as a measure of the level of information asymmetry at the first announcement and the level of anticipation at the settlement announcement. Following Horton et al. (2017), we use *Post Global Settlement Dum*, a dummy variable, which indicates whether the operational risk event announcement

[6] As Rubin et al. (2017) explain, because the analyst's information set consists of more forecasts of other analysts as time evolves, along with more private and public information released, the reduction in an analyst's forecast error is expected to be greater if a longer time has elapsed from the analyst's previous forecast.

happened after the Global Settlement of 28 April 2003 and before the Global Financial Crisis. We account separately for the Global Financial Crisis and employ the dummy variable *Global Financial Crisis Dum*, which captures operational risk event announcements that happened during the crisis period (i.e., 14 September 2007 – 14 September 2009), and another dummy variable *Post Global Financial Crisis Dum*, which captures operational risk events that were disclosed after the crisis period.

Furthermore, we measure the number of days between the actual EPS announcement and operational risk event announcement dates using the variable *Walk-Down Effect*. This variable will enable us to examine whether the gap in the number of days influences an analyst's decision to revise their forecast following an operational risk disclosure. Consistent with the literature on operational risk event announcements (Perry and de Fontnouvelle, 2005; Cummins et al., 2006; Gillet et al., 2010; Sturm, 2013; Fiordelisi et al., 2013, 2014), we measure the stock market reaction to operational risk event announcements by the cumulative abnormal return (CAR) estimated using the Fama-French Three Factor model. Our estimation period consists of 250 trading days across our different event windows. For the purpose of this study, we use the reversed CAR. As such, the higher the CAR, the more adverse is the abnormal market reaction.

We distinguish between event types using Basel-defined event type classification. We categorize events into the following four event types: internal fraud (IF); clients, products, and business practices (CPBP); external fraud (EF); and all remaining events (OTHERS). Using OTHERS as a reference group, we construct three dummy variables: *IF Dum, CPBP Dum, and EF Dum*. Dummies for severe operational losses – those exceeding \$10 million and \$35 million – are used for sub-samples in additional robustness tests.

With regard to analyst-level variables, we employ a dummy variable *EPS Forecast Bias Day −6 Dum* to determine whether analyst *i*, whose signed forecast error for firm *j* on day −6 was positive (also referred to as an optimistic analyst), will revise their forecast in the studied event window. We control for the brokerage house size (*Broker Size*), computed as the number of analysts employed by the brokerage firm employing analyst *i* on day −6. Consistent with Clement (1999), Hong and Kubik (2003), Horton et al. (2017), and Rubin et al. (2017), we also control for an analyst's firm-specific experience (*Firm Experience*), estimated as the number of years analyst *i* has been following firm *j*; analyst's general experience (*General Experience*), which is the number of years an analyst *i*, following firm *j*, has been providing forecasts in I/B/E/S; analyst's industry experience (*Industry Experience*), which is the number of years analyst *i* has been following the two-digit SIC code of firm *j*; along with proxies for analyst portfolio complexity: the number of firms (*Number of Firms*) and the number of unique two-digit SIC codes of all firms (*Number of Industries*) followed by analyst *i* on day −6.

We use several firm-level variables. Following Horton et al. (2017), we employ a dummy variable to capture whether the analyst is issuing forecasts for a potential employer. This variable is designed to capture the effects of the analyst's career concerns on forecast revision and accuracy around an operational risk event announcement. In line with Hong and Kacperczyk (2010) and Huang et al. (2017), we include the number of analysts following the firm on day −6 (*Number of Analysts Following*) as a measure of the level of competition among analysts. Similar to Rubin et al. (2017), we control for the following firm-level variables on day −6: firm size, measured by the natural logarithm of total deflated assets (*Log Total Assets*); profitability, measured by income before extraordinary items divided by total assets (*Return on Assets*); leverage, measured by the sum of short-term debt and long-term debt divided by total assets (*Leverage*); ratio of book value to market value of equity (*Book to Market Ratio*); and a market-based measure of firm riskiness, measured by the quarterly standard deviation of daily stock returns (*Equity Return Volatility*).

### 3.4.4 Descriptive Statistics

Descriptive statistics for the main variables used in the analysis are presented in Table 3.4. We observe that, on average, analysts who have been following the firm on day −6, provide a 0.3824% downward forecast revision associated with a 0.3024% reduction in forecast error following operational risk disclosures during a reaction window (−5, +5). This result provides suggestive evidence that operational risk event announcements are informative and cause equity analysts to revise their earnings forecasts downwards, which also leads to a reduced forecast error. Table 3.4 also shows that, on average, the downward revision is more pronounced during the post-announcement window (0, +5) than during the pre-announcement window (−5, −1). Specifically, analysts revise their forecasts downwards by 0.2341% following the bad news disclosure, while only by 0.1483% due to leakage of information.

In terms of operational risk event features, 33% of our sample have an unknown operational loss amount at the first press cutting date. The majority of our sample announcements is classified as ‘clients, products and business practices’ event type

(58%), followed by internal fraud (16%) and external fraud (12%). In terms of analyst characteristics, we observe that, on average, an analyst follows 16.3 firms operating within 6 industries, with a standard deviation of about 8.6 firms and 3 industries, which is similar to the numbers reported by Rubin et al. (2017). In our sample, an average analyst has been providing forecasts for almost 15.2 years with a standard deviation of 7.2 years. A typical firm in our sample has an average of 25 analysts following it.

### 3.4.5 Empirical Model

To examine the effects of an operational risk event announcement *k* incurred by firm *j* on earnings forecast revision and accuracy of analyst *i* within a reaction window (−5, +5), we estimate the following econometric model:

$$
\begin{aligned}
&Measure\ of\ Analyst\ Forecast\ Quality_{ijk} \\
&\quad = \alpha_{ijk} + \beta_1\, CAR_k + \beta_2\, Unknown\ Loss\ Amount\ Dum_k \\
&\quad + \beta_3\ Post\ Global\ Settlement\ Dum_k \\
&\quad + \beta_4\ Global\ Financial\ Crisis\ Dum_k \\
&\quad + \beta_5\ Post\ Global\ Financial\ Crisis\ Dum_k \\
&\quad + \beta_6\, EPS\ Forecast\ Bias\ Day - 6\ Dum_i + \beta_7\, Employers\ Dum_j \\
&\quad + \beta_8\, Number\ of\ Analysts\ Following_j + \sum_{l=1}^{L} \varphi_l\, X_{kl} + \sum_{m=1}^{M} \gamma_m\, Y_{im} \\
&\quad + \sum_{n=1}^{N} \delta_n\, Z_{jn} + \varepsilon_{ijk} \qquad (6)
\end{aligned}
$$

where the sets X, Y, and Z consist of event-level variables, analyst-level variables, and firm- level variables. We estimate an Ordinary Least Squares (OLS) regression model for each analyst *i* following firm *j*, which incurred an operational risk event announcement *k* for each of our two dependent variables – *Analyst Forecast Revision* and *Analyst Forecast Error Change* – that were defined in Section 3.4.2 and Equations (1) and (3).

We estimate the model in Equation (6) separately for the first announcements and settlement announcements. We further differentiate between pre- and post-announcement periods by estimating the models for (−5, −1) and (0, +5) separately. This is to determine whether the result of (−5, +5) is driven by private information that may have leaked prior to operational risk event announcement or, instead, by operational risk information that has been disclosed. Table 3.1 presents the definitions and data sources of the variables used in our empirical analysis.

## 3.5 Empirical Results

### 3.5.1 Univariate Results

Figure 3.1 presents a graphical description of our data. It illustrates average analyst forecast revision, computed using the percentage change in EPS forecasts per share price (left column) and average analyst forecast error change, computed using the percentage difference in forecast error per share price (right column). Both variables are measured on a daily basis during the event window (−5, +5) of the operational risk event announcements for different sub-samples of our explanatory variables and some control variables. Table 3.5 presents mean comparison tests for the different sub-samples of our explanatory variables.

Firstly, we observe from Figure 3.1, Panel A, that the reduction in analyst forecast revision and error change is more pronounced at the first announcement than at the settlement announcement. We argue that this is mainly because first announcements come as a surprise and reveal non-earnings bad news about the firm. In contrast, settlement announcements are relatively less unexpected as they might happen a long time after the first announcements.

In addition, irrationally optimistic analysts revise aggressively downwards by 0.5779% and see their forecast error decrease by 0.4807% at the 1% significance level, which is a greater drop than for non-optimistic analysts (Figure 3.1, Panel C). Furthermore, in line with our expectations, analysts issuing forecasts for a potential employer make a more significant reduction in their forecast error (0.3304%) than analysts issuing forecasts for a non-employer (0.0251%) at the 1% significance level (Figure 3.1, Panel D). With respect to exogenous shocks, Figure 3.1, Panel E shows that analyst forecasts become more accurate during the Global Financial Crisis. This is supported by Table 3.5, Panel A, which indicates a more pronounced downward revision by 1.2278% at the 1% significance level in the event window (−5, +5). The forecast error also decreases by 1.1295% at the 1% significance level.

### 3.5.2 Multivariate Results

The results of our Equation (6) with analyst forecast revision and analyst forecast error change as dependent variables are presented in Tables 3.6 and 3.7, respectively. Each table presents the results of our baseline regressions (Models 1) and our interaction regressions (Models 2). The reported results use an event window (−5, +5), which is further disentangled into a pre-announcement period $(-5, -1)$ and a post-announcement period (0, +5).

We do not find evidence supporting hypothesis $H_1$ that known loss amount at the first announcement causes a downward analyst forecast revision and an increase in analyst forecast accuracy around operational risk disclosures. However, our multivariate results provide strong evidence that irrationally optimistic analysts produce less upward biased and more accurate forecasts around operational risk disclosures. These analysts revise their forecasts downwards by 0.3057% (Table 3.6) more than non-optimistic analysts, a result statistically significant at the 1% level. For a firm with an average number of shares outstanding in 2016 (i.e., 3.5 billion shares), this downward revision amounts to a total additional reduction of $10 million in forecasted earnings. Subsequently, their forecast error reduces by an additional 0.3247% (Table 3.7). Hence, our results support hypothesis $H_2$.

The above result suggests that operational risk event announcements are informative to equity analysts and they enable market discipline. In contrast to Rubin et al. (2017), who document that reaction to unanticipated 8-K news leads to a 1.4% reduction in analyst forecast error, we find that the coefficient of the impact of operational risk disclosures on analyst forecasts is relatively lower. One possible explanation is that 8-K filings include several items, thus making them more informative than operational risk news published in the media.

Unlike prior empirical studies (Lin and McNicolas, 1998; Hong and Kubik, 2003; Chan et al., 2007; Horton et al., 2017), we document that banking analysts who were previously issuing excessive optimistic forecasts due to the pressure to generate trading commissions, are not affected by conflicts of interest around operational risk disclosure. This finding is in line with the rational expectations hypothesis such that this unanticipated bad news disclosure, which reveal serious internal control weaknesses (Chernobai et al., 2011), cause irrationally optimistic analysts to revise their forecasts downwards, thus improving their rationality.

With respect to hypothesis $H_3$, we find no evidence from Models 1 of Table 3.7 that analysts enhance their forecast accuracy when forecasting for a future potential employer. On the other hand, we find some evidence supporting hypothesis $H_4$ in that high competition among analysts, measured by *Number of Analysts Following*, causes analysts to revise their forecasts upwards by 0.0221% (Table 3.6) for every additional analyst, at the first announcement, a result primarily driven by the pre-announcement period. Consequently, their forecast error increases by an additional 0.0237% (Table 3.7).

This finding suggests that when more analysts are following a firm, each analyst is more likely to revise their forecast upwards and become more optimistic around operational risk disclosures, all else held equal. This is consistent with empirical studies which document that analysts bias their forecast in order to attract investment banking business and to gain sales for their brokerage house through issuance of optimistic forecasts, hence distinguishing themselves from their competitor analysts (Schipper 1991; Lim 2001; Hong and Kubik 2003; Cowen et al. 2006; Chan et al. 2007).

To test further hypothesis $H_4$, Model 2 also includes an interaction term, *Employers Dum* $*$ *Analysts Following* to test whether the competition effect depends on whether an analyst is forecasting for a future potential employer. We find a positive (although statistically insignificant) forecast revision bias for every additional analyst when forecasting for a future potential employer, which also increases forecast error (a statistically significant result). This suggests that analysts aim to distinguish themselves in the eyes of future employers when competing with other equity analysts by being positively biased to attract more businesses for their firms. However, in doing so, their forecast accuracy worsens.

In line with Hong and Kubik (2003), our findings reveal that analysts' earnings forecasts are influenced by their job environment and prospects – in terms of both career concerns and competition among analysts. Specifically, analysts who are forecasting for a potential future employer will aim to provide more accurate forecasts and, hence, maintain their credibility. However, the accuracy of their forecasts is jeopardized when these analysts are faced with high competition from other analysts. They then become more optimistic by issuing upward biased forecasts despite a bad news announcement in order to bring more businesses to their brokerage house.

Surprisingly, our findings reveal that analysts are positively biased at the post-Global Settlement period and revise their forecasts upwards by 0.4145% more than during pre-Global Settlement period, around the first announcements, and by 0.4757% more around the settlement announcements, all else held equal. This excessive optimism leads to a consequent statistical increase in analyst forecast error, which contradicts hypothesis $H_5$. In contrast to Horton et al. (2017), who find that analysts are more reluctant to bias their forecasts in order to maintain their credibility and avoid dismissal after the Global Settlement, our results show that analysts opt to issue optimistic forecasts around operational risk disclosures. We link this optimism to the rise in competition in the sell-side analyst labour market caused by the implementation of this regulation.

On the other hand, we find some evidence supporting hypothesis $H_6$, in that the Global Financial Crisis has had a strong and statistically significant impact on analysts' forecast behaviour around unanticipated bad news. This exogenous shock has caused analysts to revise their forecasts downwards by 0.7615% (Table 3.6) overall, at the first announcements. This amounts to a total reduction of $26.7 billion in forecast earnings for an average firm. During the Global Financial Crisis, the forecast error reduced significantly by 0.8931% (Table 3.7), a finding statistically significant at the 1% level. By contrast, our empirical results do not lend support to the hypothesis that, following the Global Financial Crisis, banking analysts continue to exploit the release of unanticipated bad news to enhance their forecast accuracy, because the magnitude of the coefficient (-0.1215 in Table 3.7) is only a fraction of that reported for the Global Financial Crisis (-0.8931 from Table 3.7) and is statistically insignificant.

Our results confirm the favourable effects of more stringent scrutiny of operational risk exposure in the banking industry on analyst behaviour upon the arrival of unanticipated news only during the financial crisis period. This implies that banking analysts were more careful when issuing their forecasts during the crisis period and took into account the key information revealing internal control weaknesses of banks through operational risk event announcements due to increased supervision from regulators. However, post crisis period, our results demonstrate that banking analysts' forecasting behaviour changed as they reverted to their pre-financial crisis behavioural approach by ignoring the disclosure of operational risk event announcements and being less accurate. This result raises a red flag that regulatory efforts may not have been fully successful in mitigating banking analysts' behavioural biases, particularly around unanticipated bad news. In other words, it means that the regulations and rules enacted to eliminate analysts' incentive to inflate their earnings forecasts have no meaningful implications on analysts' forecasting behaviour as they are mostly driven by their over-optimism and conflicts of interests once the financial crisis period was over.

## 3.6 Robustness Tests

In this section, we present some robustness tests in order to rule out alternative explanations of our findings.

### 3.6.1 Severe Operational Risk Events

To rule out the possibility that our findings are driven by few high magnitude losses, we re- estimate Equation (6) for severe operational risk event announcements, defined as losses that exceed a high threshold. We try two different thresholds: $10 million and $35 million. The results for the two sub-samples of severe events are presented in Tables 3.8, 3.9, and 3.10.

Table 3.8 provides some univariate mean difference test results. We observe from Table 3.8 that the impact of operational risk events on analyst forecast revision and error is even more pronounced as the loss size increases from $10 million (Panel A) to $35 million (Panel B). The higher the operational loss amount, the more downwards optimistic analysts revise their forecast. Analysts who are concerned about their careers also revise more downwards in the case of bigger losses and their forecast error decreases, a result significant at the 1% significance level. The Global Financial Crisis period and post-crisis period also cause analysts to enhance their accuracy, a result significant at the 1% significance level.

We find clear evidence that as the loss size threshold increases from $10 million (Table 3.9) to $35 million (Table 3.10), optimistic analysts revise their forecasts more aggressively downwards following operational risk disclosures, thus enhancing their accuracy. For example, Table 3.9, Panel B shows that, in the event window (−5, +5), optimistic analysts' forecast error is by 0.5433% (first announcement) and by 0.3357% (settlement announcement) lower than that of non-optimistic analysts for losses exceeding $10 million, all else held equal. During the same event window, as the loss size threshold increases to $35 million, as seen in Table 3.10 Panel B, analyst forecast error decline for optimistic analysts is even greater: 0.5654% (first announcement) and 0.4084% (settlement announcement). Both results are statistically significant at the 5% significance level and higher.

Additionally, there is some evidence (Table 3.9, Panel B) that analysts who are concerned about their future employment improve their forecast accuracy by 0.8195% more than the other analysts, around events with loss amounts exceeding $10 million around the first announcement. When the loss amount exceeds $35 million, Table 3.10 Panel A shows that analysts forecasting for a future employer issue optimistic forecasts by revising their forecasts significantly upwards by 1.1138% and 1.0707% more than the other group of analysts, around the first announcement and settlement announcement, respectively, all else held equal. This result suggests that the excessive optimism bias due to banking analysts' career concerns only show up when very big loss amounts are disclosed. In other words, banking analysts are more reluctant to penalize potential future employers when they feel the negative economic magnitude of rational forecast revision is quite high.

Moreover, our results show that the direct impact of competition on analyst forecasts is stronger for operational risk events with loss amounts exceeding $10 million. Higher analyst coverage tends to make analysts revise upwards by 0.0559% (Table 3.9, Panel A) for every additional analyst following, around the first announcement, thus causing their forecast error to increase by 0.0606% (Table 3.9, Panel B), all else held equal. As the loss size increases to $35 million, high competition causes analysts to revise upwards by 0.0699% (Table 3.10, Panel A) for every additional analyst following, but only around the settlement announcement, mainly driven by the post-announcement period. As a result, their forecast accuracy deteriorates by 0.0610% (Table 3.10, Panel B). In addition, the positive coefficient of the interaction term *Employers Dum*Analysts Following* (Tables 3.9 and 3.10, Panels A) suggests that the positive competition effect is more pronounced for analysts that forecast for an employer. This suggests that analysts, competing with a large number of analysts, eventually aim to attract more businesses for their firm to secure their current job and potentially impress future employers. However, in doing so, every additional analyst following increases their forecast error by an additional 0.0471% (Table 3.9, Panel B) relative to the group of analysts that do not forecast for an employer, around the settlement announcement of operational risk events with loss amounts exceeding $10 million. This effect, however, is much weaker for losses exceeding $35 million.

Finally, we find consistent evidence that the Global Financial Crisis period has a more pronounced impact on analyst forecast accuracy around operational risk events with loss amounts exceeding $10 million. More precisely, analysts are more careful around the disclosure of unanticipated bad news with big losses and react accurately by revising their forecasts downwards by 1.1479% (Table 3.9, Panel A) more post-crisis than in the first 13 years of the sample period. Their forecast accuracy also enhances significantly by an additional 1.4262% (Table 3.9, Panel B), a result mainly driven by the pre-announcement period. However, our results show no statistically significant impact of the Global Financial Crisis on analyst forecast accuracy.

### 3.6.2 Pre- and Post-Global Financial Crisis Subsamples

In the second robustness test, we re-estimate our model in Equation (6) separately for pre-Global Financial Crisis (i.e., prior to 14 September 2007) and post-Global Financial Crisis (i.e., following 13 September 2007) periods. This test is designed to rule out the possibility that only one of the two subsamples is driving our earlier findings. The results for the pre- and post-Global Financial Crisis subsamples are presented in Tables 3.11 and 3.12, respectively.

Firstly, our results from Table 3.11, Panel A, show that, during the pre-Global Financial Crisis period, optimistic analysts revise their forecast significantly downwards by 0.2585% and 0.2115% more than non-optimistic analysts, a result significant at the 1%

level, around the first announcement and settlement announcement. Subsequently, their forecast error decreases by an additional 0.1820% around the first announcement, all else held equal. Interestingly, in the post-Global Financial Crisis period (Table 3.12), we observe a more significant negative impact of operational risk disclosure on analyst forecast revision, mainly at the settlement announcement. Also, the forecast error reduction for optimistic analysts is notably more pronounced during post-crisis (-0.3710% around first announcement and -0.3789% around settlement announcement, from Table 3.12) compared to pre-crisis (-0.1820 and -0.0672). This confirms our main results that the Global Financial Crisis has successfully mitigated analysts' behavioural bias around unanticipated bad news.

Secondly, with respect to career concerns, we find no statistical evidence that, prior to the Global Financial Crisis, analysts were worried about their forecast accuracy to impress future potential employers. However, Table 3.11, Panel B, shows some evidence that, following the Global Financial Crisis, analysts tend to enhance their forecast accuracy in the pre-announcement period. Moreover, while analysts were already upwards biased around operational risk disclosures when faced with competition in the pre-Global Financial Crisis, we find that the impact of this optimism on forecast accuracy is more pronounced in the post-Global Financial Crisis period. This suggests that analysts fear the high level of competition more during and after the crisis period and this makes them more positively biased to attract more businesses and outperform their competitors despite the disclosure of bad news.

Finally, when including the interaction term *Employers Dum*Analysts Following*, we find some similar evidence of the direct impact of *Employers Dum* on analyst forecast accuracy both in the pre- and post-Global Financial Crisis in that analysts become more accurate when forecasting for a future employer. On the other hand, the positive coefficient of the interaction term *Employers Dum*Analysts Following* in Table 3.11, Panel B, suggests that only in the pre-Global Financial Crisis, analyst accuracy deteriorates when forecasting for a future employer and, at the same time, competing with a large number of equity analysts. No such effect is analysed in the post-Global Financial Crisis (Table 3.12). This suggests that, before the crisis period, analysts chose to become optimistic despite operational risk disclosures and bring businesses for their brokerage houses rather than improve their accuracy.

## 3.7 Conclusion

Operational risk events are unanticipated market disclosures of non-earnings bad news revealing internal control deficiencies and improper risk management practices in firms. This study investigates the impact of operational risk event announcements on banking analyst forecast revision and accuracy. We find evidence that operational risk event announcements enhance analyst forecast accuracy for optimistic analysts who had issued upward biased forecasts prior to the announcement. This is consistent with operational risk events revealing useful information about internal control deficiencies and improper risk management practices.

We extend our analysis by examining the effects of career concerns, competition among analysts, and exogenous shocks, such as the Global Settlement and the Global Financial Crisis. Overall, we find no evidence of a change in analysts' forecasting behaviour when forecasting for a potential employer. On the other hand, we find that analysts who face fierce competition revise their forecast upwards, thus decreasing forecast accuracy despite the operational risk disclosure. This raises a concern that banking analyst behaviour might be compliant with current and potential clients in order to generate business in a competitive brokerage market. Moreover, analysts revise their forecasts significantly downwards, thus improving forecast accuracy around operational risk disclosures during the global financial crisis, possibly due to the escalated scrutiny of idiosyncratic banking risks by regulatory and supervisory authorities. In contrast, no such effect is found following the Global Settlement of 2003. Moreover, these findings are more pronounced for operational risk events with a loss amount greater than $10 million and $35 million.

Our findings have two major policy implications for banking regulatory and supervisory authorities. First, banking regulators should work more actively on improving public disclosure of operational risk to reduce information asymmetry between bank managers and investors. Second, unobservable overlapping of the analyst research and brokerage business lines within the same brokerage house is potentially problematic because favourable forecasting during periods of adverse media coverage might be used to curry favour with banks to generate brokerage business. Our results show that, despite much regulation being already imposed, there are still sources of bias in banking analyst behaviour upon the arrival of unanticipated news. Hence, more stringent scrutiny by banking supervisors is still needed to ensure that rigid borderlines are maintained between the two conflicting business lines.

The main limitation of this study is that our sample is focused only on U.S. banks, hence the findings cannot be generalised. More adjustments might be required for non-banking or even non-financial institutions due to different institutional, legal, and regulatory settings in place. In addition, future research could extend the analysis to examine the impact of operational risk event announcements on analysts' stock recommendations, although it is not as dynamic as analyst forecasts.

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# APPENDIX A

## Table 3.1 Description of Variables

This table provides the definitions and the sources of the variables used in this study.

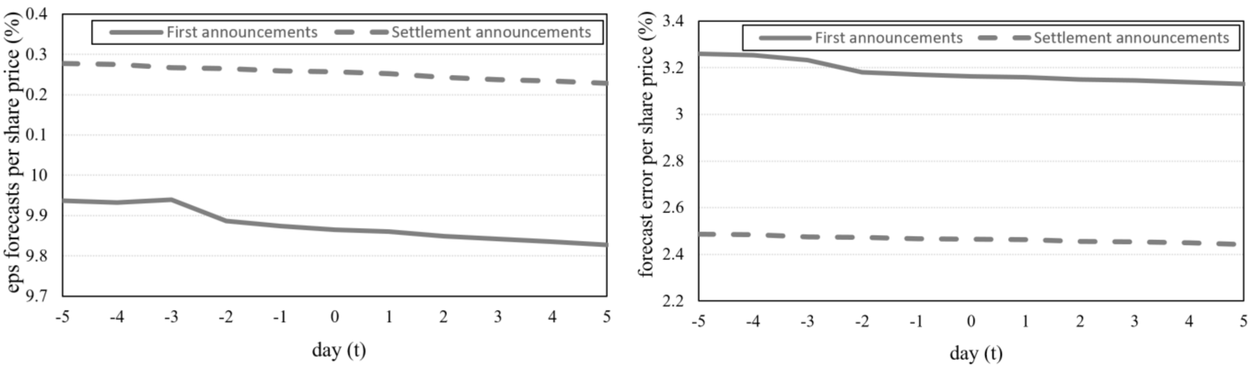
| Variable | Definition | Data Source |
|---|---|---|
| **Measures of Analyst Forecast Quality** | | |
| *Analyst Forecast Revision* | Analyst forecast revision is defined as the annualized percentage change in EPS forecast. It is computed as the difference between the current EPS and the previous EPS of analyst $i$ for firm $j$, standardized by the share price on day -6, and scaled by the number of calendar days since the previous forecast and multiplied by 365. | I/B/E/S, CRSP |
| *Analyst Forecast Error Change* | Analyst forecast error change is defined as the annualized percentage change in forecast error. It is computed as the difference between the current and the previous forecast error of analyst $i$ for firm $j$ (where, forecast error is defined as the absolute difference between the analyst's forecast and actual EPS, standardized by the share price on day -6), scaled by the number of calendar days since the previous forecast and multiplied by 365. | I/B/E/S, CRSP |
| **Event-Level Variables** | | |
| *Unknown Loss Amount Dum* | 1 if the operational loss amount is not known or there is no estimate of the loss on the first announcement date; 0 otherwise. | Algo FIRST, LexisNexis |
| *Post Global Settlement Dum* | 1 if the operational risk event announcement is after the Global Settlement of 2003 and before the Global Financial Crisis; 0 otherwise. | Algo FIRST, LexisNexis |
| *Global Financial Crisis Dum* | 1 if the operational risk event announcement happens during the Global Financial Crisis; 0 otherwise. | Algo FIRST, LexisNexis |
| *Post Global Financial Crisis Dum* | 1 if the operational risk event announcement is after the Global Financial Crisis; 0 otherwise. | Algo FIRST, LexisNexis |
| *Walk-Down Effect* | Difference between the actual EPS announcement date and day -6 of the operational risk event announcement date. Measurement units: years | Algo FIRST, LexisNexis, I/B/E/S |
| *CAR* | Negative of the Cumulative abnormal returns (CAR) over the reaction window centered on the announcement date. Measurement units: percent | WRDS Event Study |
| *IF Dum, CPBP Dum, EF Dum* | 1 if the operational risk event announced is of event types Internal Fraud; Clients, Products, and Business Practices; and External Fraud; and is 0 otherwise. | Algo FIRST, LexisNexis |

| | | |
|---|---|---|
| **Analyst-Level Variables** | | |
| *EPS Forecast Bias* | 1 if signed forecast error (i.e. bias) of analyst $i$ for firm $j$ on day -6 is positive; 0 otherwise. | I/B/E/S |
| *Broker Size* | Number of analysts employed by the brokerage firm employing analyst $i$ on day -6. | I/B/E/S |
| *Firm Experience* | Number of years of firm-specific experience for analyst $i$ following firm $j$. | I/B/E/S |
| *General Experience* | Number of years analyst $i$ following firm $j$ is providing forecasts in I/B/E/S. | I/B/E/S |
| *Industry Experience* | Number of years of industry experience for analyst $i$ following firm $j$. | I/B/E/S |
| *Number of Firms* | Number of firms covered by analyst $i$ following firm $j$ on day -6. | I/B/E/S |
| *Number of Industries* | Number of unique two-digit Standard Industrial Classification (SIC) codes of all firms covered by analyst $i$ following firm $j$ on day -6. | I/B/E/S |
| **Firm-Level Control Variables** | | |
| *Employers Dum* | 1 if the forecast is for a firm with a sell-side equity department (investment bank); 0 otherwise. | SEC Edgar, 10-K filings, I/B/E/S |
| *Number of Analysts Following* | Number of analysts following firm $j$ on day -6. | I/B/E/S |
| *Log Total Assets* | Natural logarithm of the deflated total assets at the end of the quarter prior to day -6. Measurement units: $ln$ (USD) | CRSP, Compustat |
| *Return on Assets* | Income before extraordinary items scaled by total assets at the end of the quarter prior to day -6. Measurement units: percent | CRSP, Compustat |
| *Leverage* | Sum of short-term and long-term debt scaled by total assets at the end of the quarter prior to day -6. Measurement units: percent | CRSP, Compustat |
| *Book to Market Ratio* | Book value of equity divided by the market value of equity at the end of the quarter prior to day -6. Measurement units: percent | CRSP, Compustat |
| *Equity Return Volatility* | Standard deviation of the daily equity return at the end of the quarter prior to day -6. Measurement units: percent | CRSP |

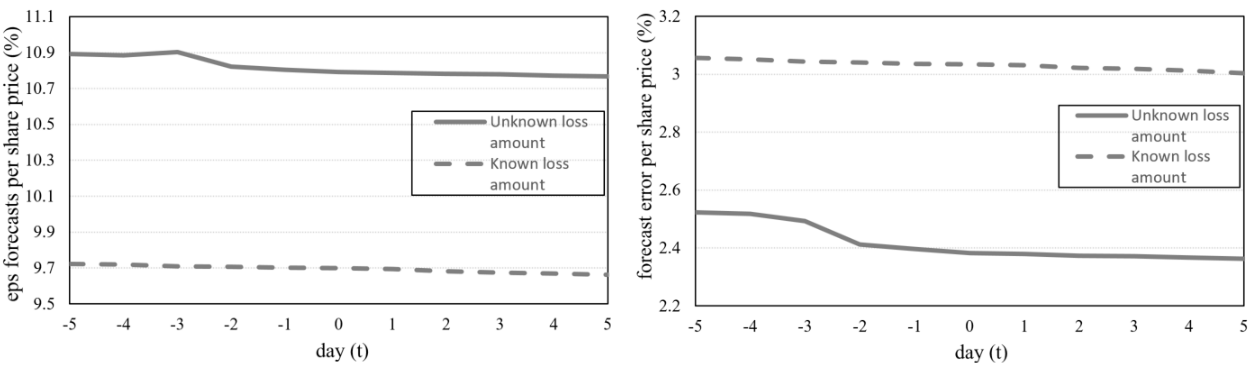
**Figure 3.1 Measures of Analyst Forecast Quality**

This figure illustrates daily average analyst forecast revision (left) and daily average analyst forecast error change (right) during the event window (-5, +5) around operational risk event announcements for our sample data, for various characteristics of the events and analysts. Daily average analyst forecast revision is computed as the percentage change in EPS forecasts per share. Daily average analyst forecast error change is computed as the difference in percentage forecast error per share.

