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The Determinants of Operational Risk in U.S. Financial Institutions

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Abstract

We examine the incidence of operational losses among U.S. financial institutions using publicly reported loss data from 1980 to 2005. We show that most operational losses can be traced to a breakdown of internal control, and that firms suffering from these losses tend to be younger and more complex, and have higher credit risk, more antitakeover provisions, and chief executive officers (CEOs) with higher stock option holdings and bonuses relative to salary. These findings highlight the correlation between operational risk and credit risk, as well as the role of corporate governance and proper managerial incentives in mitigating operational risk.

I. Introduction

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. As a distinct risk category not as well understood as market and credit risks, operational risk has received prominent

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coverage in the National Bureau of Economic Research volume *The Risk of Financial Institutions* (de Fontnouvelle, Rosengren, and Jordan (2006)). Many high-profile losses in the financial industry have been traced to operational risk. For instance, the $7.2 billion loss due to unauthorized trading at Société Générale in January 2008 spawned allegations of moral hazard and a lack of internal control in the banking industry (Arnold, Larsen, Hollinger, O'Doherty, and Milne (2008)). In addition, Securities and Exchange Commission (SEC) chairman Christopher Cox admitted that his agency failed to act for nearly a decade on credible allegations about Bernard Madoff, whose fraudulent internal controls allowed a Ponzi scheme that cost hedge fund investors as much as $50 billion (SEC Press Release 2008-297).

Because of the potential for significant losses, regulators have been prodding the banking industry toward better measurement and management of operational risk. The recently finalized Basel II Accord requires that major banks in the United States adopt the advanced measurement approach (AMA), which uses internal risk measurement systems to determine the operational risk capital charge. Specifically, the Basel Accord requires that (BCBS (2006), p. 154)

> in addition to using loss data, whether actual or scenario-based, a bank's firm-wide risk assessment methodology must capture key business environment and internal control factors that can change its operational risk profile. These factors will make a bank's risk assessment more forward-looking, more directly reflect the quality of the bank's control and operating environments, help align capital assessments with risk management objectives, and recognize both improvements and deterioration in operational risk profiles in a more immediate fashion.[1]

The purpose of our study is to provide a comprehensive analysis of the firm-specific and macroeconomic variables that contribute to the incidence of operational risk events among financial institutions. A unique feature of this study is the use of a newly available operational loss data source that identifies actual operational loss events. Our sample is derived from a database called Algo FIRST, provided by Algorithmics Inc., a member of the Fitch Group. Operational risk events have an extremely diverse set of origins, such as fraud, improper business practices and product flaws, technology failures, employment discrimination, transaction and execution errors, and natural disasters and terrorism. As evidence

[1]To promote a more resilient banking sector in response to the recent financial crisis, the Basel Committee released several consultative documents for strengthening global capital and liquidity regulations. An impact assessment of these new standards was carried out during the 1st half of 2010, with an aim of implementation by the end of 2012. The key elements of the revisions include raising the quality, consistency, and transparency of the capital base, strengthening the capital reserve requirement for counterparty credit risk exposures, monitoring and controlling the use of leverage, promoting the buildup of capital buffers in good times, and introducing a minimum liquidity standard for internationally active banks (BCBS (2009c)). Specifically for operational risk, revisions called for better management and sound compensation practices (BCBS (2009a)). BCBS (2009b) noted recent developments in the modeling of operational risk by banks in the areas of governance, data collection, and measurement that include the following key components: internal and external loss data, scenario analysis, and business environment and internal control factors. However, this document did not lay out any new set of rules beyond those presented in the 2006 Basel II Capital Accord.

of the breadth of data coverage, our database includes all of the high-profile accounting scandals and trading losses since 1980. Upon applying several filters to our data, our final sample consists of 925 publicly reported operational risk events among 176 U.S. financial institutions from 1980 to 2005.

To help identify the determinants of operational risk, we first examine the contributory factors of each operational risk event in our database. This exercise reveals that most events can be characterized as consequences of a weak internal control environment. The recent accounting literature has identified many firm characteristics associated with internal control weaknesses (ICWs) over financial reporting (Ashbaugh-Skaife, Collins, and Kinney (2007), Doyle, Ge, and McVay (2007a), and Elbannan (2009)). Although the evidence pertains to financial reporting, the material weaknesses are often attributed to deficiencies in company-level controls, suggesting that the finding could also be relevant to operational risk in general. Therefore, we draw extensively from this literature in selecting firm-specific explanatory variables for operational risk. Another potential source of explanatory variables is the literature on earnings manipulations and accounting restatements, which highlights the role of board characteristics and executive compensation (Dechow, Sloan, and Sweeney (1996), Burns and Kedia (2006), and Efendi, Srivastava, and Swanson (2007)). Since misreporting may indicate a lack of internal control, we include measures of internal and external corporate governance as well as chief executive officer (CEO) incentives in our analysis of operational risk. This is also consistent with the role of senior management oversight and accountability in enforcing risk management controls.[2]

Following the recent literature on corporate default prediction (Duffie, Saita, and Wang (2007)), we treat the arrival of operational risk events as a conditional Poisson process, whose intensity is driven by firm-specific and macroeconomic covariates.[3] Conditional on the history of the covariates, the arrivals of events, either over time or across firms, are assumed to be independent.[4] This allows us

[2]The Basel Committee surveyed 30 major banks on their operational risk management practices and made the following comments (BCBS (1998), p. 2):

> Overall the interview process uncovered a strong and consistent emphasis on the importance of management oversight and business line accountability for operational risk. Senior management commitment was deemed to be critical for successful corporate-wide risk management. Banks reported that high-level oversight of operational risk is performed by its board of directors, management committees or audit committee. In addition, most respondents referred to the important role of an internal monitor or "watchdog," such as a risk manager or risk committee, product review committee, or internal audit, and some banks identified several different internal watchdogs, who were all seen as important, such as the financial controller, the chief information officer and internal auditors. The assignment of formal responsibilities for operational risk measurement and monitoring is far from universal, with only about half of the banks interviewed having such a manager in place.

[3]In this paper, we focus exclusively on factors that cause an operational risk event to occur. We leave the severity of losses (which typically takes several years to materialize after the event starting date) to future research. We also use the terms "operational loss" and "operational risk event" interchangeably to denote the initial occurrence of a loss event.

[4]This intensity-based framework is a common modeling approach in the credit risk literature (Jarrow and Turnbull (1995), Lando (1998), and Duffie and Singleton (1999)). While it allows for substantial generality as well as ease of estimation, violations of the conditional independence assumption can occur when there are missing covariates (Duffie, Eckner, Horel, and Saita (2009)) or if

to estimate the arrival intensity by maximizing the joint likelihood of Poisson arrivals. The broadest specification of the model is estimated using 183,806 firm-month observations over 2,686 U.S. financial institutions with or without operational risk events, which is a novel approach.[5]

We identify a strong link between operational risk and firm-specific covariates. For example, firms suffering from operational risk events tend to be younger and more complex (measured by the number of segments reported in Compustat). Notably, they have a higher financial distress risk as measured by a wide range of firm characteristics, including equity volatility, Tier 1 capital, market-to-book ratio, cash holdings, and the Merton (1974) distance-to-default. The implied positive correlation between credit risk and operational risk is something that risk managers must take into account when they estimate a firm-wide loss distribution. We also find that firms suffering from operational risk events have a higher Gompers, Ishii, and Metrick (2003) G-index, suggesting that they are more insulated from the market for corporate control. Furthermore, these firms have CEOs with higher option- and bonus-based compensation relative to salary; these are characteristics that have been found to contribute to misreporting. Incidentally, the same set of covariates can explain the occurrence of operational risk events that are quite different in origin. This, along with the fact that they also explain the incidence of ICWs and misreporting, suggests that these covariates are acting as proxies for firms' internal control environment, which has an effect on operational risk in general.[6]

The Basel Committee requires banks to use both internal data (i.e., internally recorded) and external data (such as consortium-type pooled industry data) to manage their operational risk exposures. While internal data are more specific to a bank's own environment, external data provide a useful supplement, especially for large losses that could bankrupt an institution. The results of this paper provide a method to adjust external data using control variables that reflect the particular environment of a bank. We also do not find any significant difference between the determinants of operational risk for banks and nonbank financial firms in our sample. This suggests that bank supervisors could use loss data pooled across the entire financial sector to assess the operational risk capital charge for any given bank. As an application of our methodology, we use the estimated operational risk intensity to compute a time-varying operational value at risk (VaR) for a U.S. bank during 2004–2006, for which we have complete data on loss severity.

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there are contagion effects caused by interfirm linkage or information spillover (Jarrow and Yu (2001), Collin-Dufresne, Goldstein, and Helwege (2003)).

[5]This approach is beneficial because the results are not limited to firms with known histories of operational risk events. Rather, we are interested in whether the firm-specific and macroeconomic covariates are able to differentiate firms with no loss, 1 loss, and 2 or more losses. By including all financial firms in our sample, we are able to measure operational risk as a whole, and our results are applicable to any given financial firm in the general population.

[6]For anecdotal evidence, see "Good Data Security Is Not Just a Matter of Technology," *Financial Times* (July 16, 2008), by Kieran Poynter, former U.K. chairman of PriceWaterhouseCoopers. He suggests, "Organizations with weak data security are generally also weak in terms of wider risk management and governance. So a failure to adequately manage information security risks is often symptomatic of broader risk issues or a fragmented governance framework."

By its very nature as a new research area, the empirical literature on operational risk is sparse. The latest empirical studies mostly focus on documenting the size and significance of operational losses. For instance, de Fontnouvelle, DeJesus-Rueff, Jordan, and Rosengren (2006) describe the severity distribution of operational losses collected from public information. They show that capital requirements for operational losses can regularly exceed those for market risks at large U.S. banks.[7] To the best of our knowledge, current academic research that sheds light on the determinants of operational risk in financial institutions is very limited.[8] Our paper attempts to fill this void by identifying a list of variables, many of which have been shown to have a strong link to firms' internal control environments. Therefore, our empirical findings are likely to be of interest to bank regulators and risk managers, who are obligated to develop quantitative measures of operational risk mitigation.

Because of limited operational loss data coverage, we restrict the scope of our study to U.S. financial institutions. However, most of the covariates in our analysis are motivated by studies outside of the banking literature and are widely available for nonfinancial firms. To the extent that operational risk and the lack of internal control are related issues, our findings could be applicable to firms in general. Broadly speaking, our paper presents operational risk as a channel through which financial distress and poor governance can impose deadweight costs on firms.

The rest of this paper is organized as follows. Section II provides the background for the measurement of operational risk. Section III summarizes the operational loss database used in our empirical analysis. Section IV develops the main hypotheses regarding the determinants of operational risk. Section V estimates an operational risk intensity function that depends on firm characteristics and macroeconomic covariates. Sections VI and VII introduce corporate governance and CEO incentives into the model. Section VIII concludes.

II. Conditional Poisson Arrivals of Operational Risk Events

Under Pillar I of Basel II, banks are required to adopt a methodology to assess the operational risk capital charge that would serve as a shield against potential future losses given a 1-year horizon. In the order of increasing sophistication

[7]Rosenberg and Schuermann (2006) use the operational loss distribution estimated in de Fontnouvelle, DeJesus-Rueff, Jordan, and Rosengren (2006) to construct an aggregate loss distribution across market, credit, and operational risks for a typical large bank. Cummins, Lewis, and Wei (2006) find a significantly negative equity market reaction to operational loss announcements. Perry and de Fontnouvelle (2005) find a stronger equity market reaction to internal fraud announcements among firms with stronger shareholder rights as proxied by a lower G-index. Allen and Bali (2007) examine cyclicality in operational risk measures derived from the stock returns of financial institutions, after purging the effect of other sources of risks. However, their approach does not utilize any information from operational losses that actually occurred.

[8]In the hedge fund literature, Brown, Goetzmann, Liang, and Schwarz (2008) obtain operational risk information from SEC-mandated hedge fund disclosures and test if this information is redundant to hedge fund investors. Part of their analysis relates the operational risk of hedge funds (focusing more on fraudulent behavior) to observable fund characteristics, which is similar to our focus on the relation between operational risk in financial institutions (more broadly defined by the Basel Committee) and observable firm characteristics.

and risk sensitivity, the spectrum of available approaches proposed by Basel II consist of i) the basic indicator approach (BIA), ii) the standardized approach (SA), and iii) the advanced measurement approach (AMA). Banks are allowed to choose from and must move up along the spectrum as they develop more complex operational risk measurement systems. Under the BIA and SA (the "top-down" approaches) the capital charge is proportional to a fixed percentage of a bank's gross income, predetermined by the Basel Committee. The AMA is a "bottom-up" risk-sensitive approach in that it is built upon a bank's risk management practices and makes use of internal and external historic loss data in order to determine the capital charge.[9]

In this paper, we consider a sophisticated AMA approach, in which the arrival intensity of operational risk events is itself stochastic and driven by various time-varying firm-specific and macroeconomic covariates. In such cases, the arrival of operational risk events for an individual firm follows a *doubly stochastic*, or *conditional Poisson process,* which is also referred to as a *Cox process*. Such a counting process, $N_t = N\left(\Lambda\left(t\right)\right)$, where

$$\Lambda\left(t\right) = \int_0^t \lambda\left(u\right) du, \tag{1}$$

is characterized by the firm's stochastic intensity $\lambda(t) > 0$. This process yields an accumulated loss process L of the form

$$L_t = \sum_{i=1}^{N_t} \ell_{t(i)}, \tag{2}$$

where $\left\{\ell_{t(i)}, i = 1, \ldots, N_t\right\}$ describe the severities of the loss events up to time t. For simplicity, we could assume that the loss severities are independently and identically distributed random variables. More generally, ℓ can be allowed to depend on the same set of firm-specific and macroeconomic covariates that determine the loss arrival intensity. Given this accumulated loss process, the operational VaR over a horizon of 1 year can be computed as the inverse of the accumulated loss distribution function and can be used to estimate the operational risk capital charge.

We assume that conditional on the firm-specific and macroeconomic covariates that determine the event intensities, the arrivals of events are independent across firms. This assumption ensures that the joint distribution of event arrivals is completely specified by the firms' stochastic intensities. It allows for the estimation of the intensities using convenient econometric methods based on maximum likelihood.

Arrivals of events over time or across firms become independent only after conditioning on the firm-specific and macroeconomic covariates driving the arrival intensities. Given a well-specified conditional Poisson model, one can always check for the clustering of events beyond the level predicted by the arrival intensities using tests developed by Das, Duffie, Kapadia, and Saita (DDKS) (2007)

[9]The Basel II guidelines are mandatory for U.S. banks with either $250 billion or more in assets, or $10 billion or more in foreign exposure. Moreover, they are required to use only the AMA.

for detecting the excessive clustering of corporate defaults. In a companion paper, we rigorously test the validity of the conditional Poisson framework as a model of operational loss arrivals. We discuss some of these results in Section V.

III. Description of Operational Loss Data

We follow the Basel II classification of risk events according to event type.[10] The 7 plus 1 event types are as follows:

i) Internal Fraud (ET1): Events intended to defraud, misappropriate property, or circumvent regulations or company policy, involving at least one internal party, categorized into unauthorized activity and internal theft and fraud.

ii) External Fraud (ET2): Events intended to defraud, misappropriate property, or circumvent the law, by a 3rd party, categorized into theft, fraud, and breach of system security.

iii) Employment Practices and Workplace Safety (ET3): Acts inconsistent with employment, health, or safety laws or agreements, categorized into employee relations, safety of the environment, and diversity and discrimination.

iv) Clients, Products, and Business Practices (ET4): Events due to failures to comply with a professional obligation to clients, or arising from the nature or design of a product, including disclosure and fiduciary, improper business and market practices, product flaws, and advisory activities.

v) Damage to Physical Assets (ET5): Events leading to loss or damage to physical assets from natural disasters or other events, such as terrorism.

vi) Business Disruption and System Failures (ET6): Events causing disruption of business or system failures.

vii) Execution, Delivery, and Process Management (ET7): Events due to failed transaction processing or process management that occur from relations with trade counterparties and vendors, classified into categories such as transaction execution and maintenance, customer intake and documentation, and account management.

viii) Other: Events that do not fit into any of the previous 7 categories.