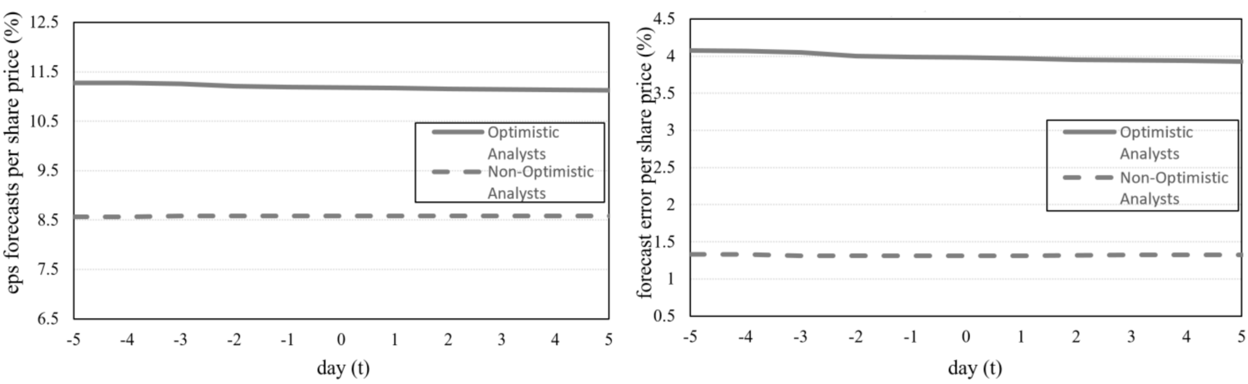
Panel A: First announcements and settlement announcements



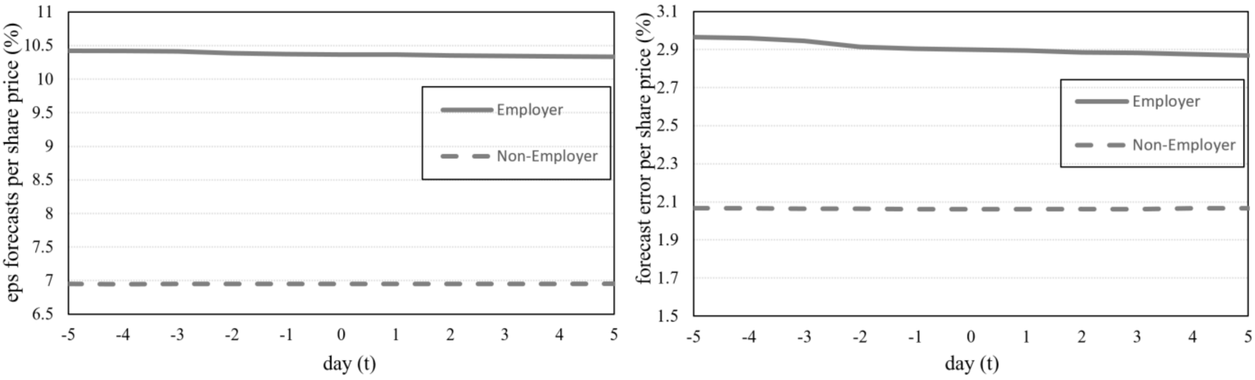

Panel B: Known and unknown loss amount



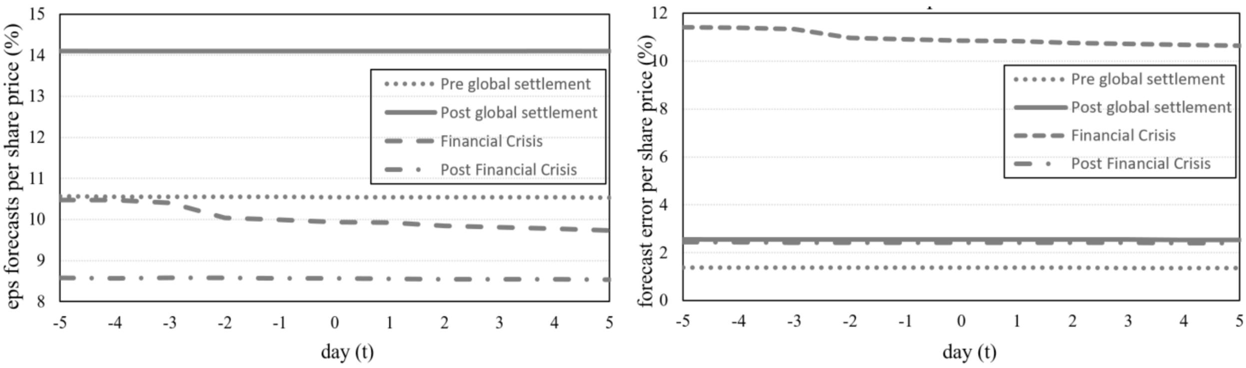

Panel C: Optimistic and non-optimistic analysts



Panel D: Employers and non-employers




Panel E: Different time periods




Panel F: Different event types

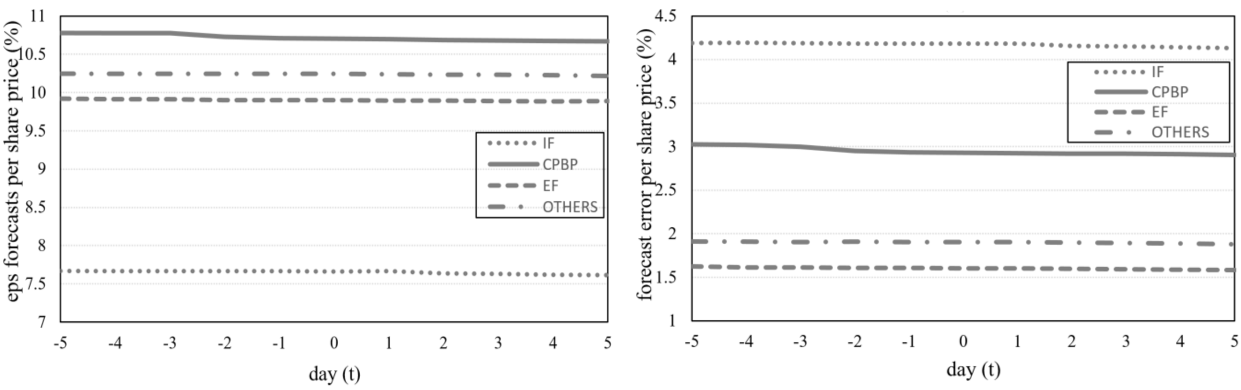


**Table 3.2 Sample Selection Procedure**

This table details the screening procedure of data on operational risk event announcements in U.S. banks for the period 1990-2016.

| Data Screening Description | Number of Operational Risk Event Announcements |
|---|---|
| 1. Algo FIRST Database | 1,630 |
| – Events with no event description information | (62) |
| – Events whose first announcement date are not available | (228) |
| – Events that occurred in listed subsidiaries are non-bank firms (two-digit SIC other than 60, 61, 62 and 67) | (2) |
| – Events from firms that are not publicly listed | (46) |
| – Events for which the first announcement date has no corresponding settlement date and settlement loss amount | (369) |
| 2. Final sample | 923 |

**Table 3.3 Composition of the Final Sample**

This table reports the composition of our final sample that is used for the first announcement and settlement announcement analyses in this study. We lose more than half of the observations after removing events that overlap with other announcements, such as 10-Qs, 10-Ks, and 8-Ks, and material events that took place within an event window of (-5, +5), i.e., one trading week before to one trading week after the announcement date.

| Sample Screening Description | Number of Event Announcements | |
|---|---|---|
| | First Announcements | Settlement Announcements |
| 1. Full sample | 923 | 923 |
| − Operational risk events that overlap with 8-K reports released during the event window (-5, +5) | (598) | (609) |
| − Operational risk events that overlap with quarterly and annual earnings announcements (10-Qs and 10-Ks) during the event window (-5, +5) | (10) | (15) |
| 2. Final sample | 315 | 299 |

## Table 3.4 Sample Descriptive Statistics

This table reports the descriptive statistics for our variables. All variable definitions are as reported in Table 3.1.

| Variable | N | Min | 1p | 5p | 25p | 50p | Mean | SD | 75p | 95p | 99p | Max |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Measures of Analyst Forecast Quality | | | | | | | | | | | | |
| *Analyst Forecast Revision (-5, -1)* | 13,417 | -9.19 | -9.19 | 0 | 0 | 0 | -0.1483 | 1.09 | 0 | 0 | 0.91 | 0.91 |
| *Analyst Forecast Revision (0, +5)* | 13,417 | -11.72 | -11.72 | -0.33 | 0 | 0 | -0.2341 | 1.48 | 0 | 0 | 1.51 | 1.51 |
| *Analyst Forecast Revision (-5, +5)* | 13,417 | -20.91 | -11.72 | -2.49 | 0 | 0 | -0.3824 | 1.84 | 0 | 0 | 1.43 | 2.29 |
| *Analyst Forecast Error Change (-5, -1)* | 13,417 | -8.37 | -8.37 | 0 | 0 | 0 | -0.1411 | 0.99 | 0 | 0 | 0.52 | 0.52 |
| *Analyst Forecast Error Change (0, +5)* | 13,417 | -9.30 | -9.30 | -0.17 | 0 | 0 | -0.1613 | 1.18 | 0 | 0 | 2.30 | 2.30 |
| *Analyst Forecast Error Change (-5, +5)* | 13,417 | -17.67 | -9.30 | -1.86 | 0 | 0 | -0.3024 | 1.55 | 0 | 0 | 2.11 | 2.82 |
| Event-Level Variables | | | | | | | | | | | | |
| *CAR (-5, -1)* | 13,417 | -15.74 | -8.18 | -4.15 | -1.16 | 0.06 | 0.07 | 2.86 | 1.49 | 3.79 | 11.09 | 16.36 |
| *CAR (0, +5)* | 13,417 | -15.47 | -7.22 | -4.14 | -1.28 | 0.44 | 0.50 | 3.35 | 2.03 | 6.39 | 10.31 | 14.43 |
| *CAR (-5, +5)* | 13,417 | -21.02 | -11.74 | -5.75 | -1.43 | 0.26 | 0.58 | 4.40 | 2.71 | 8.08 | 12.44 | 19.34 |
| *Unknown Loss Amount Dum* | 13,417 | 0 | 0 | 0 | 0 | 0 | 0.33 | 0.47 | 1 | 1 | 1 | 1 |
| *Post Global Settlement Dum* | 13,417 | 0 | 0 | 0 | 0 | 0 | 0.18 | 0.38 | 0 | 1 | 1 | 1 |
| *Global Financial Crisis Dum* | 13,417 | 0 | 0 | 0 | 0 | 0 | 0.07 | 0.26 | 0 | 1 | 1 | 1 |
| *Post Global Financial Crisis Dum* | 13,417 | 0 | 0 | 0 | 0 | 1 | 0.54 | 0.50 | 1 | 1 | 1 | 1 |
| *Walk-Down Effect* | 13,417 | 0.04 | 0.05 | 0.08 | 0.30 | 0.46 | 0.48 | 0.27 | 0.66 | 0.93 | 0.98 | 1.07 |
| *IF Dum* | 13,417 | 0 | 0 | 0 | 0 | 0 | 0.16 | 0.37 | 0 | 1 | 1 | 1 |
| *CPBP Dum* | 13,417 | 0 | 0 | 0 | 0 | 1 | 0.58 | 0.49 | 1 | 1 | 1 | 1 |
| *EF Dum* | 13,417 | 0 | 0 | 0 | 0 | 0 | 0.12 | 0.32 | 0 | 1 | 1 | 1 |
| Analyst-Level Variables | | | | | | | | | | | | |
| *EPS Forecast Bias Day -6 Dum* | 13,417 | 0 | 0 | 0 | 0 | 1 | 0.57 | 0.50 | 1 | 1 | 1 | 1 |
| *Broker Size* | 13,417 | 1 | 1 | 7 | 25 | 50 | 69.72 | 58.39 | 106 | 178 | 288 | 288 |
| *Firm Experience* | 13,417 | 0.11 | 0.68 | 1.52 | 4.12 | 6.79 | 7.71 | 4.50 | 11.44 | 15.76 | 18.39 | 26.25 |
| *General Experience* | 13,417 | 0.4 | 2.1 | 4.3 | 9.98 | 14.61 | 15.16 | 7.24 | 19.83 | 29.42 | 30.94 | 32.12 |
| *Industry Experience* | 13,417 | 0.02 | 0.39 | 1.47 | 4.62 | 9.26 | 9.62 | 5.68 | 13.81 | 20.18 | 22.86 | 27.98 |
| *Number of Firms* | 13,417 | 2 | 2 | 5 | 11 | 15 | 16.30 | 8.62 | 20 | 31 | 53 | 53 |
| *Number of Industries* | 13,417 | 1 | 1 | 2 | 4 | 6 | 5.96 | 2.97 | 7 | 12 | 17 | 17 |
| Firm-Level Variables | | | | | | | | | | | | |
| *Employers Dum* | 13,417 | 0 | 0 | 0 | 1 | 1 | 0.91 | 0.29 | 1 | 1 | 1 | 1 |
| *Number of Analysts Following* | 13,417 | 4 | 8 | 14 | 20 | 25 | 24.60 | 6.46 | 29 | 35 | 39 | 40 |
| *Log Total Assets* | 13,417 | 21.68 | 22.96 | 24.01 | 26.06 | 27.13 | 26.82 | 1.38 | 28.12 | 28.39 | 28.50 | 28.51 |
| *Return on Assets* | 13,417 | -0.31 | -0.31 | -0.05 | 0.12 | 0.21 | 0.20 | 0.15 | 0.31 | 0.41 | 0.51 | 0.51 |
| *Leverage* | 13,417 | 0.78 | 5.66 | 8.42 | 20.51 | 26.94 | 32.68 | 17.90 | 53.08 | 61.40 | 67.41 | 81.50 |
| *Book to Market Ratio* | 13,417 | 22.35 | 22.35 | 35.31 | 50.48 | 85.71 | 92.55 | 49.37 | 125.23 | 185.14 | 231.63 | 231.63 |
| *Equity Return Volatility* | 13,417 | 0.28 | 0.28 | 0.49 | 0.59 | 0.71 | 0.84 | 0.40 | 0.89 | 1.68 | 2.70 | 2.70 |

# Table 3.5 Analyst Forecast Quality: Mean Comparison Tests

This table reports mean comparison of analyst forecast revision and the mean analyst forecast error change during pre-announcement period (-5, -1), post-announcement period (0, +5), and full event window (-5, +5) around operational risk event announcements for sub-samples of independent variables. For dichotomous variables, the two sub-samples are determined by the value of the variable, labeled as 1 or 0, and for continuous variables, the two sub-samples refer to observations above and below the median value, labeled as High and Low. *t-statistics* are reported in parentheses. *, ** and *** denote statistical significance at the 10%, 5%, and 1% level, respectively, and are based on the two-tailed test of mean difference. All variable definitions are reported in Table 3.1.

| Variable | Group | Analyst Forecast Revision | | | | | | Analyst Forecast Error Change | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | (-5, -1) | | (0, +5) | | (-5, +5) | | (-5, -1) | | (0, +5) | | (-5, +5) | |
| | | N | Mean (t-stat) | N | Mean (t-stat) | N | Mean (t-stat) | N | Mean (t-stat) | N | Mean (t-stat) | N | Mean (t-stat) |
| *Unknown Loss Amount Dum* | 1 | 4,370 | -0.1865 | 4,370 | -0.2286 | 4,370 | -0.4151 | 4,370 | -0.1727 | 4,370 | -0.1754 | 4,370 | -0.3482 |
| | 0 | 9,047 | -0.1298 | 9,047 | -0.2368 | 9,047 | -0.3666 | 9,047 | -0.1258 | 9,047 | -0.1545 | 9,047 | -0.2804 |
| | | | (2.84)*** | | (-0.30) | | (1.43) | | (2.58)** | | (0.96) | | (2.38)** |
| *EPS Forecast Bias Dum* | 1 | 7,596 | -0.2391 | 7,596 | -0.3388 | 7,596 | -0.5779 | 7,596 | -0.2086 | 7,596 | -0.2722 | 7,596 | -0.4807 |
| | 0 | 5,821 | -0.0297 | 5,821 | -0.0975 | 5,821 | -0.1272 | 5,821 | -0.0531 | 5,821 | -0.0167 | 5,821 | -0.0698 |
| | | | (11.20)*** | | (9.40)*** | | (14.14)*** | | (9.05)*** | | (12.52)*** | | (15.39)*** |
| *Employers Dum* | 1 | 12,190 | -0.1622 | 12,190 | -0.2567 | 12,190 | -0.4189 | 12,190 | -0.1529 | 12,190 | -0.1774 | 12,190 | -0.3304 |
| | 0 | 1,227 | -0.0103 | 1,227 | -0.0094 | 1,227 | -0.0197 | 1,227 | -0.0236 | 1,227 | -0.0015 | 1,227 | -0.0251 |
| | | | (4.67)*** | | (5.59)*** | | (7.25)*** | | (4.37)*** | | (4.99)*** | | (6.60)*** |
| *Analysts Following* | High | 6,288 | -0.0736 | 6,288 | -0.1638 | 6,288 | -0.2374 | 6,288 | -0.0567 | 6,288 | -0.0883 | 6,288 | -0.1450 |
| | Low | 7,129 | -0.2141 | 7,129 | -0.2961 | 7,129 | -0.5102 | 7,129 | -0.2156 | 7,129 | -0.2257 | 7,129 | -0.4413 |
| | | | (-7.50)*** | | (-5.17)*** | | (-8.58)*** | | (-9.32)*** | | (-6.75)*** | | (-11.13)*** |
| *Post Global Settlement Dum* | 1 | 2,370 | -0.0104 | 2,370 | -0.0268 | 2,370 | -0.0165 | 2,370 | -0.0725 | 2,370 | -0.0559 | 2,370 | -0.1284 |
| | 0 | 2,807 | -0.0893 | 2,807 | -0.1282 | 2,807 | -0.2175 | 2,807 | -0.0856 | 2,807 | -0.0927 | 2,807 | -0.1783 |
| | | | (-5.99)*** | | (-4.05)*** | | (-6.62)*** | | (-0.67) | | (-1.77)* | | (-1.73)* |
| *Global Financial Crisis Dum* | 1 | 956 | -0.5353 | 956 | -0.6925 | 956 | -1.2278 | 956 | -0.5387 | 956 | -0.5908 | 956 | -1.1295 |
| | 0 | 2,807 | -0.0893 | 2,807 | -0.1282 | 2,807 | -0.2175 | 2,807 | -0.0856 | 2,807 | -0.0927 | 2,807 | -0.1783 |
| | | | (9.54)*** | | (9.39)*** | | (13.25)*** | | (10.26)*** | | (10.10)*** | | (14.40)*** |
| *Post Global Financial Crisis Dum* | 1 | 7,284 | -0.1718 | 7,284 | -0.2822 | 7,284 | -0.4540 | 7,284 | -0.1326 | 7,284 | -0.1657 | 7,284 | -0.2984 |
| | 0 | 2,807 | -0.0893 | 2,807 | -0.1282 | 2,807 | -0.2175 | 2,807 | -0.0856 | 2,807 | -0.0927 | 2,807 | -0.1783 |
| | | | (3.50)*** | | (4.74)*** | | (5.90)*** | | (2.34)** | | (2.89)*** | | (3.71)*** |

# Table 3.6 Estimation Results for Analyst Forecast Revision

This table reports the estimation results for *analyst forecast revision* during pre-announcement period (-5, -1), post-announcement period (0, +5), and full event window (-5, +5) around operational risk event first announcements and settlement announcements. Models 1 contain baseline regressions and Models 2 contain regressions with an interaction variable. Robust standard errors are used to correct for operational risk event clustering. *t-statistics* are reported in parentheses. *, ** and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively (two-tailed). All variable definitions are reported in Table 3.1.

| | Models 1 (baseline) | | | | | | Models 2 (with interaction) | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | First Announcements | | | Settlement Announcements | | | First Announcements | | | Settlement Announcements | | |
| | (-5, -1) | (0, +5) | (-5, +5) | (-5, -1) | (0, +5) | (-5, +5) | (-5, -1) | (0, +5) | (-5, +5) | (-5, -1) | (0, +5) | (-5, +5) |
| Event-Level Variables | | | | | | | | | | | | |
| *Unknown Loss Amount Dum* | -0.0200 | 0.0045 | -0.0166 | -0.0282 | 0.0170 | -0.0031 | -0.0193 | 0.0051 | -0.0154 | -0.0243 | 0.0171 | 0.0032 |
| | (-0.38) | (0.07) | (-0.16) | (-0.72) | (0.30) | (-0.04) | (-0.37) | (0.08) | (-0.15) | (-0.61) | (0.30) | (0.04) |
| *Post Global Settlement Dum* | 0.2104*** | 0.2279*** | 0.4145*** | 0.2156*** | 0.2405*** | 0.4757*** | 0.2058*** | 0.2237*** | 0.4059*** | 0.2074*** | 0.2404** | 0.4637*** |
| | (3.04) | (2.76) | (3.14) | (3.04) | (2.60) | (2.99) | (3.00) | (2.67) | (3.05) | (2.91) | (2.50) | (2.84) |
| *Global Financial Crisis Dum* | -0.3908** | -0.4209** | -0.7615** | -0.1901 | -0.3936 | -0.4879 | -0.3923** | -0.4223** | -0.7642** | -0.1967 | -0.3937 | -0.4950 |
| | (-2.21) | (-2.01) | (-2.22) | (-1.22) | (-1.64) | (-1.36) | (-2.22) | (-2.02) | (-2.23) | (-1.27) | (-1.64) | (-1.38) |
| *Post Global Financial Crisis Dum* | -0.1217 | -0.0664 | -0.2270 | -0.0293 | -0.0699 | -0.0981 | -0.1286 | -0.0727 | -0.2399 | -0.0401 | -0.0701 | -0.1140 |
| | (-1.17) | (-0.60) | (-1.14) | (-0.34) | (-0.63) | (-0.55) | (-1.24) | (-0.65) | (-1.20) | (-0.46) | (-0.62) | (-0.61) |
| *CAR* | -0.0396** | 0.0214 | -0.0048 | -0.0162 | 0.0119 | -0.0064 | -0.0396** | 0.0213 | -0.0048 | -0.0163 | 0.0118 | -0.0068 |
| | (-2.10) | (1.56) | (-0.23) | (-1.49) | (1.07) | (-0.46) | (-2.10) | (1.56) | (-0.24) | (-1.50) | (1.05) | (-0.49) |
| Analyst-Level Variable | | | | | | | | | | | | |
| *EPS Forecast Bias Day -6 Dum* | -0.1468*** | -0.1547*** | -0.3057*** | -0.1521*** | -0.1705*** | -0.3188*** | -0.1467*** | -0.1545*** | -0.3054*** | -0.1532*** | -0.1705*** | -0.3206*** |
| | (-3.80) | (-2.72) | (-3.54) | (-4.66) | (-3.07) | (-4.17) | (-3.80) | (-2.72) | (-3.54) | (-4.66) | (-3.06) | (-4.17) |
| Firm-Level Variables | | | | | | | | | | | | |
| *Employers Dum* | 0.0159 | -0.0229 | -0.0543 | -0.0358 | -0.0557 | -0.0736 | -0.1019 | -0.1316 | -0.2759 | -0.1863 | -0.0585 | -0.3046 |
| | (0.31) | (-0.35) | (-0.57) | (-0.76) | (-0.93) | (-0.79) | (-0.71) | (-0.67) | (-0.96) | (-1.45) | (-0.34) | (-1.14) |
| *Number of Analysts Following* | 0.0139* | 0.0074 | 0.0221* | 0.0078 | -0.0013 | 0.0061 | 0.0099 | 0.0037 | 0.0144 | 0.0027 | -0.0014 | -0.0017 |
| | (1.82) | (1.39) | (1.86) | (1.61) | (-0.25) | (0.71) | (1.30) | (0.50) | (1.07) | (0.48) | (-0.19) | (-0.14) |
| *Employers Dum*Analysts Following* | | | | | | | 0.0046 | 0.0042 | 0.0086 | 0.0057 | 0.0001 | 0.0088 |
| | | | | | | | (0.77) | (0.62) | (0.81) | (1.09) | (0.02) | (0.86) |
| Constant | 1.2952* | 1.0497 | 2.4649* | 0.6105 | 1.1285 | 1.8060 | 1.3636** | 1.1129 | 2.5935** | 0.7217 | 1.1305 | 1.9751* |
| | (1.96) | (1.39) | (1.94) | (1.26) | (1.45) | (1.60) | (2.02) | (1.52) | (2.06) | (1.47) | (1.48) | (1.80) |
| Control Variables | | | | | | | | | | | | |
| *Event-Level Control Variables* | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| *Analyst-Level Control Variables* | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| *Firm-Level Control Variables* | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Number of Observations | 6,877 | 6,877 | 6,877 | 6,540 | 6,540 | 6,540 | 6,877 | 6,877 | 6,877 | 6,540 | 6,540 | 6,540 |
| $R^2$ | 0.0516 | 0.0267 | 0.0580 | 0.0287 | 0.0228 | 0.0430 | 0.0517 | 0.0267 | 0.0581 | 0.0289 | 0.0228 | 0.0431 |

# Table 3.7 Estimation Results for Analyst Forecast Error Change

This table reports the estimation results for *analyst forecast error change* during pre-announcement period (-5, -1), post-announcement period (0, +5), and full event window (-5, +5) around operational risk event first announcements and settlement announcements. Models 1 contain baseline regressions and Models 2 contain regressions with an interaction variable. Robust standard errors are used to correct for operational risk event clustering. *t-statistics* are reported in parentheses. *, ** and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively (two-tailed). All variable definitions are reported in Table 3.1.

| | Models 1 (baseline) | | | | | | Models 2 (with interaction) | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | First Announcements | | | Settlement Announcements | | | First Announcements | | | Settlement Announcements | | |
| | (-5, -1) | (0, +5) | (-5, +5) | (-5, -1) | (0, +5) | (-5, +5) | (-5, -1) | (0, +5) | (-5, +5) | (-5, -1) | (0, +5) | (-5, +5) |
| Event-Level Variables | | | | | | | | | | | | |
| *Unknown Loss Amount Dum* | -0.0190 | -0.0183 | -0.0443 | -0.0245 | -0.0223 | -0.0415 | -0.0180 | -0.0168 | -0.0418 | -0.0174 | -0.0184 | -0.0280 |
| | (-0.44) | (-0.39) | (-0.54) | (-0.70) | (-0.51) | (-0.57) | (-0.42) | (-0.36) | (-0.51) | (-0.49) | (-0.41) | (-0.38) |
| *Post Global Settlement Dum* | 0.1315* | 0.1377** | 0.2475** | 0.0874 | 0.1246* | 0.2286* | 0.1240* | 0.1275** | 0.2302** | 0.0723 | 0.1175 | 0.2033 |
| | (1.96) | (2.21) | (2.24) | (1.19) | (1.78) | (1.67) | (1.87) | (2.04) | (2.08) | (0.98) | (1.63) | (1.45) |
| *Global Financial Crisis Dum* | -0.4519*** | -0.4619*** | -0.8931*** | -0.1948 | -0.3865* | -0.4960 | -0.4544*** | -0.4653*** | -0.8985*** | -0.2067 | -0.3902* | -0.5112 |
| | (-2.70) | (-2.66) | (-2.97) | (-1.32) | (-1.84) | (-1.54) | (-2.72) | (-2.69) | (-2.99) | (-1.40) | (-1.86) | (-1.59) |
| *Post Global Financial Crisis Dum* | -0.0573 | -0.0291 | -0.1215 | -0.0175 | -0.0386 | -0.0624 | -0.0684 | -0.0443 | -0.1473 | -0.0372 | -0.0484 | -0.0958 |
| | (-0.65) | (-0.34) | (-0.76) | (-0.23) | (-0.47) | (-0.42) | (-0.79) | (-0.52) | (-0.92) | (-0.47) | (-0.58) | (-0.62) |
| *CAR* | -0.0319* | 0.0194* | 0.0032 | -0.0159 | 0.0161* | -0.0014 | -0.0320* | 0.0194* | 0.0030 | -0.0161* | 0.0157* | -0.0023 |
| | (-1.81) | (1.78) | (0.19) | (-1.64) | (1.92) | (-0.13) | (-1.82) | (1.78) | (0.18) | (-1.67) | (1.84) | (-0.21) |
| Analyst-Level Variable | | | | | | | | | | | | |
| *EPS Forecast Bias Day -6 Dum* | -0.1107*** | -0.2087*** | -0.3247*** | -0.1018*** | -0.1937*** | -0.2911*** | -0.1105*** | -0.2084*** | -0.3241*** | -0.1039*** | -0.1947*** | -0.2947*** |
| | (-3.29) | (-5.71) | (-5.27) | (-3.51) | (-5.35) | (-5.04) | (-3.29) | (-5.72) | (-5.27) | (-3.56) | (-5.38) | (-5.09) |
| Firm-Level Variables | | | | | | | | | | | | |
| *Employers Dum* | -0.0352 | -0.0688 | -0.1345 | -0.0050 | -0.0347 | -0.0176 | -0.2261* | -0.3286** | -0.5766** | -0.2804** | -0.1744 | -0.5054** |
| | (-0.72) | (-1.34) | (-1.65) | (-0.11) | (-0.81) | (-0.22) | (-1.68) | (-2.23) | (-2.38) | (-2.42) | (-1.38) | (-2.36) |
| *Number of Analysts Following* | 0.0142** | 0.0088** | 0.0233** | 0.0068 | 0.0029 | 0.0091 | 0.0075 | -0.0002 | 0.0079 | -0.0024 | -0.0018 | -0.0072 |
| | (2.02) | (2.19) | (2.31) | (1.51) | (0.75) | (1.26) | (1.14) | (-0.03) | (0.71) | (-0.47) | (-0.33) | (-0.70) |
| *Employers Dum*Analysts Following* | | | | | | | 0.0074 | 0.0101** | 0.0171** | 0.0105** | 0.0053 | 0.0186** |
| | | | | | | | (1.38) | (2.02) | (1.98) | (2.27) | (1.12) | (2.28) |
| Constant | 0.6082 | 0.3988 | 1.1175 | 0.5147 | 0.7992 | 1.4132 | 0.7191 | 0.5498 | 1.3742 | 0.7182 | 0.9036* | 1.7701** |
| | (1.00) | (0.78) | (1.11) | (1.10) | (1.59) | (1.56) | (1.17) | (1.12) | (1.38) | (1.52) | (1.79) | (2.01) |
| Control Variables | | | | | | | | | | | | |
| *Event-Level Control Variables* | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| *Analyst-Level Control Variables* | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| *Firm-Level Control Variables* | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Number of Observations | 6,877 | 6,877 | 6,877 | 6,540 | 6,540 | 6,540 | 6,877 | 6,877 | 6,877 | 6,540 | 6,540 | 6,540 |
| $R^2$ | 0.0480 | 0.0314 | 0.0637 | 0.0208 | 0.0253 | 0.0390 | 0.0482 | 0.0316 | 0.0642 | 0.0214 | 0.0254 | 0.0397 |

## Table 3.8 Robustness Test with Severe Operational Losses Exceeding $10 and $35 Million: Mean Comparison Tests

This table reports mean comparison of analyst forecast revision and the mean analyst forecast error change during pre-announcement period (-5, -1), post-announcement period (0, +5), and full event window (-5, +5) around operational risk event announcements for sub-samples of independent variablesfor severe operational losses exceeding $10 million (Panel A) and exceeding $35 million (Panel B). For dichotomous variables, the two sub-samples are determined by the value of the variable, labeled as 1 or 0, and for continuous variables, the two sub-samples refer to observations above and below the median value, labeled as High and Low. *t-statistics* are reported in parentheses. *, ** and *** denote statistical significance at the 10%, 5%, and 1% level, respectively, and are based on the two-tailed test of mean difference. All variable definitions are reported in Table 3.1.