In this paper, we analyze operational loss data from the Algo FIRST database provided by Algorithmics Inc., a member of the Fitch Group. The vendor gathers information on operational losses from public sources such as regulatory agencies (e.g., the SEC) and the media (e.g., *The Wall Street Journal*).[11] The database provides information on more than 8,000 operational risk events in the financial and

[10]The Basel II Accord also classifies the loss events according to 8 business lines: corporate finance, trading and sales, retail banking, commercial banking, payment and settlement, agency services and custody, asset management, and retail brokerage. However, in this study we only focus on the differences among the event types, because we believe that operational risk events of the same type exhibit similar characteristics across business lines.

[11]The primary claimant is specified for the majority of risk events in the database. For U.S. firms, regulatory agencies constitute 47% of all claimants, followed by clients and business partners (16%), employees (12%), shareholders (8%), and other 3rd parties (e.g., customers, employers, and creditors). Among regulatory agencies, the dominant ones are the SEC, National Association of Securities Dealers (NASD), New York Stock Exchange (NYSE), Financial Industry Regulatory Authority (FINRA), and Federal Deposit Insurance Corporation (FDIC).

nonfinancial industries around the world. It offers a detailed description of each event, including dates of loss occurrence and settlement, loss amount, company name, geographical location of the event, claimant name, and event trigger. In addition, the format of the data conforms to the Basel Committee definition of event types and business lines. The primary clientele of the database consists of senior executives, risk management professionals, business managers, auditors, compliance personnel, and legal staff.[12]

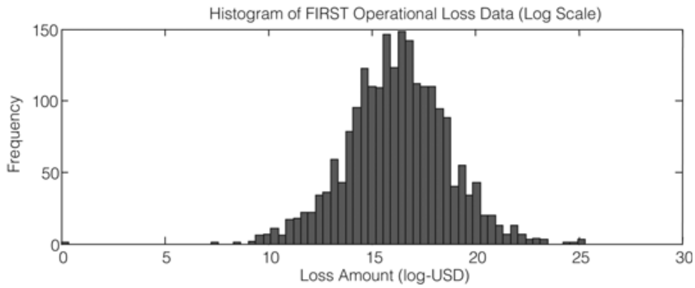
Table A1 in the Appendix summarizes the top 3 largest losses (in 2005 dollars) within each of the event types in our sample. Among the largest losses are the accounting fraud at Cendant ($3.12 billion), JPMorgan's settlement with the University of California on behalf of Enron shareholders for "aiding and abetting" Enron in its financial fraud ($3.66 billion), and Citigroup's loss due to the September 11 terrorist attack ($2.23 billion).

Since the data are culled from public sources, they may not include all of a bank's internally recorded operational losses, particularly those of a smaller magnitude. We do not believe this to be a major issue for our study. First, many losses in the database are relatively small in magnitude, with a minimum of $1, 25th percentile of $2.4 million, and median of $11.8 million. Second, there is some evidence that the loss distribution in the FIRST database is similar to the loss distribution at typical banks. Figure 1 presents the histogram of losses in the FIRST database. A formal examination of this distribution reveals that it is right skewed and approximately lognormal.[13] We also examine an item in the FIRST database that deals with the source of each recorded event. In all of the cases, the sources of the loss announcements are not the firms themselves, but 3rd parties

FIGURE 1

Operational Loss Distribution

Figure 1 illustrates the histogram of our operational loss sample data.



[12]Currently, around 100 financial institutions subscribe to the Algo FIRST Database.

[13]The Kolmogorov-Smirnov test for normality could not be rejected for the log-transformed loss severity data. Lognormal distribution is a typical distribution fitted to internal operational loss data in practice (e.g., BCBS (2009b), p. 54). Since we have access to internally recorded loss data at a U.S. bank and a European bank, we use quantile-quantile plots to compare the loss distribution of the FIRST database to those of the 2 banks. The main difference in the distributions is in their scales, while their shapes are similar. This is to be expected, as the 2 banks' total assets are $65 billion and €72 billion, respectively, while the average firm with operational losses in our sample has total assets of $204 billion.

such as SEC press reports, the NASD, court decisions, and affected customers. This suggests that the firms actually have little choice in deciding whether an event is reported to the public, mitigating concerns over selective disclosure.

We restrict our attention to operational risk events occurring after 1980 because there are relatively few earlier observations. Furthermore, we only consider events in the U.S. financial industry, which ensures some homogeneity in the sample. Approximately 60% of all events in the FIRST database occurred in the United States. Out of these events, nearly ¾ were accounted for by financial institutions.

Each event in the database is associated with a starting date, an ending date, and a settlement date. As we are primarily interested in the factors that cause an operational risk event to occur, we use the starting date to record the occurrence of an event. For some events, the starting dates are not known precisely and are therefore recorded as January 1 of the corresponding year. Such a phenomenon does not come as a surprise. In the case of internal fraud, for example, it is often impossible to determine the precise date on which the 1st incident occurred, hence the fraudulent activity is recorded as having started on January 1 of the year in which the activity began. To correct for this artificial bunching of dates, we include a January dummy variable in our frequency models with the monthly aggregated event count.

Since losses may take months or even years to materialize, it is likely that many events are currently taking place but have not yet been discovered. This means that the last several years of the database may be underpopulated. To mitigate the effect of right censoring without losing too much information, we extract loss events from the database in early 2008 and further limit the sample to events originating between the beginning of 1980 and the end of 2005. Since the median event duration is about 20 months, and ¾ of all events last no more than 48 months, this ensures that more than 50% of events originating in 2005 are included in our sample. This leaves us with 2,426 loss events from 731 unique U.S. financial firms.

Graph A of Figure 2 illustrates the annual frequency of loss events during the 1980–2005 sample period. The frequency of operational risk events has been increasing since 1980, but it experienced a sharp decline after 2001.[14] Interestingly, the pattern is similar to that of the number of financial industry defaults in the same period (see Graph B). This suggests a close relation between operational risk and credit risk, which motivates parts of our empirical analysis.[15]

We further restrict our sample to firms with at least 6 months of coverage in the Compustat and Center for Research in Security Prices (CRSP) databases.

[14]It is unlikely that this decline is solely attributed to the extended duration issue described earlier (e.g., even increasing the 2003 event count by 25% would still lead to a declining pattern). One reason for such a decline could be the release of the Basel II Accord in February 2001, and the early amendments calling for regulatory capital for operational risk (BCBS (1998), (1999), (2001)). This development likely caused banks to increase their efforts to rein in operational losses. The period of declining operational risk also coincides with the passage of the Sarbanes-Oxley Act (SOX) in 2002, which seeks to improve the quality of financial reporting and internal control, particularly with respect to corporate fraud.

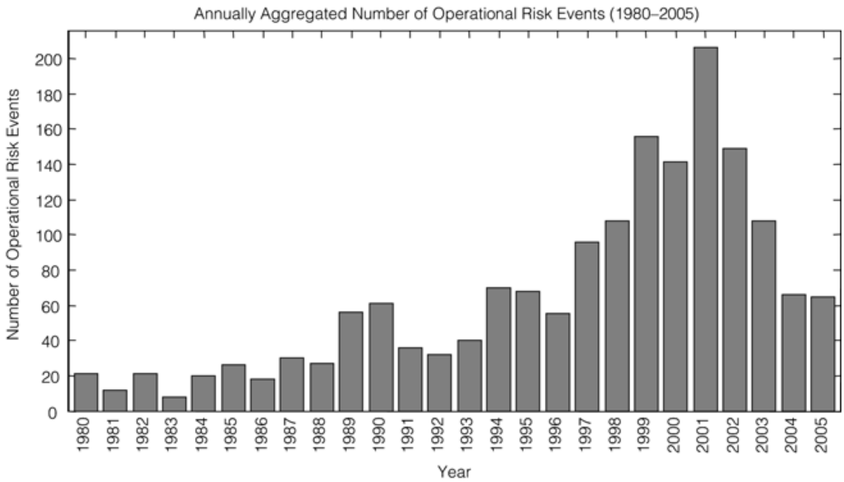
[15]Our data on financial industry defaults come from Moody's Default Risk Service. We thank Richard Cantor for providing us with the data.

FIGURE 2

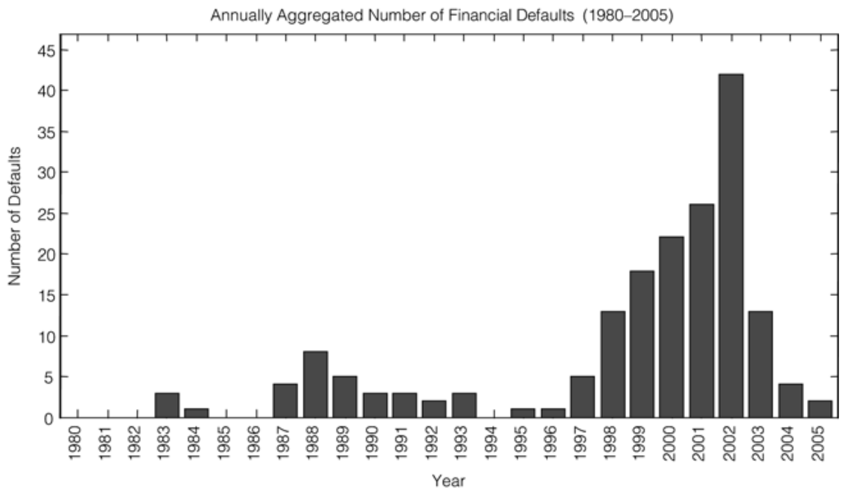
Annual Frequency of Operational Risk Events and Defaults in the U.S. Financial Industry (1980–2005)

Figure 2 illustrates the frequency of operational risk events (Graph A) and defaults (Graph B) in the U.S. financial industry, aggregated by year.

Graph A. Operational Risk Event Frequency



Graph B. Default Frequency



In addition, we include only firms with 2-digit Standard Industrial Classification (SIC) codes of 60 (depository institutions), 61 (nondepository institutions), 62 (security and commodity brokers), 63 and 64 (insurance companies), 65 (real estate companies), and 67 (other investment offices). To properly estimate the arrival intensity of events, we need to include the universe of all firms with these 2-digit SIC codes in Compustat and CRSP. Table 1 summarizes the sample selection procedure. Our final sample (Restriction 1) consists of 183,806

TABLE 1

Sample Selection Procedure

Table 1 describes the sample selection procedure used at various stages of this study.

Data Screening Description		No. of Unique Op Risk Events	No. of Unique Firms with Op Risk Events
Original sample: Operational loss data in U.S. (1980–2005).		2,426	731
Restriction 1:	*Compustat and CRSP data availability.* Poisson models with firm-specific and macroeconomic variables (1980–2005).		
Total number of firm-month observations: 183,806 Total number of firms: 2,686		925	176
Restriction 2:	*Compustat, CRSP, Governance, and Directors data availability.* Poisson models with governance and directors variables (1998–2005).		
Total number of firm observations: 265 Total number of firms: 265		437	23
Restriction 3:	*Compustat, CRSP, and Executive Compensation data availability.* Poisson models with executive compensation variables (1993–2005).		
Total number of firm-year observations: 2,060 Total number of firms: 335		533	76

firm-month observations on 2,686 firms, out of which there are 925 losses from 176 unique firms.

Evidently, these sample statistics show that many firms with operational risk events are repeat offenders. To identify the defining characteristics of these repeat offenders, we compare the means of firm-specific variables across firms with no event, 1 event, and more than 1 event during the sample period.[16] We find that repeat offenders are generally larger, older, and have a lower Tier 1 capital ratio and market-to-book, and shorter distance-to-default compared to one-time offenders. These results, based on univariate tests, are generally consistent with our subsequent results from estimating the frequency models.

Panel A of Table 2 tabulates the annual frequency of operational risk events from 1980 to 2005 for each event type. Although the number of events differs significantly across event types, its time-series behavior is similar to that of Figure 2. The frequency of events reached a peak around 2001 and then declined. Panel B presents the distribution of operational risk events by 2-digit SIC code for each event type. Slightly less than half of the events (44.8%) occurred in depository institutions, while the rest occurred among nondepository institutions, security and commodity brokers, and insurance companies. The largest category of events by event type is ET4: clients, products, and business practices (48.5%). The 2nd largest event type is ET1: internal fraud (16.4%).

IV. Hypotheses

In this section, we develop the main hypotheses regarding the determinants of operational risk. We begin by focusing on the connection between operational risk and an environment of weak internal control. Fortuitously, for each operational risk event that appears in the FIRST database, Algorithmics Inc. summarizes

[16]The longer a firm stays in the sample, the more likely that it will have a larger number of events. To eliminate this bias in identifying repeat offenders, we only consider firms that are represented over the entire 1980–2005 sample period (about 45% of the firms).

TABLE 2

Frequency of Operational Risk Events by Year, SIC Code, and Event Type (1980–2005)

Table 2 reports the distribution of operational risk events in our final sample (Restriction 1, as described in Table 1) by year (Panel A) and by SIC code (Panel B). The event type categories are defined as: internal fraud (ET1); external fraud (ET2); employment practices and workplace safety (ET3); clients, products, and business practices (ET4); damage to physical assets (ET5); business disruption and system failures (ET6); execution, delivery, and process management (ET7); and Other.

Panel A. Frequency of Operational Risk Events by Year and Event Type

Year	ET1	ET2	ET3	ET4	ET5	ET6	ET7	Other	Full Sample
1980	2	0	0	3	0	0	7	0	12
1981	2	0	0	1	0	0	0	0	3
1982	3	1	0	4	0	0	1	1	10
1983	0	1	0	1	0	1	0	0	3
1984	2	0	2	3	0	0	1	0	8
1985	4	2	0	6	0	1	0	0	13
1986	1	2	1	5	0	0	2	0	11
1987	6	1	1	8	0	1	0	0	17
1988	1	3	1	8	0	1	2	0	16
1989	8	3	0	26	1	0	5	0	43
1990	3	3	0	9	0	1	0	0	16
1991	4	2	5	12	0	2	1	1	27
1992	6	0	2	7	0	1	2	0	18
1993	4	4	7	10	0	0	0	0	25
1994	8	6	4	17	0	0	4	0	39
1995	7	5	0	24	0	1	1	1	39
1996	5	1	5	13	1	3	2	0	30
1997	8	12	5	27	0	1	3	6	62
1998	16	6	6	31	0	2	4	4	69
1999	18	6	6	52	0	1	4	1	88
2000	10	17	4	41	0	0	8	8	88
2001	18	5	5	53	11	3	6	13	114
2002	4	1	5	39	1	0	6	25	81
2003	5	7	4	37	0	0	6	0	59
2004	3	4	1	6	0	0	5	0	19
2005	4	1	1	6	0	0	2	1	15
Total	152 (16.4%)	93 (10.1%)	65 (7.0%)	449 (48.5%)	14 (1.5%)	19 (2.1%)	72 (7.8%)	61 (6.6%)	925 (100%)

Panel B. Frequency of Operational Risk Events by 2-Digit SIC Code and Event Type

Institution Type	ET1	ET2	ET3	ET4	ET5	ET6	ET7	Other	Full Sample
Depository institutions (SIC codes 60XX)	73	62	24	172	3	11	38	31	414 (44.8%)
Nondepository institutions (SIC codes 61XX)	27	10	13	53	3	2	5	5	118 (12.8%)
Security and commodity brokers (SIC codes 62XX)	40	15	19	143	0	4	23	3	247 (26.7%)
Insurance companies (SIC codes 63XX and 64XX)	12	5	8	75	8	2	5	22	137 (14.8%)
Real estate companies (SIC codes 65XX)	0	1	0	0	0	0	1	0	2 (<1%)
Other investment offices (SIC codes 67XX)	0	0	1	6	0	0	0	0	7 (<1%)
All financial firms (SIC codes 6XXX)	152 (16.4%)	93 (10.1%)	65 (7.0%)	449 (48.5%)	14 (1.5%)	19 (2.1%)	72 (7.8%)	61 (6.6%)	925 (100%)

the key contributory factors as cited in regulatory reports, court documents, and press reports.

Table 3 presents the major contributory factors for each event type.[17] Each contributory factor is usually associated with several more descriptive subcategories.

[17]For the purpose of constructing Table 3, we take 1 contributory factor for each event, so that the percentages add up to 1 for each column. When an event is associated with more than 1 contributory factor in the FIRST database, we pick the primary factor.

TABLE 3

Key Contributory Factors of Operational Risk Events

Table 3 summarizes the key contributory factors of the operational risk events in our sample. Algorithmics Inc. summarizes key contributory factors as cited in regulatory reports, legal claims, and press reports, from which the details of the events are extracted.

Major Contributory Factors	ET1	ET2	ET3	ET4	ET5	ET6	ET7	Other	All Events
Lack of control	31%	10%	22%	29%	<1%	18%	31%	6%	25%
Employee action/inaction	25%	3%	17%	7%	2%	8%	10%	<1%	10%
Management action/inaction	15%	4.5%	26%	16%	<1%	3%	18%	4%	14%
Omissions	14%	48%	9%	22%	12%	15%	23%	44%	24%
Changes in market conditions	4%	3%	3%	17%	7%	6%	4%	41%	13%
Strategy flaw	<1%	<1%	3%	3%	8%	45%	4%	8%	3%
Lax security	<1%	18%	<1%	<1%	<1%	<1%	<1%	<1%	<2%
Other	<10%	<13%	<19%	<6%	<71%	<5%	<8%	<27%	<10%
Total	100%	100%	100%	100%	100%	100%	100%	100%	100%

For example, "management action/inaction" can include, among others, improper management practices, poor execution, and excessive risk-taking; "employee action/inaction" can include employee misdeeds and errors; "lack of control" can include failure to disclose, insufficient compliance, and poor documentation; and "omission" can include inadequate due diligence, failure to comply with policies and procedures, failure to test products or equipment, and failure to supervise employees. While these subcategories may, to some extent, overlap, they can all be characterized as consequences of a breakdown in internal control. Together, these 4 contributory factors are cited for the bulk of the operational risk events in our sample. The only major contributory factor in Table 3 that appears unrelated to internal control is "changes in market conditions," which can include changes in market practice and regulatory and shareholder pressure. However, it is associated with only a small percentage of sample events.

The accounting literature has formally examined the link between internal controls for financial reporting and risk. Under SOX Section 404, which became effective after November 2004, companies must include an auditor-attested report on the effectiveness of their internal controls over financial reporting. Many companies have filed adverse opinions. These are called ICWs and are defined as deficiencies that "result in more than a remote likelihood that a material misstatement of the annual and interim financial statements will not be prevented or detected" (Public Company Accounting Oversight Board (2004), p. 156). Some of these ICWs reflect specific financial accounts. These are easier to fix, as in most cases the auditor can "audit around" these material weaknesses by performing additional checks. Others are broader in scope and reflect i) weaknesses in systems, such as poor information systems security; ii) weaknesses in organizational control processes, such as improper segregation of duties; iii) inadequate training of personnel; and even iv) top management attitude toward internal controls (i.e., tone from the top). These failures of company-level controls are much more serious because they are harder to fix.

In general, ICWs are expected to increase the risk of accounting errors, earnings manipulation, and financial fraud. Doyle, Ge, and McVay (2007b) find that companies with ICWs have lower-quality financial statements and that this relation is driven by overall company-level controls, as opposed to account-specific weaknesses. Ashbaugh-Skaife, Collins, Kinney, and LaFond (2009) report that firms with ICWs have higher idiosyncratic risk, systematic risk, and cost of equity. Elbannan (2009) finds that these firms have lower credit ratings, evidencing higher credit risk. This is confirmed by Moody's (2004), which indicates that ICWs, especially those broader in scope, can have a direct effect on credit ratings. Indeed, Hammersley, Myers, and Zhou (2009) find that companies that fail to remediate previously disclosed ICWs experience lower bond ratings. In summary, the accounting literature has reported a strong link between the quality of internal controls and risk variables, including accounting risk, market risk, and credit risk. Even though these ICWs pertain to financial reporting, they are attributed to broader deficiencies in controls, which we expect would also cause a greater incidence of losses due to operational risk.

We draw from a wide range of studies in order to develop measures of the quality of internal control. First, we look to the accounting literature that examines firm characteristics as potential determinants of ICWs. Ashbaugh-Skaife et al. (2007) and Doyle et al. (2007a) find that firms disclosing ICWs tend to be smaller, younger, financially weaker, more complex, and growing rapidly. Motivated by these studies, we construct frequency models of operational risk events using commonly observed firm-specific covariates. Specifically, we expect the following:

Hypothesis 1. Firms with characteristics associated with a higher incidence of ICWs also have a higher frequency of operational risk events.

Besides firm-specific risk variables, we examine the role of corporate governance in mitigating operational risk. The recently revised Basel II Capital Accord requires that senior management and the board of directors play an active role in operational risk management. Specifically, the second pillar of Basel II mandates the regular reporting of operational risk exposure and loss experience to senior management and the board of directors, and the regular review of risk management systems and processes by internal or external auditors (BCBS (2006), pp. 149–151). While the link between internal corporate governance (as measured by board characteristics) and firms' internal control environment seems intuitive, external corporate governance could also play a role. Bertrand and Mullainathan (2003) show that, when shielded from an open market for corporate control, managers are reluctant to perform cognitively difficult tasks such as closing old plants, opening new plants, or bargaining with suppliers and labor unions. It is conceivable that this managerial preference for the "quiet life" could have a negative effect on risk management controls. Indeed, Elbannan (2009) finds that firms with more antitakeover provisions, as proxied by the Gompers et al. (2003) G-index, are more likely to suffer from ICWs.[18] Collectively, these empirical observations motivate the following hypothesis:

[18]While this intuition may hold for nonbank financial firms, hostile takeovers of commercial banks are extremely rare because of the long regulatory approval process required for mergers and acquisitions. As a result, we examine whether external corporate governance is more relevant for nonbank financial institutions in Section VI. We thank the referee for suggesting this analysis.

Hypothesis 2. Firms with weaker internal and external corporate governance are associated with a higher frequency of operational risk events.

The last group of variables that we relate to operational risk pertains to CEO incentives. This is because the structure of executive compensation is likely to be relevant to a firm's internal control environment. For example, a strong equity incentive might cause management to focus too much on beating earnings forecasts or stock price targets, while giving short shrift to risk management controls. The recent studies by Burns and Kedia (2006) and Efendi et al. (2007) present evidence that the likelihood of financial misreporting is positively related to CEO incentives, such as the size and stock price sensitivity of executive stock option holdings. Regardless of how one measures the importance of CEO compensation components, we are motivated by the belief that factors contributing to more frequent financial misreporting should also give rise to a corporate environment that tolerates fraudulent behavior, excessive risk taking, and loose internal control, resulting in operational risk events of the types defined by the Basel Committee. Therefore, we hypothesize the following:

Hypothesis 3. Firms with stronger CEO incentives are associated with a higher frequency of operational risk events.

V. Frequency Models with Firm-Specific and Macroeconomic Covariates

Our primary goal is to develop a model for the frequency of operational risk events among a broad sample of financial institutions. We do this by conditioning the event intensity $\lambda(t)$ on a set of widely available firm-specific and macroeconomic covariates. In subsequent sections, we will specialize in the effect of corporate governance and executive compensation at the expense of a more restrictive sample.

A. Explanatory Variables

In choosing firm-specific covariates for the frequency model, we are motivated by the accounting literature on the determinants of ICWs, which has shown that firms experiencing ICWs tend to be smaller, younger, financially weaker, more complex, and growing rapidly.

Specifically, we use the logarithm of the market value of equity (MVE) to control for firm size in our regression specifications.[19] While larger firms tend to have better controls in place, they have to process a higher volume of trades and deal with more complex transactions, and therefore are more likely to experience a greater incidence of operational risk events. Separately, since higher magnitude losses are more likely to attract managerial attention and catch the public eye,

[19]Basel II suggests a number of alternatives in this regard, including the number of transactions, trading volume, value of assets, and net income (BCBS (2001)). We find the strongest correlation between operational risk event frequency and firm size when we measure the latter by the logarithm of MVE.

firms with losses recorded in the Algo FIRST database may be larger than firms not in the database.

We include firm age as the number of months that the firm has been public. Younger firms are expected to have higher operational risk because they could still be in the process of developing internal control procedures. We use the sum of the number of operating and geographical segments reported in Compustat to measure the complexity of the firm. Intuitively, more complex organizations are expected to have higher operational risk because they are more difficult to control and monitor. Since the number of segments is available for only ⅓ of our original sample, we include it in a specification outside of our main results. We define a dummy variable that equals 1 if a firm's liability growth and asset growth over the past quarter are both positive and the liability growth exceeds the asset growth. Consistent with the accounting literature related to ICWs, Moody's (2002) and the Office of the Comptroller of the Currency (OCC) (2001) argue that banks with preexisting risk management deficiencies may experience escalating problems under aggressive growth strategies (in particular, growth in liabilities), because their management is not able to cope with and sustain exceptional growth. Therefore, we expect to see a positive relation between the excessive growth dummy variable and operational risk.

We pay particular attention to the empirical finding that financially weaker firms tend to have more ICWs. Combined with Hypothesis 1, this finding suggests a positive relation between operational risk and credit risk. This conjecture, if confirmed, would be important for risk managers who are trying to estimate a firm-wide loss distribution that accounts for market risk, credit risk, and operational risk (Rosenberg and Schuermann (2006)).[20]

The classical Merton (1974) structural model suggests that the risk of financial distress is positively related to firm leverage and volatility. In the context of commercial banks, the Basel Accord requires sufficient capital reserves in the form of Tier 1 capital, which basically is the sum of shareholders' equity and retained earnings. The Tier 1 capital ratio is defined as the ratio of Tier 1 capital to risk-weighted assets. By construction, it can be roughly considered as the inverse of the leverage ratio, and it is therefore negatively correlated with the risk of financial distress. Since information on risk-weighted assets is available for only a small fraction of the firms in our sample, we compute a proxy for Tier 1 capital ratio using total assets in lieu of risk-weighted assets as the denominator.[21] We compute equity volatility as the trailing standard deviation of monthly stock returns for the previous year. Moreover, we use a combination of information from

[20]This conjecture is also consistent with management taking actions to avoid debt covenant violations (DeFond and Jiambalvo (1994), Sweeney (1994), and Dichev and Skinner (2002)), which would imply that the likelihood of misreporting is positively related to financial leverage (Richardson, Tuna, and Wu (2002), Burns and Kedia (2006), and Efendi et al. (2007)).

[21]Estrella, Park, and Peristiani (2000) show that a simple capital ratio (measured by equity capital to total assets) predicts bank failure just as well as more complex risk-weighted ratios. They argue that using risk-weighted assets in the denominator of a capital ratio is not optimal, because it is difficult to correctly assess the riskiness of a bank's assets. The ratio of equity capital to total assets is also used in Jarrow, Bennett, Fu, Nuxoll, and Zhang (2003). Furthermore, FDIC (1998) shows that the ratio of equity capital to total assets was lower for banks that failed during the 1980s and 1990s.

both leverage and equity volatility, in the form of Merton's distance-to-default, constructed following the procedure described in Vassalou and Xing (2004) and Duffie et al. (2007). Since it is essentially a volatility-adjusted measure of leverage that directly relates to the probability of default, the distance-to-default serves as a robustness check of the relation between operational risk and credit risk. We also include the market-to-book ratio because it is commonly interpreted as a proxy for default risk, with lower values signaling distress (Fama and French (1992)). If operational risk and credit risk are indeed positively correlated, we would expect a higher incidence of operational risk events among financial institutions with a lower Tier 1 capital ratio, market-to-book ratio, and distance-to-default, and a higher equity volatility.

For additional credit risk-related variables, we use the ratio of cash holdings to total assets as an indicator of a troubled bank. In a related study, Acharya, Davydenko, and Strebulaev (2007) identify a robust positive relation between cash holdings and credit spreads, as riskier firms that face financial constraints hoard cash in order to reduce the possibility of a future cash shortage. Hence, we predict a positive association between cash holdings and operational risk. Another potential indicator of distress in financial institutions is the ratio of dividends to assets. Specifically, dividend payout may be restricted for financial institutions that experienced large losses and were identified by regulators as troubled banks (OCC (2001), Collier, Forbush, Nuxoll, and O'Keefe (2003)). We define a high dividend ratio dummy variable that equals 1 if the dividend asset ratio is higher than the monthly median across all sample firms. We expect a negative association between the high dividend ratio dummy variable and operational risk. We include the return on equity (ROE), measured as the ratio of net income to the book value of equity, which is a common measure of profitability. On the one hand, more profitable firms are less constrained, allowing them to devote more resources to internal control. On the other hand, profitability can be positively correlated with operational risk due to the presence of moral hazard. For instance, employees might be tempted to commit fraud when average returns are high, or embezzle funds when money is "left on the table." Alternatively, senior management can look the other way at failures of internal control when profitability is high, or needs to be juiced up (Jin and Myers (2006)).

We control for the effect of the general economic environment by including such macroeconomic covariates as Moody's monthly Baa-Aaa credit spread, quarterly growth rates of gross domestic product (GDP) and disposable personal income, monthly returns of the S&P 500 index, and the trailing standard deviation of monthly S&P 500 returns over the past 3 years. On the one hand, we may expect to see a higher incidence of fraud during good times (Povel, Singh, and Winton (2007)). On the other hand, firms have fewer resources to allocate to improvements in internal controls during an economic downturn, which can contribute to more operational risk. BCBS ((2009b), p. 49) notes that economic difficulties resulting from business cycles may cause an increase in rogue trading and fraud.

We use 2 variables to capture the effect of changes in the regulatory environment. First, we control for the growth in the SEC regulatory budget per financial institution. We expect 2 effects from an increase in the SEC regulatory budget. The 1st is a detection effect, leading to a higher number of "discovered" events that occurred in the past. The 2nd is a deterrence effect, which prevents potential loss events from occurring in the first place. Focusing on the deterrence effect, we estimate the relation between event occurrence and the lagged (by 1 year) SEC regulatory budget growth rate. Second, we construct a dummy variable for the period after February 2001, which corresponds to the release of a Basel Committee consultative document on operational risk (BCBS (2001)).[22] Table A2 in the Appendix summarizes the definitions of the variables that will be used in our empirical analysis.

B. Econometric Framework

The conditional Poisson model of operational risk events described in Section II can be estimated using different methods. One could estimate a Cox proportional hazard regression based on the distribution of interarrival times between events. Alternatively, one could estimate a Poisson regression based on the distribution of the count of events over sample intervals. In our case, since the covariates are measured at monthly, quarterly, or annual frequencies, we split our sample period into 1-month intervals to achieve the highest level of granularity, and we compute the monthly aggregated event count for each firm. When the baseline hazard is assumed to be constant and the arrival time of events is measured in months, the likelihood functions of the Cox and Poisson models are identical. Generally, even when these conditions are not met, Poisson regressions provide estimates similar to Cox proportional hazard regressions and are computationally more efficient (Callas, Pastides, and Hosmer (1998)). We also choose to estimate Poisson regressions because of our interest in the count of events rather than the duration between events.[23]

We organize our data as a cross-sectional time-series panel. The panel represents individual firms and is unbalanced due to unequal lengths of time the firms are represented within the sample. For different event types, we estimate regressions of the number of events per month, where the independent variables can include various firm-specific and macroeconomic covariates. The firms' balance sheet data are obtained from Compustat, and the market values of equity from CRSP. If a firm is not in the Algo FIRST database, we assume that its number of operational loss events is 0 in the sample period. By including all of the firms with SIC code beginning with a "6" in our empirical analysis, we are effectively capturing operational risk rather than a mere occurrence of operational risk events within firms with at least 1 reported loss (i.e., firms in the Algo FIRST database).

We estimate Poisson regression models based on the following arrival intensities:

$$\lambda_{ijts} = \exp\left(\alpha_j + \beta_s + \delta D_t + \gamma' X_{it}\right), \tag{3}$$

$$\lambda_{ijts} = \exp\left(\alpha_j + \eta' Y_t + \delta D_t + \gamma' X_{it}\right), \tag{4}$$

[22] See footnote 14 for further discussions related to this variable.