Panel A: Severe operational risk events with loss exceeding $10 million

| Variable | Group | Analyst Forecast Revision | | | | | | Analyst Forecast Error Change | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | (-5, -1) | | (0, +5) | | (-5, +5) | | (-5, -1) | | (0, +5) | | (-5, +5) | |
| | | N | Mean (t-stat) | N | Mean (t-stat) | N | Mean (t-stat) | N | Mean (t-stat) | N | Mean (t-stat) | N | Mean (t-stat) |
| *Unknown Loss Amount Dum* | 1 | 1,986 | -0.2885 | 1,986 | -0.3175 | 1,986 | -0.6060 | 1,986 | -0.2636 | 1,986 | -0.2552 | 1,986 | -0.5187 |
| | 0 | 2,783 | -0.1805 | 2,783 | -0.2958 | 2,783 | -0.4762 | 2,783 | -0.1649 | 2,783 | -0.2121 | 2,783 | -0.3769 |
| | | | (2.78)* | | (-0.45) | | (2.07)** | | (2.82)*** | | (1.09) | | (2.66)*** |
| *EPS Forecast Bias Dum* | 1 | 2,693 | -0.3664 | 2,693 | -0.4838 | 2,693 | -0.8501 | 2,693 | -0.3218 | 2,693 | -0.3996 | 2,693 | -0.7214 |
| | 0 | 2,076 | -0.0427 | 2,076 | -0.0727 | 2,076 | -0.1153 | 2,076 | -0.0557 | 2,076 | -0.0101 | 2,076 | -0.0657 |
| | | | (8.45)*** | | (8.61)*** | | (11.97)*** | | (7.69)*** | | (10.04)*** | | (12.56)*** |
| *Employers Dum* | 1 | 4,419 | -0.2430 | 4,419 | -0.3264 | 4,419 | -0.5694 | 4,419 | -0.2205 | 4,419 | -0.2497 | 4,419 | -0.4701 |
| | 0 | 350 | -0.0038 | 350 | -0.0324 | 350 | -0.0362 | 350 | -0.0232 | 350 | 0.0181 | 350 | -0.0051 |
| | | | (3.26)*** | | (3.22)*** | | (4.51)*** | | (2.98)*** | | (3.60)*** | | (4.62)*** |
| *Analysts Following* | High | 2,535 | -0.0741 | 2,535 | -0.1868 | 2,535 | -0.2609 | 2,535 | -0.0399 | 2,535 | -0.1211 | 2,535 | -0.1610 |
| | Low | 2,234 | -0.3972 | 2,234 | -0.4388 | 2,234 | -0.8360 | 2,234 | -0.3945 | 2,234 | -0.3536 | 2,234 | -0.7480 |
| | | | (-8.49)*** | | (-5.29)*** | | (-9.38)*** | | (-10.36)*** | | (-5.99)*** | | (-11.29)*** |
| *Post Global Settlement Dum* | 1 | 538 | 0.0257 | 538 | -0.0086 | 538 | -0.2090 | 538 | -0.1083 | 538 | -0.0758 | 538 | -0.1841 |
| | 0 | 1,078 | -0.0866 | 1,078 | -0.1224 | 1,078 | 0.0170 | 1,078 | -0.0807 | 1,078 | -0.0944 | 1,078 | -0.1751 |
| | | | (-3.50)*** | | (-2.50)*** | | (-3.91)*** | | (0.75) | | (-0.49) | | (0.16) |
| *Global Financial Crisis Dum* | 1 | 401 | -0.9774 | 401 | -0.8707 | 401 | -1.8481 | 401 | -0.5988 | 401 | -0.7690 | 401 | -1.7278 |
| | 0 | 1,078 | -0.0866 | 1,078 | -0.1224 | 1,078 | -0.2090 | 1,078 | -0.0807 | 1,078 | -0.0944 | 1,078 | -0.1751 |
| | | | (9.87)*** | | (7.24)*** | | (11.88)*** | | (10.31)*** | | (7.92)*** | | (12.91)*** |
| *Post Global Financial Crisis Dum* | 1 | 2,752 | -0.2194 | 2,752 | -0.3517 | 2,752 | -0.5711 | 2,752 | -0.1645 | 2,752 | -0.2347 | 2,752 | -0.3992 |
| | 0 | 1,078 | -0.0866 | 1,078 | -0.1224 | 1,078 | -0.2090 | 1,078 | -0.0807 | 1,078 | -0.0944 | 1,078 | -0.1751 |
| | | | (3.20)*** | | (4.12)*** | | (5.22)*** | | (2.40)** | | (3.15)** | | (3.94)*** |

Panel B: Severe operational risk events with loss exceeding $35 million

| Variable | Group | Analyst Forecast Revision | | | | | | Analyst Forecast Error Change | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | (-5, -1) | | (0, +5) | | (-5, +5) | | (-5, -1) | | (0, +5) | | (-5, +5) | |
| | | N | Mean (t-stat) | N | Mean (t-stat) | N | Mean (t-stat) | N | Mean (t-stat) | N | Mean (t-stat) | N | Mean (t-stat) |
| *Unknown Loss Amount Dum* | 1 | 1,269 | -0.3540 | 1,269 | -0.3730 | 1,269 | -0.7270 | 1,269 | -0.3044 | 1,269 | -0.2807 | 1,269 | -0.5851 |
| | 0 | 1,131 | -0.3263 | 1,131 | -0.3257 | 1,131 | -0.6520 | 1,131 | -0.2797 | 1,131 | -0.2095 | 1,131 | -0.4892 |
| | | | (0.42) | | (0.66) | | (0.75) | | (0.42) | | (1.26) | | (1.16) |
| *EPS Forecast Bias Dum* | 1 | 1,436 | -0.5016 | 1,436 | -0.5184 | 1,436 | -1.0200 | 1,436 | -0.4314 | 1,436 | -0.4147 | 1,436 | -0.8461 |
| | 0 | 964 | -0.1017 | 964 | -0.1009 | 964 | -0.2026 | 964 | -0.0862 | 964 | 0.0024 | 964 | -0.0838 |
| | | | (5.93)*** | | (5.74)*** | | (8.19)*** | | (5.80)*** | | (7.35)*** | | (9.18)*** |
| *Employers Dum* | 1 | 2,275 | -0.3588 | 2,275 | -0.3652 | 2,275 | -0.7240 | 2,275 | -0.3091 | 2,275 | -0.2635 | 2,275 | -0.5726 |
| | 0 | 125 | -0.0160 | 125 | -0.0877 | 125 | -0.1037 | 125 | 0.0041 | 125 | 0.0510 | 125 | 0.0552 |
| | | | (2.29)** | | (1.72)* | | (2.78)*** | | (2.37)** | | (2.49)** | | (3.37)*** |
| *Analysts Following* | High | 1,145 | -0.1390 | 1,145 | -0.2489 | 1,145 | -0.3879 | 1,145 | -0.0431 | 1,145 | -0.1537 | 1,145 | -0.1968 |
| | Low | 1,255 | -0.5253 | 1,255 | -0.4436 | 1,255 | -0.9688 | 1,255 | -0.5206 | 1,255 | -0.3324 | 1,255 | -0.8530 |
| | | | (-5.84)*** | | (-2.71)*** | | (-5.89)*** | | (-8.23)*** | | (-3.18)*** | | (-8.02)*** |
| *Post Global Settlement Dum* | 1 | 115 | 0.1012 | 115 | 0.0509 | 115 | 0.1521 | 115 | -0.4111 | 115 | -0.0706 | 115 | -0.4818 |
| | 0 | 491 | -0.1272 | 491 | -0.1723 | 491 | -0.2994 | 491 | -0.0825 | 491 | -0.1344 | 491 | -0.2170 |
| | | | (-2.78)*** | | (-1.89)* | | (-3.11)*** | | (3.54)*** | | (-0.66) | | (1.96)* |
| *Global Financial Crisis Dum* | 1 | 219 | -1.3829 | 219 | -1.0248 | 219 | -2.4077 | 219 | -1.3676 | 219 | -0.8660 | 219 | -2.2337 |
| | 0 | 491 | -0.1272 | 491 | 0.1723 | 491 | -0.2994 | 491 | -0.0825 | 491 | -0.1344 | 491 | -0.2170 |
| | | | (8.13)*** | | (5.04)*** | | (9.17)*** | | (9.02)*** | | (5.35)*** | | (10.25)*** |
| *Post Global Financial Crisis Dum* | 1 | 1,575 | -0.2950 | 1,575 | -0.3419 | 1,575 | -0.6369 | 1,575 | -0.2002 | 1,575 | -0.2091 | 1,575 | -0.4093 |
| | 0 | 491 | -0.1272 | 491 | -0.1723 | 491 | -0.2994 | 491 | -0.0825 | 491 | -0.1344 | 491 | -0.2170 |
| | | | (2.36)*** | | (2.12)** | | (3.16)*** | | (2.07)** | | (1.21) | | (2.28)** |

## Table 3.9 Robustness Test: Estimation Results for Severe Operational Losses Exceeding $10 Million

This table reports the estimation results for analyst forecast quality during pre-announcement period (-5, -1), post-announcement period (0, +5), and full event window (-5, +5) around operational risk event first announcements and settlement announcements for a sub-sample of operational loss amounts exceeding $10 million. Models 1 contain baseline regressions and Models 2 contain regressions with an interaction variable. Robust standard errors are used to correct for operational risk event clustering. *t-statistics* are reported in parentheses. *, ** and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively (two-tailed). All variable definitions are reported in Table 3.1.

Panel A: Analyst forecast revision

| | Models 1 (baseline) | | | | | | Models 2 (with interaction) | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | First Announcements | | | Settlement Announcements | | | First Announcements | | | Settlement Announcements | | |
| | (-5, -1) | (0, +5) | (-5, +5) | (-5, -1) | (0, +5) | (-5, +5) | (-5, -1) | (0, +5) | (-5, +5) | (-5, -1) | (0, +5) | (-5, +5) |
| Event-Level Variables | | | | | | | | | | | | |
| *Unknown Loss Amount Dum* | 0.1402 | 0.1168 | 0.2600 | -0.0067 | 0.1973* | 0.2063 | 0.1517 | 0.1277 | 0.2829 | 0.0088 | 0.2053* | 0.2328 |
| | (1.07) | (1.08) | (1.18) | (-0.08) | (1.72) | (1.07) | (1.11) | (1.14) | (1.23) | (0.10) | (1.76) | (1.19) |
| *Post Global Settlement Dum* | 0.3156* | 0.3413** | 0.6139** | 0.3872*** | 0.3399** | 0.7239*** | 0.3261* | 0.3515** | 0.6338** | 0.3670*** | 0.3310** | 0.6952*** |
| | (1.95) | (2.26) | (2.25) | (2.82) | (2.26) | (2.74) | (1.95) | (2.31) | (2.26) | (2.76) | (2.19) | (2.64) |
| *Global Financial Crisis Dum* | -0.8070** | -0.4368 | -1.1479* | -0.3736 | -0.4630 | -0.8345 | -0.8119** | -0.4427 | -1.1551* | -0.4095 | -0.4751 | -0.8681 |
| | (-2.38) | (-1.24) | (-1.73) | (-1.18) | (-0.93) | (-1.06) | (-2.39) | (-1.25) | (-1.74) | (-1.36) | (-0.96) | (-1.12) |
| *Post Global Financial Crisis Dum* | -0.3607* | -0.0873 | -0.5216 | 0.0095 | 0.0332 | 0.0232 | -0.3528* | -0.0799 | -0.5075 | -0.0472 | 0.0071 | -0.0616 |
| | (-1.86) | (-0.47) | (-1.47) | (0.06) | (0.17) | (0.07) | (-1.86) | (-0.44) | (-1.47) | (-0.29) | (0.04) | (-0.18) |
| *CAR* | -0.0609** | 0.0178 | -0.0404* | -0.0447** | -0.0085 | -0.0239 | -0.0614** | 0.0176 | -0.0413* | -0.0472*** | -0.0100 | -0.0276 |
| | (-2.59) | (0.93) | (-1.68) | (-2.53) | (-0.46) | (-1.06) | (-2.62) | (0.92) | (-1.73) | (-2.76) | (-0.52) | (-1.19) |
| Analyst-Level Variable | | | | | | | | | | | | |
| *EPS Forecast Bias Day -6 Dum* | -0.2021** | -0.3205*** | -0.5070*** | -0.1791*** | -0.3793*** | -0.5543*** | -0.2093** | -0.3276*** | -0.5210*** | -0.1768*** | -0.3777*** | -0.5489*** |
| | (-2.05) | (-3.48) | (-2.86) | (-2.95) | (-5.18) | (-4.76) | (-2.09) | (-3.49) | (-2.89) | (-2.91) | (-5.15) | (-4.71) |
| Firm-Level Variables | | | | | | | | | | | | |
| *Employers Dum* | -0.3720 | -0.1080 | -0.6127 | -0.0524 | -0.0413 | -0.0088 | 0.3169 | 0.5652 | 0.7425 | -0.7010* | -0.3273 | -0.9840 |
| | (-1.29) | (-0.41) | (-1.13) | (-0.45) | (-0.37) | (-0.05) | (0.49) | (1.10) | (0.70) | (-1.73) | (-1.03) | (-1.54) |
| *Number of Analysts Following* | 0.0364* | 0.0182 | 0.0559* | 0.0132 | -0.0040 | 0.0087 | 0.0667 | 0.0479 | 0.1158 | -0.0055 | -0.0125 | -0.0198 |
| | (1.88) | (1.46) | (1.93) | (1.26) | (-0.49) | (0.55) | (1.58) | (1.49) | (1.62) | (-0.45) | (-0.97) | (-0.83) |
| *Employers Dum*Analysts Following* | | | | | | | -0.0311 | -0.0304 | -0.0614 | 0.0224 | 0.0101 | 0.0341 |
| | | | | | | | (-0.91) | (-1.14) | (-1.06) | (1.53) | (0.88) | (1.46) |
| Constant | 2.5513* | 0.9393 | 3.5763 | 1.1142 | 0.1506 | 0.9629 | 2.0008 | 0.4016 | 2.4929 | 1.7530* | 0.4116 | 1.8660 |
| | (1.73) | (0.79) | (1.48) | (1.30) | (0.14) | (0.58) | (1.31) | (0.34) | (1.01) | (1.68) | (0.38) | (1.05) |
| Control Variables | | | | | | | | | | | | |
| *Event-Level Control Variables* | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| *Analyst-Level Control Variables* | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| *Firm-Level Control Variables* | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Number of Observations | 2,565 | 2,565 | 2,565 | 2,204 | 2,204 | 2,204 | 2,565 | 2,565 | 2,565 | 2,204 | 2,204 | 2,204 |
| $R^2$ | 0.1197 | 0.0457 | 0.1243 | 0.0719 | 0.0480 | 0.0958 | 0.1203 | 0.0461 | 0.1253 | 0.0741 | 0.0482 | 0.0975 |

Panel B: Analyst forecast error change

| | Models 1 (baseline) | | | | | | Models 2 (with interaction) | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | First Announcements | | | Settlement Announcements | | | First Announcements | | | Settlement Announcements | | |
| | (-5, -1) | (0, +5) | (-5, +5) | (-5, -1) | (0, +5) | (-5, +5) | (-5, -1) | (0, +5) | (-5, +5) | (-5, -1) | (0, +5) | (-5, +5) |
| Event-Level Variables | | | | | | | | | | | | |
| *Unknown Loss Amount Dum* | 0.1157 | 0.0772 | 0.1881 | 0.0109 | 0.1311 | 0.1581 | 0.1255 | 0.0851 | 0.2054 | 0.0334 | 0.1414 | 0.1947 |
| | (1.05) | (0.91) | (1.04) | (0.13) | (1.39) | (0.93) | (1.10) | (0.96) | (1.08) | (0.40) | (1.48) | (1.13) |
| *Post Global Settlement Dum* | 0.1888 | 0.2095* | 0.3727 | 0.1634 | 0.2327* | 0.3913 | 0.1977 | 0.2168* | 0.3878 | 0.1341 | 0.2214* | 0.3516 |
| | (1.25) | (1.69) | (1.53) | (1.16) | (1.78) | (1.55) | (1.27) | (1.73) | (1.55) | (1.00) | (1.69) | (1.41) |
| *Global Financial Crisis Dum* | -0.9356*** | -0.5121* | -1.4262** | -0.4017 | -0.5035 | -0.9117 | -0.9398*** | -0.5163* | -1.4317** | -0.4538 | -0.5189 | -0.9582 |
| | (-3.01) | (-1.85) | (-2.53) | (-1.31) | (-1.13) | (-1.23) | (-3.02) | (-1.86) | (-2.54) | (-1.58) | (-1.17) | (-1.33) |
| *Post Global Financial Crisis Dum* | -0.2693 | -0.1254 | -0.4401 | -0.0436 | 0.0056 | -0.0616 | -0.2627 | -0.1200 | -0.4294 | -0.1259 | -0.0278 | -0.1788 |
| | (-1.63) | (-0.83) | (-1.49) | (-0.30) | (0.04) | (-0.21) | (-1.63) | (-0.81) | (-1.48) | (-0.82) | (-0.17) | (-0.59) |
| *CAR* | -0.0493** | 0.0115 | -0.0241 | -0.0416** | 0.0007 | -0.0163 | -0.0498** | 0.0114 | -0.0248 | -0.0452*** | -0.0012 | -0.0214 |
| | (-2.25) | (0.79) | (-1.29) | (-2.53) | (0.05) | (-0.83) | (-2.28) | (0.79) | (-1.33) | (-2.90) | (-0.08) | (-1.07) |
| Analyst-Level Variable | | | | | | | | | | | | |
| *EPS Forecast Bias Day -6 Dum* | -0.1863** | -0.3647*** | -0.5433*** | -0.0882 | -0.2719*** | -0.3557*** | -0.1925** | -0.3699*** | -0.5538*** | -0.0849 | -0.2698*** | -0.3482*** |
| | (-2.30) | (-4.95) | (-4.01) | (-1.52) | (-4.43) | (-3.37) | (-2.32) | (-4.92) | (-3.99) | (-1.48) | (-4.39) | (-3.31) |
| Firm-Level Variables | | | | | | | | | | | | |
| *Employers Dum* | -0.4196 | -0.3356* | -0.8195* | 0.0517 | 0.0527 | 0.2006 | 0.1669 | 0.1498 | 0.2087 | -0.8898** | -0.3125 | -1.1471** |
| | (-1.61) | (-1.80) | (-1.91) | (0.46) | (0.59) | (1.16) | (0.31) | (0.38) | (0.25) | (-2.57) | (-1.10) | (-2.10) |
| *Number of Analysts Following* | 0.0385** | 0.0212** | 0.0606** | 0.0133 | 0.0012 | 0.0138 | 0.0643* | 0.0426* | 0.1060* | -0.0138 | -0.0096 | -0.0255 |
| | (2.19) | (2.32) | (2.53) | (1.35) | (0.20) | (1.05) | (1.73) | (1.74) | (1.80) | (-1.39) | (-0.91) | (-1.28) |
| *Employers Dum*Analysts Following* | | | | | | | -0.0265 | -0.0219 | -0.0466 | 0.0325** | 0.0129 | 0.0471** |
| | | | | | | | (-0.90) | (-1.05) | (-0.97) | (2.58) | (1.32) | (2.38) |
| Constant | 1.4091 | 0.7758 | 2.2299 | 0.8583 | 0.7715 | 1.3038 | 0.9405 | 0.3881 | 1.4080 | 1.7855* | 1.1048 | 2.5519* |
| | (1.13) | (0.90) | (1.25) | (1.04) | (1.01) | (0.94) | (0.74) | (0.48) | (0.77) | (1.84) | (1.42) | (1.80) |
| Control Variables | | | | | | | | | | | | |
| *Event-Level Control Variables* | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| *Analyst-Level Control Variables* | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| *Firm-Level Control Variables* | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Number of Observations | 2,565 | 2,565 | 2,565 | 2,204 | 2,204 | 2,204 | 2,565 | 2,565 | 2,565 | 2,204 | 2,204 | 2,204 |
| $R^2$ | 0.1325 | 0.0616 | 0.1549 | 0.0587 | 0.0511 | 0.0925 | 0.1330 | 0.0619 | 0.1557 | 0.0638 | 0.0516 | 0.0969 |

## Table 3.10 Robustness Test: Estimation Results for Severe Operational Losses Exceeding $35 Million

This table reports the estimation results for analyst forecast quality during pre-announcement period (-5, -1), post-announcement period (0, +5), and full event window (-5, +5) around operational risk event first announcements and settlement announcements for a sub-sample of operational loss amounts exceeding $35 million. Models 1 contain baseline regressions and Models 2 contain regressions with an interaction variable. Robust standard errors are used to correct for operational risk event clustering. *t-statistics* are reported in parentheses. *, ** and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively (two-tailed). All variable definitions are reported in Table 3.1.

Panel A: Analyst forecast revision

| | Models 1 (baseline) | | | | | | Models 2 (with interaction) | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | First Announcements | | | Settlement Announcements | | | First Announcements | | | Settlement Announcements | | |
| | (-5, -1) | (0, +5) | (-5, +5) | (-5, -1) | (0, +5) | (-5, +5) | (-5, -1) | (0, +5) | (-5, +5) | (-5, -1) | (0, +5) | (-5, +5) |
| Event-Level Variables | | | | | | | | | | | | |
| *Unknown Loss Amount Dum* | 0.2650 | 0.1768 | 0.5928 | 0.1934 | 0.3076* | 0.5335 | 0.2491 | 0.1761 | 0.5759 | 0.1898 | 0.3058* | 0.5359 |
| | (1.09) | (0.92) | (1.61) | (1.00) | (1.91) | (1.62) | (1.00) | (0.91) | (1.53) | (0.97) | (1.91) | (1.61) |
| *Post Global Settlement Dum* | 0.2153 | 0.2596 | 0.5581 | 0.7223*** | 0.4211 | 1.1905** | 0.1156 | 0.2551 | 0.4520 | 0.7408*** | 0.4070 | 1.2456** |
| | (0.52) | (0.71) | (0.74) | (3.26) | (1.41) | (2.20) | (0.25) | (0.66) | (0.54) | (3.46) | (1.36) | (2.31) |
| *Global Financial Crisis Dum* | -0.9483** | -0.4107 | -1.0596* | 0.0665 | -0.1115 | 0.0219 | -0.9863** | -0.4124 | -1.0998* | 0.0950 | -0.1362 | 0.1165 |
| | (-2.52) | (-1.04) | (-1.74) | (0.24) | (-0.20) | (0.03) | (-2.59) | (-1.03) | (-1.78) | (0.34) | (-0.25) | (0.14) |
| *Post Global Financial Crisis Dum* | -0.5698 | 0.2259 | -0.1538 | -0.1758 | 0.0465 | -0.1050 | -0.6311 | 0.2232 | -0.2193 | -0.1650 | 0.0387 | -0.0750 |
| | (-1.47) | (0.81) | (-0.26) | (-0.69) | (0.16) | (-0.20) | (-1.55) | (0.77) | (-0.35) | (-0.64) | (0.13) | (-0.14) |
| *CAR* | -0.0812** | 0.0247 | -0.0670* | -0.0903*** | -0.0313 | -0.0614*** | -0.0812** | 0.0247 | -0.0670* | -0.0985*** | -0.0274 | -0.0714** |
| | (-2.16) | (0.83) | (-1.86) | (-3.33) | (-1.26) | (-2.70) | (-2.16) | (0.83) | (-1.86) | (-3.09) | (-0.83) | (-2.36) |
| Analyst-Level Variable | | | | | | | | | | | | |
| *EPS Forecast Bias Day -6 Dum* | -0.1981 | -0.2509** | -0.4617 | -0.1606* | -0.4321*** | -0.5637*** | -0.1724 | -0.2497** | -0.4344 | -0.1722* | -0.4321*** | -0.5694*** |
| | (-1.05) | (-2.29) | (-1.59) | (-1.75) | (-3.83) | (-3.08) | (-0.90) | (-2.23) | (-1.46) | (-1.93) | (-3.83) | (-3.10) |
| Firm-Level Variables | | | | | | | | | | | | |
| *Employers Dum* | 0.5134 | 0.6417*** | 1.1138*** | 0.5946* | 0.2946 | 1.0707* | -5.6063 | 0.3676 | -5.4102 | -0.8972 | 0.8099 | -1.1584 |
| | (1.65) | (3.10) | (2.93) | (1.82) | (0.96) | (1.94) | (-1.48) | (0.13) | (-0.80) | (-0.83) | (0.61) | (-0.58) |
| *Number of Analysts Following* | 0.0534 | 0.0052 | 0.0700 | 0.0495** | 0.0192* | 0.0699*** | -0.2336 | -0.0076 | -0.2359 | -0.0016 | 0.0374 | -0.0077 |
| | (1.44) | (0.31) | (1.29) | (2.50) | (1.86) | (2.76) | (-1.43) | (-0.06) | (-0.82) | (-0.05) | (0.71) | (-0.10) |
| *Employers Dum*Analysts Following* | | | | | | | 0.2888 | 0.0129 | 0.3079 | 0.0521 | -0.0189 | 0.0801 |
| | | | | | | | (1.58) | (0.09) | (0.95) | (1.32) | (-0.38) | (1.07) |
| Constant | 2.7386 | -0.6111 | 2.1593 | 2.3458 | 1.0860 | 2.6838 | 8.5460 | -0.3510 | 8.3498 | 4.1931 | 0.5120 | 5.2758 |
| | (0.93) | (-0.28) | (0.46) | (1.28) | (0.67) | (0.93) | (1.52) | (-0.09) | (0.85) | (1.47) | (0.34) | (1.36) |
| Control Variables | | | | | | | | | | | | |
| *Event-Level Control Variables* | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| *Analyst-Level Control Variables* | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| *Firm-Level Control Variables* | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Number of Observations | 1,348 | 1,348 | 1,348 | 1,052 | 1,052 | 1,052 | 1,348 | 1,348 | 1,348 | 1,052 | 1,052 | 1,052 |
| $R^2$ | 0.1293 | 0.0449 | 0.1268 | 0.1152 | 0.0781 | 0.1601 | 0.1305 | 0.0449 | 0.1274 | 0.1167 | 0.0783 | 0.1613 |

Panel B: Analyst forecast error change

| | Models 1 (baseline) | | | | | | Models 2 (with interaction) | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | First Announcements | | | Settlement Announcements | | | First Announcements | | | Settlement Announcements | | |
| | (-5, -1) | (0, +5) | (-5, +5) | (-5, -1) | (0, +5) | (-5, +5) | (-5, -1) | (0, +5) | (-5, +5) | (-5, -1) | (0, +5) | (-5, +5) |
| Event-Level Variables | | | | | | | | | | | | |
| *Unknown Loss Amount Dum* | 0.1519 | 0.0139 | 0.2581 | 0.1855 | 0.2087 | 0.4255 | 0.1402 | 0.0096 | 0.2420 | 0.1819 | 0.2100 | 0.4286 |
| | (0.78) | (0.09) | (0.91) | (1.03) | (1.47) | (1.42) | (0.70) | (0.06) | (0.83) | (0.99) | (1.48) | (1.41) |
| *Post Global Settlement Dum* | -0.2314 | 0.1429 | -0.0446 | 0.1241 | 0.2686 | 0.4287 | -0.3042 | 0.1159 | -0.1458 | 0.1422 | 0.2790 | 0.4992 |
| | (-0.64) | (0.50) | (-0.07) | (0.52) | (0.86) | (0.76) | (-0.76) | (0.37) | (-0.22) | (0.62) | (0.90) | (0.91) |
| *Global Financial Crisis Dum* | -1.0914*** | -0.4715 | -1.3990** | -0.0277 | -0.2369 | -0.2171 | -1.1192*** | -0.4817 | -1.4373*** | 0.0002 | -0.2185 | -0.0961 |
| | (-3.41) | (-1.44) | (-2.62) | (-0.10) | (-0.49) | (-0.28) | (-3.48) | (-1.45) | (-2.67) | (0.00) | (-0.45) | (-0.13) |
| *Post Global Financial Crisis Dum* | -0.3919 | 0.0630 | -0.1972 | -0.2061 | -0.0301 | -0.2171 | -0.4368 | 0.0463 | -0.2596 | -0.1956 | -0.0243 | -0.1786 |
| | (-1.25) | (0.24) | (-0.39) | (-0.84) | (-0.12) | (-0.46) | (-1.34) | (0.17) | (-0.50) | (-0.78) | (-0.10) | (-0.36) |
| *CAR* | -0.0630* | 0.0103 | -0.0457* | -0.0810*** | -0.0177 | -0.0468** | -0.0629* | 0.0102 | -0.0457* | -0.0890*** | -0.0206 | -0.0596** |
| | (-1.84) | (0.43) | (-1.73) | (-3.27) | (-0.87) | (-2.28) | (-1.84) | (0.42) | (-1.73) | (-3.06) | (-0.76) | (-2.21) |
| Analyst-Level Variable | | | | | | | | | | | | |
| *EPS Forecast Bias Day -6 Dum* | -0.2063* | -0.3552*** | -0.5654*** | -0.1367 | -0.2984*** | -0.4084** | -0.1875 | -0.3482*** | -0.5394** | -0.1480* | -0.2983*** | -0.4158** |
| | (-1.75) | (-3.57) | (-2.78) | (-1.54) | (-3.31) | (-2.48) | (-1.58) | (-3.38) | (-2.61) | (-1.70) | (-3.31) | (-2.52) |
| Firm-Level Variables | | | | | | | | | | | | |
| *Employers Dum* | 0.2305 | -0.2334 | -0.0412 | 0.5446* | 0.2510 | 0.9728* | -4.2444 | -1.8941 | -6.2590 | -0.9136 | -0.1316 | -1.8800 |
| | (0.87) | (-1.28) | (-0.12) | (1.78) | (0.93) | (1.92) | (-1.26) | (-0.78) | (-1.12) | (-0.91) | (-0.12) | (-1.00) |
| *Number of Analysts Following* | 0.0587* | 0.0145 | 0.0805* | 0.0478** | 0.0124 | 0.0610** | -0.1511 | -0.0634 | -0.2110 | -0.0021 | -0.0011 | -0.0382 |
| | (1.77) | (0.98) | (1.74) | (2.61) | (1.41) | (2.61) | (-1.00) | (-0.57) | (-0.86) | (-0.07) | (-0.03) | (-0.54) |
| *Employers Dum*Analysts Following* | | | | | | | 0.2112 | 0.0784 | 0.2934 | 0.0510 | 0.0140 | 0.1025 |
| | | | | | | | (1.28) | (0.67) | (1.08) | (1.39) | (0.34) | (1.48) |
| Constant | 1.8810 | 0.3636 | 2.3601 | 2.2676 | 1.0374 | 2.5844 | 6.1275 | 1.9395 | 8.2601 | 4.0734 | 1.4637 | 5.9017 |
| | (0.76) | (0.21) | (0.64) | (1.36) | (0.77) | (1.01) | (1.28) | (0.59) | (1.03) | (1.56) | (1.12) | (1.67) |
| Control Variables | | | | | | | | | | | | |
| *Event-Level Control Variables* | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| *Analyst-Level Control Variables* | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| *Firm-Level Control Variables* | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Number of Observations | 1,348 | 1,348 | 1,348 | 1,052 | 1,052 | 1,052 | 1,348 | 1,348 | 1,348 | 1,052 | 1,052 | 1,052 |
| $R^2$ | 0.1580 | 0.0481 | 0.1566 | 0.1028 | 0.0748 | 0.1506 | 0.1588 | 0.0482 | 0.1573 | 0.1044 | 0.0749 | 0.1534 |

# Table 3.11 Robustness Test: Estimation Results for the Subsample of Announcements Prior to the Global Financial Crisis

This table reports the estimation results for analyst forecast quality during pre-announcement period (-5, -1), post-announcement period (0, +5), and full event window (-5, +5) around operational risk event first announcements and settlement announcements for a subsample of events that occurred (or settled) prior to the Global Financial Crisis. Models 1 contain baseline regressions and Models 2 contain regressions with an interaction variable. Robust standard errors are used to correct for operational risk event clustering. *t-statistics* are reported in parentheses. *, ** and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively (two-tailed). All variable definitions are reported in Table 3.1.