[23] As Section II shows, the distribution of the number of events over a fixed interval (e.g., 1 year) is directly related to the accumulated loss distribution and the operational VaR.

where i, j, t, and s represent firm, industry (2-digit SIC), month, and year, respectively. Here, α denotes industry fixed effects, β year fixed effects, D a January dummy variable, X a set of firm characteristics, and Y a set of macroeconomic covariates. To ensure that there is no look-ahead bias, we apply a 1-quarter lag to all Compustat variables. In equation (4), the year fixed effects are dropped to allow for the inclusion of macroeconomic covariates.[24] We use the maximum likelihood estimator (MLE) for this model based on the conditional Poisson count of events.[25] Because this frequency model provides as an output the expected number of risk events each month, the estimation of the model is equivalent to estimating the time series of the stochastic intensity of the count process. A similar methodology is used by Duffie et al. (2007) to estimate the arrival intensity of defaults for U.S. industrial firms from 1980 to 2004.

Since some of our independent variables are measured quarterly or annually, the monthly regression residuals could contain a significant amount of serial correlation at the firm level. To address this issue, we compute standard errors of the estimates clustered at the firm level. As shown in Petersen (2009), this is an effective way to account for arbitrary correlation among observations belonging to the same firm. As a robustness check, we also estimate the frequency model using quarterly aggregated count of events; the results remain qualitatively the same.

For the purpose of better delineating our results in the subsequent analysis, we group the 7 event types into several broad categories. We eliminate ET5 from subsequent analysis due to the unpredictable nature of such losses: It is unlikely that losses caused by natural disasters or terrorism can be effectively controlled by internal oversight.[26] We then designate specific categories for internal fraud (ET1), external fraud (ET2), and clients, products, and business practices (ET4) (Models 1–3, respectively). Table 2 reveals that these 3 event types have the highest frequency of losses. Model 4 includes all other events (ET3, ET6, ET7, and Other). We also include as Model 5 the aggregation of all event types with the exception of ET5.

C. Empirical Findings

Table 4 summarizes our results from the MLE of the frequency models. We first focus on the interpretation of the firm-specific covariates. In Section IV, we have hypothesized that variables associated with the incidence of ICWs could also help explain the frequency of operational risk events (Hypothesis 1). Our empirical results support this hypothesis; the frequency of events depends positively on equity volatility and cash-to-assets, and negatively on firm age, Tier 1 capital

[24]We include firm fixed effects in the initial modeling. However, they are mostly insignificant. Therefore, we drop firm fixed effects from all models. Later, we check the robustness of our results by including 2-digit SIC fixed effects to control for differences among various types of financial institutions.

[25]Because operational loss count data are highly right skewed, applying the ordinary least squares (OLS) estimator is inappropriate and would result in biased, inefficient, and inconsistent estimates.

[26]In our preliminary estimation, we include ET5 as a distinct event type category. However, there are only a small number of events in this category, and the estimated coefficients and their significance levels appear random, suggesting that the results are spurious.

TABLE 4

Operational Risk Frequency Model with Microeconomic and Macroeconomic Covariates

In Table 4, the dependent variable is the monthly aggregated event count for each firm during 1980–2005. Columns denoted by "A" indicate models with only firm-specific covariates. Columns denoted by "B" indicate models with firm-specific and macroeconomic covariates. Subscripts t and $t-3$ indicate that the variable is measured during the current and the previous quarter, respectively. The panel data Poisson regression models are estimated with the method of maximum likelihood. All models are adjusted for the lengths of unbalanced panels. t-statistics (in parentheses) are based on standard errors clustered by firm. ***, **, and * denote statistical significance of the coefficients at the 1%, 5%, and 10% levels, respectively. For directional hypotheses, we use 1-tailed tests;[a] if the coefficient's sign is opposite from the one hypothesized, then we do not indicate significance levels.

		Model 1		Model 2		Model 3		Model 4		Model 5	
		Internal Fraud		External Fraud		Clients, Prod., & Bus. Practices		Other Events		All Events	
Variables	Expected Sign	A	B	A	B	A	B	A	B	A	B
Panel A. Variables Related to Firm Characteristics											
logMVE_t	(?)	0.9110	0.9240	0.9709	0.9594	1.1166	1.0975	0.9391	0.9442	1.0175	1.0113
		(10.33)***	(10.59)***	(9.50)***	(10.10)***	(16.81)***	(19.38)***	(10.16)***	(11.78)***	(14.94)***	(17.24)***
$\text{MARKET-TO-BOOK}_{t-3}$	(−)	−0.2779	−0.2275	−0.2198	−0.2263	−0.3703	−0.3714	−0.1949	−0.1623	−0.2881	−0.2720
		(−1.81)**	(−1.75)**	(−1.34)*	(−1.22)	(−2.40)***	(−2.61)***	(−1.56)*	(−1.42)*	(−2.20)**	(−2.25)**
CASH_TA_{t-3}	(+)	0.0994	0.0958	2.0086	0.0830	0.1669	0.1367	0.1061	0.1035	0.1280	0.1115
		(3.14)***	(3.23)***	(3.40)***	(2.55)***	(4.78)***	(4.31)***	(3.75)***	(3.82)***	(4.62)***	(4.23)***
TIER1R_{t-3}	(−)	−0.5902	−0.5757	−0.8425	−1.0665	−0.1722	−0.2212	−0.5631	−0.5573	−0.5046	−0.5185
		(−1.58)*	(−1.49)*	(−3.50)***	(−4.29)***	(−0.38)	(−0.49)	(−2.15)**	(−2.04)**	(−1.73)**	(−1.73)**
ROE_{t-3}	(?)	0.6624	0.6031	0.1324	0.1863	0.8041	0.9175	0.1971	0.2357	0.5541	0.6182
		(0.82)	(0.73)	(0.10)	(0.14)	(0.92)	(1.08)	(0.24)	(0.29)	(0.68)	(0.77)
RETSD_t	(+)	3.4893	3.8606	3.2312	2.7319	4.7373	4.4583	3.6005	3.9526	4.0531	4.0492
		(3.56)***	(4.60)***	(2.62)***	(1.94)**	(6.57)***	(5.98)***	(5.41)***	(6.41)***	(7.50)***	(7.41)***
DUM_EXCESS_GR_t	(+)	0.3314	0.3456	0.1334	0.1868	−0.0031	0.0356	−0.2964	−0.3258	−0.0077	0.0153
		(1.75)**	(1.99)**	(0.54)	(0.75)	(−0.02)	(0.25)	(−1.86)	(−2.05)	(−0.08)	(0.16)
$\text{DUM\_HIGH\_DIVR}_{t-3}$	(−)	−0.3015	−0.2956	0.2925	0.1578	−0.2105	−0.1851	−0.4221	−0.3773	−0.2313	−0.2075
		(−1.29)*	(−1.22)	(0.67)	(0.37)	(−0.86)	(−0.78)	(−1.67)**	(−1.48)*	(−1.15)	(−1.03)
AGE_FIRM_t	(−)	−0.0030	−0.0031	−0.0022	−0.0023	−0.0034	−0.0035	−0.0026	−0.0026	−0.0031	−0.0031
		(−2.97)***	(−2.96)***	(−1.24)	(−1.36)*	(−2.84)***	(−2.92)***	(−2.58)***	(−2.64)***	(−3.11)***	(−3.19)***

(continued on next page)

TABLE 4 (continued)

Operational Risk Frequency Model with Microeconomic and Macroeconomic Covariates

		Model 1 Internal Fraud		Model 2 External Fraud		Model 3 Clients, Prod., & Bus. Practices		Model 4 Other Events		Model 5 All Events	
Variables	Expected Sign	A	B	A	B	A	B	A	B	A	B
Panel B. Variables Related to the Macroeconomic Environment											
$SPREAD_t$	(?)		−0.1210		−0.7911		−0.4141		−0.1403		−0.3034
			(−0.24)		(−1.30)		(−1.51)		(−0.42)		(−1.15)
$DISP\_INCOME\_GR_t$	(?)		−3.2294		7.0938		−12.3186		−9.7259		−8.1816
			(−0.37)		(0.59)		(−2.33)**		(−1.78)*		(−2.24)**
$S\&P500R_t$	(?)		0.8427		4.3244		1.0935		−4.7751		−0.0340
			(0.36)		(1.55)		(1.04)		(−2.75)***		(−0.04)
$S\&P500RSD_t$	(?)		−4.0224		31.2544		22.1571		−6.6836		12.0307
			(−0.41)		(2.05)**		(2.88)***		(−0.74)		(2.25)**
GDP_GR_t	(?)		−0.0976		−0.0026		−0.0213		−0.1494		−0.0655
			(−1.48)		(−0.03)		(−0.41)		(−3.15)***		(−2.50)**
$SEC\_BUDGET\_GR_{t-12}$	(−)		−2.6113		−0.3441		−2.0443		−0.8483		−1.6802
			(−1.49)*		(−0.19)		(−1.96)**		(−0.61)		(−2.04)**
$DUM\_POST2001_t$	(−)		−0.3374		−1.2385		−0.4049		−0.2092		−0.4276
			(−0.80)		(−2.59)***		(−1.71)**		(−0.48)		(−1.67)**
January dummy		Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects		Yes	No	Yes	No	Yes	No	Yes	No	Yes	No
No. of obs.		183,806	183,806	183,806	183,806	183,806	183,806	183,806	183,806	183,806	183,806
χ^2 firm			217.80		135.36		789.32		428.23		706.24
[*p*-value]			[0.0000]***		[0.0000]***		[0.0000]***		[0.0000]***		[0.0000]***
χ^2 macro			13.26		44.44		74.66		22.34		71.44
[*p*-value]			[0.0659]*		[0.0000]***		[0.0000]***		[0.0022]***		[0.0000]***
Pseudo R^2		0.3029	0.2908	0.3381	0.3115	0.4811	0.4664	0.3335	0.3209	0.4448	0.4345

[a]For 1-tailed tests, the critical values for the *t*-statistics are 1.28, 1.65, and 2.33 in absolute value, for the 10%, 5%, and 1% levels, respectively.

ratio, and market-to-book. The size and statistical significance of these coefficients are similar across different event types, which is consistent with the overarching idea that operational risk can, in general, be traced to a lack of internal control. This finding suggests that an operational risk event of one type may signal broader firm-wide risk management deficiencies, causing losses of other types.

One of the most significant covariates is equity volatility; its coefficient is significant at the 1% level for almost all event types. The coefficient of 4.05 for Model 5B (all events, inclusive of macroeconomic covariates) indicates that a 10-percentage-point increase in equity volatility (say, from 20% to 30%) is associated with a $\exp(0.1 \times 4.05) \approx 1.5$ times increase in the expected number of operational risk events per month. Since higher equity volatility and cash-to-assets and lower Tier 1 capital ratio and market-to-book are indicators of financial distress, our results are consistent with a positive correlation between operational risk and credit risk in financial institutions.

We find that the coefficient for the logarithm of the MVE is highly significant and stable across all models. The estimate is close to 1 for all event types, indicating that the average number of events per month roughly scales with the firm's market capitalization. This might mean that larger firms are likely to have more frequent risk events, or it could be caused by events at smaller firms being overlooked by public scrutiny (see discussions in Section III).

With respect to the profitability measure (proxied by ROE), we find that its coefficient is positive and insignificant across all models. For the high dividend ratio dummy variable, we find that its coefficient is negative as hypothesized in most cases, but it is often insignificant. The evidence on the excessive growth dummy variable also appears inconclusive.

We obtain generally weaker results with respect to macroeconomic covariates, as the estimates are never significant across all models. In cases where we do have statistical significance, however, results are consistent with more frequent operational risk events during economic downturns. For example, for Model 5 (all events), the coefficients of GDP and disposable income growth are negative and significant, and the coefficient of the standard deviation of S&P 500 index returns is positive and significant. For variables measuring the regulatory environment, we find a negative coefficient for the lagged growth rate of the SEC regulatory budget per financial institution. Interestingly, this coefficient is significant only for Model 1 (Internal Fraud) and Model 3 (Clients, Products, and Business Practices). This is consistent with the stated objective of the SEC Enforcement Division, which is to investigate possible violations of securities laws. We also find a negative coefficient for the post-February 2001 dummy variable, consistent with a reduction of the number of events after 2001, previously identified in Figure 2.[27]

[27]The sign of this coefficient could also be consistent with the effect of the Sarbanes-Oxley Act, which was passed in July 2002. In a separate analysis, we remove the post-February 2001 dummy variable from the frequency models; we find similar results on the macroeconomic covariates. We also estimate an alternative version of the frequency model, which explains the aggregate event count across all firms using only macroeconomic covariates; the results remain qualitatively the same.

In Panel A of Table 5, we conduct several robustness checks of our preceding results. In column (0), we replicate the specification in Table 4 that includes all event types and macroeconomic covariates (Model 5B). In column (1), we add fixed effects for 2-digit SIC codes to control for differences in various types of financial institutions. In column (2), we add the number of operating and geographical segments to the model. In columns (3) and (4), we add the Merton (1974) distance-to-default to the model. We find that most of our previous findings remain robust under these alternative specifications. In particular, the frequency of events has a positive and significant dependence on the number of segments, indicating a higher incidence of events among more complex firms. Also, the event frequency has a negative and significant dependence on the distance-to-default, confirming the positive correlation between operational risk and credit risk.

Since the Basel regulators are mainly concerned with the operational risk of banks, we examine whether there are differences in the determinants of operational risk across banks and nonbank financial institutions in our sample. Among other things, this would indicate the extent to which bank supervisors could use financial-sector-wide external data sets like ours in assessing the adequacy of any given bank's capital allocation for operational risk.

Panel B of Table 5 presents separate estimations of the operational risk intensity for banks (2-digit SIC code 60) and nonbanks (2-digit SIC codes 61–67) in our sample. Many covariates, such as firm size, market-to-book, firm age, and distance-to-default, have significant coefficients across both banks and nonbanks. For the Tier 1 capital ratio, we find that it is generally more significant among banks; this is consistent with the important role of Tier 1 capital in regulatory requirements for depository institutions. For the ratio of cash to total assets, we find that it is only significant among nonbanks. Acharya et al. (2007) argue that the positive relation between cash holdings and credit risk is explained by a precautionary savings motive.[28] However, the precautionary motive to save is presumably less important among banks, because depository institutions are insured by the FDIC and have access to a liquidity backstop in the form of the Federal Reserve's discount window. We also find that equity volatility is generally not significant among banks, although its explanatory power is apparently supplanted by the distance-to-default. It seems that, with a couple of exceptions, the operational risk for banks and nonbank financial firms can be explained by the same set of covariates.[29]

In summary, consistent with Hypothesis 1, we find that firms with more ICWs tend to have higher operational risk, and among these are younger firms, firms with more segments, and firms with an elevated level of credit risk. These results are found to hold uniformly across different event types, consistent with the lack of internal control as the common source of operational risk events. We also find similar behavior between banks and nonbanks, suggesting that our use

[28]Their findings are derived from a sample of nonfinancial firms.

[29]It also appears that banks have their "fair" share of events in the database. Our sample consists of 76 banks and 100 nonbanks (the proportion of banks is 43.2%). Panel B of Table 2 shows that there are 414 events among banks and 511 events among nonbanks (the proportion of events in banks is 44.8%).

TABLE 5

Robustness Checks and Other Specifications: Operational Risk Frequency Model

Panel A of Table 5 summarizes results of several robustness checks for all operational risk event types (Model 5B) and all financial firms. Specification (0) is the original specification from the last column of Table 4. In Specification (1), we add SIC fixed effects. In Specification (2), we add the number of business and geographical segments to the original model specification. In Specifications (3) and (4), we add Merton's (1974) distance-to-default to the original model and to the model with the number of segments. Panel B repeats each of the "B" columns from Table 4 separately for banks (SIC 60xx) and nonbanks (SIC 61xx–69xx). *t*-statistics (in parentheses) are based on standard errors clustered by firm. ***, **, and * denote statistical significance of the coefficients at the 1%, 5%, and 10% levels, respectively. For directional hypotheses, we use 1-tailed tests;[a] if the coefficient's sign is opposite from the one hypothesized, then we do not indicate significance levels.

Panel A. Robustness Checks and Other Specifications for All Financial Firms

Variables	Expected Sign	(0)	(1)	(2)	(3)	(4)
Variables Related to Firm Characteristics						
logMVE_t	(?)	1.0113	1.0265	0.8810	0.9957	0.8625
		(17.24)***	(13.46)***	(18.03)***	(17.88)***	(17.44)***
$\text{MARKET-TO-BOOK}_{t-3}$	(−)	−0.2720	−0.2361	−0.1900	−0.2631	−0.1716
		(−2.25)**	(−3.19)***	(−2.21)**	(−2.54)***	(−2.02)**
CASH_TA_{t-3}	(+)	0.1115	0.1106	2.6996	1.9896	2.8582
		(4.23)***	(3.87)***	(5.55)***	(9.65)***	(5.50)***
TIER1R_{t-3}	(−)	−0.5185	−0.4833	−0.3131	−0.5014	−0.3687
		(−1.73)**	(−1.77)**	(−1.77)**	(−1.49)*	(−1.45)*
ROE_{t-3}	(?)	0.6182	−0.0372	0.7745	0.5168	0.6320
		(0.77)	(−0.07)	(1.62)	(0.71)	(1.30)
RETSD_t	(+)	4.0492	3.3036	3.4450	4.2201	3.4485
		(7.41)***	(4.28)***	(4.63)***	(5.81)***	(3.84)***
DUM_EXCESS_GR_t	(+)	0.0153	0.0257	−0.0979	0.0262	−0.1038
		(0.16)	(0.31)	(−0.83)	(0.28)	(−0.86)
$\text{DUM\_HIGH\_DIVR}_{t-3}$	(−)	−0.2075	−0.1427	−0.3664	−0.0751	−0.2862
		(−1.03)	(−0.73)	(−1.67)**	(−0.41)	(−1.34)*
FIRM_AGE_t	(−)	−0.0031	−0.0031	−0.0042	−0.0027	−0.0039
		(−3.19)***	(−3.62)***	(−3.07)***	(−3.00)***	(−2.83)***
NUM_SEGMENTS_t	(+)			0.0472		0.0464
				(3.02)***		(2.86)***
$\text{DISTANCE-TO-DEFAULT}_t$	(−)				−0.0169	−0.0154
					(−6.38)***	(−5.88)***
Variables Related to the Macroeconomic Environment						
SPREAD_t	(?)	−0.3034	−0.2807	0.2815	−0.3705	0.2494
		(−1.15)	(−1.21)	(0.74)	(−1.31)	(0.64)
DISP_INCOME_GR_t	(?)	−8.1816	−8.3725	−5.9828	−9.0696	−7.2206
		(−2.24)**	(−2.37)**	(−1.09)	(−2.36)**	(−1.23)
$\text{S\&P500R}_t$	(?)	−0.0340	−0.2155	0.6709	−0.0047	0.8017
		(−0.04)	(−0.26)	(0.50)	(−0.01)	(0.58)
$\text{S\&P500RSD}_t$	(?)	12.0307	11.2251	7.2728	10.8411	5.3366
		(2.25)**	(2.13)**	(0.88)	(2.04)**	(0.65)
GDP_GR_t	(?)	−0.0655	−0.0660	−0.0163	−0.0587	−0.0139
		(−2.50)**	(−2.72)***	(−0.37)	(−2.27)**	(−0.32)
$\text{SEC\_BUDGET\_GR}_{t-12}$	(−)	−1.6802	−1.6587	−1.5717	−1.4931	−1.4016
		(−2.04)**	(−1.99)**	(−1.67)**	(−1.83)**	(−1.45)*
DUM_POST2001_t	(−)	−0.4276	−0.5139	−0.7472	−0.4424	−0.7872
		(−1.67)**	(−2.14)**	(−2.83)***	(−1.72)**	(−3.04)***
January dummy		Yes	Yes	Yes	Yes	Yes
Year fixed effects		No	No	No	No	No
SIC fixed effects		No	Yes	No	No	No
No. of obs.		183,806	183,806	68,861	161,289	54,640
χ^2 firm		706.24	430.02	866.96	764.86	818.46
[*p*-value]		[0.0000]***	[0.0000]***	[0.0000]***	[0.0000]***	[0.0000]***
χ^2 macro		71.44	72.27	52.39	64.31	58.39
[*p*-value]		[0.0000]***	[0.0000]***	[0.0000]***	[0.0000]***	[0.0000]***
Pseudo R^2		0.4345	0.4546	0.4759	0.4424	0.4793

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TABLE 5 (continued)

Robustness Checks and Other Specifications: Operational Risk Frequency Model

Panel B. Frequency Models with Microeconomic and Macroeconomic Covariates for Banks and Nonbanks

		Model 1		Model 2		Model 3		Model 4		Model 5	
		Internal Fraud		External Fraud		Clients, Prod., and Bus. Practices		Other Events		All Events	
Variables	Expected Sign	A: Banks	B: Nonbanks	A: Banks	B: Nonbanks	A: Banks	B: Nonbanks	A: Banks	B: Nonbanks	A: Banks	B: Nonbanks
Variables Related to Firm Characteristics											
$\log MVE_t$	(?)	0.8600	0.9547	1.0347	1.0040	1.3347	0.9186	1.1100	0.8729	1.1206	0.9160
		(4.31)***	(10.23)***	(7.29)***	(6.94)***	(11.99)***	(15.46)***	(6.64)***	(14.30)***	(8.66)***	(20.25)***
MARKET-TO-BOOK$_{t-3}$	(−)	−0.0078	−0.3149	−0.5319	−0.1191	−0.4710	−0.2191	−0.2092	−0.1372	−0.2958	−0.2010
		(−0.05)	(−1.91)**	(−2.74)***	(−1.24)	(−3.71)***	(−2.30)**	(−1.36)*	(−1.57)*	(−2.79)***	(−2.32)**
CASH_TA$_{t-3}$	(+)	−0.9497	2.9583	−3.8544	4.0652	−1.9802	3.1639	0.9552	2.6923	−0.6812	3.0784
		(−0.60)	(4.24)***	(−1.97)	(2.67)***	(−1.13)	(5.01)***	(1.12)	(2.52)***	(−0.71)	(5.20)***
TIER1R$_{t-3}$	(−)	−1.2257	−0.1690	−1.2205	0.2286	−1.8040	−0.3737	−0.9144	−0.5545	−1.3446	−0.3814
		(−1.97)**	(−0.23)	(−1.37)	(0.24)	(−3.95)***	(−1.15)	(−1.90)**	(−2.92)***	(−3.15)***	(−1.46)*
ROE$_{t-3}$	(?)	−2.0216	−0.0679	4.6922	0.2016	−0.4993	0.6219	1.4179	0.5237	0.8301	0.4670
		(−1.26)	(−0.10)	(2.11)**	(0.14)	(−0.17)	(1.05)	(0.93)	(0.99)	(0.48)	(0.86)
RETSD$_t$	(+)	−2.9960	4.5946	−2.7782	2.8331	−6.4093	3.3450	4.9648	3.8790	−0.6406	3.7567
		(−0.78)	(3.33)***	(−0.40)	(0.94)	(−1.33)	(2.94)***	(1.95)**	(3.80)***	(−0.24)	(4.39)***
DUM_EXCESS_GR$_t$	(+)	0.3704	0.2862	0.0329	0.4582	0.2084	−0.2353	−0.3278	−0.2669	0.0875	−0.1161
		(1.62)*	(1.02)	(0.12)	(0.87)	(1.16)	(−1.47)	(−1.72)	(−1.03)	(0.71)	(−0.92)
DUM_HIGH_DIVR$_{t-3}$	(−)	−0.2472	−1.0197	0.0585	−1.1786	−0.3527	−0.1914	−0.7517	−0.0810	−0.3799	−0.3122
		(−0.67)	(−2.46)***	(0.08)	(−1.71)**	(−0.83)	(−0.80)	(−2.86)***	(−0.22)	(−1.41)*	(−1.40)*
FIRM_AGE$_t$	(−)	−0.0011	−0.0037	0.0001	−0.0056	−0.0024	−0.0036	−0.0039	−0.0020	−0.0024	−0.0034
		(−0.44)	(−2.85)***	(0.04)	(−1.90)**	(−1.25)	(−1.90)**	(−1.69)**	(−1.10)	(−1.33)*	(−1.99)**
DISTANCE-TO-DEFAULT$_t$	(−)	−0.0323	−0.0180	0.0027	−0.0144	−0.0546	−0.0166	−0.0419	−0.0120	−0.0405	−0.0160
		(−1.50)*	(−5.85)***	(2.45)***	(−2.16)**	(−6.35)***	(−5.86)***	(−6.32)***	(−2.36)***	(−4.18)***	(−5.96)***

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TABLE 5 (continued)

Robustness Checks and Other Specifications: Operational Risk Frequency Model

Panel B. Frequency Models with Microeconomic and Macroeconomic Covariates for Banks and Nonbanks (continued)

		Model 1		Model 2		Model 3		Model 4		Model 5	
		Internal Fraud		External Fraud		Clients, Prod., and Bus. Practices		Other Events		All Events	
Variables	Expected Sign	A: Banks	B: Nonbanks	A: Banks	B: Nonbanks	A: Banks	B: Nonbanks	A: Banks	B: Nonbanks	A: Banks	B: Nonbanks
Variables Related to the Macroeconomic Environment											
$SPREAD_t$	(?)	0.2143	0.1862	−0.1642	−2.1351	−0.1442	−0.2504	−0.7071	0.2132	−0.3323	−0.0460
		(0.38)	(0.21)	(−0.31)	(−1.35)	(−0.32)	(−0.64)	(−2.41)**	(0.33)	(−1.14)	(−0.10)
$DISP\_INCOME\_GR_t$	(?)	0.7041	−1.8217	−4.3277	35.4672	−6.7479	−21.5585	−21.4863	−0.4828	−8.7635	−8.5632
		(0.06)	(−0.16)	(−0.45)	(1.02)	(−1.89)*	(−3.24)***	(−3.43)***	(−0.05)	(−2.18)**	(−1.51)
$S\&P500R_t$	(?)	0.2170	2.0883	−0.3707	15.9857	1.8868	0.2067	−4.9769	−3.5786	−0.4238	0.5448
		(0.07)	(0.53)	(−0.15)	(3.92)***	(1.73)*	(0.12)	(−2.23)**	(−1.27)	(−0.42)	(0.39)
$S\&P500RSD_t$	(?)	−19.5297	17.8040	30.6763	54.5390	24.1581	28.7598	−3.7246	−12.2735	9.8537	17.9261
		(−1.14)	(1.41)	(1.77)*	(2.02)**	(2.09)**	(3.97)***	(−0.42)	(−0.74)	(1.78)*	(2.27)**
GDP_GR_t	(?)	−0.0438	−0.2007	0.0422	−0.0603	−0.0660	0.0356	−0.1779	−0.0849	−0.0779	−0.0514
		(−0.56)	(−1.93)*	(0.50)	(−0.22)	(−0.99)	(0.45)	(−3.34)***	(−1.09)	(−2.93)***	(−1.13)
$SEC\_BUDGET\_GR_{t-12}$	(−)	−2.0805	−2.5221	−1.3147	4.2293	−1.1978	−2.4384	−0.5709	−1.0520	−1.3039	−1.7884
		(−0.92)	(−0.87)	(−0.55)	(1.11)	(−0.64)	(−2.07)**	(−0.30)	(−0.49)	(−0.96)	(−1.87)**
$DUM\_POST2001_t$	(−)	−0.0238	−1.4880	−1.1930	−3.2091	−1.1177	−0.2552	0.0229	−0.2807	−0.4951	−0.5704
		(−0.04)	(−2.17)**	(−2.41)***	(−2.98)***	(−2.05)**	(−1.07)	(0.04)	(−0.58)	(−1.16)	(−2.01)**
January dummy		Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects		No	No	No	No	No	No	No	No	No	No
No. of obs.		105,318	55,971	105,318	55,971	105,318	55,971	105,318	55,971	105,318	55,971
χ^2 firm		72.37	251.83	100.73	124.17	400.56	395.73	182.93	298.00	397.94	627.63
[p-value]		[0.0000]***	[0.0000]***	[0.0000]***	[0.0000]***	[0.0000]***	[0.0000]***	[0.0000]***	[0.0000]***	[0.0000]***	[0.0000]***
χ^2 macro		3.13	43.50	17.79	77.35	55.97	45.70	39.27	10.62	38.26	47.59
[p-value]		[0.8731]	[0.0000]***	[0.0130]**	[0.0000]***	[0.0000]***	[0.0000]***	[0.0000]***	[0.1562]	[0.0000]***	[0.0000]***
Pseudo R^2		0.2707	0.3497	0.3390	0.3970	0.4957	0.4760	0.3313	0.3443	0.4383	0.4655

[a]For 1-tailed tests, the critical values for the t-statistics are 1.28, 1.65, and 2.33 in absolute value, for the 10%, 5%, and 1% levels, respectively.

of financial-sector-wide external loss data is appropriate for assessing the operational risk capital charge for any given bank.

D. Goodness-of-Fit Tests

The preceding regression results show that the conditional Poisson model can explain a significant part of the time-series and cross-sectional variations in the count of operational risk events. We have performed additional goodness-of-fit tests of the conditional Poisson framework as a description of the operational risk data in a separate empirical study. These tests are based on the idea that a time-scale transformation, based on the arrival intensity, can convert a conditional Poisson process into a standard Poisson process with a unit arrival rate. One can then use the Fisher dispersion test (Cochran (1952), (1954)) to check if the time-scale transformed count data are indeed consistent with a standard Poisson arrival. This idea has been applied to the analysis of default clustering by DDKS (2007).[30]

On average, each sample firm in the FIRST database has more than 5 operational risk events (see Restriction 1 in Table 1). This suggests that we can apply the goodness-of-fit test to each firm separately. Our results indicate that the conditional Poisson model performs well for each firm. Specifically, the conditional Poisson assumption cannot be rejected for over ⅔ of the sample firms. We also apply a similar test to the aggregated event count across all firms for which the conditional Poisson assumption cannot be rejected at the firm level. This allows us to check if event arrivals are conditionally independent across firms. Results show that we cannot reject the hypothesis that event arrivals are jointly conditional Poisson across these firms. These goodness-of-fit results are available from the authors.

E. Operational VaR

As an illustration of the methodology outlined in Section II, we use the intensity function estimated in Section C to compute the operational VaR for a U.S. bank. This bank ranks among the top 40 U.S. banks by total assets, and we have access to its complete operational loss data for 2004–2006. To estimate the severity distribution, we standardize each loss amount by the bank's total assets at the time when the loss occurred.[31] This ensures that, in every quarter of the 2-year period, the distribution of loss amounts is proportional to the total assets of the bank (from Compustat quarterly data). Since most of the financial institutions in our sample have no recorded losses, we need to scale up the intensity estimated from our frequency model. Specifically, we multiply the estimated intensity by a scaling factor, so that the average estimated monthly frequency of events coincides with the average observed monthly frequency over 2004–2006. We compare

[30]While DDKS (2007) reject the conditional Poisson model of default arrivals using U.S. corporate default data, Lando and Nielsen (2010) do not reject this assumption using a different specification of the default intensity. Nevertheless, they argue that the DDKS test might miss default contagion that works through the firm-level covariates.

[31]We experiment with 3 different continuous distributions: lognormal, Pareto, and exponential. The lognormal distribution results in the best fit, as measured by the Kolmogorov-Smirnov statistic. Our results are therefore based on the lognormal distribution.

this with the naive approach, in which the arrival rate of losses is set to the average observed monthly frequency. In both approaches, the severity distribution is the same and scales with the bank's total assets each quarter. Thus, the key difference between the 2 approaches is that one uses an intensity that depends on the bank's internal and external environment, while the other assumes a constant intensity.

Following Basel II guidelines, our VaR estimates are at the 99.9th percentile and are annualized. We estimate the average and the error bands of the VaR using 1,000 Monte Carlo simulations. Figure 3 presents the operational VaR and its 95% confidence intervals, the fitted number of events, and the average loss size for this bank during 2004–2006. In the naive approach, the operational VaR inherits the time-series behavior of the average loss size because the arrival rate of losses is assumed to be constant. Once we adopt the estimated frequency model, the operational VaR is driven primarily by the variation of the stochastic intensity. Although the 2 VaRs are similar in average levels, their time-series patterns are clearly different. For example, the naive approach would overestimate the VaR by more than 20% toward the end of 2005. Overall, this example illustrates the importance of allowing the count of events to be conditioned on the firm-specific and macroeconomic environment.