Panel A: Analyst forecast revision

| | Models 1 (baseline) | | | | | | Models 2 (with interaction) | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | First Announcements | | | Settlement Announcements | | | First Announcements | | | Settlement Announcements | | |
| | (-5, -1) | (0, +5) | (-5, +5) | (-5, -1) | (0, +5) | (-5, +5) | (-5, -1) | (0, +5) | (-5, +5) | (-5, -1) | (0, +5) | (-5, +5) |
| Event-Level Variables | | | | | | | | | | | | |
| *Unknown Loss Amount Dum* | -0.0159 | -0.0681 | -0.1040 | 0.0265 | 0.0922* | 0.1068 | -0.0104 | -0.0517 | -0.0822 | 0.0523 | 0.1188** | 0.1550 |
| | (-0.51) | (-1.18) | (-1.51) | (0.51) | (1.83) | (1.19) | (-0.32) | (-0.94) | (-1.22) | (0.82) | (2.08) | (1.45) |
| *CAR* | -0.0096 | 0.0218 | 0.0202 | 0.0018 | 0.0329* | 0.0381** | -0.0093 | 0.0224 | 0.0212 | 0.0010 | 0.0300* | 0.0346* |
| | (-0.98) | (1.01) | (0.82) | (0.21) | (1.90) | (2.02) | (-0.96) | (1.05) | (0.86) | (0.12) | (1.78) | (1.98) |
| Analyst-Level Variable | | | | | | | | | | | | |
| *EPS Forecast Bias Day -6 Dum* | -0.0975*** | -0.1390*** | -0.2585*** | -0.0956*** | -0.1163*** | -0.2115*** | -0.0989*** | -0.1423*** | -0.2637*** | -0.1018*** | -0.1222*** | -0.2224*** |
| | (-3.42) | (-3.27) | (-3.69) | (-2.82) | (-3.05) | (-3.25) | (-3.44) | (-3.38) | (-3.77) | (-2.89) | (-3.18) | (-3.33) |
| Firm-Level Variables | | | | | | | | | | | | |
| *Employers Dum* | 0.0063 | -0.0795 | -0.1159 | -0.0215 | -0.0063 | -0.0091 | -0.1960 | -0.6790** | -0.9481** | -0.4194* | -0.3997* | -0.7201* |
| | (0.18) | (-1.01) | (-1.22) | (-0.45) | (-0.09) | (-0.08) | (-1.60) | (-2.50) | (-2.36) | (-1.83) | (-1.79) | (-1.84) |
| *Number of Analysts Following* | 0.0068 | 0.0102* | 0.0177 | 0.0135* | 0.0185** | 0.0333** | 0.0007 | -0.0078 | -0.0072 | 0.0031 | 0.0081 | 0.0146 |
| | (1.22) | (1.85) | (1.62) | (1.84) | (2.25) | (2.11) | (0.21) | (-1.20) | (-0.92) | (0.73) | (1.10) | (1.24) |
| *Employers Dum*Analysts Following* | | | | | | | 0.0072 | 0.0215** | 0.0298** | 0.0145 | 0.0144* | 0.0259* |
| | | | | | | | (1.63) | (2.16) | (2.08) | (1.61) | (1.70) | (1.72) |
| Constant | 0.6297 | -0.4207 | 0.0703 | 0.5829 | 1.8282** | 3.0649* | 0.7118 | -0.1784 | 0.3989 | 0.8001 | 2.0303** | 3.3870* |
| | (0.87) | (-0.43) | (0.05) | (0.81) | (2.32) | (1.75) | (0.95) | (-0.19) | (0.29) | (0.98) | (2.40) | (1.82) |
| Control Variables | | | | | | | | | | | | |
| *Event-Level Control Variables* | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| *Analyst-Level Control Variables* | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| *Firm-Level Control Variables* | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Number of Observations | 2,911 | 2,911 | 2,911 | 2,266 | 2,266 | 2,266 | 2,911 | 2,911 | 2,911 | 2,266 | 2,266 | 2,266 |
| $R^2$ | 0.0294 | 0.0356 | 0.0467 | 0.0427 | 0.0586 | 0.0916 | 0.0302 | 0.0383 | 0.0505 | 0.0459 | 0.0601 | 0.0950 |

Panel B: Analyst forecast error change

| | Models 1 (baseline) | | | | | | Models 2 (with interaction) | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | First Announcements | | | Settlement Announcements | | | First Announcements | | | Settlement Announcements | | |
| | (-5, -1) | (0, +5) | (-5, +5) | (-5, -1) | (0, +5) | (-5, +5) | (-5, -1) | (0, +5) | (-5, +5) | (-5, -1) | (0, +5) | (-5, +5) |
| Event-Level Variables | | | | | | | | | | | | |
| *Unknown Loss Amount Dum* | 0.0021 | -0.0439 | -0.0582 | 0.0314 | 0.0573 | 0.0796 | 0.0083 | -0.0306 | -0.0388 | 0.0636 | 0.0779 | 0.1300 |
| | (0.07) | (-0.92) | (-0.96) | (0.65) | (1.27) | (0.97) | (0.25) | (-0.68) | (-0.66) | (1.08) | (1.52) | (1.34) |
| *CAR* | -0.0046 | 0.0261* | 0.0217 | 0.0089 | 0.0303** | 0.0350** | -0.0043 | 0.0265* | 0.0226 | 0.0079 | 0.0281** | 0.0314** |
| | (-0.48) | (1.66) | (1.05) | (0.98) | (2.28) | (2.16) | (-0.46) | (1.71) | (1.11) | (0.91) | (2.18) | (2.09) |
| Analyst-Level Variable | | | | | | | | | | | | |
| *EPS Forecast Bias Day -6 Dum* | -0.0464 | -0.1149*** | -0.1820*** | -0.0097 | -0.0581* | -0.0672 | -0.0480* | -0.1175*** | -0.1866*** | -0.0175 | -0.0626* | -0.0786 |
| | (-1.62) | (-3.17) | (-2.98) | (-0.32) | (-1.80) | (-1.22) | (-1.66) | (-3.28) | (-3.06) | (-0.55) | (-1.92) | (-1.40) |
| Firm-Level Variables | | | | | | | | | | | | |
| *Employers Dum* | 0.0091 | -0.0503 | -0.0841 | 0.0364 | 0.0463 | 0.0956 | -0.2213* | -0.5368** | -0.8232** | -0.4601** | -0.2583 | -0.6486* |
| | (0.28) | (-0.82) | (-1.09) | (0.81) | (0.84) | (0.92) | (-1.90) | (-2.47) | (-2.47) | (-2.16) | (-1.46) | (-1.97) |
| *Number of Analysts Following* | 0.0058 | 0.0091** | 0.0159* | 0.0106 | 0.0158** | 0.0274** | -0.0010 | -0.0056 | -0.0063 | -0.0024 | 0.0078 | 0.0077 |
| | (1.08) | (2.19) | (1.72) | (1.51) | (2.47) | (2.01) | (-0.32) | (-1.00) | (-0.96) | (-0.66) | (1.34) | (0.77) |
| *Employers Dum*Analysts Following* | | | | | | | 0.0082** | 0.0174** | 0.0265** | 0.0181** | 0.0111* | 0.0271** |
| | | | | | | | (1.98) | (2.26) | (2.24) | (2.17) | (1.78) | (2.18) |
| Constant | 0.5101 | -0.5841 | -0.1662 | 1.1935* | 1.2339* | 2.9084* | 0.6036 | -0.3875 | 0.1256 | 1.4646* | 1.3903* | 3.2455* |
| | (0.72) | (-0.74) | (-0.15) | (1.68) | (1.80) | (1.86) | (0.82) | (-0.51) | (0.11) | (1.86) | (1.94) | (1.98) |
| Control Variables | | | | | | | | | | | | |
| *Event-Level Control Variables* | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| *Analyst-Level Control Variables* | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| *Firm-Level Control Variables* | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Number of Observations | 2,911 | 2,911 | 2,911 | 2,266 | 2,266 | 2,266 | 2,911 | 2,911 | 2,911 | 2,266 | 2,266 | 2,266 |
| $R^2$ | 0.0140 | 0.0336 | 0.0335 | 0.0184 | 0.0453 | 0.0599 | 0.0148 | 0.0365 | 0.0370 | 0.0219 | 0.0466 | 0.0637 |

# Table 3.12 Robustness Test: Estimation Results for the Subsample of Announcements During and After the Global Financial Crisis

This table reports the estimation results for analyst forecast quality during pre-announcement period (-5, -1), post-announcement period (0, +5), and full event window (-5, +5) around operational risk event first announcements and settlement announcements for a subsample of events that occurred (or settled) during or after the Global Financial Crisis. Models 1 contain baseline regressions and Models 2 contain regressions with an interaction variable. Robust standard errors are used to correct for operational risk event clustering. *t-statistics* are reported in parentheses. *, ** and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively (two-tailed). All variable definitions are reported in Table 3.1.

Panel A: Analyst forecast revision

| | Models 1 (baseline) | | | | | | Models 2 (with interaction) | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | First Announcements | | | Settlement Announcements | | | First Announcements | | | Settlement Announcements | | |
| | (-5, -1) | (0, +5) | (-5, +5) | (-5, -1) | (0, +5) | (-5, +5) | (-5, -1) | (0, +5) | (-5, +5) | (-5, -1) | (0, +5) | (-5, +5) |
| Event-Level Variables | | | | | | | | | | | | |
| *Unknown Loss Amount Dum* | 0.0000 | 0.0882 | 0.0998 | -0.0414 | -0.0017 | -0.0152 | -0.0025 | 0.0891 | 0.0965 | -0.0408 | -0.0016 | -0.0144 |
| | (0.00) | (0.80) | (0.53) | (-0.76) | (-0.02) | (-0.13) | (-0.02) | (0.80) | (0.51) | (-0.74) | (-0.02) | (-0.12) |
| *CAR* | -0.0510* | 0.0160 | -0.0139 | -0.0219 | -0.0063 | -0.0320* | -0.0510* | 0.0161 | -0.0142 | -0.0220 | -0.0063 | -0.0321* |
| | (-1.86) | (0.92) | (-0.53) | (-1.48) | (-0.51) | (-1.66) | (-1.86) | (0.92) | (-0.54) | (-1.49) | (-0.51) | (-1.67) |
| Analyst-Level Variable | | | | | | | | | | | | |
| *EPS Forecast Bias Day -6 Dum* | -0.1575** | -0.1041 | -0.2233 | -0.1351*** | -0.1693* | -0.2887** | -0.1566** | -0.1046 | -0.2218 | -0.1355*** | -0.1694* | -0.2892** |
| | (-2.20) | (-1.03) | (-1.49) | (-2.91) | (-1.92) | (-2.46) | (-2.19) | (-1.04) | (-1.49) | (-2.91) | (-1.92) | (-2.46) |
| Firm-Level Variables | | | | | | | | | | | | |
| *Employers Dum* | -0.1218 | 0.0073 | -0.1203 | -0.1086 | -0.0809 | -0.1711 | -0.2788 | 0.0726 | -0.3417 | -0.2682 | -0.1161 | -0.3894 |
| | (-1.03) | (0.06) | (-0.56) | (-1.39) | (-0.94) | (-1.10) | (-1.02) | (0.23) | (-0.64) | (-1.50) | (-0.42) | (-0.96) |
| *Number of Analysts Following* | 0.0187 | 0.0108 | 0.0300* | 0.0075 | -0.0049 | 0.0025 | 0.0116 | 0.0137 | 0.0199 | 0.0003 | -0.0065 | -0.0075 |
| | (1.54) | (1.30) | (1.67) | (1.12) | (-0.83) | (0.26) | (0.70) | (0.79) | (0.66) | (0.03) | (-0.52) | (-0.36) |
| *Employers Dum*Analysts Following* | | | | | | | 0.0075 | -0.0031 | 0.0105 | 0.0075 | 0.0017 | 0.0103 |
| | | | | | | | (0.54) | (-0.21) | (0.40) | (0.87) | (0.14) | (0.53) |
| Constant | 1.5087 | 2.4306** | 3.9534** | 0.3567 | 1.0815 | 1.2980 | 1.6077 | 2.3905** | 4.0888** | 0.4672 | 1.1060 | 1.4490 |
| | (1.50) | (2.14) | (2.08) | (0.63) | (1.07) | (0.99) | (1.58) | (2.22) | (2.18) | (0.83) | (1.19) | (1.18) |
| Control Variables | | | | | | | | | | | | |
| *Event-Level Control Variables* | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| *Analyst-Level Control Variables* | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| *Firm-Level Control Variables* | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Number of Observations | 3,966 | 3,966 | 3,966 | 4,274 | 4,274 | 4,274 | 3,966 | 3,966 | 3,966 | 4,274 | 4,274 | 4,274 |
| $R^2$ | 0.0523 | 0.0208 | 0.0516 | 0.0278 | 0.0196 | 0.0404 | 0.0523 | 0.0208 | 0.0516 | 0.0279 | 0.0196 | 0.0404 |

Panel B: Analyst forecast error change

| | Models 1 (baseline) | | | | | | Models 2 (with interaction) | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | First Announcements | | | Settlement Announcements | | | First Announcements | | | Settlement Announcements | | |
| | (-5, -1) | (0, +5) | (-5, +5) | (-5, -1) | (0, +5) | (-5, +5) | (-5, -1) | (0, +5) | (-5, +5) | (-5, -1) | (0, +5) | (-5, +5) |
| Event-Level Variables | | | | | | | | | | | | |
| *Unknown Loss Amount Dum* | -0.0274 | 0.0089 | -0.0119 | -0.0377 | -0.0379 | -0.0514 | -0.0321 | 0.0055 | -0.0210 | -0.0367 | -0.0368 | -0.0492 |
| | (-0.32) | (0.11) | (-0.08) | (-0.78) | (-0.61) | (-0.51) | (-0.36) | (0.06) | (-0.14) | (-0.76) | (-0.60) | (-0.49) |
| *CAR* | -0.0457* | 0.0091 | -0.0116 | -0.0254* | 0.0007 | -0.0264* | -0.0457* | 0.0086 | -0.0122 | -0.0256* | 0.0007 | -0.0266* |
| | (-1.76) | (0.65) | (-0.55) | (-1.95) | (0.08) | (-1.75) | (-1.76) | (0.61) | (-0.57) | (-1.96) | (0.07) | (-1.76) |
| Analyst-Level Variable | | | | | | | | | | | | |
| *EPS Forecast Bias Day -6 Dum* | -0.1509** | -0.2503*** | -0.3710*** | -0.1407*** | -0.2562*** | -0.3789*** | -0.1491** | -0.2486*** | -0.3671*** | -0.1413*** | -0.2569*** | -0.3803*** |
| | (-2.48) | (-4.23) | (-3.82) | (-3.91) | (-4.72) | (-4.78) | (-2.46) | (-4.20) | (-3.79) | (-3.92) | (-4.74) | (-4.80) |
| Firm-Level Variables | | | | | | | | | | | | |
| *Employers Dum* | -0.2061* | -0.1395 | -0.3420 | -0.0373 | -0.0587 | -0.0641 | -0.4993* | -0.3665 | -0.9499* | -0.2935* | -0.3663* | -0.6403* |
| | (-1.66) | (-1.23) | (-1.58) | (-0.35) | (-0.64) | (-0.35) | (-1.79) | (-1.41) | (-1.97) | (-1.68) | (-1.66) | (-1.80) |
| *Number of Analysts Following* | 0.0201* | 0.0104 | 0.0309** | 0.0066 | -0.0008 | 0.0053 | 0.0068 | 0.0001 | 0.0034 | -0.0051 | -0.0148 | -0.0210 |
| | (1.79) | (1.63) | (1.98) | (1.06) | (-0.17) | (0.64) | (0.44) | (0.01) | (0.12) | (-0.47) | (-1.37) | (-1.04) |
| *Employers Dum*Analysts Following* | | | | | | | 0.0139 | 0.0108 | 0.0288 | 0.0120 | 0.0145 | 0.0271 |
| | | | | | | | (1.01) | (0.82) | (1.17) | (1.24) | (1.40) | (1.45) |
| Constant | 0.8289 | 1.1261 | 2.0281 | 0.2705 | 0.7408 | 0.8959 | 1.0138 | 1.2653* | 2.3998 | 0.4478 | 0.9542 | 1.2945 |
| | (0.90) | (1.51) | (1.31) | (0.51) | (1.17) | (0.88) | (1.10) | (1.74) | (1.55) | (0.85) | (1.58) | (1.34) |
| Control Variables | | | | | | | | | | | | |
| *Event-Level Control Variables* | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| *Analyst-Level Control Variables* | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| *Firm-Level Control Variables* | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Number of Observations | 3,966 | 3,966 | 3,966 | 4,274 | 4,274 | 4,274 | 3,966 | 3,966 | 3,966 | 4,274 | 4,274 | 4,274 |
| $R^2$ | 0.0540 | 0.0263 | 0.0606 | 0.0268 | 0.0242 | 0.0466 | 0.0542 | 0.0264 | 0.0610 | 0.0270 | 0.0244 | 0.0470 |

# 4 The Impact of Operational Risk Event Announcements on CEO Compensation in the Banking Industry

## 4.1 Abstract

CEOs are held personally accountable for firms' performance. Idiosyncratic operational risk event announcements reveal bad news about firms' internal control systems, poor corporate governance and ineffective risk management. In this study, we examine the impact of operational risk event announcements, which reflect bad firm performance, in U.S. banks from 1992 to 2016 on different elements of CEO compensation in both a static and dynamic setting. We find evidence that banking executives are penalised following the frequency of operational risk events announced, mainly in terms of their option-based compensation. However, our findings are not consistent when operational risk event announcements are measured by their resulting stock market reactions. We document that the higher the compensation committee size as a proportion to board size, the more adverse is the impact of the frequency of operational risk event announcements on CEO option-based compensation. Interestingly, we also find statistical evidence that the negative effect of the frequency of operational risk events disclosed on CEO option-based compensation increases after different time periods including following the Sarbanes-Oxley Act in 2002, the Global Financial Crisis in 2007 and the Dodd-Frank Act in 2010.

## 4.2 Introduction

The rise in Chief Executive Officer (CEO) compensation in financial firms over the years has triggered a considerable amount of public controversy, regulatory scrutiny and academic research. The media in particular flagged up the striking pattern in the level of CEO's pay. Average CEO compensation in S&P 500 firms experienced a significant increase from under $1 million in 1970 to $14.5 million in 2018 (Jensen et al., 2004; Bereskin and Cicero, 2013; AFI-CIO, 2019). A concern for critics is that the increase in CEO compensation is not related to firm performance (Hubbard and Palia, 1995).

Executive compensation is a key part of corporate governance (Sapp, 2008)[7]. Generally, shareholders (principals) own the firm and employ the CEO (agent) to manage the firm on their behalf. This separation of ownership and control, however, gives rise to an agency problem. If CEOs are self-interested and shareholders cannot perfectly monitor them, they are likely to pursue interests that result in their private benefits not necessarily coinciding with the shareholder's objective of value maximisation (Jensen and Meckling, 1976).

Agency theory also suggests that there are divergent risk preferences. Shareholders are assumed to be risk-neutral because they can hold a diversified portfolio of shares, while executives are typically assumed to be risk-averse because their income is derived from one source (Dittmann et al., 2017). Consequently, CEOs may turn down positive net present value projects, which are risky, but attractive to shareholders who require an

[7] Corporate governance considers the means by which shareholders (i.e., owners) of firms assure themselves an adequate return on their investment.

increased return from a higher level of risk (McColgan, 2001). The corporate governance problem is therefore concerned with how to align the interest of senior executives with shareholders' objectives.

Optimal CEO compensation packages are designed to incentivise CEOs to take business risks where the expected return is expected to maximise shareholder value. CEO compensation usually comprises of a base salary, an annual bonus, stock options and long-term incentive plans (Murphy, 1999). Salary is a fixed pay, i.e., insensitive to firm performance, and is typically smaller than variable pay, which consists of bonus, restricted stocks and stock options. Variable pay is often tied directly to operating performance related to earnings or stock prices. Therefore, the components of pay linked to firm performance can serve to align goals of the executives with shareholders' goal of value maximisation.

If CEO compensation is uniquely salary-based, the CEO would have no incentive to take risk because she would want the firm to keep going along steadily to avoid dismissal. In contrast, compensation that is highly dependent on short-term financial performance may give rise to manipulative and opportunistic behaviour on the part of CEOs at the expense of shareholders' interest (Bebchuk and Fried, 2003). The concern is that, such manipulation adversely affects the firm's long-term performance. Such opportunistic behaviour is predicted by the managerial power theory. Therefore, there is concern with the design of CEO compensation schemes because of the difficulty in creating appropriate incentives.

The run-up to the financial crisis in 2007 was a result of excessive risk-taking in the financial industry (Gande and Kalpathy, 2017) and the repercussions were so severe that they even led to the failure of many financial institutions. While credit and market risks were argued to be the major causes of the global financial crisis, operational risk also played a significant role in fuelling the severity and duration of the crisis period through a series of mortgage frauds, negligent underwriting standards and failed due diligence (Robertson, 2011). Consequently, there has been an increased focus on CEO compensation in the U.S., especially in the banking sector, mainly due to their role in encouraging risk-taking that contributed to the crisis. Banks have since been under pressure to balance shareholders' demands to align pay and performance against regulators' enforcements to mitigate CEOs' excessive risk-taking (O'Donnell and Rodda, 2016). The Dodd-Frank Wall Street Reform and the Consumer Protection Act of 2010 enforce new proposals to limit incentive compensation for CEOs of financial firms. They require disclosure of information detailing the association between executive compensation paid and the firm's financial performance (Seitzinger, 2010).

Prior studies provide evidence that CEO compensation is a function of performance and that a positive relationship between pay and performance exists for samples of publicly listed firms (Murphy, 1985, 1986; Barro and Barro, 1990; Jensen and Murphy, 1990; Houston and James,1992; Smith and Watts, 1992; Rose and Shepard, 1994). More recent studies find that changes in CEO cash compensation are more sensitive to poor firm performance compared to good firm performance (Leone et al., 2006; Shaw and Zhang, 2010). The results vary depending on the sample and years studied.

The empirical studies on pay-for-performance relationship employ different specifications of how firm performance influences CEO compensation. These specifications include accounting performance measures (e.g. return on assets, debt ratio) and market-based performance measures (e.g. stock returns, changes in earnings yield). However, it is argued that managers manipulate the accounting-based performance measure, such as earnings, so that they benefit from a higher compensation, which is linked to the firm's performance (Healy, 1985). Our empirical study, on the other hand, captures an idiosyncratic risk in the form of operational risk event announcements as a measure of performance, which is not manipulated by CEOs, and examines whether their compensation is affected by it. While operational risk event announcements might be reflected in stock returns, we want to disentangle the impact by controlling for the stock return effect. Therefore, we contribute to this literature by employing a new measure of performance, more specifically a negative measure, that is, operational risk, which previous studies have failed to consider. One of the concerns is whether the CEO pay actually reflects firm performance (Hubbard and Palia, 1995) and one of the measures of firm performance we use in this study is operational risk event announcements, which is important in the banking sector.

The Basel Committee on Banking Supervision (BCBS) defines operational risk as 'the risk of loss resulting from inadequate or failed internal processes, people, and systems, or from external events. This definition includes legal risk, but excludes strategic and reputational risk' (BCBS, 2006, p.144). Over the last two decades, numerous banks all over the globe have suffered from large-scale operational losses, which have even resulted in the collapse of some banks. Some prominent examples of operational losses include: Barings Bank in 1995 losing $1.4 billion from rogue trading in its branch in

Singapore leading to the failure of the whole institution (Ross, 1997; Stonham, 1996), Allied Irish Bank (AIB) in 2002 losing $750 million in rogue trading (Dunne and Helliar, 2002), Société Générale in 2008 incurring a $7.2 billion trading loss, amongst others. The financial fallout of operational risk failures usually extends beyond the initial operational loss incurred to a severe drop in stock market prices. Equity markets penalize firms that incur operational losses as they indicate serious firms' internal control weaknesses.

Following the wave of these high-profile corporate scandals, academics, professionals and regulators (e.g. BCBS, 1998, 2001, 2006b; Cummins et al., 2006; Helbok and Wagner, 2006; Chernobai et al., 2011) have started paying more attention to operational risk exposure and its management practices in financial institutions. In the finance literature, empirical studies have shown that operational risk event announcements lead to subsequent negative market reaction (Perry and de Fontnouvelle, 2005; Cummins et al., 2006; Gillet et al., 2010; Sturm, 2013). Additionally, they reveal serious internal control weakness, poor corporate governance mechanisms in place, fraudulent behaviour of management and excessive risk-taking (Chernobai et al., 2011).

We employ a sample of 1,289 operational risk event announcements in 92 U.S. banks from 1992 to 2016 extracted from Algo FIRST database and applying several empirical methods, namely ordinary least squares (OLS), fixed effects (FE) and the generalized method of moments (GMM) to analyse the impact of operational risk event announcements on CEO compensation. In countries such as the U.S, where equity holdings are substantial, focussing on salary only, which is fixed, disregards the majority of incentives (Murphy, 1999). Therefore, in this study, we focus on CEO compensation in the form of bonus, stocks and options. More specifically, we test whether there is a change in CEO variable pay as a consequence of unexpected bad news about the firm performance.

We find evidence that the frequency of operational risk event announcements has a negative and significant effect on CEO option-based compensation. However, this result does not hold when the stock market reaction following operational risk event announcements is used instead. Our evidence also shows that CEOs are penalised for their bad performance, measured by the frequency of operational risk event announcements, through their option-based compensation if the compensation committee ratio is high. This implies that effective corporate governance mechanism in place, in the form of compensation committee as a proportion to board size, contributes to tackling the agency problems. We further examine the impact of operational risk event disclosures on CEO compensation across different time periods including post Sarbanes-Oxley Act (SOX), Global Financial Crisis and the Dodd-Frank Act. We find evidence that the reduction in CEO option-based compensation following the number of operational risk events disclosed increases after each legislation.

Our study attempts to provide two contributions to the literature on CEO compensation and on operational risk in the banking sector. First, this is the first study to explicitly examine whether operational risk event announcements impact on CEO compensation. This has practical implications for regulators, practitioners and academics in understanding the role of executive compensation in contributing to effective operational risk management. Second, the study sheds light on the effects of SOX, the Global Financial Crisis and the Dodd-Frank Act on the impact of operational risk failures on CEO compensation. This would enable us to better understand the implications of the different legislations, especially the compensation reforms introduced, and analyse whether U.S. banks have indeed adjusted their CEO compensation practices.

The remainder of the paper is organised as follows. Section 4.3 briefly reviews the literature and develops the research hypotheses. Section 4.4 clarifies data sources and sample selection procedure and explains the research methodology used. Section 4.5 presents and discusses the empirical results. Lastly, Section 4.6 concludes.

## 4.3 Literature and Hypotheses Development

Agency models posit risk-neutral shareholders (principals) delegating decision-making authority to CEO (agent), who is assumed to be risk-averse. With the separation of control from ownership, the interests of the CEO and shareholders are not aligned, and this thereby gives rise to the principal-agent problem (Jensen and Meckling, 1976). One of the principals' main concerns is to structure compensation pay packages to create a strong link between pay and performance (Nourayi and Daroca, 2008). Ideally, optimal compensation contracts link CEO compensation with firm performance, thereby inducing the CEO to operate in shareholders' interests and remedy the agency problems (Shaw and Zhang, 2010). In other words, CEO compensation will increase when the firm's performance is higher, and vice versa.

Motivated by the managerial power theory, Bebchuk and Fried (2003) argue that CEOs tend to exercise major influence on their own compensation given the information asymmetry context. However, if the principals feel that the CEO is acting in his or her own-interest rather than theirs, as reflected by excessive risk-taking and fraudulent behaviour, they may penalise the CEO, through dismissal or a reduction in their compensation, in order to improve the market performance and restore the trust of other stakeholders.

The link between firm performance and CEO compensation has been widely studied in the economics and finance as well as accounting literature. The empirical studies have focused on the stock market-based measures of firm performance (Murphy, 1985; Barro and Barro, 1990; Jensen and Murphy, 1990a; Gibbons and Murphy, 1992; Hubbard and Palia, 1994) and the accounting-based measures of firm performance (Antle and Smith, 1986; Lambert and Larcker, 1987; Sloan, 1993). While earnings-based metrics are the most popular accounting measures, total shareholder return is the common stock market-based metric (Edmans et al., 2017). Most empirical studies have found a small but significant association between firm performance and CEO compensation.

Jensen and Murphy (1990a) examine the pay-performance relationship and find a $3.25 change in CEO wealth per $1,000 change in shareholder wealth. While this pay-performance sensitivity has increased over time, Murphy (1999) points out that most of it comes from option and stock holdings. Wallsten (2000) argues that the CEO should however be punished less when the firm's performance is bad, as reflected by a decrease in the firm's market value, than he or she would be rewarded for an equal rise in the market value in order to prevent the CEO from becoming too risk-averse. Their results hence demonstrate that pay is strongly associated with performance when there is a rise in firm's market value, but not following a reduction in the market value.

Analysing the sensitivity of cash- and equity-based compensation to bad news (measured using negative stock returns), Leone et al. (2006) show that cash compensation is twice as sensitive to bad news as it is to good ones. Also, they find that equity-based compensation reacts symmetrically to both good and bad news. On the other hand, Taylor (2013) investigates how learning about a CEO's ability, defined as CEO's contribution to firm profitability, can influence the level of his or her pay. He argues that, since perceived CEO ability cannot be directly observed, the best signal would be stock returns, which in turn depends endogenously on perceived ability. As such, stock prices, return volatility and changes in CEO pay level respond endogenously to news about CEO ability. Unlike Leone et al. (2006), his findings reveal that CEO pay responds asymmetrically to good and bad news about ability such that bad news does not have a significant impact on the level of pay while following good news about CEO ability, level of pay rises significantly.

Another stream of literature argues that CEOs intentionally disclose good news right away to increase their compensation while bad news tends to lag due to career concerns (Kothari et al., 2009; Baginski et al., 2017). In the case of bad news, the CEO is likely to delay its release as long as possible in the hope that upcoming good news will come along to offset the bad news, such that the bad news may never have to be released. However, operational risk event announcements are considered as non-earnings bad surprises, that hit the market unexpectedly without the consent of the CEO and therefore, is likely to have an adverse impact on CEO compensation. The disclosure of these adverse media news is usually not under the control of the affected firms' management. Hence, we expect the sensitivity of CEO compensation to performance to be higher after operational risk event announcements. To the best of our knowledge, this is the first empirical study to focus on the impact of operational risk event disclosures on CEO compensation in U.S. banks.

The pioneering work of Chernobai et al. (2011) points out that operational risk event announcements reveal serious internal control deficiencies, weak corporate governance mechanisms and poor risk management practices in financial firms. As such, corporate governance is a crucial factor in operational risk management and having a proper corporate governance structure contributes to better firm performance, higher stock market valuation, more effective internal controls and eventually reduces the occurrence of operational risk events. The findings of Chernobai et al. (2011) show that external corporate governance, measured using Gompers et al. (2003) G-index, plays a significant role in mitigating operational risk. A higher G-index implies that the firm has a greater number of antitakeover provisions, which is an indicator of weaker external governance, and results in a rise in the number of operational risk events.

Additionally, empirical studies by Beasley (1996), de Andres and Vallelado (2008) and regulatory report by BCBS (2011) state that the effectiveness of the corporate board is a vital element in the governance structure of the firm. Wang and Hsu (2013) further investigate the relationship between board composition and the frequency of operational risk events and their results support the fact that that stronger governance, through both board size and age heterogeneity, contributes to more efficient operational risk management as both variables are negatively linked to the occurrence of an operational risk event.

On the other hand, Barakat (2014) analyses the effects of the reputational damage caused by operational risk event announcements and financial statement restatements on ex post corporate governance changes including top management position (i.e., the CEO), board composition (i.e., non-CEO executive directors, independent directors and board size) and board activity. The findings reveal that operational risk events, caused by internal fraud, force the CEO to resign only in the next fiscal year (for high losses), result in more outgoing of incumbent executive directors and less independent directors to be recruited, thereby reducing the board size. Also, higher losses from non-fraud event announcements force the CEO to resign and encourage the board to enhance its activity. Most importantly, it is argued that changes in board composition reflect measures taken by shareholders to signal to market investors their serious intent to improve internal controls within the firm that have failed to prevent and detect the operational risk failures.

Furthermore, Chernobai et al. (2011) find that CEOs with higher option- and bonus-based compensation relative to salary are more likely to suffer from operational risk events. Their study focuses on how the composition of pay is going to impact on CEOs' risk-taking behaviour and the number of operational risk events that consequently occur. In other words, if CEO pay is solely stock option-based compensation, then he or she will end up taking risks to increase the value of his or her stock option. Moreover, if the pay structure in the banking sector is heavily skewed towards a bonus culture, it will encourage risk-taking.

Our study, instead, focuses on operational risk event announcements as a new negative firm performance measure and analyses whether this unanticipated bad news disclosure has an impact on ex post CEO compensation (by controlling for lagged CEO compensation and corporate governance variables), hence contributing to the pay-performance literature. A potential endogeneity problem that may arise in our study is that pay induces executives to take excessive risks for better firm performance as their bonus, stocks and options are tied to the firm performance, and performance in turn affects CEO pay. To correct for this endogeneity, we also employ the GMM model.