VI. Corporate Governance and Operational Risk

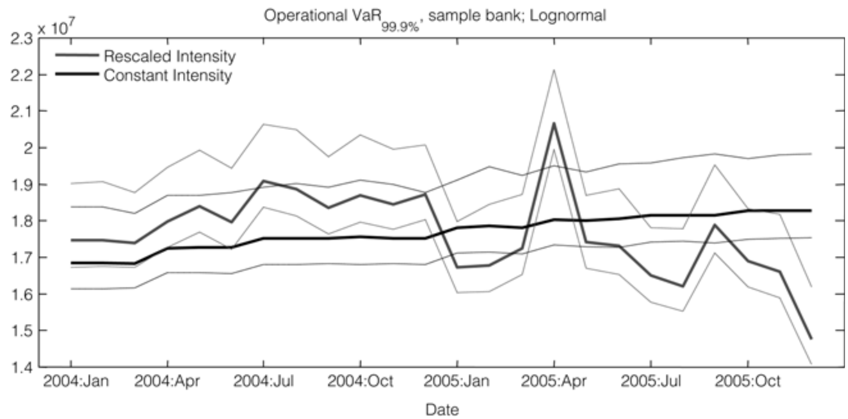
In this section, we study the relation between internal and external corporate governance and the incidence of operational risk events. We use the Gompers et al. (2003) G-index to measure external governance. A higher G-index

FIGURE 3

Implications of the Conditional Poisson Frequency Model for the Operational Value at Risk: An Illustration

Figure 3 illustrates an application of our model from Table 4 to the estimation of operational value at risk (VaR) for a large U.S. bank with available operational risk data for 2004–2006. Graph A compares the 99.9% annualized VaR estimated using our model with the VaR that uses a constant frequency. Graph B shows the conditional Poisson frequency process alongside the constant frequency. Graph C illustrates the average severity of losses modeled using the lognormal distribution. VaR figures and the confidence interval bounds are each obtained using 1,000 Monte Carlo simulations.

Graph A. 99.9% Operational VaR with 95% Confidence Interval Bounds

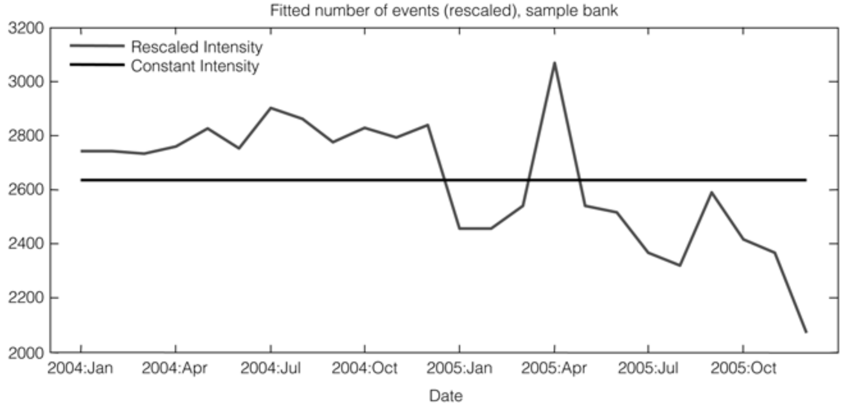


(continued on next page)

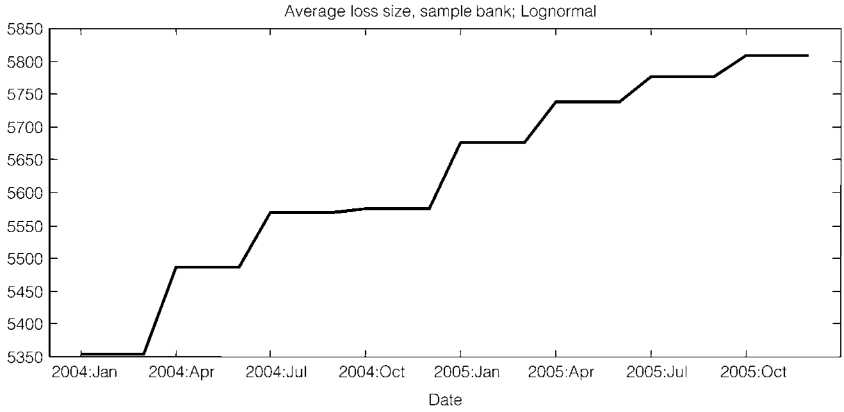
FIGURE 3 (continued)

Implications of the Conditional Poisson Frequency Model for the Operational Value at Risk: An Illustration

Graph B. Frequency Process



Graph C. Loss Severity Process



means that the firm has a larger number of antitakeover provisions, which is typically interpreted as an indicator of weaker external governance. According to Hypothesis 2, it should be positively related to the frequency of operational risk events.

We use the ratio of auditors on the board as a proxy of internal governance. According to the mandate of the Basel Accord, the audit committee serves an important monitoring role and is responsible for ensuring a transparent and consistent risk management process. Therefore, firms with a higher ratio of auditors on the board should have lower operational risk. We also construct a dummy variable that equals 1 if the fraction of independent board members exceeds 75%. Firms with more independent boards are likely to have better internal controls, resulting in fewer operational risk events. These hypotheses are consistent with Dechow et al. (1996), who find that firms with boards dominated by management are more likely to be subject to SEC enforcement actions for alleged violation of generally accepted accounting principles (GAAP). For additional board characteristics, we include the number of board members and the number of board meetings in a year. A larger number of board members and board meetings could mean that more effort and resources are devoted to improving internal control, but they could also be proxying for the complexity of the firm. Therefore, we use both the linear and squared terms of these variables to control for possible nonlinear effects.

For this part of the analysis, we are limited to a sample period of 1998–2005, in which relevant governance data are available. We estimate a Poisson regression model similar to that of Section V, with arrival intensities of the form

$$\lambda_{ij} \quad = \quad \exp\left(\alpha_j + \beta^{'} G_i + \gamma^{'} X_i\right), \tag{5}$$

where i and j represent firm and industry, respectively, α denotes industry fixed effects, G governance-related variables, and X other firm-level control variables.[32] The dependent variable is the number of operational risk events experienced by the firm during 1998–2005, and the governance and control variables are measured at the beginning of the period. We use a cross-sectional regression framework because governance metrics, such as the G-index, are relatively stable over time. By measuring the explanatory variables at the beginning of the sample period, it is more likely that our empirical specification is picking up the deterrence effect of better internal control rather than an improvement of control as a result of earlier loss events. To better differentiate firms with loss events during 1998–2005 from those without, we remove firms without a loss during 1998–2005 but with 1 or more earlier losses during 1980–1997. Overall, the sample includes 256 firms, in which 23 firms incurred 437 operational risk events (see Restriction 2 in Table 1). Since this sample is much smaller than the sample we use to estimate the earlier frequency models, our results below are less strong in comparison.

We present summary statistics of the governance-related variables for firms suffering at least 1 event during 1998–2005 (treatment sample) and firms with no recorded event during 1980–2005 (control sample) in Table 6. A comparison of the sample means of the variables across these 2 groups shows that firms with operational risk events have a higher G-index, a lower ratio of auditors on the board, a lower likelihood that the firm has more than 75% of independent board members, a larger board, and a slightly higher number of board meetings in a year. Among these variables, the differences in means are statistically significant for only the auditor ratio, the board independence dummy variable, and board size. These tests are, however, univariate in nature and provide results that can only be viewed as suggestive. In particular, board size may be closely correlated with firm size, which we control for below.

[32]As a robustness check, we also estimate a logit specification, in which the dependent variable is dichotomous. The results are qualitatively the same. The Poisson model is preferred because it can be viewed as a generalization of the logit model. While the logit specification focuses on the overall probability of experiencing a loss, the Poisson specification effectively categorizes firms with 0, 1, or more than 1 event, thus allowing us to use operational loss data more efficiently.

TABLE 6

Summary Statistics for Governance and Directors Characteristics

Table 6 presents the governance characteristics for firms with at least 1 recorded operational risk event during 1998–2005 (treatment sample) and firms with no recorded event during 1980–2005 (control sample). We focus on 1998–2005, which is the period in which all governance data are available. We use 1 observation per firm. Governance variables are measured in 1998 (60% of the firms) or the 1st year after 1998, in which all necessary governance characteristics are available. G-INDEX is the governance index as defined in Gompers et al. (2003). A higher G-INDEX indicates a larger number of antitakeover provisions and is associated with weaker governance. AUDITR is the ratio of auditors on board, DUM_BOARD_INDEPR_Q4 is an indicator variable that takes a value of 1 if the ratio of independent board members exceeds 3⁄4, BOARD_SIZE is the board size, and NUM_MEETINGS is the number of board meetings in a year. *t*-statistics and *p*-values (reported in square brackets) in the last column are associated with the 2-sided *t*-test for the difference in population means. ***, **, and * denote statistical significance of the mean difference at the 1%, 5%, and 10% levels, respectively. For directional hypotheses, we use 1-tailed tests;[a] if the coefficient's sign is opposite from the one hypothesized, then we do not indicate significance levels.

			Percentile				*t*-Test for $\mu_{\text{TREATMENT}} - \mu_{\text{CONTROL}}$	
Variables	Mean	SD	25th	50th	75th	95th	Expected Sign	*t*-Statistic [*p*-value]
G-INDEX								
Control firms	8.909	2.846	7.000	9.000	11.000	14.000	(+)	0.4437
Firms with losses	9.174	2.725	7.000	9.000	11.000	13.000		[0.3304]
AUDITR								
Control firms	0.314	0.130	0.222	0.310	0.375	0.571	(−)	−1.6111
Firms with losses	0.271	0.123	0.167	0.235	0.364	0.444		[0.0594]*
DUM_BOARD_INDEPR_Q4								
Control firms	0.260	0.440	0.000	0.000	1.000	1.000	(−)	−1.6833
Firms with losses	0.130	0.344	0.000	0.000	0.000	1.000		[0.0515]*
BOARD_SIZE								
Control firms	11.674	4.127	9.000	11.000	14.000	20.000	(?)	2.7690
Firms with losses	14.522	4.766	10.000	14.000	17.000	22.000		[0.0104]**
NUM_MEETINGS								
Control firms	7.756	3.209	5.000	7.000	9.000	14.000	(?)	0.0477
Firms with losses	7.783	2.467	5.000	7.000	9.000	12.000		[0.9623]

[a]For 1-tailed tests, the critical values for the *t*-statistics are 1.28, 1.65, and 2.33 in absolute value, for the 10%, 5%, and 1% levels, respectively.

Table 7 reports the estimation results from the Poisson regression model. To select the firm-level control variables, we perform stepwise regressions, initially including all of the firm-specific covariates present in the earlier frequency models. After dropping those with insignificant coefficients, we end up including the MVE, market-to-book, cash-to-assets, Tier 1 capital ratio, and ROE.[33] In terms of the goodness-of-fit of the model, a Wald test of the hypothesis that the coefficients of the governance-related variables are jointly 0 is strongly rejected for all models. Among the control variables, we find that variables that play an important role in the frequency models, such as firm size, market-to-book, cash-to-assets, and Tier 1 capital ratio, continue to be significant in the cross-sectional Poisson regressions. More importantly, we find that the most significant governance-related variable is the G-index, which is significant at the 1% level for 3 of the 4 models. The size of the coefficient (Model 5) indicates that a change in the G-index from the 25th

[33]For details of the stepwise regression procedure, see Hocking (1976) and Draper and Smith (1981).

TABLE 7

Governance and Directors Characteristics and Operational Risk

In Table 7 the dependent variable equals the number of operational risk events during 1998–2005. We focus on 1998–2005, which is the period in which all governance data are available. We use 1 observation per firm. For each firm, control variables are measured in 1998 and governance variables are measured in 1998 (60% of firms) or the 1st year after 1998, in which all necessary governance characteristics are available. Here, firm size is measured in billions of dollars. z-statistics (in parentheses) are based on heteroskedasticity-robust standard errors. ***, **, and * denote statistical significance of the coefficients at the 1%, 5%, and 10% levels, respectively. For directional hypotheses, we use 1-tailed tests;[a] if the coefficient's sign is opposite from the one hypothesized, then we do not indicate significance levels.

		Models 1 & 2[b]	Model 3	Model 4	Model 5
Variables	Expected Sign	Internal & External Fraud	Clients, Prod., & Bus. Practices	Other Events	All Events
Gompers, Ishii, and Metrick (2003) External Governance Index					
G-INDEX	(+)	0.2097	0.2395	0.1908	0.2243
		(0.69)	(2.63)***	(2.94)***	(3.20)***
Internal Governance Variables					
AUDITR	(−)	−7.1261	0.5376	−3.5028	−1.5404
		(−2.33)***	(0.22)	(−0.68)	(−0.68)
DUM_BOARD_INDEPR_Q4	(−)	0.2495	−0.3394	0.6266	0.0021
		(0.41)	(−0.38)	(0.56)	(0.00)
BOARD_SIZE	(?)	−0.4086	0.0749	−0.5298	−0.2150
		(−0.93)	(0.32)	(−2.06)**	(−1.19)
BOARD_SIZE^2	(?)	0.0132	−0.0007	0.0155	0.0079
		(1.50)	(−0.09)	(2.04)**	(1.37)
NUM_MEETINGS	(?)	0.2036	0.4506	−0.4003	0.2585
		(0.80)	(0.97)	(−0.64)	(0.76)
NUM_MEETINGS^2	(?)	−0.0064	−0.0184	0.0241	−0.0096
		(−0.41)	(−0.82)	(0.82)	(−0.58)
Control Variables					
MVE	(?)	0.0832	0.0503	0.0849	0.0596
		(4.02)***	(2.95)***	(3.87)***	(4.72)***
MARKET-TO-BOOK	(−)	−0.0945	−0.1369	−0.9694	−0.2896
		(−0.24)	(−0.65)	(−2.10)**	(−1.63)*
CASH_TA	(+)	4.7963	2.3202	10.2925	4.2372
		(1.38)*	(1.25)	(3.50)***	(3.04)***
TIER1R	(−)	−8.9177	0.2408	−9.2394	−1.7874
		(−4.49)***	(0.12)	(−2.51)***	(−0.81)
ROE	(?)	−1.7569	2.1054	0.6384	1.1768
		(−0.62)	(1.11)	(0.62)	(0.91)
SIC fixed effects		Yes	Yes	Yes	Yes
No. of obs.		265	265	265	265
χ^2 governance		30.43	17.95	16.66	14.81
[p-value]		[0.0001]***	[0.0122]**	[0.0197]**	[0.0385]**
Pseudo R^2		0.6350	0.3291	0.5109	0.4601

[a]For 1-tailed tests, the critical values for the t-statistics are 1.28, 1.65, and 2.33 in absolute value, for the 10%, 5%, and 1% levels, respectively. [b]Internal and external fraud categories are combined into 1 group because during 1998–2005 there was only 1 firm that experienced external fraud events with available governance data.

to 75th percentiles (a change of 4 points) will produce a $\exp(0.22 \times 4) \approx 2.4$ times increase in the expected number of events over the sample period. This result suggests that external corporate governance plays an important role in mitigating operational risk.

Since hostile takeovers of commercial banks are extremely rare because of the long regulatory approval process required for mergers and acquisitions, we check whether the G-index is more relevant for the operational risk of nonbank financial institutions. Specifically, we include a dummy variable indicating whether the sample firm is a nonbank as well as the interaction between this dummy variable and the G-index. With the exception of fraud-related events (which constitute the smallest event type category in this part of the analysis), we find that nonbanks tend to have fewer operational risk events, but their frequency is more positively related to the G-index. To conserve space, these additional results are available from the authors.

VII. Executive Compensation and Operational Risk

In this section we conduct empirical tests of Hypothesis 3, which states that firms with stronger CEO incentives are associated with a higher frequency of operational risk events.

CEO compensation usually consists of salary, bonuses, restricted stocks, stock options, and long-term incentive plans (LTIP). Certain components, such as bonuses, restricted stocks, and stock options, have values that depend on short-term firm performance related to earnings or the stock price. Efendi et al. (2007) argue that CEOs who have a large amount of stock- and bonus-based compensation relative to their salary are more likely to misstate earnings. Consistent with their hypothesis, they find that the ratio of the value of the CEO's in-the-money option holdings to salary plays an important role in explaining earnings manipulation. Burns and Kedia (2006) argue that certain components, such as stock options and bonuses, depend on short-term performance in a convex manner, allowing the CEO to profit from the upside while bearing little of the downside. They find that the stock price sensitivity of a CEO's stock option holdings acts as an important gauge of the propensity to misstate earnings. Since misreporting is likely to be associated with weak internal controls, we conjecture with Hypothesis 3 that factors contributing to more misreporting are positively related to operational risk.