CEO's salary is likely to be insensitive to firm performance. However, we anticipate that CEO compensation in the form of bonus, stocks and options decreases following an operational risk event disclosure since it reveals serious firm's internal control weaknesses, poor corporate governance and excessive risk-taking, i.e., bad firm performance. Additionally, we hypothesize that since the causes of operational risk events are mostly idiosyncratic, the CEO should be penalised and cannot claim that the events happened due to a systemic cause such as market risk or credit risk. Hence, we argue that operational risk events should be part of a regulatory disclosure. Thus, our first hypothesis is formulated as below:

**Hypothesis 1***: CEO compensation in the banking industry is adversely affected by operational risk event announcements.*

In line with the agency theory, the Securities and Exchange Commission (SEC) highlights that compensation committees are considered as a powerful monitoring mechanism that ensure the effective functioning of the executive-level compensation systems to enable shareholders to protect themselves from managerial self-interest (Daily et al., 1998). The compensation committee members are expected to be objective in decision-making and hence, can potentially enhance alignment of executive compensation contracts with firm performance (Murphy,1985; Mangel and Singh, 1993).

However, Finkelstein and Boyd (1998) argue that the role of the compensation committee in determining CEO pay could depend on the CEO's power over these committees and on the amount of discretion the CEO can exercise. Advocates of agency theory believe that, if the appointment of the compensation committee members are subject to CEO's influence, then this affiliation would hinder the committee members' ability to exercise independent judgement about CEO compensation, as they may feel the obligation to protect the CEO (Daily et al., 1998). This is supported by the empirical findings of Hoitash (2011), which show that social ties between managers and independent compensation committee members are linked with a statistically higher CEO salary and total cash compensation. Moreover, Boyle and Roberts (2010) find that, in cases where the CEO is a member of his own compensation committee, the CEO compensation is less sensitive to accounting performance.

On the other hand, Sun et al. (2009) observe that higher compensation committee quality is associated to a higher pay-performance sensitivity of CEO compensation. They used different measures of compensation committee quality including committee size, CEO appointed directors, long-serving directors on the compensation committee amongst others. Overall, prior studies find that the relationship between the composition of compensation committee and CEO compensation vary considerably (Anderson and Bizjak, 2003; Conyon and Peck,1998).

The importance of the compensation committee and executive pay is usually reflected in firms' proxy statements. For instance, the Bank of America Corporation (BOA) Proxy Statement has a 'Compensation Discussion and Analysis' section, where it briefly details how the compensation committee evaluates executives' compensation pay (BOA, 2018). Interestingly, it points out that its equity-based awards are subject to being affected or even cancelled if the employee engages in certain "detrimental conduct", including illegal activity, negligent disregard of policies and trading positions, that results in a need for restatements or significant loss etc. Such types of misconduct are categorised as operational risk events as per Basel II. However, studies have not investigated whether compensation committees truly consider operational risk event announcements to have a statistical impact on CEO compensation.

Since recent regulation requires members of the compensation committee to be independent (SEC, 2012), we argue that the compensation committee independence measure would be highly correlated to board independence. As such, in this paper, we use the compensation committee size to board size ratio as a measure of the proportion of board resources devoted to executive compensation. We expect a high ratio to have a more negative impact on CEO compensation following the announcement of a bad news about the firm performance. Our second hypothesis is thus formulated as follows:

**Hypothesis 2:** *The higher the compensation committee ratio, the more adverse is the impact of operational risk event announcements on CEO compensation in the banking industry.*

The Sarbanes-Oxley Act of 2002 was enacted as a result of fraudulent accounting practices and self-dealing of executives (Cianci et al., 2011; SEC, 2013). Analysing the impact of changes in corporate governance via SOX on executive compensation, Cianci et al. (2011) show that SOX changed the corporate governance-compensation relation only when corporate governance is defined in terms of CEO duality; however, it has no impact on the CEO dominance-compensation relation. This implies that the success of SOX, to strengthen corporate governance and change the governance-compensation relation, essentially depends on the measure of corporate governance. On the other hand, studies have failed to further examine whether SOX changed the compensation-performance relation, which is what our study will investigate.

Despite the implementation of SOX, executive compensation is still argued to have played a major role in incentivising CEOs to undertake excessive risks, which contributed to the financial crisis in 2008, causing adverse impact on the world's economy (Gande and Kalpathy, 2017). It may imply that CEOs were compensated even in the case of failures. This historical rise in the level of CEO compensation, together with the large-scale corporate scandals and the consequent collapse of high-profile institutions during the crisis period, emphasised the need for corporate governance reform. The banks' executive compensation is highly criticized and blamed as the root cause of the crisis. Empirical studies claim that corporate governance variables play a crucial role in shaping CEO compensation. Weaker governance mechanisms enable executives to have more control over their own pay and is therefore positively related to CEO compensation (Tosi and Gomez-Mejia, 1989; Boyd, 1994; Wright et al., 2002).

In response to the financial meltdown, the government imposed a new legislation known as the Dodd-Frank Act in 2010, which requires all public companies to obtain annual advisory shareholder votes on top executive pay (now referred to as “Say-on-Pay”). The Dodd-Frank Act also mandated the SEC to amend its executive compensation disclosure rules to more clearly demonstrate the “relationship between compensation actually paid and the financial performance of the issuer” (PricewaterhouseCoopers, 2010; Liu, 2012). In the wake of these regulations, we anticipate that the impact of operational risk event announcements on CEO compensation differs according to different time periods including the pre and post SOX, the pre and post Global Financial Crisis as well as pre and post Dodd-Frank Act.

Since SOX was implemented with the aim to remedy poor governance practices (Paligorova, 2008; Dicks, 2012), we would expect that executives to start being penalised in the case of bad firm performance post SOX. Nevertheless, despite SOX’s attempt to increase accountability and control risk-taking, the global financial crisis still occurred (Pollock, 2009). As a result, greater emphasis was placed on governance reform following the occurrence of the global financial crisis and therefore, we anticipate CEO compensation to be more sensitive to operational risk event announcements post crisis period. In addition, we expect an even greater reduction in executive pay following bad firm performance post Dodd-Frank Act due to stricter rules imposed to tackle excessive executive compensation (Dunning, 2010). Our third hypothesis is formulated as follows:

**Hypothesis 3:** *CEO compensation in the banking industry is more adversely affected by operational risk event announcements following SOX, GFC, and Dodd-Frank.*

## 4.4 Data and Methodology

### 4.4.1 Data and Sample Selection

The source of our data on CEO's pay and characteristics is the ExecuComp database. Due to data availability on executive compensation, we are limited to a sample period of 1992 – 2016. We collate data on operational risk event announcements from the Financial Institutions Risk Scenario Trends (FIRST) database, provided by Algorithmics Inc, a member of IBM. FIRST is a repository of operational risk events and contains more than 15,000 real-life case studies disclosed in the public media (e.g. the Wall Street Journal), SEC press releases and court orders. It provides a range of information including name of the company, date of the loss occurrence, settlement date, loss amount, event type, business line as well as a detailed narrative of each loss event. For the purpose of this study, we use information on operational risk events' first announcement dates, loss amounts and event types in publicly traded U.S. banks. For each event in our sample, the first announcement date as well as the respective nominal loss amount reported by the news have been double-checked manually through LexisNexis news database for accuracy. Our novel dataset comprises of 1,289 events from 92 publicly listed banks from 1992 to 2016 as shown in Table 4.2.

Operational risk events have been further categorized as per Basel II into the following event types: internal fraud (IF); clients, products and business practices (CPBP); external fraud (EF) and the remaining events (OTHERS). We use OTHERS as a reference group. Data on corporate governance factors such as board size, independent board and compensation committee size are collected from Proxy Statements. Finally, the firm-specific accounting data are obtained from Compustat and daily share prices are downloaded from the Center for Research in Security Prices (CRSP).

### 4.4.2 Dependent Variables

In this study, we employ the following measures of CEO compensation namely: total compensation, bonus, stock and option compensation. Firstly, total compensation is measured with ExecuComp variable, TDC1, which is a sum of salary, bonus, restricted stock grants and Black-Scholes value of stock-options granted during the fiscal year. In 2006, there was a major change in the computation of TDC1 as the SEC required equity compensation to be based on ex ante value of awards. Following Walker (2011), we adjusted TDC1 pre-2006 by deducting the amount paid under the company's long-term incentive plan (i.e., ex post value of performance shares) and adding the target number of performance shares granted multiplied by the stock price at the end of the fiscal year (i.e., ex ante value of performance shares).

Bonus is part of the CEO's cash compensation and is based on annual performance targets. Stock compensation is a non-cash component of the total CEO's compensation and is reported as the total value of restricted stock grants in ExecuComp prior to 2006. Following 2006, stock compensation is reported as the fair value (estimated by the company as of the grant date) of restricted stock grants and performance-based pay that is yet unearned but will result in stock awards in the future. For performance-based pay, the fair value is typically based on target pay-outs. Target pay is generally viewed as the standard for setting pay opportunities and indicates what the firm has planned executives to pay at targeted levels of performance (Tonello, 2012). Option compensation is also a non-cash component of the total compensation. It is reported as the total value of options granted during the year and is estimated using Black-Scholes methodology prior to 2006. Post-2006 period, option compensation is reported as the fair value (estimated by the company as of the grant date) of option grants and performance-based pay that is yet unearned but will result in option awards in the future. All compensation numbers have been adjusted for inflation using the Consumer Price Index obtained from the Bureau of Labour Statistics.

### 4.4.3 Independent Variables

Our independent variables are divided into the following: event-level variables, corporate governance variables and firm-level variables and are described in Table 4.1.

Because our main focus is to analyse the impact of operational risk events, as new measures of performance, on CEO compensation, we employ the following event-level variables as our explanatory variables. We use the frequency (*Oprisk Frequency*) i.e., the number of operational risk events announced during the fiscal year and the severity of operational risk events i.e., the dollar operational loss amounts during the fiscal year (*Maximum Loss*). We include the frequency of operational risk events caused by internal fraud (*IF Frequency*); clients, products and business practices (*CPBP Frequency*); and external fraud (*EF Frequency*). The stock market reaction to operational risk events (*Minimum CAR*) is also employed. We account for the different time periods such as the post Sarbanes-Oxley Act of 2002 (*Post Sarbanes-Oxley Act Dum);* the Global Financial Crisis period and post Global Financial Crisis period

(*Global Financial Crisis Dum*); and the post Dodd-Frank Act of 2010 (*Post Dodd-Frank Act Dum*).

With regards to CEO characteristics, following extant literature (Gibbons and Murphy, 1992; Mangel and Singh, 1993; Jalbert et al., 2010), we use CEO age (*Age*), gender which is coded as 1 if CEO is male, 0 otherwise (*Gender)* and the number of years the CEO has worked in the current firm (*Tenure*). In line with Cyert et al. (2002) and Fahlenbrach (2009), we also account for CEO duality role, which is a dummy variable coded as 1 if the CEO is also the current chairman, otherwise 0 (*Duality Dum*). Finkelstein and D'Aveni (1994) document that when the CEO also holds the Chairman position, agency theory advocates that it may result in CEO entrenchment and thus lead to weak monitoring. Furthermore, according to prior empirical studies (Jensen, 1993; Vafeas, 2003; Sun, 2009), we employ some corporate governance variables including the number of directors sitting on the board (*Board Size*), board independence ratio (*Board Independence Ratio*) and compensation committee size as a proportion of the board size (*Compensation Committee Ratio*).

In line with the literature on compensation (Tosi et al., 2000; Nourayi and Mintz (2008), we control for several firm-level variables. We include firm size, measured by the natural logarithm of total deflated assets (*Log Total Assets*). According to prior studies, CEO in larger firms are expected to deal with a greater amount of complexities and thus deserve a higher compensation for their increased responsibilities (Canarella and Gasparyan, 2008; Nourayi and Mintz, 2008). To control for firm performance, we include profitability, measured by income before extraordinary items divided by total assets (*Return on Assets*). Following Smith and Watts (1992), we include Tobin's Q, measured by the sum of market value of equity and total liabilities divided by total assets, to capture bank's growth opportunities (*Tobin Q*). We control for leverage as an accounting-based measure of credit risk, measured by the sum of short-term debt and long-term debt divided by total assets (*Leverage*). Liquidity risk is captured using the ratio of cash and short-term investments to total assets (*CSTI to Total Assets*). Lastly, we control for stock price-based measure of firm performance to capture the volatility of the operating environment, measured by annual standard deviation of daily stock returns (*Equity Return Volatility*).

### 4.4.4 Descriptive Statistics

Descriptive statistics for all the variables employed in this study are presented in Table 4.3. We find that total compensation, bonus, stock and option compensation in our sample averaged to $6.27 million, $1.08 million, $1.81 million and $1.94 million. The average age of the CEOs is approximately 57 years and average tenure is 10.7 years. Interestingly, 90% of CEOs from our sample firms are also the current chairman. Moreover, we observe that 74% of the board members are classified as independent.

Table 4.4 presents the Pearson's pairwise correlation coefficient values for each of the dependent variables (i.e. total compensation, bonus, stock and option-based compensation) and the explanatory and control variables. There is a negative correlation between CEO option-based compensation and operational risk variables including operational risk frequency and maximum loss announced. However, we find a positive correlation between the other elements of CEO pay (i.e. bonus and stock) and operational risk variables. The Global Financial Crisis and Dodd-Frank Act are negatively correlated with CEO option-based compensation unlike the Sarbanes-Oxley Act (significant at the 1% level). Furthermore, there is a positive correlation of 17.32% between CEO duality role and CEO option-based compensation (significant at 1% level). We also find a negative correlation of 17.36% between compensation committee ratio and CEO option-based compensation (significant at 1% level). The signs of these correlation coefficients support our hypotheses. The variance inflation factor (VIF) for each explanatory variable is calculated to indicate the presence of multicollinearity. We note that the VIFs for each variable are below 0.10, which do not raise any multicollinearity concerns.

### 4.4.5 Empirical Model

For our panel dataset, we employ the pooled ordinary least square (OLS), the fixed effects specification (FE), and the dynamic panel generalized methods of moments (GMM), where the instruments used are the lags of the dependent variable. FE regression model is used to control for missing or unobserved time invariant factors that may affect CEO compensation. The main motivation for the use of GMM is to tackle the potential endogeneity issue between CEO compensation and operational risk exposure. Chernobai et al. (2011) observe that higher pay in the form of option- and bonus- based compensation induces executives to take more risks to enhance firm performance and are thereby more likely to suffer from operational risk events. On the other hand, our study explores whether bad firm performance as reflected by the number of operational risk event announcements have a significant impact on CEO compensation. As such, we argue that there is a causal relation between CEO pay and operational risk and we address this endogeneity problem by employing the dynamic panel GMM methods.

Using the three econometric methods, we estimate the impact of operational risk on ex post CEO compensation changes for firm $i$ in the current fiscal year $t$ using the below empirical model:

$$
\begin{aligned}
ln(Compensation)_{it} \\
&= \alpha_i + \beta_1 ln(Compensation)_{i,t-1} \\
&+ \beta_2 \ln\,(Oprisk\ characteristics)_{i,t-1} \\
&+ \beta_3\ (Post\ Sarbanes - Oxley\ Act\ Dum)_{i,t} \\
&+ \beta_4\ (Global\ Financial\ Crisis\ Dum)_{i,t} \\
&+ \beta_5\ (Post\ Dodd - Frank\ Act\ Dum)_{i,t} \\
&+\ \beta_6\ (Corporate\ Governance)_{i,t-1} + \beta_7 ln(Log\ Total\ Assets)_{i,t-1} \\
&+ \beta_8 Return\ on\ Assets_{i,t-1} + \beta_9 Tobin\ Q_{i,t-1} + \beta_{10} Leverage_{i,t-1} \\
&+ \beta_{11} CSTI\ to\ Total\ Assets_{i,t-1} + \beta_{12} Equity\ Return\ Volatility_{i,t-1} \\
&+ \varepsilon_{it} \qquad (7)
\end{aligned}
$$

We employ the natural logarithm of *Compensation*, which is either CEO's total compensation, bonus, stock or option compensation of firm $i$ in year $t$ as our dependent variable. Operational risk characteristics (*Oprisk characteristics*) captures the frequency and the severity of operational risk failures for firm $i$ during the previous fiscal year $t-1$. We therefore assume that it takes the board of directors of firms suffering from operational risk event announcements a year to penalise the CEOs for failure. We control for corporate governance variables and firm-level variables, as listed in Table 4.1, at the end of the previous fiscal year $t-1$ in line with prior studies (John et al., 2010; Guo et al., 2015).

## 4.5 Empirical Results

Regression analyses are performed using three different models to test our hypotheses. Model 1 reports a pooled OLS. Model 2 reports the fixed effects estimates for CEO compensation. An F-test on the significance of the fixed effects that all $\gamma_i = 0$ is easily rejected for all our dependent variables. We also compare the fixed effects regression model with the random effects model and for both sets of regressions a Hausman test rejects the random effects. Hence, in interpreting the main regression analysis for our dependent variables, we will draw on the fixed effects model. Model 3 reports GMM estimates. Lagged dependent variables are used as instruments and we ensure all instrument tests are passed to ensure instrument validity. We observe that the lagged dependent variable is highly correlated, and the coefficient is higher than 0.1. We document several findings of note.

### 4.5.1 Frequency and Severity of Operational Risk Event Announcements

We observe a significant negative association between total CEO compensation and the frequency of operational risk event announcements using the three different models. The adverse impact on CEO pay is driven predominantly by CEO option-based compensation. It implies that the higher the number of operational risk events disclosed, which reflects bad firm performance, the greater is the reduction in CEO compensation in the form of options. Model 1 of Table 4.5, Panel A shows that there is a significant performance-pay elasticity such that CEO option-based compensation reduces by 1.16% at 1% significance level following 1% increase in the number of operational risk event announcements. This is consistent in a dynamic setting where the reduction in executive options is 1.26% at 5% significance level. This result is supported by empirical studies which find evidence of a positive relationship between pay and performance (Murphy, 1985; Jensen and Murphy, 1990; Smith and Watts, 1992).

However, we observe that other elements of executive pay such as bonus and stocks are both insensitive to the announcements of this unanticipated bad news. This finding is in line with Hubbard and Palia (1995) who raise concerns whether CEO pay, in this case, being bonus and stock-based compensation, actually reflects firm performance. As such, we argue that our results only partially support the first hypothesis $H_1$. Model 1 and Model 2 of Table 4.5, Panel B further demonstrate that CEOs are penalised in terms of their option-based compensation following operational risk events caused by 'clients, processes and business practices' only. In contrast, events caused by other factors, including internal fraud, tend to have no negative effect on executive pay.

Additionally, we find mostly consistent evidence when measuring operational risk events using the maximum loss amount disclosed as shown in Table 4.6, although the frequency of operational risk events announced seems to have a greater negative impact on CEO option-based compensation. Surprisingly, we find statistical evidence from Table 4.7, Panel A that adverse market reactions following operational risk event disclosures have a positive impact on CEO option-based compensation. Under a fixed-effects setting, CEOs are rewarded by a 0.06% increase in their option-based compensation at 10% significance level despite drop in market prices, resulting from operational risk event announcements, while no effect is observed under a dynamic setting. Further analysis into operational risk events types (Table 4.7, Panel B, Model 3) shows that banking executives are only penalised slightly by a 0.10% reduction in their option-based compensation at 1% significance level following drop in market prices as a consequence of operational risk events caused by internal fraud.

It is worth acknowledging that the coefficient of our explanatory variable disclosure on CEO compensation is not substantial and this is supported by Wallsten (2000), who argues that CEOs should be punished less in case of bad firm performance, as reflected by a decrease in the firm's market value. Overall, our findings suggest that the effect of this idiosyncratic risk in the form of operational risk events, which convey bad news about firm performance and whose disclosure are not manipulated by banking executives, on CEO compensation vary according to the measure of operational risk. In the case where the frequency of operational risk events announced is used, we document a negative impact on the CEO option-based compensation.

In line with Murphy (1999), the pay-performance relationship is positive and significant in the case of options only unlike cash-based compensation. Consistent with the fact that executives' equity holdings are substantial, at least in countries such as the U.S., comprising of the majority of their compensation (Edmans et al., 2017), our results show that CEOs are penalised, mainly in terms of their options, following their bad firm performance. We argue that since CEO option-based compensation is conditional upon firm's performance, then options tend to act as incentives for banking executives to increase long-term shareholder value in order to gain higher reward in the future (Jensen and Murphy, 1990).

### 4.5.2 Compensation Committee

We find statistical evidence that a high proportion of compensation committee to board size is negatively associated with CEO-option based compensation following the frequency of operational risk event announcements. In other words, with effective corporate governance mechanism in place within firms, measured by compensation committee ratio, CEOs face consequences for their negative actions. They are penalised by a 1.96% reduction in their option-based compensation at 1% significance level under a static setting and 2.94% reduction under a dynamic setting as shown in Table 4.5, Panel A. Inconsistent with the managerial power theory, it implies that the higher the compensation committee as a proportion of the board size, the more powerful the compensation committee members are in terms of influencing the CEO compensation as a result of the firm performance. This result is consistent when operational risk events are measured by the market reactions to these bad news announcements, as evidenced in Table 4.7, Panel A. In line with the empirical findings of Sun et al. (2009), our findings reveal that a high compensation committee ratio drives a stronger CEO compensation-performance sensitivity, hence supporting our second hypothesis, $H_2$.

### 4.5.3 Sarbanes-Oxley Act, Global Financial Crisis and Dodd-Frank Act

We document strong evidence from Table 4.5, Panel A that SOX, the Global Financial Crisis and Dodd-Frank Act each have meaningful effect on pay-performance relationship. CEO compensation in the form of options mainly is significantly reduced following the number of operational risk events disclosed post-SOX. The reduction in the executives' options is higher following the Global Financial Crisis and even more post-Dodd Frank Act. More specifically, banking executives are held more responsible for operational risk event announcements, which reflect internal control weaknesses and poor corporate governance within firms.

Model 1 shows that CEOs' options reduced by 1.85% at 1% significance level during the crisis period and 2.22% at 1% significance level post-Dodd Frank Act. When CEO fixed effects are introduced (Model 2), the correlation of options with the frequency of operational risk event announcements stays negative at 10% significance level. In a dynamic panel as shown by Model 3, executives' options reduce by 2.10% at 1% significance level during the crisis period and 2.73% at 5% significance level post-Dodd Frank Act. Interestingly, even CEO bonus are significantly affected such that they fell by 1.84% during the crisis period and 2.05% post-Dodd Frank Act, both at 1% significance level. These findings support our third hypothesis $H_3$. When employing adverse market reactions as alternative measure of operational risk event announcements, our results show consistent evidence.

Overall, our evidence reveals that irrespective of a financial crisis, firm performance in the form of operational risk event disclosure has a negative relationship with CEO option-based compensation. However, the effect is greater following the crisis period and even more post-Dodd Frank Act. In line with Dunning (2010), this implies that the Global Financial Crisis and the Dodd-Frank Act imposed stricter rules on CEO compensation such that it is more aligned to their performance and our results show that CEO compensation contracts indeed become more sensitive to performance following these regulations.

Among our corporate governance variables, we find that age, gender and tenure have a significant effect on CEO compensation. With respect to firm-level control variables, firm size is positively associated with CEO option-based compensation at 1% significance level under Model 1 and 3, which implies that larger firms pay greater compensation for their CEOs. This may be due to the fact that larger corporate boards become less effective and slower to react to decisions that require an immediate action (Jensen, 1993).

### 4.5.4 Interaction of Compensation Committee with Frequency of Operational Risk Event Types

In Table 4.8 we interact event types with a corporate governance variable, which is *Compensation Committee Ratio.* In doing so, we examine the effect of the compensation committee as a proportion of board size on CEO compensation following operational risk event announcements, caused by a specific event type. We find strong evidence that, in the case where operational risk events result from internal fraud and the compensation committee ratio is high, CEOs are greatly penalised for the bad firm performance. Under Model 1, CEOs' bonus are reduced by 11.03% at 1% significance level following 1% increase in operational risk event disclosures, caused by internal fraud. The result is consistent when fixed effects are introduced (Model 2) as well as under a dynamic setting (Model 3). In contrast, we document that, in the case where operational risk events are caused by external fraud and the compensation committee ratio is high, CEOs' stocks are reduced by 20.56% at 10% significance level under a static model only. Overall, a higher compensation committee ratio shows that the pay-performance sensitivity is stronger in the presence of more effective corporate governance mechanism. Additionally, our results reveal that CEOs are held more liable to fraud events caused within the bank relative to events caused by third parties, and hence face consequences for these internal frauds through a reduction in their bonus-based compensation, when stronger corporate governance is in place within firms.

## 4.6 Conclusion

This paper empirically investigates the impact of an idiosyncratic risk in the form of operational risk event announcements on CEO compensation. There is concern in the executive compensation literature about whether CEO pay reflects firm performance. This is of particular concern in the banking sector where there is a perception of large rewards, even when the banks do not perform well. The banking sector therefore provides an interesting setting for a systematic analysis on the pay-performance relationship. Operational risk events are unexpected bad news, which reflect internal control weaknesses within firms, and whose disclosure are not under the control of executives. Our results show that the effect of this bad firm performance on CEO compensation vary according to the type of compensation (i.e., bonus, stocks and options).

We find evidence that the pay-performance elasticity for CEO option-based compensation is up to 1.26%. It implies that the more the number of operational risk events announced, the more negative and significant is the impact on CEO's option-based compensation. In that sense, the bad firm performance is hitting executives. However, for bonus and stock compensation, no significant relationship with CEO pay is found. We also report a high compensation committee ratio leads to CEOs being penalised for their negative actions, through a reduction in their option-based compensation. We argue this is indicative of a strong compensation committee ensuring CEO pay reflects the bad performance arising from operational risk events. We further extend our analysis to examine the implications of SOX, the Global Financial Crisis and the Dodd-Frank Act on CEO compensation following operational risk event disclosures. We find strong evidence that the negative impact of bad firm performance on executives' option-based compensation is even greater after the following time periods: SOX in 2002, the Global Financial Crisis in 2007 and the Dodd-Frank Act in 2010. This implies that the implementation of the different legislations, whose aim was to address the weak pay-performance relationship, effectively help in strengthening this relationship and improve pay as a governance device.

Overall, our results illustrate that option-based compensation is a key instrument compensation committees' use to financially motivate executives to adopt effective operational risk management within their firms. Surprisingly, compensation committees appear not to link bonus payments to negative operational risk events. This suggests that there is still scope for banks' compensation committees to improve the link between pay and performance.

As such, the findings of this study have few practical implications. Since option-based compensation is the main component of CEO pay that truly reflects executives' performance, the compensation committee could therefore design pay package such that a higher proportion of the CEO compensation comprise of options in order to minimise agency risk. In addition, since CEO bonus and stocks are insensitive to bad firm performance, the compensation committee may consider introducing elements of downside risk with executives’ bonus and stock-based compensation for e.g. a clawback provision where the CEOs repay their bonuses if certain actions occur. Alternatively, the committee may consider providing bonus bonds as compensation that would only pay a benefit if certain thresholds are met. This will motivate CEOs to ensure appropriate risk-taking while taking into account potential long-term impact.

The main research limitation is that our sample is focused only on U.S. banks, hence the findings cannot be generalised. More adjustments might be required for non-banking or even non-financial institutions due to different institutional, legal, and regulatory settings in place. In terms of future research, the analysis could be extended to investigate the impact of operational risk event announcements on the turnover of non-CEO directors of banks, especially the Chief Risk Officer (CRO), and the key features of new CRO post loss event disclosure.