We group our CEO incentive measures into 2 sets of variables. The 1st set of variables is ratios of the various components of CEO compensation relative to salary, which closely follow the definitions adopted by Efendi et al. (2007). The following ratios are included: in-the-money option holdings to salary, options awarded during the year to salary, bonuses to salary, restricted stocks granted during the year to salary, restricted stock holdings to salary, and LTIP payout to total compensation. With the exception of LTIP (which effectively lengthens the CEO's horizon), we expect these compensation components to contribute to short-termist behavior and weak internal control. In addition, we include the CEO's salary and a dummy variable equal to 1 if the rate of the CEO's salary growth is positive and exceeds the growth in net income, earnings per share, and revenue. While salary is used mainly as a control for firm size, the dummy variable is likely associated with poor governance and weak internal control. We also include the proportion of all common shares outstanding owned by the CEO. When this ratio is close to 1, the CEO personally bears the cost of all operational risk events. Therefore, we expect a negative relation between the CEO's ownership stake in his/her company and operational risk.

The 2nd set of variables is sensitivities of CEO compensation components to either earnings or the stock price, which closely follow the definitions used by Burns and Kedia (2006). The following sensitivity measures are included: option holdings to the firm value (Core and Guay (2002)), and salary and bonuses to earnings. The detailed definitions of all compensation-related variables can be found in Table A2.

Because of the data requirement on executive compensation variables, we are limited to a sample period of 1993–2005. Unlike corporate governance variables, CEO incentive measures exhibit a substantial amount of variation over time at the annual frequency. Therefore, for this part of the analysis we try to explain the incidence of operational risk events for each firm-year, rather than for each firm over the entire sample period, as was done in Section VI.

Specifically, we estimate Poisson regressions with the following intensity specification:

$$\lambda_{ijt} = \exp\left(\alpha_j + \beta_t + \eta' E_{it} + \gamma' X_{it}\right), \tag{6}$$

where i, j, and t represent firm, industry, and year, respectively.[34] The dependent variable is the count of events for each firm-year, α denotes industry fixed effects, β year fixed effects, E various CEO incentive measures, and X a set of control variables. We lag all compensation-related variables by 1 year, which allows us to use information available at the beginning of a year to explain the occurrence of losses during that year. We compute standard errors clustered at the firm level to account for potential serial correlations among yearly observations for the same firm. To select firm-level control variables, we again follow the stepwise regression procedure, initially including all of the firm-specific covariates in the frequency model of Section V. After removing all control variables with insignificant coefficients, we are left with the logarithm of total assets as the only firm-level control variable. We use the logarithm of total assets rather than the logarithm of the MVE because the latter is highly correlated with several CEO incentive measures. Restriction 3 of Table 1 shows that our sample consists of 2,060 firm-year observations on 335 firms, of which 76 firms suffered 533 distinct operational risk events.

In Table 8, we present summary statistics of CEO compensation-related variables. Specifically, we examine the differences in means of these variables across firm-years with 1 or more events (treatment sample) and firm-years with no event (control sample). We find that the size of stock-, option-, and bonus-based compensation (relative to salary) is significantly larger for the treatment group, as expected. The CEO's stock holdings as a fraction of common shares outstanding are negatively related to the likelihood of events, suggesting that CEOs with a substantial amount of wealth tied up in company stocks are potentially more concerned about internal control. Among the sensitivity-related measures, we find that the treatment group has a substantially higher option sensitivity to the stock price; however, there is no significant difference across the 2 groups in terms of the sensitivity of salary and bonuses to earnings. Again, these results are based on a univariate analysis and are thus only suggestive in nature. For example, the presence of higher salary among the treatment group is likely explained by the firm size effect documented earlier. In addition, since we use firm-year

[34]As a robustness check, we also estimate a logit specification, in which the dependent variable is dichotomous. The results are qualitatively the same.

TABLE 8

Summary Statistics for CEO Compensation

Table 8 presents the characteristics of CEO compensation for firm-years with at least 1 recorded operational risk event (treatment sample) and firm-years with no recorded event (control firms) during 1993–2005. The first 5 variables are the ratios of in-the-money options, option awards, bonuses, restricted stock awards granted during the year, and total restricted stock holdings, to salary. STOCK_HOLDINGR is the CEO's stock holdings as a ratio of common shares outstanding. SALARY is the CEO's annual salary, and ΔSALARY > FIRM_PERFORMANCE is an indicator variable equal to 1 if the 1-year salary increase exceeds the change in firm performance. LTIP/COMPENS is the ratio of LTIP to total compensation. OPTION_PPS is the option delta defined following Core and Guay (2002), and SALARY_BONUS_SENS is the sensitivity of salary and bonuses to a change in firm income. Subscripts t and $t-12$ indicate that a variable is measured at the beginning of the current and the previous years, respectively. t-statistics and p-values (reported in square brackets) in the last column are associated with the 2-sided t-test for the difference in population means. ***, **, and * denote statistical significance of the mean difference at the 1%, 5%, and 10% levels, respectively. For directional hypotheses, we use 1-tailed tests;[a] if the coefficient's sign is opposite from the one hypothesized, then we do not indicate significance levels.

			Percentile				t-Test for $\mu_{\text{TREATMENT}} - \mu_{\text{CONTROL}}$	
Variables	Mean	SD	25th	50th	75th	95th	Expected Sign	t-Statistic [p-value]
IN_MON_OPT$_{t-12}$/SALARY$_{t-12}$								
Control firms	16.617	28.830	1.834	6.597	18.419	67.058	(+)	5.5479
Firms with losses	31.020	42.021	2.439	13.684	44.947	127.032		[0.0000]***
OPT_AWARDS$_{t-12}$/SALARY$_{t-12}$								
Control firms	2.728	5.626	0.000	0.960	2.742	11.171	(+)	5.5963
Firms with losses	5.656	8.437	0.709	2.759	6.762	24.673		[0.0000]***
BONUS$_{t-12}$/SALARY$_{t-12}$								
Control firms	1.478	2.472	0.437	0.853	1.506	4.910	(+)	8.3508
Firms with losses	4.364	5.687	0.900	2.050	5.043	22.214		[0.0000]***
RESTR_ST_GRNT$_{t-12}$/SALARY$_{t-12}$								
Control firms	0.665	2.003	0.000	0.000	0.361	3.514	(+)	6.6769
Firms with losses	2.532	4.602	0.000	0.000	2.767	17.354		[0.0000]***
RESTR_ST_HOLD$_{t-12}$/SALARY$_{t-12}$								
Control firms	2.476	7.437	0.000	0.000	1.767	12.028	(+)	7.2774
Firms with losses	10.907	19.107	0.000	3.034	11.999	77.500		[0.0000]***
STOCK_HOLDINGR$_{t-12}$								
Control firms	0.023	0.048	0.001	0.005	0.020	0.125	(−)	−2.7435
Firms with losses	0.016	0.040	0.001	0.002	0.012	0.078		[0.0064]***
SALARY$_{t-12}$								
Control firms	761.832	349.380	521.260	728.325	984.546	1,273.301	(?)	7.8444
Firms with losses	935.717	348.399	734.331	1,012.536	1,125.381	1,440.981		[0.0000]***
ΔSALARY > FIRM_PERFORMANCE$_t$								
Control firms	0.176	0.381	0.000	0.000	0.000	1.000	(+)	−2.3497
Firms with losses	0.122	0.328	0.000	0.000	0.000	1.000		[0.9806]
LTIP$_{t-12}$/COMPENS$_{t-12}$								
Control firms	0.038	0.103	0.000	0.000	0.000	0.269	(−)	2.6468
Firms with losses	0.059	0.128	0.000	0.000	0.048	0.341		[0.9957]
OPTION_PPS$_t$								
Control firms	260.777	505.552	35.222	95.773	268.305	1,041.623	(+)	6.4603
Firms with losses	606.241	849.247	89.262	285.975	747.953	2,413.299		[0.0000]***
SALARY_BONUS_SENS$_t$								
Control firms	0.007	0.240	−0.009	0.004	0.030	0.249	(+)	−0.6413
Firms with losses	−0.001	0.207	−0.002	0.003	0.021	0.134		[0.4730]

[a]For 1-tailed tests, the critical values for the t-statistics are 1.28, 1.65, and 2.33 in absolute value, for the 10%, 5%, and 1% levels, respectively.

observations in the comparison of means, the results are sensitive to serial correlations at the firm level.

Results of the Poisson regressions are presented in Table 9. First, we note that the pseudo R^2 of the regression is between 28% and 58%, and a Wald test of the hypothesis that compensation-related coefficients are jointly 0 is strongly rejected for all models. For the control variable, we find that larger firms have a

TABLE 9

CEO Compensation and Operational Risk

In Table 9, the dependent variable equals the annually aggregated event count for each firm during the 1993–2005 sample period. The firm size variable is measured in USD billions, and equity and stock sensitivity variables are measured in USD millions. Subscript t indicates that a variable is measured in the beginning of the current year, and subscript t–12 indicates that a variable is measured in the beginning of the previous year. z-statistics (in parentheses) are based on standard errors clustered by firm. ***, **, and * denote statistical significance of the coefficients at the 1%, 5%, and 10% levels, respectively. For directional hypotheses, we use 1-tailed tests;[a] if the coefficient's sign is opposite from the one hypothesized, then we do not indicate significance levels.

Variables	Expected Sign	Model 1 Internal Fraud	Model 2 External Fraud	Model 3 Clients, Products and Bus. Practices	Model 4 Other Events	Model 5 All Events
$\log TA_{t-12}$	(?)	0.8293 (5.02)***	0.7184 (3.53)***	0.7390 (6.23)***	0.7093 (6.04)***	0.7067 (6.55)***
CEO Compensation Structure at Beginning of Previous Year						
IN_MON_OPT$_{t-12}$/SALARY$_{t-12}$	(+)	0.0052 (1.61)*	0.0112 (2.26)**	0.0026 (1.59)*	0.0079 (3.14)***	0.0039 (2.25)**
OPT_AWARDS$_{t-12}$/SALARY$_{t-12}$	(+)	0.0188 (0.91)	0.0270 (1.28)*	0.0187 (2.07)**	0.0372 (4.87)***	0.0260 (2.96)***
BONUS$_{t-12}$/SALARY$_{t-12}$	(+)	−0.0194 (−0.49)	0.0497 (1.25)	0.0480 (3.28)***	0.0602 (2.57)***	0.0345 (2.38)***
RESTR_ST_GRNT$_{t-12}$/SALARY$_{t-12}$	(+)	0.0554 (1.17)	−0.1758 (−3.17)	0.0304 (2.45)***	−0.0092 (−0.50)	0.0066 (0.46)
RESTR_ST_HOLD$_{t-12}$/Salary$_{t-12}$	(+)	−0.0006 (−0.07)	0.0280 (1.84)**	−0.0004 (−0.11)	−0.0090 (−1.30)	−0.0015 (−0.36)
STOCK_HOLDINGR$_{t-12}$	(−)	4.1837 (1.23)	−0.3019 (−0.04)	−2.4396 (−0.53)	−2.2698 (−0.70)	−1.3602 (−0.41)
SALARY$_{t-12}$	(?)	0.0004 (0.95)	0.0005 (0.94)	0.0007 (2.64)***	0.0007 (1.81)**	0.0007 (2.62)***
ΔSALARY > FIRM_PERFORMANCE$_t$	(+)	−0.3275 (−0.58)	−0.9457 (−1.36)	−0.2911 (−0.98)	−0.2345 (−0.58)	−0.3117 (−1.40)
LTIP$_{t-12}$/COMPENS$_{t-12}$	(−)	1.2207 (1.24)	−3.2334 (−1.21)	−1.0976 (−1.22)	−0.3009 (−0.32)	−0.3102 (−0.40)
CEO Compensation Sensitivity Measures at Beginning of Year with Operational Losses						
OPTION_PPS$_t$	(+)	−0.0001 (−0.30)	−0.0004 (−1.97)	0.0000 (0.25)	−0.0002 (−1.58)	0.0000 (−0.73)
SALARY_BONUS_SENS$_t$	(+)	−0.4628 (−0.95)	0.5542 (1.32)*	−0.4641 (−1.47)	0.7715 (1.43)*	−0.0794 (−0.36)
Year fixed effects		Yes	Yes	Yes	Yes	Yes
SIC fixed effects		Yes	Yes	Yes	Yes	Yes
No. of obs.		1,681	1,681	1,681	1,681	1,681
χ^2 ExecuComp [p-value]		22.50 [0.0208]**	30.84 [0.0012]***	36.71 [0.0001]***	59.50 [0.0000]***	29.23 [0.0021]***
Pseudo R^2		0.2945	0.2779	0.4008	0.3246	0.4179

[a]For 1-tailed tests, the cutoff points for the t-statistics are 1.28, 1.65, and 2.33 in absolute value, for the 10%, 5%, and 1% levels, respectively.

significantly higher number of events, which is consistent with earlier findings. Among ratios measuring the size of compensation components, 3 variables are consistently related to the frequency of loss events in a positive way: in-the-money option holdings to salary, options awarded during the year to salary, and bonuses to salary. Of the 2 included sensitivity measures, the coefficient of the sensitivity of salary and bonuses to earnings is marginally significant and positive for Model 2 and Model 4.[35] These results lend support to Hypothesis 3.

VIII. Concluding Remarks

The Basel Accord requires that banks in the United States create internal risk management systems to quantify the amount of capital reserve for operational risk, defined as the risk of loss resulting from inadequate or failed internal processes, people, and systems, or from external events. This study provides a comprehensive analysis of the factors underlying operational risk. Using 26 years of publicly reported operational loss data, we relate the incidence of operational risk events to quantifiable measures of firms' internal control environment. These measures include, among others, firm characteristics related to the incidence of ICWs over financial reporting, as well as corporate governance metrics and the size and sensitivity of CEO compensation components.

Although the official definition of operational risk encompasses seemingly unrelated events such as those caused by fraud, improper business practices, technology failures, employment discrimination, and execution errors, a common thread is that all of these events could be mitigated by an improvement of internal control and management oversight. This is confirmed by our findings. Specifically, firms suffering from different types of operational risk events tend to be younger, more complex, and financially weaker. They have a higher number of antitakeover provisions, and they have CEOs with a larger amount of option- and bonus-based compensation relative to salary. These results shed new light on the importance of financial distress, corporate governance, and executive compensation in our understanding of the risk in financial institutions.

Our results have important implications for the treatment of correlations among operational risk events. As shown in BCBS ((2009b), p. 50), currently a large number of banks simply treat operational losses as independent events, either unconditionally or within the same event type or business line. Only a small number of banks are considering incorporating more complex dependence structures. Although we have shown that macroeconomic covariates play a lesser role in explaining the arrival of operational risk events, the evidence suggests that many factors internal to the firm contribute to the occurrence of operational risk events of all types. This implies that the common assumption of independence of events within the firm may be seriously flawed and that internal measures of operational risk capital are understated.

Appendix. Description of Data and Variables Used in the Study

In Tables A1 and A2 we summarize additional information about the operational risk events and provide details about all variables used in this study.

[35]We perform a number of robustness checks, which are omitted here for brevity. Among others, the sensitivity of option holdings to the firm value becomes positive and significant at the 5% level when we replicate the Burns and Kedia (2006) specification, which contains only sensitivity measures and has most of the CEO compensation component measures removed.

TABLE A1

Description of the Largest Operational Losses

Table A1 summarizes the largest operational losses (by direct loss amount) within each of the 7 event type categories during our sample period of 1980–2005. All losses are adjusted for inflation and are measured in 2005 U.S. dollars.