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# APPENDIX A

## Table 4.1 Description of Variables

This table provides the definitions and the sources of the variables used in this study.

| Variable | Definition | Data Source |
|---|---|---|
| **Dependent Variables** | | |
| *Total Comp* | Total pay earned by the CEO for the fiscal year. Measurement units: *ln* (USD) | ExecuComp |
| *Bonus* | Bonus earned by the CEO for the fiscal year. Measurement units: *ln* (USD) | ExecuComp |
| *Stock* | Total value of CEO's restricted stock grants for the fiscal year. Measurement units: *ln* (USD) | ExecuComp |
| *Option* | Total value of CEO's option grants for the fiscal year. Measurement units: *ln* (USD) | ExecuComp |
| **Event-Level Variables** | | |
| *Oprisk Frequency* | Number of operational risk events whose first announcement dates fell during the fiscal year. | Algo FIRST, LexisNexis |
| *IF Frequency, CPBP Frequency, EF Frequency* | Number of operational risk events announced that is of event types Internal Fraud; Clients, Products, and Business Practices; and External Fraud. | Algo FIRST, LexisNexis |
| *Maximum Loss* | Maximum deflated loss amount of all operational risk events whose first announcement dates fell during the fiscal year. Measurement units: *ln* (USD million) | Algo FIRST, LexisNexis |
| *Mininum CAR* | Minimum cumulative abnormal returns (CAR) over the reaction window (-5, +5) of all operational risk events whose first announcement dates fell during the fiscal year. Measurement units: percent | Algo FIRST, LexisNexis, WRDS |
| *Post Sarbanes-Oxley Act Dum* | 1 if the current fiscal year of the CEO compensation is after the Sarbanes-Oxley Act and before the Global Financial Crisis (i.e. 2002 ≤ year ≤ 2006); 0 otherwise. | ExecuComp |
| *Global Financial Crisis Dum* | 1 if the current fiscal year of the CEO compensation is during and post Global Financial Crisis and before the Dodd-Frank Act (2007 ≤ year ≤ 2010); 0 otherwise. | ExecuComp |
| *Post Dodd-Frank Act Dum* | 1 if the current fiscal year of the CEO compensation is after the Dodd-Frank Act (year ≥ 2011); 0 otherwise. | ExecuComp |

| | | |
|---|---|---|
| **Corporate Governance Variables** | | |
| *Age* | Age of the CEO. | ExecuComp |
| *Gender* | 1 if the CEO is male; 0 otherwise. | ExecuComp |
| *Tenure* | Number of years the CEO has been in the current firm. | ExecuComp |
| *Duality* | 1 if the CEO is also the current board chairman; 0 otherwise. | ExecuComp |
| *Board Size* | The number of board directors. | Proxy |
| *Board Independence Ratio* | Ratio of independent directors to the number of board directors. | Proxy Statements |
| *Compensation Committee Ratio* | Ratio of directors in the compensation committee to the number of board directors. | Proxy Statements |
| **Firm-Level Control Variables** | | |
| *Log Total Assets* | Natural logarithm of the deflated total assets at the end of the fiscal year. Measurement units: *ln* (USD) | CRSP, Compustat |
| *Return on Assets* | Income before extraordinary items scaled by total assets at the end of the fiscal year. Measurement units: percent | CRSP, Compustat |
| *Tobin Q* | Sum of market value of equity and total liabilities scaled by total assets at the end of the fiscal year. Measurement units: percent | CRSP, Compustat |
| *Leverage* | Sum of short-term debt and long-term debt scaled by total assets at the end of the fiscal year. Measurement units: percent | CRSP, Compustat |
| *CSTI to Total Assets* | Cash and short-term investments scaled by total assets at the end of the fiscal year. Measurement units: percent | CRSP, Compustat |
| *Equity Return Volatility* | Standard deviation of the daily equity return at the end of the fiscal year. Measurement units: percent | CRSP |

**Table 4.2 Sample Selection Procedure**

This table details the screening procedure of data on operational risk event announcements in U.S. banks for the period 1992-2016.

| Data Screening Description | Number of Operational Risk Event Announcements |
|---|---|
| 1. Algo FIRST Database | 1,627 |
| – Events with no event description information | (62) |
| – Events whose first announcement date are not available | (228) |
| – Events that occurred in listed subsidiaries that are non-bank firms (two-digit SIC other than 60, 61, 62 and 67) | (2) |
| – Events from firms that are not publicly listed | (46) |
| 2. Final sample | 1,289 |

## Table 4.3 Sample Descriptive Statistics

This table reports the descriptive statistics for our variables. All variable definitions are as reported in Table 4.1.

| Variable | N | Min | 1p | 5p | 25p | 50p | Mean | SD | 75p | 95p | 99p | Max |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Dependent Variables | | | | | | | | | | | | |
| *Total Comp (millions)* | 1,205 | 0 | 0.28 | 0.52 | 1.47 | 3.18 | 6.27 | 9.19 | 7.44 | 21.63 | 36.11 | 165.04 |
| *Bonus (millions)* | 1,218 | 0 | 0 | 0 | 0 | 0.19 | 1.08 | 2.38 | 0.91 | 5.70 | 11.47 | 23.31 |
| *Stock (millions)* | 1,212 | 0 | 0 | 0 | 0 | 0.35 | 1.81 | 3.60 | 1.76 | 9.80 | 16.44 | 31.26 |
| *Option (millions)* | 1,199 | 0 | 0 | 0 | 0 | 0.36 | 1.94 | 6.45 | 1.64 | 8.39 | 22.46 | 144.50 |
| Event-Level Variables | | | | | | | | | | | | |
| *Oprisk Frequency* | 1,218 | 0 | 0 | 0 | 0 | 0 | 0.98 | 2.60 | 1 | 6 | 14 | 27 |
| *IF Frequency* | 1,218 | 0 | 0 | 0 | 0 | 0 | 0.14 | 0.46 | 0 | 1 | 2 | 5 |
| *CPBP Frequency* | 1,218 | 0 | 0 | 0 | 0 | 0 | 0.55 | 1.65 | 0 | 4 | 8 | 18 |
| *EF Frequency* | 1,218 | 0 | 0 | 0 | 0 | 0 | 0.11 | 0.39 | 0 | 1 | 2 | 4 |
| *Maximum Loss (millions)* | 1,218 | 0 | 0 | 0 | 0 | 0 | 101.24 | 853.82 | 0.25 | 178.78 | 2,085.52 | 16,200 |
| *Minimum CAR* | 1,218 | -30.45 | -16.53 | -7 | 0 | 0 | -0.85 | 3.51 | 0 | 1.99 | 5.75 | 22.43 |
| *Post Sarbanes-Oxley Act Dum* | 1,218 | 0 | 0 | 0 | 0 | 0 | 0.16 | 0.36 | 0 | 1 | 1 | 1 |
| *Global Financial Crisis Dum* | 1,218 | 0 | 0 | 0 | 0 | 0 | 0.17 | 0.38 | 0 | 1 | 1 | 1 |
| *Post Dodd-Frank Act Dum* | 1,218 | 0 | 0 | 0 | 0 | 0 | 0.25 | 0.43 | 1 | 1 | 1 | 1 |
| Corporate Governance Variables | | | | | | | | | | | | |
| *Age (years)* | 1,141 | 32 | 39 | 47 | 53 | 57 | 57.23 | 6.44 | 61 | 68 | 74 | 80 |
| *Gender* | 1,143 | 0 | 1 | 1 | 1 | 1 | 1 | 0.07 | 1 | 1 | 1 | 1 |
| *Duality* | 1,143 | 0 | 0 | 0 | 1 | 1 | 0.90 | 0.30 | 1 | 1 | 1 | 1 |
| *Tenure (years)* | 1,104 | 0 | 0 | 0 | 3 | 7 | 10.65 | 10.41 | 15 | 34 | 39 | 42 |
| *Board Size* | 838 | 6 | 7 | 9 | 11 | 13 | 13.40 | 3.76 | 15 | 20 | 24 | 39 |
| *Board Independence Ratio* | 838 | 0.18 | 0.28 | 0.45 | 0.67 | 0.78 | 0.74 | 0.15 | 0.85 | 0.92 | 0.93 | 0.94 |
| *Compensation Committee Ratio* | 760 | 0.08 | 0.11 | 0.16 | 0.25 | 0.33 | 0.33 | 0.12 | 0.39 | 0.50 | 0.77 | 0.88 |
| Firm-Level Variables | | | | | | | | | | | | |
| *Log Total Assets* | 1,209 | 19.41 | 20.97 | 21.74 | 22.85 | 23.83 | 24.08 | 1.67 | 25.17 | 27.36 | 28.30 | 28.56 |
| *Return on Assets* | 1,209 | -16.20 | -2.40 | -0.11 | 0.78 | 1.08 | 1.08 | 1.11 | 1.39 | 2.49 | 4.25 | 7.68 |
| *Tobin Q* | 1,209 | 91.27 | 93.28 | 96.14 | 101.44 | 105.87 | 108.35 | 11.95 | 111.62 | 128.91 | 157.19 | 234.43 |
| *Leverage* | 1,209 | 0.00 | 1.58 | 4.07 | 10.98 | 17.35 | 20.82 | 15.48 | 25.47 | 60.00 | 73.11 | 81.00 |
| *CSTI to Total Assets* | 1,209 | 0.07 | 0.50 | 1.53 | 3.24 | 6.24 | 10.28 | 10.49 | 13.85 | 32.97 | 49.13 | 64.50 |
| *Equity Return Volatility* | 1,203 | 0.35 | 0.39 | 0.41 | 0.59 | 0.72 | 0.87 | 0.43 | 1.08 | 1.78 | 2.20 | 2.54 |

## Table 4.4 Correlation Matrix

This table reports the Pearson's pairwise correlation coefficients between the dependent variables and explanatory and control variables used in the multivariate regressions of the impact of operational risk event announcements on CEO compensation. *p-values* are reported in parentheses. *, ** and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively (two-tailed). All variable definitions are reported in Table 4.1.

| Variable | Dependent Variables | | | |
|---|---|---|---|---|
| | $ln(Total\ Comp)_{i,t}$ | $ln(Bonus)_{i,t}$ | $ln(Stock)_{i,t}$ | $ln(Option)_{i,t}$ |
| Event-Level Variables | | | | |
| $Oprisk\ Frequency_{i,t-1}$ | 0.3834 | 0.0778 | 0.3026 | -0.046 |
| | (0.0000)*** | (0.0066)*** | (0.0000)*** | (0.1117) |
| $ln(IF\ Frequency)_{i,t-1}$ | 0.0541 | -0.0278 | 0.072 | -0.0612 |
| | (0.0603)* | (0.3323) | (0.0121)** | (0.0342)** |
| $ln(CPBP\ Frequency)_{i,t-1}$ | 0.3176 | 0.0584 | 0.2649 | -0.0918 |
| | (0.0000)*** | (0.0416)** | (0.0000)*** | (0.0015)*** |
| $ln(EF\ Frequency)_{i,t-1}$ | 0.1725 | 0.0028 | 0.1521 | -0.0429 |
| | (0.0000)*** | (0.9218) | (0.0000)*** | (0.1374) |
| $ln(Maximum\ Loss)_{i,t-1}$ | 0.3782 | 0.0433 | 0.3226 | -0.0356 |
| | (0.0000)*** | (0.1312) | (0.0000)*** | (0.2183) |
| $Minimum\ CAR_{i,t-1}$ | -0.1403 | 0.003 | -0.1592 | 0.0478 |
| | (0.0000)*** | (0.9165) | (0.0000)*** | (0.0979)* |
| $Post\ Sarbanes-Oxley\ Act\ Dum_{i,t}$ | 0.1406 | 0.1835 | 0.0106 | 0.1402 |
| | (0.0000)*** | (0.0000)*** | (0.7117) | (0.0000)*** |
| $Global\ Financial\ Crisis\ Dum_{i,t}$ | -0.1028 | -0.3710 | 0.0318 | -0.1215 |
| | (0.0004)*** | (0.0000)*** | (0.2685) | (0.0000)*** |
| $Post\ Dodd-Frank\ Act\ Dum_{i,t}$ | 0.1316 | -0.4160 | 0.3577 | -0.3683 |
| | (0.0000)*** | (0.0000)*** | (0.0000)*** | (0.0000)*** |
| Corporate Governance Variables | | | | |
| $Age_{i,t-1}$ | 0.1358 | 0.0597 | 0.0871 | -0.0374 |
| | (0.0000)*** | (0.0436)** | (0.0033)*** | (0.2090) |
| $Gender_{i,t-1}$ | -0.0403 | 0.0715 | -0.0653 | -0.0326 |
| | (0.1747) | (0.0156)** | (0.0276)** | (0.2738) |
| $Duality_{i,t-1}$ | 0.0545 | 0.0975 | -0.0670 | 0.1732 |
| | (0.0660)* | (0.0010)*** | (0.0238)** | (0.0000)*** |
| $Tenure_{i,t-1}$ | -0.0317 | 0.0929 | -0.1812 | 0.057 |
| | (0.2940) | (0.0020)*** | (0.0000)*** | (0.0597)* |
| $Board\ Size_{i,t-1}$ | 0.1328 | 0.1706 | -0.0147 | 0.2100 |
| | (0.0001)*** | (0.0000)*** | (0.6713) | (0.0000)*** |
| $Board\ Independence\ Ratio_{i,t-1}$ | 0.1444 | -0.2809 | 0.2400 | -0.0430 |
| | (0.0000)*** | (0.0000)*** | (0.0000)*** | (0.2150) |
| $Compensation\ Committee\ Ratio_{i,t-1}$ | 0.0182 | -0.0244 | 0.0885 | -0.1736 |
| | (0.6160) | (0.5017) | (0.0150)** | (0.0000)*** |
| Firm-Level Variables | | | | |
| $Log\ Total\ Assets_{i,t-1}$ | 0.6824 | 0.1146 | 0.4355 | 0.2089 |
| | (0.0000)*** | (0.0001)*** | (0.0000)*** | (0.0000)*** |
| $Return\ on\ Assets_{i,t-1}$ | 0.0663 | 0.2038 | -0.0457 | 0.1305 |
| | (0.0219)** | (0.0000)*** | (0.1129) | (0.0000)*** |
| $Tobin\ Q_{i,t-1}$ | 0.0851 | 0.2119 | -0.1561 | 0.2366 |
| | (0.0032)*** | (0.0000)*** | (0.0000)*** | (0.0000)*** |
| $Leverage_{i,t-1}$ | 0.3419 | 0.3436 | 0.0488 | 0.2141 |
| | (0.0000)*** | (0.0000)*** | (0.0907)* | (0.0000)*** |
| $CSTI\ to\ Total\ Assets_{i,t-1}$ | 0.2413 | 0.2730 | 0.1205 | 0.0250 |
| | (0.0000)*** | (0.0000)*** | (0.0000)*** | (0.3888) |
| $Equity\ Return\ Volatility_{i,t-1}$ | -0.0099 | -0.3013 | 0.1274 | -0.1456 |
| | (0.7341) | (0.0000)*** | (0.0000)*** | (0.0000)*** |

# Table 4.5 Impact of the Frequency of Operational Risk Event Announcements on CEO Compensation

This table reports the estimation results for CEO compensation following the frequency of operational risk event announcements. Models 1 contain ordinary least squares (OLS) regressions; Models 2 contain panel data fixed-effects (FE) regressions and Models 3 contain dynamic panel data generalized method of moments (GMM) regressions. Robust standard errors are used to correct for operational risk event clustering in OLS and FE regressions. *t-statistics* are reported in parentheses. *, ** and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively (two-tailed). All variable definitions are reported in Table 4.1.

Panel A: Full sample

| Variable | Model 1 - OLS | | | | Model 2 - FE | | | | Model 3 - GMM | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | $ln(Total\ Comp)_{i,t}$ | $ln(Bonus)_{i,t}$ | $ln(Stock)_{i,t}$ | $ln(Option)_{i,t}$ | $ln(Total\ Comp)_{i,t}$ | $ln(Bonus)_{i,t}$ | $ln(Stock)_{i,t}$ | $ln(Option)_{i,t}$ | $ln(Total\ Comp)_{i,t}$ | $ln(Bonus)_{i,t}$ | $ln(Stock)_{i,t}$ | $ln(Option)_{i,t}$ |
| Event-Level Variables | | | | | | | | | | | | |
| $ln(Total\ Comp)_{i,t-1}$ | 0.3864*** | | | | 0.1517 | | | | 0.2169** | | | |
| | (3.58) | | | | (1.55) | | | | (2.04) | | | |
| $ln(Bonus)_{i,t-1}$ | | 0.4982*** | | | | 0.3336*** | | | | 0.3884*** | | |
| | | (7.57) | | | | (3.88) | | | | (5.42) | | |
| $ln(Stock)_{i,t-1}$ | | | 0.5131*** | | | | 0.2840*** | | | | 0.5393 | |
| | | | (10.81) | | | | (5.82) | | | | (1.40) | |
| $ln(Option)_{i,t-1}$ | | | | 0.4820*** | | | | 0.2825*** | | | | 0.2285 |
| | | | | (8.59) | | | | (4.93) | | | | (0.94) |
| $ln(Oprisk\ Frequency)_{i,t-1}$ | -0.2255*** | 0.4039 | 0.0674 | -1.1578*** | -0.2073*** | -0.1031 | 0.3486 | -0.7953** | -0.1889** | 0.0404 | 0.1669 | -1.2595** |
| | (-2.81) | (1.50) | (0.31) | (-4.39) | (-2.91) | (-0.34) | (0.87) | (-2.56) | (-2.45) | (0.17) | (0.54) | (-2.45) |
| $Post\ Sarbanes-Oxley\ Act\ Dum_{i,t}$ | 0.0847 | -0.3775 | 0.3210 | -0.7554*** | 0.2398** | 0.0841 | 0.6040 | -0.2318 | 0.0958 | -0.5306 | 0.3599 | -0.7236** |
| | (0.99) | (-1.43) | (1.16) | (-2.96) | (2.07) | (0.22) | (1.60) | (-0.76) | (1.20) | (-1.44) | (0.66) | (-2.04) |
| $Global\ Financial\ Crisis\ Dum_{i,t}$ | -0.1131 | -2.3614*** | 0.5535 | -1.8510*** | 0.2481** | -1.9912*** | 1.4533** | -0.9162* | 0.0013 | -1.8371*** | 0.5162 | -2.1006*** |
| | (-1.24) | (-6.63) | (1.46) | (-5.70) | (2.15) | (-3.75) | (2.58) | (-1.74) | (0.01) | (-3.70) | (0.56) | (-3.07) |
| $Post\ Dodd-Frank\ Act\ Dum_{i,t}$ | 0.1972 | -1.8735*** | 1.2789** | -2.2165*** | 0.6566*** | -1.4612* | 2.6702*** | -1.3889* | 0.1922 | -2.0489*** | 1.2560 | -2.7288** |
| | (1.52) | (-4.23) | (2.63) | (-5.24) | (3.50) | (-1.91) | (3.95) | (-1.84) | (1.34) | (-3.39) | (0.92) | (-2.39) |
| Corporate Governance Variables | | | | | | | | | | | | |
| $Age_{i,t-1}$ | 0.0023 | 0.0259** | 0.0401* | -0.0445** | 0.0196 | 0.0219 | 0.0313 | 0.0344 | 0.0015 | 0.0283** | 0.0360 | -0.0625** |
| | (0.41) | (2.08) | (1.71) | (-2.42) | (1.63) | (0.81) | (0.98) | (1.13) | (0.22) | (2.03) | (1.20) | (-2.01) |
| $Gender_{i,t-1}$ | -0.0576 | 0.4199** | -0.0849 | -1.1415*** | 0.3332** | 1.3583*** | 0.5751 | -0.6471 | -0.1216* | 0.7287*** | -0.0619 | -1.2727 |
| | (-0.99) | (2.30) | (-0.46) | (-3.18) | (2.36) | (3.47) | (1.38) | (-1.50) | (-1.92) | (2.97) | (-0.21) | (-1.32) |
| $Duality_{i,t-1}$ | 0.1248 | -0.4279 | 0.3418 | 0.4110 | 0.2395 | -0.0567 | 1.0964* | 0.0665 | 0.1261 | -0.5020 | 0.6942 | 0.3136 |
| | (0.89) | (-1.34) | (0.86) | (1.28) | (1.16) | (-0.14) | (1.86) | (0.13) | (1.00) | (-1.39) | (1.51) | (0.62) |
| $Tenure_{i,t-1}$ | 0.0002 | -0.0175 | -0.0421*** | 0.0194* | -0.0072 | -0.0061 | -0.0839*** | 0.0081 | -0.0009 | -0.0291* | -0.0399 | 0.0272* |
| | (0.06) | (-1.66) | (-2.79) | (1.94) | (-1.08) | (-0.23) | (-4.18) | (0.36) | (-0.18) | (-1.73) | (-1.29) | (1.65) |
| $Board\ Size_{i,t-1}$ | 0.0012 | 0.0534 | 0.0340 | -0.0210 | 0.0262 | 0.1245* | 0.0977* | 0.0247 | -0.0007 | 0.0441 | 0.0791 | -0.0179 |
| | (0.09) | (1.48) | (0.83) | (-0.71) | (1.38) | (1.90) | (1.86) | (0.44) | (-0.05) | (0.86) | (1.46) | (-0.36) |
| $Board\ Independence\ Ratio_{i,t-1}$ | 0.1368 | -0.1359 | 0.0831 | 1.4920* | 0.0735 | 1.3256 | -1.1744 | -0.8993 | 0.1208 | -0.2932 | -0.0871 | 1.7041 |
| | (0.47) | (-0.16) | (0.08) | (1.72) | (0.13) | (0.89) | (-0.87) | (-0.69) | (0.35) | (-0.28) | (-0.07) | (1.14) |
| $Compensation\ Committee\ Ratio_{i,t-1}$ | 0.0236 | 2.5570*** | 0.8410 | -1.9631*** | -0.2267 | 2.4659** | 0.8597 | -1.9079 | -0.0421 | 2.6829*** | 0.6521 | -2.9436** |
| | (0.08) | (3.69) | (0.84) | (-3.05) | (-0.28) | (2.03) | (0.47) | (-1.46) | (-0.14) | (2.60) | (0.47) | (-2.27) |
| Firm-Level Variables | | | | | | | | | | | | |
| $Log\ Total\ Assets_{i,t-1}$ | 0.3146*** | -0.0197 | 0.3206*** | 0.5276*** | 0.0337 | -0.9501* | 0.4002 | -0.6388 | 0.3946*** | 0.0949 | 0.1956 | 0.7235** |
| | (4.74) | (-0.21) | (2.73) | (3.97) | (0.39) | (-1.67) | (0.90) | (-1.45) | (5.43) | (0.73) | (0.57) | (2.24) |
| $Return\ on\ Assets_{i,t-1}$ | 0.0168 | 0.1985*** | 0.1464 | 0.1671 | 0.0327* | 0.1986*** | 0.1251 | 0.1605 | 0.0415*** | 0.2658*** | 0.2676** | 0.1939 |
| | (0.85) | (3.08) | (1.48) | (1.46) | (1.77) | (3.04) | (1.22) | (1.29) | (4.25) | (3.69) | (2.55) | (1.48) |
| $Tobin\ Q_{i,t-1}$ | 0.0136*** | -0.0080 | -0.0086 | 0.0195** | 0.0120*** | -0.0162 | -0.0142 | 0.0111 | 0.0147*** | -0.0088 | -0.0213 | 0.0279** |
| | (3.49) | (-0.75) | (-0.72) | (2.38) | (2.99) | (-1.06) | (-1.14) | (0.96) | (3.91) | (-0.61) | (-1.44) | (2.07) |
| $Leverage_{i,t-1}$ | 0.0056 | 0.0183* | -0.0083 | 0.0063 | -0.0153* | -0.0126 | -0.0435* | -0.0158 | 0.0047 | 0.0249** | -0.0038 | 0.0070 |
| | (1.58) | (1.72) | (-0.94) | (0.61) | (-1.85) | (-0.52) | (-1.67) | (-0.58) | (0.85) | (2.24) | (-0.25) | (0.46) |
| $CSTI\ to\ Total\ Assets_{i,t-1}$ | 0.0081** | 0.0261** | 0.0111 | 0.0044 | -0.0058 | 0.0494* | -0.0321 | 0.0236 | 0.0093** | 0.0299** | 0.0143 | 0.0280 |
| | (2.45) | (2.08) | (0.81) | (0.28) | (-1.04) | (1.97) | (-1.10) | (0.94) | (2.12) | (2.06) | (0.65) | (1.27) |
| $Equity\ Return\ Volatility_{i,t-1}$ | -0.1265 | 0.4062* | 0.0658 | -0.3408 | -0.1610 | 0.2039 | -0.0356 | -0.3367 | -0.1017 | 0.1129 | 0.3322 | -0.1136 |
| | (-0.97) | (1.96) | (0.21) | (-1.17) | (-1.26) | (0.87) | (-0.10) | (-1.11) | (-1.49) | (0.47) | (0.82) | (-0.37) |
| Constant | -0.1710 | 3.3581 | -4.6408 | -4.5820 | 9.1395*** | 26.0227* | -3.2577 | 23.3903** | 0.4408 | 1.8343 | -1.5453 | -6.1791 |
| | (-0.19) | (1.42) | (-1.43) | (-1.50) | (3.91) | (1.85) | (-0.30) | (2.23) | (0.43) | (0.52) | (-0.27) | (-1.14) |
| Number of Observations | 734 | 736 | 729 | 727 | 734 | 736 | 729 | 727 | 734 | 736 | 729 | 727 |
| $R^2$ | 0.6037 | 0.5809 | 0.4938 | 0.5760 | | | | | | | | |
| Within $R^2$ | | | | | 0.2302 | 0.4086 | 0.4111 | 0.3423 | | | | |
| AR(1) test (p-value) | | | | | | | | | 0.081 | 0.000 | 0.073 | 0.024 |
| AR(2) test (p-value) | | | | | | | | | 0.254 | 0.649 | 0.359 | 0.194 |
| Hansen test of over-identification (p-value) | | | | | | | | | 0.319 | 0.657 | 0.307 | 0.148 |
| Diff-in-Hansen tests of exogeneity (p-value) | | | | | | | | | 0.825 | 0.434 | 0.906 | 0.470 |

Panel B: Impact of the frequency of operational risk event announcements on CEO compensation according to event types

| Variable | Model 1 - OLS | | | | Model 2 - FE | | | | Model 3 - GMM | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | $ln(Total\ Comp)_{i,t}$ | $ln(Bonus)_{i,t}$ | $ln(Stock)_{i,t}$ | $ln(Option)_{i,t}$ | $ln(Total\ Comp)_{i,t}$ | $ln(Bonus)_{i,t}$ | $ln(Stock)_{i,t}$ | $ln(Option)_{i,t}$ | $ln(Total\ Comp)_{i,t}$ | $ln(Bonus)_{i,t}$ | $ln(Stock)_{i,t}$ | $ln(Option)_{i,}$ |
| Event-Level Variables | | | | | | | | | | | | |
| $ln(Total\ Comp)_{i,t-1}$ | 0.3731*** | | | | 0.1236 | | | | 0.2193** | | | |
| | (3.27) | | | | (1.18) | | | | (2.25) | | | |
| $ln(Bonus)_{i,t-1}$ | | 0.4935*** | | | | 0.3294*** | | | | 0.3901*** | | |
| | | (7.54) | | | | (3.83) | | | | (5.43) | | |
| $ln(Stock)_{i,t-1}$ | | | 0.5106*** | | | | 0.2784*** | | | | 0.5645 | |
| | | | (10.41) | | | | (5.48) | | | | (1.30) | |
| $ln(Option)_{i,t-1}$ | | | | 0.4845*** | | | | 0.2769*** | | | | 0.8474 |
| | | | | (8.67) | | | | (4.70) | | | | (1.54) |
| $ln(IF\ Frequency)_{i,t-1}$ | -0.3729 | -0.6820 | -0.5421 | -0.1078 | -0.5371 | -1.0300 | -0.6966 | -0.0172 | -0.2611 | -0.9051 | 0.9460 | 0.5864 |
| | (-1.29) | (-0.83) | (-0.72) | (-0.13) | (-1.55) | (-1.15) | (-0.73) | (-0.02) | (-1.59) | (-1.39) | (0.66) | (0.50) |
| $ln(CPBP\ Frequency)_{i,t-1}$ | -0.3080** | 0.6401** | -0.1090 | -1.4732*** | -0.2913*** | 0.2276 | -0.0105 | -1.1977*** | -0.2846** | 0.3236 | 0.0971 | -1.0793 |
| | (-2.59) | (2.08) | (-0.40) | (-4.58) | (-3.31) | (0.63) | (-0.02) | (-3.33) | (-2.12) | (0.97) | (0.19) | (-1.57) |
| $ln(EF\ Frequency)_{i,t-1}$ | 0.4718* | -0.2733 | 1.4577* | 0.2093 | 0.6008* | -0.4333 | 2.2562*** | -0.0861 | 0.2453 | -0.6496 | 0.9655 | 1.6659 |
| | (1.81) | (-0.36) | (1.68) | (0.65) | (1.88) | (-0.93) | (3.45) | (-0.17) | (0.86) | (-1.64) | (0.75) | (1.13) |
| $Post\ Sarbanes-Oxley\ Act\ Dum_{i,t}$ | 0.1070 | -0.4284 | 0.3420 | -0.6555** | 0.2624** | 0.0557 | 0.6283* | -0.1590 | 0.1115 | -0.5493 | 0.3424 | -0.1701 |
| | (1.18) | (-1.64) | (1.21) | (-2.52) | (2.17) | (0.14) | (1.67) | (-0.52) | (1.34) | (-1.49) | (0.59) | (-0.30) |
| $Global\ Financial\ Crisis\ Dum_{i,t}$ | -0.0873 | -2.4581*** | 0.5755 | -1.7092*** | 0.2769** | -2.0505*** | 1.4777** | -0.8153 | 0.0037 | -1.8837*** | 0.5064 | -0.7747 |
| | (-0.94) | (-6.82) | (1.51) | (-5.38) | (2.38) | (-3.87) | (2.59) | (-1.54) | (0.03) | (-3.79) | (0.51) | (-0.77) |
| $Post\ Dodd-Frank\ Act\ Dum_{i,t}$ | 0.2393 | -1.9652*** | 1.3366** | -2.0521*** | 0.7261*** | -1.5141** | 2.7779*** | -1.2587 | 0.2146 | -2.0739*** | 1.1820 | 0.0681 |
| | (1.64) | (-4.62) | (2.65) | (-4.97) | (3.76) | (-2.02) | (4.05) | (-1.64) | (1.39) | (-3.50) | (0.77) | (0.03) |
| Corporate Governance Variables | | | | | | | | | | | | |
| $Age_{i,t-1}$ | 0.0017 | 0.0261** | 0.0397* | -0.0463** | 0.0173 | 0.0216 | 0.0257 | 0.0296 | 0.0009 | 0.0272** | 0.0374 | -0.0311 |
| | (0.30) | (2.07) | (1.68) | (-2.44) | (1.51) | (0.80) | (0.82) | (0.99) | (0.12) | (1.97) | (1.21) | (-0.93) |
| $Gender_{i,t-1}$ | -0.0810 | 0.4737** | -0.0659 | -1.2445*** | 0.3125** | 1.3420*** | 0.5514 | -0.6887 | -0.1202* | 0.7234*** | -0.0841 | 0.9439 |
| | (-1.40) | (2.35) | (-0.40) | (-3.55) | (2.39) | (3.41) | (1.35) | (-1.60) | (-1.71) | (2.88) | (-0.32) | (0.46) |
| $Duality_{i,t-1}$ | 0.1025 | -0.4514 | 0.2781 | 0.4032 | 0.2022 | -0.0503 | 0.9916* | 0.0192 | 0.1227 | -0.4882 | 0.7082 | 0.3941 |
| | (0.83) | (-1.44) | (0.73) | (1.27) | (1.13) | (-0.12) | (1.76) | (0.04) | (1.06) | (-1.37) | (1.52) | (0.79) |
| $Tenure_{i,t-1}$ | 0.0003 | -0.0170 | -0.0431*** | 0.0198* | -0.0057 | -0.0052 | -0.0837*** | 0.0100 | -0.0009 | -0.0277* | -0.0387 | 0.0156 |
| | (0.08) | (-1.54) | (-2.84) | (1.94) | (-0.92) | (-0.19) | (-4.29) | (0.45) | (-0.17) | (-1.67) | (-1.17) | (0.78) |
| $Board\ Size_{i,t-1}$ | -0.0005 | 0.0553 | 0.0318 | -0.0256 | 0.0236 | 0.1275* | 0.0906* | 0.0189 | -0.0015 | 0.0499 | 0.0781 | -0.0340 |
| | (-0.04) | (1.49) | (0.77) | (-0.87) | (1.32) | (1.92) | (1.77) | (0.35) | (-0.11) | (0.97) | (1.42) | (-0.69) |
| $Board\ Independence\ Ratio_{i,t-1}$ | 0.1262 | -0.0861 | 0.0641 | 1.4274* | 0.0359 | 1.5094 | -1.1945 | -1.1721 | 0.0942 | -0.1816 | -0.0553 | 0.2854 |
| | (0.42) | (-0.10) | (0.06) | (1.67) | (0.06) | (1.01) | (-0.86) | (-0.91) | (0.27) | (-0.18) | (-0.04) | (0.17) |
| $Compensation\ Committee\ Ratio_{i,t-1}$ | 0.0126 | 2.4884*** | 0.8413 | -1.9495*** | -0.3292 | 2.4274* | 0.5225 | -1.9131 | -0.0608 | 2.6045** | 0.6470 | -2.2064 |
| | (0.04) | (3.58) | (0.85) | (-2.96) | (-0.42) | (1.99) | (0.29) | (-1.40) | (-0.19) | (2.53) | (0.46) | (-1.23) |
| Firm-Level Variables | | | | | | | | | | | | |
| $Log\ Total\ Assets_{i,t-1}$ | 0.3134*** | 0.0055 | 0.3369*** | 0.4757*** | 0.0410 | -0.9649 | 0.4398 | -0.5949 | 0.3968*** | 0.0839 | 0.1494 | 0.1957 |
| | (4.63) | (0.06) | (2.95) | (3.95) | (0.47) | (-1.67) | (1.06) | (-1.37) | (6.39) | (0.65) | (0.37) | (0.44) |
| $Return\ on\ Assets_{i,t-1}$ | 0.0163 | 0.2039*** | 0.1473 | 0.1600 | 0.0324* | 0.2013*** | 0.1303 | 0.1527 | 0.0391*** | 0.2680*** | 0.2683*** | 0.1306 |
| | (0.83) | (3.23) | (1.49) | (1.43) | (1.73) | (3.09) | (1.29) | (1.25) | (3.98) | (3.71) | (2.60) | (0.93) |
| $Tobin\ Q_{i,t-1}$ | 0.0139*** | -0.0082 | -0.0083 | 0.0197** | 0.0115*** | -0.0163 | -0.0159 | 0.0109 | 0.0145*** | -0.0088 | -0.0218 | 0.0190 |
| | (3.53) | (-0.77) | (-0.68) | (2.44) | (2.94) | (-1.07) | (-1.26) | (0.99) | (4.12) | (-0.62) | (-1.40) | (0.93) |
| $Leverage_{i,t-1}$ | 0.0069* | 0.0161 | -0.0058 | 0.0099 | -0.0128* | -0.0122 | -0.0389 | -0.0103 | 0.0054 | 0.0228** | -0.0015 | 0.0112 |
| | (1.78) | (1.58) | (-0.66) | (0.92) | (-1.75) | (-0.51) | (-1.64) | (-0.37) | (0.97) | (2.08) | (-0.09) | (0.84) |
| $CSTI\ to\ Total\ Assets_{i,t-1}$ | 0.0084** | 0.0258** | 0.0117 | 0.0052 | -0.0082 | 0.0522** | -0.0387 | 0.0238 | 0.0096** | 0.0303** | 0.0135 | 0.0064 |
| | (2.54) | (2.04) | (0.84) | (0.33) | (-1.38) | (2.09) | (-1.39) | (0.94) | (2.27) | (2.06) | (0.56) | (0.41) |
| $Equity\ Return\ Volatility_{i,t-1}$ | -0.1108 | 0.4178** | 0.1096 | -0.3295 | -0.1399 | 0.2083 | 0.0344 | -0.3219 | -0.0966 | 0.1243 | 0.3432 | 0.0039 |
| | (-0.89) | (2.02) | (0.36) | (-1.11) | (-1.16) | (0.90) | (0.10) | (-1.05) | (-1.33) | (0.52) | (0.84) | (0.01) |
| Constant | 0.0531 | 2.8394 | -5.0341 | -3.3145 | 9.6260*** | 26.2408* | -3.3972 | 22.8106** | 0.4142 | 2.0245 | -0.7680 | -4.0480 |
| | (0.06) | (1.16) | (-1.60) | (-1.16) | (4.36) | (1.84) | (-0.34) | (2.20) | (0.39) | (0.57) | (-0.12) | (-1.27) |
| Number of Observations | 734 | 736 | 729 | 727 | 734 | 736 | 729 | 727 | 734 | 736 | 729 | 727 |
| $R^2$ | 0.6099 | 0.5821 | 0.4963 | 0.5786 | | | | | | | | |
| Within $R^2$ | | | | | 0.2523 | 0.4114 | 0.4172 | 0.3497 | | | | |
| AR(1) test (p-value) | | | | | | | | | 0.077 | 0.000 | 0.094 | 0.066 |
| AR(2) test (p-value) | | | | | | | | | 0.231 | 0.744 | 0.327 | 0.104 |
| Hansen test of over-identification (p-value) | | | | | | | | | 0.374 | 0.748 | 0.257 | 0.419 |
| Diff-in-Hansen tests of exogeneity (p-value) | | | | | | | | | 0.688 | 0.550 | 0.844 | 0.187 |

# Table 4.6 Impact of the Loss Severity of Operational Risk Event Announcements on CEO Compensation

This table reports the estimation results for CEO compensation following the loss severity of operational risk event announcements. Models 1 contain ordinary least squares (OLS) regressions; Models 2 contain panel data fixed-effects (FE) regressions and Models 3 contain dynamic panel data generalized method of moments (GMM) regressions. Robust standard errors are used to correct for operational risk event clustering in OLS and FE regressions. *t-statistics* are reported in parentheses. *, ** and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively (two-tailed). All variable definitions are reported in Table 4.1.

Panel A: Full sample

| Variable | Model 1 - OLS | | | | Model 2 - FE | | | | Model 3 - GMM | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | $ln(Total\ Comp)_{i,t}$ | $ln(Bonus)_{i,t}$ | $ln(Stock)_{i,t}$ | $ln(Option)_{i,t}$ | $ln(Total\ Comp)_{i,t}$ | $ln(Bonus)_{i,t}$ | $ln(Stock)_{i,t}$ | $ln(Option)_{i,t}$ | $ln(Total\ Comp)_{i,t}$ | $ln(Bonus)_{i,t}$ | $ln(Stock)_{i,t}$ | $ln(Option)_{i,}$ |
| Event-Level Variables | | | | | | | | | | | | |
| $ln(Total\ Comp)_{i,t-1}$ | 0.4007*** | | | | 0.1547 | | | | 0.2253** | | | |
| | (3.76) | | | | (1.57) | | | | (2.34) | | | |
| $ln(Bonus)_{i,t-1}$ | | 0.4997*** | | | | 0.3348*** | | | | 0.3874*** | | |
| | | (7.71) | | | | (3.89) | | | | (5.40) | | |
| $ln(Stock)_{i,t-1}$ | | | 0.5135*** | | | | 0.2836*** | | | | 0.5182 | |
| | | | (10.99) | | | | (5.79) | | | | (1.30) | |
| $ln(Option)_{i,t-1}$ | | | | 0.5050*** | | | | 0.2920*** | | | | 0.8674* |
| | | | | (9.60) | | | | (5.29) | | | | (1.92) |
| $ln(Maximum\ Loss)_{i,t-1}$ | -0.0346* | 0.0835 | 0.0786 | -0.3149*** | -0.0334* | -0.0017 | 0.0465 | -0.2233*** | -0.0143 | 0.0167 | 0.0573 | -0.1817** |
| | (-1.68) | (1.28) | (1.37) | (-4.74) | (-1.86) | (-0.03) | (0.67) | (-3.40) | (-0.86) | (0.26) | (0.87) | (-2.12) |
| $Post\ Sarbanes-Oxley\ Act\ Dum_{i,t}$ | 0.0812 | -0.3706 | 0.3217 | -0.7594*** | 0.2458** | 0.0863 | 0.5947 | -0.2056 | 0.0961 | -0.5291 | 0.3723 | -0.2225 |
| | (0.98) | (-1.40) | (1.17) | (-3.13) | (2.15) | (0.22) | (1.59) | (-0.68) | (1.20) | (-1.43) | (0.67) | (-0.43) |
| $Global\ Financial\ Crisis\ Dum_{i,t}$ | -0.1263 | -2.3276*** | 0.5579 | -1.8617*** | 0.2531** | -1.9855*** | 1.4397** | -0.8541 | -0.0065 | -1.8397*** | 0.5518 | -0.8515 |
| | (-1.41) | (-6.52) | (1.47) | (-5.79) | (2.16) | (-3.77) | (2.55) | (-1.59) | (-0.06) | (-3.69) | (0.58) | (-0.99) |
| $Post\ Dodd-Frank\ Act\ Dum_{i,t}$ | 0.1772 | -1.8451*** | 1.2411** | -2.1200*** | 0.6733*** | -1.4602* | 2.6485*** | -1.2036 | 0.1682 | -2.0593*** | 1.3100 | 0.0705 |
| | (1.40) | (-4.08) | (2.59) | (-5.07) | (3.46) | (-1.93) | (3.88) | (-1.53) | (1.15) | (-3.39) | (0.93) | (0.04) |
| Corporate Governance Variables | | | | | | | | | | | | |
| $Age_{i,t-1}$ | 0.0028 | 0.0252* | 0.0410* | -0.0421** | 0.0211* | 0.0229 | 0.0283 | 0.0389 | 0.0021 | 0.0283** | 0.0362 | -0.0287 |
| | (0.52) | (1.98) | (1.77) | (-2.38) | (1.71) | (0.86) | (0.93) | (1.27) | (0.31) | (2.01) | (1.18) | (-1.10) |
| $Gender_{i,t-1}$ | -0.1288** | 0.5315** | -0.1366 | -1.2963*** | 0.3541** | 1.3541*** | 0.5487 | -0.4570 | -0.1831** | 0.7275*** | -0.0572 | 0.9590 |
| | (-2.20) | (2.65) | (-0.83) | (-3.85) | (2.33) | (3.51) | (1.32) | (-1.03) | (-2.57) | (3.00) | (-0.21) | (0.52) |
| $Duality_{i,t-1}$ | 0.1509 | -0.4714 | 0.3423 | 0.5218 | 0.2462 | -0.0539 | 1.0878* | 0.0993 | 0.1446 | -0.5040 | 0.6763 | 0.4398 |
| | (0.98) | (-1.43) | (0.86) | (1.57) | (1.13) | (-0.13) | (1.88) | (0.18) | (1.09) | (-1.39) | (1.46) | (0.95) |
| $Tenure_{i,t-1}$ | 0.0005 | -0.0177 | -0.0404*** | 0.0168* | -0.0069 | -0.0054 | -0.0848*** | 0.0050 | -0.0006 | -0.0286* | -0.0407 | 0.0141 |
| | (0.14) | (-1.66) | (-2.73) | (1.70) | (-0.98) | (-0.20) | (-4.34) | (0.23) | (-0.12) | (-1.70) | (-1.27) | (0.76) |
| $Board\ Size_{i,t-1}$ | 0.0035 | 0.0508 | 0.0372 | -0.0173 | 0.0270 | 0.1255* | 0.0957* | 0.0239 | 0.0013 | 0.0446 | 0.0783 | -0.0181 |
| | (0.27) | (1.39) | (0.93) | (-0.58) | (1.44) | (1.91) | (1.82) | (0.44) | (0.09) | (0.87) | (1.46) | (-0.37) |
| $Board\ Independence\ Ratio_{i,t-1}$ | 0.2099 | -0.2498 | 0.1087 | 1.7291** | 0.0527 | 1.3157 | -1.1370 | -0.9800 | 0.1471 | -0.3098 | -0.1234 | 0.2521 |
| | (0.75) | (-0.30) | (0.11) | (2.03) | (0.10) | (0.88) | (-0.83) | (-0.76) | (0.44) | (-0.30) | (-0.10) | (0.16) |
| $Compensation\ Committee\ Ratio_{i,t-1}$ | 0.0528 | 2.5099*** | 0.8595 | -1.7831*** | -0.1450 | 2.5185** | 0.7211 | -1.7123 | -0.0403 | 2.6988*** | 0.6648 | -2.0845 |
| | (0.18) | (3.62) | (0.85) | (-2.74) | (-0.18) | (2.04) | (0.40) | (-1.33) | (-0.13) | (2.61) | (0.48) | (-1.34) |
| Firm-Level Variables | | | | | | | | | | | | |
| $Log\ Total\ Assets_{i,t-1}$ | 0.2704*** | 0.0290 | 0.2730** | 0.4393*** | -0.0113 | -0.9822* | 0.4803 | -0.7437 | 0.3557*** | 0.0936 | 0.2120 | 0.1763 |
| | (4.34) | (0.32) | (2.39) | (4.32) | (-0.13) | (-1.75) | (1.13) | (-1.63) | (4.99) | (0.80) | (0.61) | (0.69) |
| $Return\ on\ Assets_{i,t-1}$ | 0.0197 | 0.1945*** | 0.1477 | 0.1718 | 0.0334* | 0.1984*** | 0.1249 | 0.1656 | 0.0414*** | 0.2652*** | 0.2638*** | 0.1404 |
| | (1.00) | (3.02) | (1.50) | (1.50) | (1.77) | (3.04) | (1.22) | (1.34) | (3.64) | (3.68) | (2.62) | (0.99) |
| $Tobin\ Q_{i,t-1}$ | 0.0130*** | -0.0076 | -0.0088 | 0.0178** | 0.0117*** | -0.0164 | -0.0138 | 0.0104 | 0.0142*** | -0.0087 | -0.0206 | 0.0173 |
| | (3.35) | (-0.70) | (-0.73) | (2.26) | (2.97) | (-1.08) | (-1.12) | (0.90) | (4.13) | (-0.60) | (-1.38) | (1.00) |
| $Leverage_{i,t-1}$ | 0.0048 | 0.0195* | -0.0089 | 0.0052 | -0.0163* | -0.0135 | -0.0415 | -0.0172 | 0.0041 | 0.0248** | -0.0044 | 0.0071 |
| | (1.34) | (1.79) | (-1.03) | (0.47) | (-1.91) | (-0.55) | (-1.59) | (-0.60) | (0.74) | (2.21) | (-0.29) | (0.52) |
| $CSTI\ to\ Total\ Assets_{i,t-1}$ | 0.0076*** | 0.0264** | 0.0107 | 0.0034 | -0.0068 | 0.0487* | -0.0298 | 0.0183 | 0.0088** | 0.0300** | 0.0155 | 0.0042 |
| | (2.67) | (2.04) | (0.79) | (0.22) | (-1.22) | (1.93) | (-1.04) | (0.71) | (2.28) | (2.06) | (0.70) | (0.32) |
| $Equity\ Return\ Volatility_{i,t-1}$ | -0.1232 | 0.3999* | 0.0377 | -0.2973 | -0.1539 | 0.2019 | -0.0382 | -0.2851 | -0.1244* | 0.1060 | 0.3190 | 0.0781 |
| | (-0.97) | (1.90) | (0.12) | (-1.06) | (-1.23) | (0.86) | (-0.11) | (-0.98) | (-1.72) | (0.44) | (0.77) | (0.18) |
| Constant | 0.6680 | 2.2025 | -3.5621 | -2.9061 | 10.0801*** | 26.7281* | -4.9942 | 25.4307** | 1.2870 | 1.8719 | -1.7577 | -3.9349 |
| | (0.72) | (0.96) | (-1.09) | (-1.09) | (4.21) | (1.92) | (-0.47) | (2.33) | (1.23) | (0.56) | (-0.30) | (-1.22) |
| Number of Observations | 734 | 736 | 729 | 727 | 734 | 736 | 729 | 727 | 734 | 736 | 729 | 727 |
| $R^2$ | 0.5986 | 0.5797 | 0.4947 | 0.5739 | | | | | | | | |
| Within $R^2$ | | | | | 0.2263 | 0.4085 | 0.4103 | 0.3452 | | | | |
| AR(1) test (p-value) | | | | | | | | | 0.078 | 0.000 | 0.087 | 0.038 |
| AR(2) test (p-value) | | | | | | | | | 0.248 | 0.658 | 0.361 | 0.103 |
| Hansen test of over-identification (p-value) | | | | | | | | | 0.389 | 0.651 | 0.292 | 0.410 |
| Diff-in-Hansen tests of exogeneity (p-value) | | | | | | | | | 0.934 | 0.429 | 0.878 | 0.147 |

Panel B: Impact of the loss severity of operational risk event announcements on CEO compensation according to event types

| Variable | Model 1 - OLS | | | | Model 2 - FE | | | | Model 3 - GMM | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | $ln(Total\ Comp)_{i,t}$ | $ln(Bonus)_{i,t}$ | $ln(Stock)_{i,t}$ | $ln(Option)_{i,t}$ | $ln(Total\ Comp)_{i,t}$ | $ln(Bonus)_{i,t}$ | $ln(Stock)_{i,t}$ | $ln(Option)_{i,t}$ | $ln(Total\ Comp)_{i,t}$ | $ln(Bonus)_{i,t}$ | $ln(Stock)_{i,t}$ | $ln(Option)_{i,}$ |
| Event-Level Variables | | | | | | | | | | | | |
| $ln(Total\ Comp)_{i,t-1}$ | 0.3957*** | | | | 0.1464 | | | | 0.2050* | | | |
| | (3.57) | | | | (1.34) | | | | (1.69) | | | |
| $ln(Bonus)_{i,t-1}$ | | 0.5027*** | | | | 0.3370*** | | | | 0.3908*** | | |
| | | (7.71) | | | | (3.91) | | | | (5.50) | | |
| $ln(Stock)_{i,t-1}$ | | | 0.5137*** | | | | 0.2784*** | | | | 0.4207 | |
| | | | (10.71) | | | | (5.46) | | | | (1.21) | |
| $ln(Option)_{i,t-1}$ | | | | 0.4990*** | | | | 0.2907*** | | | | 0.1746 |
| | | | | (9.59) | | | | (5.29) | | | | (0.81) |
| $ln(IF\ Maximum\ Loss)_{i,t-1}$ | -0.0458 | -0.0329 | -0.2223* | 0.1531 | -0.0732 | -0.0786 | -0.2588 | 0.1583 | -0.0163 | -0.0520 | -0.2238* | 0.1567 |
| | (-0.55) | (-0.24) | (-1.81) | (0.83) | (-0.78) | (-0.50) | (-1.49) | (0.83) | (-0.23) | (-0.64) | (-1.72) | (0.61) |
| $ln(CPBP\ Maximum\ Loss)_{i,t-1}$ | -0.0716** | 0.0688 | 0.0445 | -0.4640*** | -0.0691** | 0.0133 | -0.0157 | -0.3981*** | -0.0493* | -0.0071 | 0.0145 | -0.3960*** |
| | (-2.07) | (0.99) | (0.70) | (-5.31) | (-2.51) | (0.21) | (-0.21) | (-4.74) | (-1.66) | (-0.11) | (0.14) | (-3.53) |
| $ln(EF\ Maximum\ Loss)_{i,t-1}$ | 0.1010** | 0.2244* | 0.1287 | 0.1399 | 0.0871** | 0.1185 | 0.0642 | 0.1895 | 0.1076* | 0.1849 | 0.0228 | 0.3003* |
| | (2.60) | (1.95) | (0.83) | (0.97) | (2.01) | (1.17) | (0.50) | (1.23) | (1.91) | (1.50) | (0.16) | (1.68) |
| $Post\ Sarbanes-Oxley\ Act\ Dum_{i,t}$ | 0.0737 | -0.3809 | 0.3318 | -0.8030*** | 0.2307** | 0.0766 | 0.6133 | -0.3005 | 0.0680 | -0.5624 | 0.4971 | -0.7427** |
| | (0.86) | (-1.46) | (1.20) | (-3.29) | (2.07) | (0.20) | (1.63) | (-1.04) | (0.86) | (-1.56) | (1.04) | (-2.21) |
| $Global\ Financial\ Crisis\ Dum_{i,t}$ | -0.1433 | -2.3288*** | 0.5620 | -1.9582*** | 0.2185** | -2.0032*** | 1.4722** | -1.0646** | -0.0362 | -1.8736*** | 0.6481 | -2.4342*** |
| | (-1.55) | (-6.47) | (1.47) | (-6.14) | (2.03) | (-3.79) | (2.56) | (-2.07) | (-0.33) | (-3.78) | (0.82) | (-3.74) |
| $Post\ Dodd-Frank\ Act\ Dum_{i,t}$ | 0.2069 | -1.8174*** | 1.3035*** | -2.0948*** | 0.6815*** | -1.4761* | 2.7610*** | -1.2791 | 0.1499 | -2.0773*** | 1.5533 | -2.9256*** |
| | (1.56) | (-4.03) | (2.66) | (-5.05) | (3.83) | (-1.99) | (4.02) | (-1.65) | (1.01) | (-3.51) | (1.25) | (-2.71) |
| Corporate Governance Variables | | | | | | | | | | | | |
| $Age_{i,t-1}$ | 0.0026 | 0.0258** | 0.0411* | -0.0445** | 0.0186* | 0.0220 | 0.0264 | 0.0276 | 0.0015 | 0.0285** | 0.0481 | -0.0583* |
| | (0.48) | (2.02) | (1.77) | (-2.43) | (1.69) | (0.82) | (0.91) | (0.92) | (0.21) | (2.00) | (1.41) | (-1.80) |
| $Gender_{i,t-1}$ | -0.0368 | 0.5375*** | -0.1450 | -0.8153** | 0.3290** | 1.2864*** | 0.5596 | -0.4854 | -0.1283 | 0.7550*** | -0.2665 | -1.4034 |
| | (-0.38) | (2.66) | (-0.84) | (-2.45) | (2.23) | (3.32) | (1.33) | (-1.13) | (-1.56) | (2.93) | (-1.11) | (-1.43) |
| $Duality_{i,t-1}$ | 0.1565 | -0.4368 | 0.3248 | 0.5581* | 0.2326 | -0.0724 | 1.0407* | 0.1493 | 0.1084 | -0.4987 | 0.2397 | 0.4813 |
| | (1.00) | (-1.39) | (0.84) | (1.73) | (1.13) | (-0.18) | (1.86) | (0.28) | (0.77) | (-1.35) | (0.50) | (0.97) |
| $Tenure_{i,t-1}$ | -0.0007 | -0.0192* | -0.0435*** | 0.0157 | -0.0073 | -0.0044 | -0.0898*** | 0.0072 | -0.0005 | -0.0287* | -0.0417 | 0.0283 |
| | (-0.20) | (-1.78) | (-2.88) | (1.57) | (-1.20) | (-0.16) | (-4.37) | (0.31) | (-0.09) | (-1.70) | (-1.41) | (1.57) |
| $Board\ Size_{i,t-1}$ | 0.0011 | 0.0481 | 0.0327 | -0.0227 | 0.0262 | 0.1243* | 0.0906* | 0.0271 | -0.0020 | 0.0395 | 0.0708 | -0.0065 |
| | (0.09) | (1.31) | (0.80) | (-0.80) | (1.43) | (1.89) | (1.74) | (0.52) | (-0.13) | (0.77) | (1.37) | (-0.12) |
| $Board\ Independence\ Ratio_{i,t-1}$ | 0.2075 | -0.1791 | 0.1360 | 1.6458* | 0.1121 | 1.3769 | -0.9911 | -0.9519 | 0.2131 | -0.2437 | 0.3290 | 2.0967 |
| | (0.72) | (-0.22) | (0.14) | (1.87) | (0.19) | (0.92) | (-0.73) | (-0.76) | (0.61) | (-0.24) | (0.27) | (1.38) |
| $Compensation\ Committee\ Ratio_{i,t-1}$ | 0.0188 | 2.4885*** | 0.8209 | -1.9495*** | -0.2084 | 2.5367** | 0.7054 | -2.1792 | -0.0365 | 2.7125*** | 1.3498 | -2.9067** |
| | (0.07) | (3.55) | (0.83) | (-3.07) | (-0.27) | (2.04) | (0.40) | (-1.64) | (-0.11) | (2.63) | (0.97) | (-2.17) |
| Firm-Level Variables | | | | | | | | | | | | |
| $Log\ Total\ Assets_{i,t-1}$ | 0.2914*** | 0.0239 | 0.3218*** | 0.4865*** | 0.0354 | -0.9828* | 0.5497 | -0.5455 | 0.3808*** | 0.0986 | 0.3651 | 0.6319*** |
| | (4.22) | (0.25) | (2.76) | (4.52) | (0.42) | (-1.73) | (1.27) | (-1.28) | (4.53) | (0.83) | (0.99) | (2.72) |
| $Return\ on\ Assets_{i,t-1}$ | 0.0205 | 0.1959*** | 0.1493 | 0.1709 | 0.0347** | 0.2006*** | 0.1350 | 0.1532 | 0.0390*** | 0.2685*** | 0.1535 | 0.1840 |
| | (1.05) | (3.06) | (1.54) | (1.46) | (2.00) | (3.07) | (1.35) | (1.23) | (4.06) | (3.75) | (0.78) | (1.36) |
| $Tobin\ Q_{i,t-1}$ | 0.0129*** | -0.0075 | -0.0085 | 0.0169** | 0.0117*** | -0.0165 | -0.0131 | 0.0090 | 0.0140*** | -0.0095 | -0.0143 | 0.0286** |
| | (3.32) | (-0.68) | (-0.70) | (2.12) | (2.95) | (-1.07) | (-1.05) | (0.83) | (3.74) | (-0.66) | (-0.76) | (2.09) |
| $Leverage_{i,t-1}$ | 0.0051 | 0.0209* | -0.0068 | 0.0029 | -0.0152* | -0.0135 | -0.0377 | -0.0158 | 0.0039 | 0.0247** | -0.0035 | 0.0051 |
| | (1.46) | (1.88) | (-0.78) | (0.26) | (-1.92) | (-0.56) | (-1.49) | (-0.58) | (0.71) | (2.22) | (-0.20) | (0.30) |
| $CSTI\ to\ Total\ Assets_{i,t-1}$ | 0.0087*** | 0.0270** | 0.0118 | 0.0071 | -0.0065 | 0.0484* | -0.0277 | 0.0175 | 0.0099** | 0.0308** | 0.0198 | 0.0343 |
| | (2.76) | (2.10) | (0.84) | (0.45) | (-1.18) | (1.88) | (-0.93) | (0.79) | (2.46) | (2.13) | (0.75) | (1.44) |
| $Equity\ Return\ Volatility_{i,t-1}$ | -0.0955 | 0.4120* | 0.0846 | -0.2222 | -0.1248 | 0.2130 | 0.0157 | -0.2029 | -0.0877 | 0.1434 | 0.3417 | -0.0034 |
| | (-0.78) | (1.96) | (0.26) | (-0.82) | (-1.04) | (0.92) | (0.05) | (-0.74) | (-1.01) | (0.59) | (1.00) | (-0.01) |
| Constant | 0.1709 | 2.1646 | -4.7485 | -4.1072 | 9.2038*** | 26.8016* | -6.6745 | 21.4671** | 1.0012 | 1.7436 | -5.6433 | -4.1761 |
| | (0.19) | (0.94) | (-1.44) | (-1.53) | (3.81) | (1.91) | (-0.62) | (2.07) | (0.92) | (0.54) | (-0.75) | (-0.93) |
| Number of Observations | 734 | 736 | 729 | 727 | 734 | 736 | 729 | 727 | 734 | 736 | 729 | 727 |
| $R^2$ | 0.6082 | 0.5808 | 0.4958 | 0.5892 | | | | | | | | |
| Within $R^2$ | | | | | 0.2462 | 0.4094 | 0.4132 | 0.3704 | | | | |
| AR(1) test (p-value) | | | | | | | | | 0.092 | 0.000 | 0.098 | 0.019 |
| AR(2) test (p-value) | | | | | | | | | 0.260 | 0.557 | 0.218 | 0.265 |
| Hansen test of over-identification (p-value) | | | | | | | | | 0.318 | 0.601 | 0.278 | 0.134 |
| Diff-in-Hansen tests of exogeneity (p-value) | | | | | | | | | 0.699 | 0.386 | 0.635 | 0.425 |

# Table 4.7 Impact of the Market Reaction to Operational Risk Event Announcements on CEO Compensation

This table reports the estimation results for CEO compensation following the market reaction to operational risk event announcements. Models 1 contain ordinary least squares (OLS) regressions; Models 2 contain panel data fixed-effects (FE) regressions and Models 3 contain dynamic panel data generalized method of moments (GMM) regressions. Robust standard errors are used to correct for operational risk event clustering in OLS and FE regressions. *t-statistics* are reported in parentheses. *, ** and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively (two-tailed). All variable definitions are reported in Table 4.1.

Panel A: Full sample

| Variable | Model 1 - OLS | | | | Model 2 - FE | | | | Model 3 - GMM | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | $ln(Total\ Comp)_{i,t}$ | $ln(Bonus)_{i,t}$ | $ln(Stock)_{i,t}$ | $ln(Option)_{i,t}$ | $ln(Total\ Comp)_{i,t}$ | $ln(Bonus)_{i,t}$ | $ln(Stock)_{i,t}$ | $ln(Option)_{i,t}$ | $ln(Total\ Comp)_{i,t}$ | $ln(Bonus)_{i,t}$ | $ln(Stock)_{i,t}$ | $ln(Option)_{i,}$ |
| Event-Level Variables | | | | | | | | | | | | |
| $ln(Total\ Comp)_{i,t-1}$ | 0.4028*** | | | | 0.1594* | | | | 0.2260** | | | |
| | (3.96) | | | | (1.75) | | | | (2.54) | | | |
| $ln(Bonus)_{i,t-1}$ | | 0.4986*** | | | | 0.3276*** | | | | 0.3843*** | | |
| | | (7.65) | | | | (3.77) | | | | (5.34) | | |
| $ln(Stock)_{i,t-1}$ | | | 0.5133*** | | | | 0.2822*** | | | | 0.5762 | |
| | | | (10.93) | | | | (5.85) | | | | (1.48) | |
| $ln(Option)_{i,t-1}$ | | | | 0.5166*** | | | | 0.2940*** | | | | 0.2312 |
| | | | | (9.94) | | | | (5.32) | | | | (0.93) |
| $Minimum\ CAR_{i,t-1}$ | 0.0329 | 0.0151 | -0.0226 | 0.1075*** | 0.0327 | 0.0473* | -0.0028 | 0.0644* | 0.0273* | 0.0380 | -0.0455 | 0.0585 |
| | (1.61) | (0.64) | (-0.70) | (3.06) | (1.56) | (1.71) | (-0.09) | (1.97) | (1.68) | (1.32) | (-1.15) | (1.38) |
| $Post\ Sarbanes - Oxley\ Act\ Dum_{i,t}$ | 0.0595 | -0.3814 | 0.3378 | -0.8279*** | 0.2140** | 0.0442 | 0.5998 | -0.2747 | 0.0780 | -0.5573 | 0.3704 | -0.7115** |
| | (0.72) | (-1.44) | (1.21) | (-3.37) | (2.00) | (0.12) | (1.58) | (-0.90) | (1.04) | (-1.54) | (0.68) | (-2.17) |
| $Global\ Financial\ Crisis\ Dum_{i,t}$ | -0.1127 | -2.3344*** | 0.5452 | -1.7780*** | 0.2381** | -2.0295*** | 1.4515** | -0.9035* | -0.0205 | -1.8511*** | 0.4546 | -2.1546*** |
| | (-1.27) | (-6.46) | (1.44) | (-5.50) | (2.09) | (-3.87) | (2.56) | (-1.69) | (-0.19) | (-3.71) | (0.49) | (-3.24) |
| $Post\ Dodd - Frank\ Act\ Dum_{i,t}$ | 0.1629 | -1.7974*** | 1.2853** | -2.2359*** | 0.6313*** | -1.5091* | 2.6959*** | -1.4220* | 0.1663 | -2.0688*** | 1.1940 | -2.9031** |
| | (1.34) | (-3.93) | (2.65) | (-5.20) | (3.50) | (-2.00) | (3.97) | (-1.86) | (1.17) | (-3.43) | (0.88) | (-2.57) |
| Corporate Governance Variables | | | | | | | | | | | | |
| $Age_{i,t-1}$ | 0.0022 | 0.0230* | 0.0405* | -0.0399** | 0.0204* | 0.0211 | 0.0277 | 0.0399 | 0.0013 | 0.0270* | 0.0350 | -0.0578* |
| | (0.40) | (1.83) | (1.75) | (-2.37) | (1.78) | (0.78) | (0.93) | (1.30) | (0.19) | (1.94) | (1.20) | (-1.90) |
| $Gender_{i,t-1}$ | -0.1371** | 0.6376*** | -0.0703 | -1.5038*** | 0.2892** | 1.3118*** | 0.5937 | -0.7206 | -0.1727** | 0.7880*** | -0.0178 | -1.8130 |
| | (-2.29) | (2.92) | (-0.45) | (-4.23) | (2.28) | (3.26) | (1.47) | (-1.66) | (-2.47) | (3.23) | (-0.06) | (-1.63) |
| $Duality_{i,t-1}$ | 0.1475 | -0.4877 | 0.3383 | 0.5294 | 0.2689 | -0.0190 | 1.0915* | 0.1210 | 0.1677 | -0.5073 | 0.6658 | 0.3683 |
| | (1.01) | (-1.42) | (0.86) | (1.58) | (1.21) | (-0.05) | (1.87) | (0.22) | (1.22) | (-1.39) | (1.45) | (0.67) |
| $Tenure_{i,t-1}$ | 0.0004 | -0.0202* | -0.0418*** | 0.0212** | -0.0083 | -0.0089 | -0.0866*** | 0.0089 | -0.0010 | -0.0309* | -0.0366 | 0.0338* |
| | (0.11) | (-1.86) | (-2.78) | (2.09) | (-1.05) | (-0.33) | (-4.15) | (0.38) | (-0.19) | (-1.86) | (-1.21) | (1.91) |
| $Board\ Size_{i,t-1}$ | 0.0029 | 0.0450 | 0.0346 | -0.0079 | 0.0292 | 0.1271* | 0.0937* | 0.0346 | 0.0018 | 0.0432 | 0.0803 | -0.0056 |
| | (0.23) | (1.19) | (0.85) | (-0.25) | (1.53) | (1.96) | (1.79) | (0.61) | (0.11) | (0.85) | (1.49) | (-0.11) |
| $Board\ Independence\ Ratio_{i,t-1}$ | 0.1797 | -0.3229 | 0.0905 | 1.7514** | 0.0093 | 1.2525 | -1.1350 | -1.0568 | 0.0478 | -0.3491 | -0.0188 | 1.5610 |
| | (0.63) | (-0.39) | (0.09) | (2.01) | (0.02) | (0.85) | (-0.83) | (-0.79) | (0.13) | (-0.33) | (-0.02) | (1.04) |
| $Compensation\ Committee\ Ratio_{i,t-1}$ | 0.0206 | 2.4515*** | 0.8567 | -1.7660*** | -0.2594 | 2.3189* | 0.6905 | -1.7742 | -0.0576 | 2.5866** | 0.6699 | -2.8608** |
| | (0.07) | (3.59) | (0.85) | (-2.70) | (-0.33) | (1.80) | (0.39) | (-1.31) | (-0.18) | (2.52) | (0.48) | (-2.19) |
| Firm-Level Variables | | | | | | | | | | | | |
| $Log\ Total\ Assets_{i,t-1}$ | 0.2701*** | 0.1148 | 0.3197*** | 0.2623*** | 0.0244 | -0.8970 | 0.5075 | -0.7755 | 0.3623*** | 0.1407 | 0.1716 | 0.4415* |
| | (5.00) | (1.08) | (3.66) | (2.77) | (0.34) | (-1.61) | (1.15) | (-1.57) | (5.51) | (1.20) | (0.53) | (1.84) |
| $Return\ on\ Assets_{i,t-1}$ | 0.0188 | 0.1918*** | 0.1468 | 0.1725 | 0.0346* | 0.2010*** | 0.1264 | 0.1616 | 0.0394*** | 0.2623*** | 0.2672** | 0.1982 |
| | (0.95) | (2.97) | (1.51) | (1.55) | (1.76) | (3.02) | (1.23) | (1.33) | (3.16) | (3.58) | (2.52) | (1.45) |
| $Tobin\ Q_{i,t-1}$ | 0.0135*** | -0.0070 | -0.0090 | 0.0187** | 0.0121*** | -0.0155 | -0.0137 | 0.0109 | 0.0136*** | -0.0088 | -0.0208 | 0.0255* |
| | (3.37) | (-0.64) | (-0.75) | (2.35) | (2.98) | (-1.03) | (-1.09) | (0.90) | (3.99) | (-0.61) | (-1.41) | (1.86) |
| $Leverage_{i,t-1}$ | 0.0054 | 0.0207* | -0.0087 | 0.0051 | -0.0142* | -0.0095 | -0.0405 | -0.0178 | 0.0049 | 0.0266** | -0.0037 | 0.0022 |
| | (1.50) | (1.86) | (-1.00) | (0.47) | (-1.70) | (-0.39) | (-1.57) | (-0.64) | (0.90) | (2.31) | (-0.23) | (0.13) |
| $CSTI\ to\ Total\ Assets_{i,t-1}$ | 0.0079*** | 0.0275** | 0.0109 | 0.0026 | -0.0077 | 0.0477* | -0.0299 | 0.0167 | 0.0097** | 0.0306** | 0.0132 | 0.0301 |
| | (2.67) | (2.04) | (0.78) | (0.18) | (-1.40) | (1.88) | (-1.05) | (0.63) | (2.41) | (2.05) | (0.58) | (1.34) |
| $Equity\ Return\ Volatility_{i,t-1}$ | -0.0871 | 0.4625** | 0.0386 | -0.2721 | -0.1171 | 0.2668 | -0.0262 | -0.2767 | -0.0979 | 0.1448 | 0.3360 | -0.1113 |
| | (-0.81) | (2.19) | (0.12) | (-0.99) | (-1.13) | (1.12) | (-0.08) | (-0.96) | (-1.37) | (0.58) | (0.82) | (-0.39) |
| Constant | 0.6446 | 0.2602 | -4.6176 | 0.8950 | 9.1857*** | 24.7971* | -5.6247 | 26.1761** | 1.2517 | 0.8773 | -1.4773 | 0.8829 |
| | (0.75) | (0.11) | (-1.59) | (0.37) | (3.74) | (1.80) | (-0.51) | (2.20) | (1.19) | (0.26) | (-0.27) | (0.22) |
| Number of Observations | 734 | 736 | 729 | 727 | 734 | 736 | 729 | 727 | 734 | 736 | 729 | 727 |
| $R^2$ | 0.6083 | 0.5788 | 0.4942 | 0.5707 | | | | | | | | |
| Within $R^2$ | | | | | 0.2469 | 0.4119 | 0.4099 | 0.3413 | | | | |
| AR(1) test (p-value) | | | | | | | | | 0.070 | 0.000 | 0.066 | 0.028 |
| AR(2) test (p-value) | | | | | | | | | 0.243 | 0.665 | 0.352 | 0.247 |
| Hansen test of over-identification (p-value) | | | | | | | | | 0.421 | 0.688 | 0.294 | 0.157 |
| Diff-in-Hansen tests of exogeneity (p-value) | | | | | | | | | 0.879 | 0.461 | 0.914 | 0.512 |

Panel B: Impact of the market reaction to operational risk event announcements on CEO compensation according to event types

| Variable | Model 1 - OLS | | | | Model 2 - FE | | | | Model 3 - GMM | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | $ln(Total\ Comp)_{i,t}$ | $ln(Bonus)_{i,t}$ | $ln(Stock)_{i,t}$ | $ln(Option)_{i,t}$ | $ln(Total\ Comp)_{i,t}$ | $ln(Bonus)_{i,t}$ | $ln(Stock)_{i,t}$ | $ln(Option)_{i,t}$ | $ln(Total\ Comp)_{i,t}$ | $ln(Bonus)_{i,t}$ | $ln(Stock)_{i,t}$ | $ln(Option)_{i,t}$ |
| Event-Level Variables | | | | | | | | | | | | |
| $ln(Total\ Comp)_{i,t-1}$ | 0.3824*** | | | | 0.1420 | | | | 0.2208*** | | | |
| | (3.61) | | | | (1.58) | | | | (2.64) | | | |
| $ln(Bonus)_{i,t-1}$ | | 0.4990*** | | | | 0.3303*** | | | | 0.3740*** | | |
| | | (7.60) | | | | (3.79) | | | | (5.21) | | |
| $ln(Stock)_{i,t-1}$ | | | 0.5126*** | | | | 0.2804*** | | | | 0.5956 | |
| | | | (10.77) | | | | (5.72) | | | | (1.41) | |
| $ln(Option)_{i,t-1}$ | | | | 0.5008*** | | | | 0.2740*** | | | | 0.1962 |
| | | | | (9.16) | | | | (4.90) | | | | (0.88) |
| $IF\ Minimum\ CAR_{i,t-1}$ | 0.0256* | 0.0350 | 0.0165 | -0.0464 | 0.0264 | 0.0361 | 0.0158 | -0.0772*** | 0.0181 | 0.0301 | -0.0090 | -0.1004*** |
| | (1.80) | (1.45) | (0.80) | (-1.53) | (1.58) | (1.44) | (0.58) | (-3.11) | (1.60) | (1.21) | (-0.33) | (-3.21) |
| $CPBP\ Minimum\ CAR_{i,t-1}$ | 0.0406 | -0.0365 | -0.0230 | 0.1457*** | 0.0380 | 0.0012 | -0.0044 | 0.1201** | 0.0410 | -0.0078 | -0.0406 | 0.1074 |
| | (1.60) | (-1.42) | (-0.59) | (2.82) | (1.53) | (0.03) | (-0.13) | (2.49) | (1.54) | (-0.24) | (-0.63) | (1.50) |
| $EF\ Minimum\ CAR_{i,t-1}$ | 0.0307 | 0.0790** | 0.0375 | 0.0380 | 0.0269 | 0.0820* | 0.0566 | 0.0177 | 0.0085 | 0.0794* | 0.0291 | 0.0159 |
| | (0.86) | (2.02) | (0.51) | (0.64) | (0.96) | (1.71) | (0.94) | (0.35) | (0.52) | (1.72) | (0.50) | (0.26) |
| $Post\ Sarbanes-Oxley\ Act\ Dum_{i,t}$ | 0.0834 | -0.4013 | 0.3076 | -0.7633*** | 0.2384** | 0.0495 | 0.5691 | -0.2396 | 0.1202 | -0.5501 | 0.2735 | -0.5967* |
| | (0.98) | (-1.49) | (1.10) | (-2.96) | (2.19) | (0.13) | (1.50) | (-0.80) | (1.51) | (-1.48) | (0.48) | (-1.87) |
| $Global\ Financial\ Crisis\ Dum_{i,t}$ | -0.0876 | -2.3616*** | 0.5396 | -1.7331*** | 0.2587** | -2.0369*** | 1.4303** | -0.8217 | 0.0029 | -1.9042*** | 0.3767 | -2.0728*** |
| | (-1.02) | (-6.68) | (1.44) | (-5.40) | (2.23) | (-4.01) | (2.52) | (-1.57) | (0.03) | (-3.91) | (0.38) | (-3.22) |
| $Post\ Dodd-Frank\ Act\ Dum_{i,t}$ | 0.1956 | -1.8454*** | 1.2641** | -2.2150*** | 0.6659*** | -1.5289** | 2.6601*** | -1.3806* | 0.2386 | -2.1132*** | 1.0666 | -3.0780*** |
| | (1.53) | (-4.15) | (2.58) | (-5.19) | (3.53) | (-2.09) | (3.88) | (-1.90) | (1.54) | (-3.52) | (0.72) | (-2.97) |
| Corporate Governance Variables | | | | | | | | | | | | |
| $Age_{i,t-1}$ | 0.0027 | 0.0225* | 0.0392* | -0.0368** | 0.0205* | 0.0210 | 0.0267 | 0.0447 | 0.0028 | 0.0278** | 0.0331 | -0.0597* |
| | (0.50) | (1.75) | (1.68) | (-2.11) | (1.82) | (0.78) | (0.91) | (1.47) | (0.41) | (2.02) | (1.15) | (-1.75) |
| $Gender_{i,t-1}$ | -0.1461** | 0.5606** | -0.0874 | -1.4896*** | 0.2746** | 1.2932*** | 0.5574 | -0.6806 | -0.1653** | 0.7388*** | -0.0030 | -1.8905* |
| | (-2.55) | (2.60) | (-0.59) | (-3.97) | (2.20) | (3.28) | (1.40) | (-1.47) | (-2.25) | (2.97) | (-0.01) | (-1.84) |
| $Duality_{i,t-1}$ | 0.1391 | -0.5066 | 0.3217 | 0.5347 | 0.2549 | -0.0686 | 1.0845* | 0.1688 | 0.2023 | -0.5424 | 0.6681 | 0.2338 |
| | (1.07) | (-1.46) | (0.83) | (1.64) | (1.18) | (-0.17) | (1.86) | (0.32) | (1.48) | (-1.48) | (1.44) | (0.40) |
| $Tenure_{i,t-1}$ | 0.0001 | -0.0191* | -0.0420*** | 0.0204** | -0.0080 | -0.0075 | -0.0885*** | 0.0059 | -0.0021 | -0.0303* | -0.0364 | 0.0368* |
| | (0.02) | (-1.75) | (-2.78) | (2.01) | (-1.00) | (-0.28) | (-4.16) | (0.25) | (-0.39) | (-1.84) | (-1.17) | (1.92) |
| $Board\ Size_{i,t-1}$ | 0.0037 | 0.0467 | 0.0333 | -0.0105 | 0.0302 | 0.1279* | 0.0942* | 0.0240 | 0.0066 | 0.0466 | 0.0795 | -0.0297 |
| | (0.30) | (1.24) | (0.81) | (-0.31) | (1.64) | (1.93) | (1.79) | (0.43) | (0.41) | (0.90) | (1.44) | (-0.55) |
| $Board\ Independence\ Ratio_{i,t-1}$ | 0.1735 | -0.3146 | 0.0552 | 1.7535* | 0.0310 | 1.2676 | -1.1790 | -1.2425 | -0.0149 | -0.4507 | -0.1072 | 1.7798 |
| | (0.60) | (-0.38) | (0.06) | (1.99) | (0.05) | (0.86) | (-0.84) | (-0.91) | (-0.04) | (-0.43) | (-0.09) | (1.11) |
| $Compensation\ Committee\ Ratio_{i,t-1}$ | 0.0596 | 2.6035*** | 0.9035 | -2.0296*** | -0.2250 | 2.4787* | 0.6640 | -1.8717 | 0.0482 | 2.8061*** | 0.6090 | -3.3099** |
| | (0.20) | (3.72) | (0.90) | (-2.99) | (-0.28) | (1.88) | (0.38) | (-1.38) | (0.15) | (2.69) | (0.42) | (-2.41) |
| Firm-Level Variables | | | | | | | | | | | | |
| $Log\ Total\ Assets_{i,t-1}$ | 0.2778*** | 0.0910 | 0.3330*** | 0.2659** | 0.0371 | -0.9122 | 0.5522 | -0.8134 | 0.3579*** | 0.1225 | 0.1726 | 0.5282** |
| | (4.95) | (0.88) | (3.81) | (2.57) | (0.53) | (-1.64) | (1.27) | (-1.67) | (5.81) | (1.04) | (0.48) | (2.06) |
| $Return\ on\ Assets_{i,t-1}$ | 0.0155 | 0.1925*** | 0.1458 | 0.1677 | 0.0298 | 0.1959*** | 0.1257 | 0.1555 | 0.0334** | 0.2571*** | 0.2692** | 0.1746 |
| | (0.76) | (2.98) | (1.49) | (1.51) | (1.47) | (2.91) | (1.22) | (1.26) | (2.54) | (3.53) | (2.48) | (1.33) |
| $Tobin\ Q_{i,t-1}$ | 0.0135*** | -0.0069 | -0.0083 | 0.0166** | 0.0126*** | -0.0150 | -0.0130 | 0.0071 | 0.0139*** | -0.0080 | -0.0221 | 0.0255* |
| | (3.52) | (-0.62) | (-0.69) | (2.07) | (3.20) | (-0.94) | (-1.04) | (0.57) | (4.15) | (-0.55) | (-1.46) | (1.83) |
| $Leverage_{i,t-1}$ | 0.0063* | 0.0191* | -0.0087 | 0.0061 | -0.0124 | -0.0114 | -0.0397 | -0.0160 | 0.0064 | 0.0252** | -0.0037 | -0.0010 |
| | (1.72) | (1.73) | (-1.02) | (0.56) | (-1.55) | (-0.46) | (-1.56) | (-0.59) | (1.15) | (2.17) | (-0.24) | (-0.06) |
| $CSTI\ to\ Total\ Assets_{i,t-1}$ | 0.0083*** | 0.0265** | 0.0109 | 0.0036 | -0.0075 | 0.0490* | -0.0299 | 0.0171 | 0.0101** | 0.0303** | 0.0134 | 0.0338 |
| | (2.72) | (2.03) | (0.77) | (0.24) | (-1.37) | (1.93) | (-1.04) | (0.63) | (2.40) | (2.05) | (0.55) | (1.33) |
| $Equity\ Return\ Volatility_{i,t-1}$ | -0.0805 | 0.4159* | 0.0539 | -0.2798 | -0.1093 | 0.2250 | -0.0173 | -0.2891 | -0.0829 | 0.1075 | 0.3385 | -0.1484 |
| | (-0.77) | (1.94) | (0.17) | (-1.04) | (-1.07) | (0.95) | (-0.05) | (-1.04) | (-1.26) | (0.44) | (0.81) | (-0.57) |
| Constant | 0.6705 | 0.9412 | -4.8498* | 1.0783 | 8.9856*** | 25.1067* | -6.6086 | 27.6793** | 1.1515 | 1.3899 | -1.2966 | -0.1190 |
| | (0.75) | (0.38) | (-1.68) | (0.42) | (3.68) | (1.83) | (-0.60) | (2.33) | (1.08) | (0.41) | (-0.22) | (-0.03) |
| Number of Observations | 734 | 736 | 729 | 727 | 734 | 736 | 729 | 727 | 734 | 736 | 729 | 727 |
| $R^2$ | 0.6168 | 0.5817 | 0.4945 | 0.5727 | | | | | | | | |
| Within $R^2$ | | | | | 0.2628 | 0.4131 | 0.4113 | 0.3547 | | | | |
| AR(1) test (p-value) | | | | | | | | | 0.062 | 0.000 | 0.082 | 0.017 |
| AR(2) test (p-value) | | | | | | | | | 0.238 | 0.653 | 0.385 | 0.197 |
| Hansen test of over-identification (p-value) | | | | | | | | | 0.401 | 0.656 | 0.305 | 0.101 |
| Diff-in-Hansen tests of exogeneity (p-value) | | | | | | | | | 0.979 | 0.425 | 0.972 | 0.642 |

# Table 4.8 Impact of the Frequency of Operational Risk Event Announcements on CEO Compensation with an Interaction Term

This table reports the estimation results for CEO compensation following the frequency of operational risk event announcements with an interaction variable. Models 1 contain ordinary least squares (OLS) regressions; Models 2 contain panel data fixed-effects (FE) regressions and Models 3 contain dynamic panel data generalized method of moments (GMM) regressions. Robust standard errors are used to correct for operational risk event clustering in OLS and FE regressions. *t-statistics* are reported in parentheses. *, ** and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively (two-tailed). All variable definitions are reported in Table 4.1.

| Variable | Model 1 - OLS | | | | Model 2 - FE | | | | Model 3 - GMM | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | $ln(Total\ Comp)_{i,t}$ | $ln(Bonus)_{i,t}$ | $ln(Stock)_{i,t}$ | $ln(Option)_{i,t}$ | $ln(Total\ Comp)_{i,t}$ | $ln(Bonus)_{i,t}$ | $ln(Stock)_{i,t}$ | $ln(Option)_{i,t}$ | $ln(Total\ Comp)_{i,t}$ | $ln(Bonus)_{i,t}$ | $ln(Stock)_{i,t}$ | $ln(Option)_{i,}$ |
| Event-Level Variables | | | | | | | | | | | | |
| $ln(Total\ Comp)_{i,t-1}$ | 0.3685*** | | | | 0.1135 | | | | 0.2143* | | | |
| | (3.12) | | | | (1.02) | | | | (1.84) | | | |
| $ln(Bonus)_{i,t-1}$ | | 0.4918*** | | | | 0.3257*** | | | | 0.3950*** | | |
| | | (7.45) | | | | (3.82) | | | | (5.19) | | |
| $ln(Stock)_{i,t-1}$ | | | 0.5143*** | | | | 0.2845*** | | | | 0.5430 | |
| | | | (10.58) | | | | (5.67) | | | | (1.32) | |
| $ln(Option)_{i,t-1}$ | | | | 0.4845*** | | | | 0.2787*** | | | | 0.8608 |
| | | | | (8.81) | | | | (4.88) | | | | (1.63) |
| $ln(IF\ Frequency)_{i,t-1}$ | -0.6287 | 2.6803* | -1.4634 | 0.0369 | -1.1338 | 2.2884 | -2.4356 | 0.3629 | -0.5334 | 1.9678 | 0.7926 | 4.8746 |
| | (-0.58) | (1.78) | (-0.72) | (0.01) | (-0.91) | (1.29) | (-0.84) | (0.08) | (-0.60) | (1.05) | (0.25) | (0.80) |
| $ln(CPBP\ Frequency)_{i,t-1}$ | -0.3372 | 0.3650 | -0.3935 | -1.1605** | -0.3829 | -0.5314 | -0.7091 | -0.8629 | -0.1739 | 0.3611 | -0.7197 | -0.6108 |
| | (-1.37) | (0.74) | (-0.89) | (-2.39) | (-1.31) | (-1.10) | (-1.00) | (-1.37) | (-0.74) | (0.71) | (-0.72) | (-0.63) |
| $ln(EF\ Frequency)_{i,t-1}$ | 0.1348 | -1.1676 | 7.6620* | -2.4999 | 0.7782 | 0.1639 | 7.9332 | -1.6707 | -1.0926 | -2.1373 | 9.0161* | -7.6227 |
| | (0.09) | (-0.44) | (1.98) | (-0.55) | (0.37) | (0.08) | (1.55) | (-0.29) | (-0.42) | (-1.52) | (1.69) | (-1.14) |
| $ln(IF\ Frequency)_{i,t-1}*Compensation\ Committee\ Ratio_{i,t-1}$ | 0.8486 | -11.0342*** | 3.1132 | -0.5794 | 1.9160 | -10.6963** | 5.7758 | -1.2799 | 0.8410 | -9.2174** | 0.2204 | -13.1794 |
| | (0.29) | (-2.83) | (0.61) | (-0.04) | (0.61) | (-2.03) | (0.79) | (-0.09) | (0.32) | (-1.99) | (0.03) | (-0.70) |
| $ln(CPBP\ Frequency)_{i,t-1}*Compensation\ Committee\ Ratio_{i,t-1}$ | 0.0874 | 0.7874 | 1.0107 | -1.0266 | 0.2898 | 2.4035* | 2.3989* | -1.1039 | -0.3961 | -0.1771 | 2.7416 | -1.9215 |
| | (0.16) | (0.77) | (1.06) | (-0.94) | (0.38) | (1.94) | (1.83) | (-0.63) | (-0.73) | (-0.12) | (1.02) | (-0.97) |
| $ln(EF\ Frequency)_{i,t-1}*Compensation\ Committee\ Ratio_{i,t-1}$ | 1.1174 | 3.0350 | -20.5602* | 8.9490 | -0.6158 | -1.9388 | -18.5118 | 5.2040 | 4.2547 | 4.5039 | -25.5199 | 29.8169 |
| | (0.22) | (0.39) | (-1.68) | (0.61) | (-0.09) | (-0.33) | (-1.15) | (0.29) | (0.54) | (1.08) | (-1.57) | (1.35) |
| $Post\ Sarbanes-Oxley\ Act\ Dum_{i,t}$ | 0.1049 | -0.4342 | 0.3210 | -0.6400** | 0.2600** | 0.0468 | 0.6007 | -0.1507 | 0.1164 | -0.6158* | 0.3418 | -0.1362 |
| | (1.17) | (-1.65) | (1.14) | (-2.46) | (2.14) | (0.12) | (1.60) | (-0.49) | (1.36) | (-1.70) | (0.58) | (-0.25) |
| $Global\ Financial\ Crisis\ Dum_{i,t}$ | -0.0913 | -2.4961*** | 0.5763 | -1.6961*** | 0.2817** | -2.0759*** | 1.4871** | -0.8186 | -0.0020 | -1.8608*** | 0.5343 | -0.7490 |
| | (-0.95) | (-6.60) | (1.49) | (-5.24) | (2.49) | (-3.88) | (2.61) | (-1.55) | (-0.02) | (-3.44) | (0.53) | (-0.79) |
| $Post\ Dodd-Frank\ Act\ Dum_{i,t}$ | 0.2359 | -1.9932*** | 1.2898** | -2.0157*** | 0.7314*** | -1.5492** | 2.7436*** | -1.2483 | 0.2304 | -2.0734*** | 1.1880 | 0.1871 |
| | (1.66) | (-4.47) | (2.50) | (-4.85) | (3.79) | (-2.06) | (3.98) | (-1.64) | (1.45) | (-3.31) | (0.79) | (0.09) |
| Corporate Governance Variables | | | | | | | | | | | | |
| $Age_{i,t-1}$ | 0.0016 | 0.0266** | 0.0408* | -0.0469** | 0.0169 | 0.0229 | 0.0260 | 0.0296 | 0.0005 | 0.0279** | 0.0391 | -0.0300 |
| | (0.28) | (2.07) | (1.73) | (-2.48) | (1.53) | (0.85) | (0.85) | (0.99) | (0.07) | (2.01) | (1.25) | (-0.93) |
| $Gender_{i,t-1}$ | -0.0810 | 0.4945** | -0.0730 | -1.2455*** | 0.3042** | 1.4020*** | 0.5412 | -0.6825 | -0.1167 | 0.7353*** | -0.1115 | 1.0417 |
| | (-1.29) | (2.43) | (-0.44) | (-3.58) | (2.34) | (3.49) | (1.32) | (-1.57) | (-1.51) | (2.82) | (-0.43) | (0.53) |
| $Duality_{i,t-1}$ | 0.1004 | -0.4339 | 0.2438 | 0.4249 | 0.2054 | -0.0529 | 1.0309* | 0.0083 | 0.1304 | -0.3690 | 0.6558 | 0.4694 |
| | (0.80) | (-1.39) | (0.65) | (1.28) | (1.18) | (-0.12) | (1.85) | (0.02) | (1.06) | (-1.01) | (1.43) | (0.95) |
| $Tenure_{i,t-1}$ | 0.0006 | -0.0179 | -0.0430*** | 0.0196* | -0.0056 | -0.0068 | -0.0851*** | 0.0106 | -0.0008 | -0.0328** | -0.0392 | 0.0122 |
| | (0.15) | (-1.59) | (-2.77) | (1.94) | (-0.94) | (-0.25) | (-4.23) | (0.48) | (-0.15) | (-2.01) | (-1.25) | (0.62) |
| $Board\ Size_{i,t-1}$ | -0.0012 | 0.0526 | 0.0312 | -0.0231 | 0.0233 | 0.1222* | 0.0896* | 0.0200 | -0.0021 | 0.0663 | 0.0780 | -0.0317 |
| | (-0.10) | (1.37) | (0.73) | (-0.80) | (1.35) | (1.81) | (1.68) | (0.38) | (-0.14) | (1.38) | (1.41) | (-0.67) |
| $Board\ Independence\ Ratio_{i,t-1}$ | 0.1284 | -0.0793 | 0.1010 | 1.3977 | 0.0439 | 1.4310 | -1.2332 | -1.1529 | 0.0890 | -0.2147 | -0.0434 | 0.4045 |
| | (0.42) | (-0.10) | (0.10) | (1.64) | (0.08) | (0.95) | (-0.91) | (-0.88) | (0.25) | (-0.20) | (-0.03) | (0.26) |
| $Compensation\ Committee\ Ratio_{i,t-1}$ | -0.0564 | 2.5066*** | 0.6978 | -1.7307** | -0.4647 | 2.3016 | 0.0846 | -1.7047 | -0.0470 | 3.2578*** | 0.4567 | -1.5620 |
| | (-0.18) | (2.92) | (0.58) | (-2.18) | (-0.60) | (1.61) | (0.04) | (-1.16) | (-0.13) | (2.82) | (0.28) | (-0.90) |
| Firm-Level Variables | | | | | | | | | | | | |
| $Log\ Total\ Assets_{i,t-1}$ | 0.3169*** | 0.0088 | 0.3288*** | 0.4757*** | 0.0476 | -0.9882* | 0.4436 | -0.5970 | 0.4016*** | 0.0578 | 0.1668 | 0.1877 |
| | (4.45) | (0.09) | (2.97) | (3.94) | (0.52) | (-1.69) | (1.08) | (-1.36) | (5.63) | (0.48) | (0.45) | (0.44) |
| $Return\ on\ Assets_{i,t-1}$ | 0.0156 | 0.2015*** | 0.1500 | 0.1603 | 0.0316* | 0.1951*** | 0.1282 | 0.1545 | 0.0384*** | 0.2530*** | 0.2661** | 0.1332 |
| | (0.81) | (3.25) | (1.51) | (1.43) | (1.76) | (3.07) | (1.25) | (1.26) | (3.94) | (3.71) | (2.55) | (0.95) |
| $Tobin\ Q_{i,t-1}$ | 0.0140*** | -0.0086 | -0.0080 | 0.0196** | 0.0115*** | -0.0165 | -0.0165 | 0.0112 | 0.0146*** | -0.0107 | -0.0208 | 0.0185 |
| | (3.47) | (-0.80) | (-0.66) | (2.49) | (2.93) | (-1.06) | (-1.28) | (1.01) | (3.96) | (-0.76) | (-1.39) | (0.93) |
| $Leverage_{i,t-1}$ | 0.0068 | 0.0151 | -0.0077 | 0.0117 | -0.0126* | -0.0163 | -0.0386 | -0.0099 | 0.0062 | 0.0246** | -0.0055 | 0.0164 |
| | (1.67) | (1.33) | (-0.81) | (1.06) | (-1.75) | (-0.67) | (-1.67) | (-0.36) | (1.02) | (2.08) | (-0.37) | (1.14) |
| $CSTI\ to\ Total\ Assets_{i,t-1}$ | 0.0084** | 0.0261** | 0.0105 | 0.0059 | -0.0085 | 0.0486** | -0.0409 | 0.0249 | 0.0099** | 0.0283** | 0.0134 | 0.0088 |
| | (2.57) | (2.11) | (0.77) | (0.37) | (-1.38) | (2.01) | (-1.46) | (1.01) | (2.36) | (2.06) | (0.58) | (0.59) |
| $Equity\ Return\ Volatility_{i,t-1}$ | -0.1112 | 0.4166** | 0.1057 | -0.3277 | -0.1440 | 0.1956 | 0.0174 | -0.3145 | -0.0869 | 0.0313 | 0.3197 | 0.0022 |
| | (-0.90) | (2.07) | (0.34) | (-1.11) | (-1.19) | (0.86) | (0.05) | (-1.04) | (-1.17) | (0.14) | (0.79) | (0.01) |
| Constant | 0.0730 | 2.8237 | -4.8591 | -3.4266 | 9.6844*** | 27.0669* | -3.3199 | 22.6950** | 0.3480 | 2.3964 | -0.9321 | -4.6348 |
| | (0.08) | (1.15) | (-1.56) | (-1.20) | (4.36) | (1.87) | (-0.33) | (2.18) | (0.33) | (0.70) | (-0.15) | (-1.53) |
| Number of Observations | 734 | 736 | 729 | 727 | 734 | 736 | 729 | 727 | 734 | 736 | 729 | 727 |
| $R^2$ | 0.6103 | 0.5846 | 0.4995 | 0.5794 | | | | | | | | |
| Within $R^2$ | | | | | 0.2548 | 0.4155 | 0.4217 | 0.3503 | | | | |
| AR(1) test (p-value) | | | | | | | | | 0.083 | 0.000 | 0.084 | 0.057 |
| AR(2) test (p-value) | | | | | | | | | 0.259 | 0.623 | 0.342 | 0.109 |
| Hansen test of over-identification (p-value) | | | | | | | | | 0.377 | 0.793 | 0.225 | 0.500 |
| Diff-in-Hansen tests of exogeneity (p-value) | | | | | | | | | 0.730 | 0.798 | 0.841 | 0.251 |

# 5 Conclusion

This thesis examines three distinct essays with a common theme: operational risk. Operational risk is an idiosyncratic risk relevant to firms' internal controls. Operational risk event disclosure is an adverse idiosyncratic informational shock, disclosed by the media and hitting financial markets conveying valuable signals about internal control weaknesses and possible deterioration of expected future cash flows of the affected firms.

The first essay investigates the effects on credit rating of various operational risk features including the frequency of undisclosed operational risk events (i.e., internal data), the frequency and the severity of disclosed operational risk events in terms of the loss amount and the stock market reactions (i.e., external data). Employing random effects regression models, our findings reveal that the maximum loss to market value as well as drops in stock prices following operational risk event announcements are informative to the rating agency S&P as it consequently downgrades credit ratings of the affected banks. Moreover, the downgrade is relatively more significant for severe operational losses exceeding $10 million. Our results are robust to the post-Global Financial Crisis period. The findings of this study have practical implications for banks to better understand whether their credit ratings assigned by rating agencies are affected by operational risk events that they suffer from. Therefore, affected banks may plan post-announcement actions such as press releases to restore their reputation and reassure their stakeholders.

The second paper examines analyst behaviour, in terms of their forecast revision and accuracy, around operational risk disclosure. Employing ordinary least squares regression models, we find that overoptimistic analysts react to operational risk event announcements by revising their forecasts downwards, hence suggesting that this unanticipated bad news is informative for banking analysts. Competition among analysts, however, encourages analysts to become upward biased in order to increase sales for their brokerage house and their trading commission. Our results are more pronounced for severe operational losses exceeding $10 and $35 million. Regulators could draw policy implications from these findings to improve public disclosure of operational risk events and reduce information asymmetry through market discipline. In addition, banking supervisors could impose more severe regulations to eliminate sources of bias in analyst forecasting behaviour upon the arrival of these unanticipated bad news due to competition or career concerns.

The third paper explores the impact of operational risk event announcements, which are considered as a negative measure of firm performance, on CEO compensation. Employing several empirical regression models, including ordinary least squares, fixed effects and generalized method of moments, we find that CEOs are penalized in terms of their option-based compensation mainly following the frequency of operational risk events disclosed. Interestingly, high compensation committee to board size ratio improves the pay-performance sensitivity, such that the negative and significant impact of the number of operational risk events disclosed on banking executives' pay is more pronounced. Additionally, the Global Financial Crisis and the Dodd-Frank Act both have meaningful impact on the CEO compensation around operational risk disclosure. The findings in this study have practical implications for banking executives to improve firms' performance, in terms of implementing better operational risk management, in order to avoid being penalized for operational risk events through a reduction in their option-based compensation. Moreover, the compensation committee can better design pay packages in order to minimise agency risk.

Overall, the findings of this thesis have wider implications for a range of stakeholders. Operational risk disclosure contributes to a reduction in information asymmetry between firms and outside stakeholders and enables market discipline. Since ratings agencies and analysts are those that closely follow the banks, the way they react is indicative of the severity of operational risk events and, hence, provides even more information to outside investors. As such, these findings imply that there should be a regulatory requirement for firms to publicly disclose aggregated or detailed information on operational risk events suffered, mainly the severe ones exceeding $10 million. In addition, since operational risk events can be used as a new adverse measure of firm performance, which have a consequent negative impact on CEO compensation, they encourage firms to have more effective operational risk management practices in place.

The main constraint of this thesis is that our sample size is not big according to the common standards in the finance literature. This is due to data availability and strict sample selection criteria employed to avoid overlap of operational risk event announcements with other regulators disclosures. However, relatively small samples are common in the operational risk literature. In addition, our thesis focuses on U.S. banks to mitigate concerns about regulatory, institutional and cultural environments of different countries driving credit ratings, analyst forecast revisions and CEO compensation. Future research could extend the analysis by exploring other countries and other sectors.

Furthermore, our thesis draws attention to other avenues for future research. While the thesis provides first evidence on the impact of operational risk disclosure on credit ratings, analyst forecasts and CEO compensation, future research may go a step further and explore the relative effect of reputational risk. Additionally, as cyber security is currently on top of board agenda, it would be interesting to investigate the implications of cyber risk and technology risk on banks' operational resilience. Moreover, with the increasing collaboration between banks and FinTechs in recent years, banks are more exposed to the General Data Protection Regulation (GDPR), which relates to customer data protection and privacy. Hence, it would be interesting to examine the measures taken by banks to mitigate such risk, that could have disastrous effects on their reputation.