Year of Initial Occurrence	Firm Name	Loss Amount (in 2005 USD)	Brief Description of Event
ET1 (Internal Fraud): Includes unauthorized activity involving at least 1 internal party, theft, and fraud.			
1985	Cendant Corporation	$3.12 billion	Three former executives of Cendant Corporation were found liable for accounting fraud that lasted 12 years.
1982	Western Savings Association	$962.6 million	A former owner of WSA was indicted on 37 charges of bank fraud, misuse of funds, and conspiracy, totaling approximately $1 billion in losses and actions that defrauded the institution.
2001	Marsh and McLennan Companies Inc.	$837.4 million	Marsh and McLennan Co. conspired with insurance underwriters in a bid-rigging scheme resulting in a fine of over $800 million to be paid in the form of restitution to its clients. The incident also resulted in the resignation of CEO Jeffrey Greenberg.
ET2 (External Fraud): Includes theft and fraud by 3rd party and system security.			
1982	Mutual of Omaha Insurance	$567.9 million	Two independent managing general agents affiliated with Mutual of Omaha were responsible for a fraudulent scheme involving the diversion of millions of dollars of premium assets during the mid-1980s. Most of the losses came from claims on policies that were sold too cheaply to high-risk clients.
1988	Citigroup	$277.8 million	Travelers Insurance Co., a subsidiary of Citigroup Inc., and Prudential Insurance Co., a subsidiary of Merrill Lynch, lost millions through fraudulent claims filed by National Medical Enterprises
1988	Merrill Lynch	$238.4 million	(NME), which filed nearly $0.5 billion of false health care claims between January 1988 and December 1991. During that time, NME hospitalized patients who did not need to be hospitalized, inflated charges for services provided, submitted claims for treatments that had not been provided, and subjected patients to procedures they did not need.
ET3 (Employment Practices and Workplace Safety): Includes employee relations, safety of environment, diversity, and discrimination.			
2000	American Int'l Group	$235.5 million	American General Corporation, a subsidiary of AIG, was found responsible in charging African-American clients higher premiums for smaller life insurance policies.
1991	Bank of America	$225.4 million	From 1991 through 1994, Fleet Financial Group, a subsidiary of Bank of America, was going through a lawsuit stemming from its questionable lending practices in low-income communities in Boston. It was charged with racial discrimination, fraud, and loan sharking because it issued high-interest loans to minority borrowers.
1980	State Farm Group	$207.8 million	State Farm General Insur. Co. was found guilty of violating Title VII of the 1964 Civil Rights Act by engaging in extensive sex discrimination in its recruitment and hiring of insurance agents and agreed to pay over $230 million to 814 past and current female employees.
ET4 (Clients, Products, and Business Practices): Includes improper business or market practices, product flaws, and advisory activities.			
1997	JPMorgan Chase	$3.66 billion	In 2005 JPMorgan reached a $2.2 billion settlement with shareholder plaintiffs who sued the company for "aiding and abetting" Enron in its financial fraud since 1997. It also agreed to pay Enron $350 million in settlement of a "megaclaims" lawsuit and to subordinate $660 million in credit claims held against the failed energy company.
1982	Prudential Financial, Inc.	$2.82 billion	In the 1980s, questionable sales practices at Prudential Insurance Co. led to a major lawsuit that plagued the company throughout the 1990s, tarnished its reputation, and led to over $3 billion in restitution payments and penalties.
1997	Citigroup	$2.05 billion	In 2005, Citigroup paid out over $2 billion to the SEC and a class of Enron shareholders in settlement of charges that the bank aided and abetted the energy company in hiding its true financial condition since 1997.
ET5 (Damage to Physical Assets): Includes natural disasters, terrorism, and vandalism.			
2001	Citigroup	$2.23 billion	Losses due to "9/11" terrorist attack.
2001	American Int'l Group	$846.7 million	Losses due to "9/11" terrorist attack (which did not arise from insurance claims).
2001	Bank of New York	$757.4 million	Losses due to "9/11" terrorist attack.

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TABLE A1 (continued)

Description of the Largest Operational Losses

Year of Initial Occurrence	Firm Name	Loss Amount (in 2005 USD)	Brief Description of Event
ET6 (Business Disruption and System Failures): Includes disruption of business and system failures.			
2001	Federal Home Loan Mortgage Corp.	$207.5 million	Freddie Mac disclosed in 2005 that computer errors resulted in its previously published earnings being overstated by $220 million. The errors were attributed to miscalculated interest accruals for mortgage-related securities committed by a legacy computer system.
1996	Wells Fargo & Co.	$175.8 million	Wells Fargo reported a near-$200 million write-off to cover lost or misplaced deposits during its struggle to merge with First Interstate Bank in 1996.
1983	Bank of America	$124.7 million	Bank of America lost over $120 million as a result of the failure of its MasterNet computer system, designed to keep track of pension funds and other employee-benefit programs.
ET7 (Execution, Delivery, and Process Management): Includes transaction capture, execution and maintenance, monitoring and reporting, documentation, customer/client account management, and vendors and suppliers.			
1998	Cendant Corporation	$459.3 million	Cendant Corp. scrapped an attempted acquisition of America Bankers Insurance at a cost. Although the agreement to acquire the group was canceled, the organization was faced with a payout to abort the deal, which included a penalty.
2000	Washington Mutual Inc.	$437.0 million	Providian Financial Corp., a subsidiary of Washington Mutual, agreed to pay over $480 million to settle a class action lawsuit brought by a group of plaintiffs who claim they had been billed and signed up for services they never requested.
1996	Nextcard, Inc.	$322.9 million	NextBank, an Internet bank that began operations by issuing credit cards through its Web site, was shut down and seized by the U.S. Federal Deposit Insurance Corp. (FDIC) and the Office of the Comptroller in February 2002. According to the OCC's Material Loss Review report, NextBank issued credit cards to unqualified borrowers and failed to institute proper debt collection facilities.

TABLE A2

Description of Variables Used in the Study

Definitions of the variables used in this study are provided in Table A2. All dollar-denominated variables are measured in 2005 U.S. dollars. Equity prices are adjusted for splits. Missing values are filled with the values from the most recent year or quarter.

Variable	Description and Source
Firm Basic Characteristics: Accounting and Market Variables (1980–2005):	
MVE	Market value of equity is a proxy for firm size. It is estimated as the number of common shares outstanding times the share price: Compustat quarterly DATA61 × Price, where monthly Price is obtained from DATA12, DATA13, and DATA14. Measurement units: USD million.
TA	Total assets is a proxy for firm size. It is estimated as Compustat quarterly DATA44. The variable is winsorized at 1%. Measurement units: USD million.
MARKET-TO-BOOK	Market-to-book ratio is a proxy for growth opportunities. Market-to-book ratio is inversely related to default risk (Fama and French (1992)). It is estimated as the ratio of MVE to book equity: Compustat quarterly DATA61 × Price/DATA59, where monthly Price is obtained from Compustat quarterly DATA12, DATA13, and DATA14. The variable is winsorized at 1% and 99%.
CASH_TA	Ratio of cash and short-term investments to assets is used in this study as a proxy for a "problem bank" (Acharya et al. (2007)). It is estimated as Compustat quarterly DATA36/DATA44. Each of the 2 component variables is winsorized at 1%.
TIER1R	Tier 1 ratio is a ratio of regulatory Tier 1 capital to risk-weighted assets. The Basel Capital Accord requires financial institutions to hold regulatory Tier 1 capital as a protection mechanism against financial risks. It is estimated as Compustat quarterly (DATA60+DATA58)/DATA44. The variable is winsorized at 1% and 99%.
ROE	Return on equity is a measure of profitability. It is calculated as the ratio of net income to book equity: Compustat quarterly DATA21/DATA59. The variable is winsorized at 1% and 99%.
RETSD	Equity volatility is a measure of riskiness. High equity volatility often signals financial distress. It is estimated as the rolling 12-month standard deviation of monthly equity returns. Equity returns are from CRSP monthly RET data item. Measurement units: decimal.

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TABLE A2 (continued)

Description of Variables Used in the Study

Variable	Description and Source
DUM_EXCESS_GR	Excessive growth in liabilities is a proxy for aggressive growth. Aggressive growth strategies, especially growth in liabilities, often accompany risk management deficiencies and management's inability to effectively sustain exceptional growth (Moody's (2002), OCC (2001)). DUM_EXCESS_GR is expressed as a dummy variable equal to 1 if a firm experiences positive growth of liabilities (Δliabilities) and assets (ΔTA) in the previous quarter and the growth of liabilities exceeds the growth of assets. Liabilities are measured using Compustat quarterly DATA54. Both Δliabilities and ΔTA are winsorized at 1% and 99%.
DUM_HIGH_DIV_RATIO	High dividend payout ratio is used in this study to capture "troubled banks." Dividend payout may be restricted by the OCC for firms experiencing large losses and identified by regulators as problem banks (OCC (2001), Collier et al. (2003)). DUM_HIGH_DIV_RATIO is expressed as a dummy variable equal to 1 if the dividend ratio during the previous quarter exceeds the quarterly median across all sample firms. Dividend-to-assets ratio is measured as Compustat quarterly (DATA20 × DATA61 + DATA24)/DATA44.
FIRM_AGE	Older firms are likely to have better risk management practices. The firm age variable is estimated as the number of months a firm's market data has been covered by CRSP since its 1st appearance in the database.
NUM_SEGMENTS	Business complexity of a firm is measured by the number of business and geographic segments (see Doyle et al. (2007a)). It is estimated as the number of distinct segments from the Compustat Segments' STYPE data item.
DISTANCE-TO-DEFAULT	Merton's (1974) distance-to-default measure is inversely related to the probability of default. We calculate it following an iterative algorithm described in Bharath and Shumway (2008). One-year distance to default is calculated as $$\text{DISTANCE-TO-DEFAULT} = \frac{\ln(V/D) + (\mu - 0.5\sigma_V^2)T}{\sigma_V\sqrt{T}}$$ and uses the parameters V, μ, and σ_V obtained from simultaneously solving 2 equations: $$\text{MVE} = V\Phi(d_1) - e^{-rT}D\,\Phi(d_2) \quad \text{and} \quad \sigma_E = \frac{V}{\text{MVE}}\Phi(d_1)\sigma_V.$$ Here $\Phi(\cdot)$ denotes the cumulative standard normal distribution, $$d_1 = \frac{\ln(V/D) + (r + 0.5\sigma_V^2)T}{\sigma_V\sqrt{T}}, \quad d_2 = d_1 - \sigma_V\sqrt{T},$$ T is 1 year, V is the total value of the firm, μ is the expected annual return on V, D is the face value of the firm's debt, and r is the risk-free rate. D is estimated as Compustat quarterly (DATA45 + 0.5 × DATA51), and r is the T-bill rate.
SIC fixed effects	2-digit SIC industry code dummy variables.
Governance and Directors Data (1998–2005)	
G-INDEX	*G-index* is a governance index developed by Gompers et al. (2003). It is an additive index constructed by adding 1 point for each of the 22 firm-level antitakeover provisions and 6 state antitakeover laws (a total of 24 unique provisions). The G-INDEX can take values from 0 to 24. Source: RiskMetrics (formerly, Investor Responsibility Research Center (IRRC) takeover Defenses Database) data item GINDEX.
AUDITR	Ratio of auditors on board, estimated as the number of auditors divided by the board size. The variable is calculated using RiskMetrics Group Historical Directors Database AUDIT_COMM_MEM data item.
DUM_BOARD_INDEPR_Q4	High board independence ratio, expressed as a dummy variable equal to 1 if the ratio of independent board members exceeds 75%. The variable is calculated using RiskMetrics Group Historical Directors Database AUDIT_COMM_MEM and DIRTYPE data items.
BOARD_SIZE	Board size is measured by the number of board members. Source: RiskMetrics Group Historical Directors Database.
NUM_MEETINGS	Annual number of board meetings. Source: Compustat Executive Compensation Database NUMMTGS item.
Executive Compensation Data (1993–2005)	
IN_MON_OPT/SALARY	The ratio of the aggregate value of the CEO's in-the-money options (vested plus unvested) to salary. It is calculated from the Compustat Executive Compensation Database as (OPT_UNEX_EXER_EST_VAL + OPT_UNEX_UNEXER_EST_VAL)/SALARY. The variable is winsorized at 99%.
OPT_AWARDS/SALARY	The ratio of the aggregate value of the CEO's stock options granted during the year to salary using the Black-Scholes (1973) methodology. It is calculated from the Compustat Executive Compensation Database as OPTION_AWARDS_BLK_VALUE/SALARY. The variable is winsorized at 0 (5%) and 99%.
BONUS/SALARY	The ratio of the CEO's bonus to salary. It is calculated from the Compustat Executive Compensation Database as BONUS/SALARY. Both variables are winsorized at 0 (1%).
RESTR_ST_GRNT/SALARY	The ratio of the value of restricted stocks granted to the CEO during the year to his salary. It is calculated from the Compustat Executive Compensation Database as RSTKGRNT/SALARY. The variable is winsorized at 99%.
RESTR_ST_HOLD/SALARY	The ratio of the aggregate market value of restricted shares held by the CEO by year-end to his salary. It is calculated from the Compustat Executive Compensation Database as STOCK_UNVEST_VAL/SALARY. The numerator is winsorized at 0 (<5%).

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TABLE A2 (continued)

Description of Variables Used in the Study

Variable	Description and Source
STOCK_HOLDINGR	CEO's stock holding ratio, estimated as the proportion of all common shares outstanding owned by the CEO. It is calculated from the Compustat Executive Compensation Database as SHROWN_EXCL_OPTS/(SHRSOUT $\times$ 1,000).
SALARY	CEO's salary, calculated as the Compustat Executive Compensation Database item SALARY. The variable is winsorized at 0 (1%).
ΔSALARY > FIRM_PERFORMANCE	CEO salary increase exceeds firm performance (Efendi et al. (2007)). This dummy variable takes a value of 1 if the CEO's 1-year increase in salary is positive and exceeds the rate of increase in net income, earnings per share, and revenues. The variable is estimated using the Compustat Executive Compensation Database item SALARY and Compustat quarterly items DATA69, DATA177, and DATA21, respectively.
LTIP/COMPENS	The ratio of the amount paid out to the CEO under the company's long-term incentive plan (LTIP) to his total compensation. The variable is estimated from the Compustat Executive Compensation Database as LTIP/TDC1. The variable is winsorized at 0 ($<$5%).
OPTION_PPS	Option sensitivity to price change is estimated as the change in the value of stock options held for a percentage change in firm value (Core and Guay (2002)). It is estimated as $\frac{\partial(\text{OPTION\_VALUE})}{\partial(\text{PRICE})} \times \frac{\text{PRICE}}{100} = e^{-dT}\Phi\left(\frac{\ln(S/X) + T(r - d + \sigma^2/2)}{\sigma\sqrt{T}}\right) \times \frac{\text{PRICE}}{100}$, multiplied by the number of options held (in USD thousands). Here $\Phi(\cdot)$ denotes the cumulative standard normal distribution, S is the stock price, X is the exercise price of the option, r is the risk-free rate (T-bill rate), d is the dividend yield over the life of the option, σ is the expected stock-return volatility over the life of the option, and T is the time to maturity of the option in years. The appropriate option value-related variables are taken from the Compustat Executive Compensation Database.
SALARY_BONUS_SENS	Sensitivity of salary and bonus payments to a \$1,000 change in the firm's earnings (Burns and Kedia (2006)). It is estimated from the Compustat Executive Compensation Database as ΔSALARY + ΔBONUS divided by ΔDATA69 $\times$ 1,000 from Compustat quarterly. The variable is winsorized at 1% and 99%.
Macroeconomic Data (1980–2005)	
SPREAD	Corporate bond yield spread (in percentage), estimated as Moody's monthly Baa corporate bond yield minus Aaa corporate bond yield.
DISP_INCOME_GR	One-quarter rate of growth (in decimal) in personal disposable income. Data source: U.S. Department of Commerce, Bureau of Economic Analysis, monthly.
S&P500R	S&P 500 1-month return. Data source: S&P Web site (http://www.standardandpoors.com/indices/sp-500/en/us/?indexId=spusa-500-usduf–p-us-l—).
S&P500RSD	Trailing standard deviation of S&P 500 1-month returns over the previous 3 years.
GDP_GR	One-quarter rate of growth (in percentage) in gross domestic product. Data source: Datastream, quarterly.
SEC_BUDGET_GR	One-year rate of growth (in decimal) in the SEC budget divided by the number of financial institutions. The data on the SEC budget amounts are from the SEC annual reports, available at the SEC Web site (http://www.sec.gov/about/annrep.shtml). The data on the number of financial institutions is from the FDIC Web site (http://www.fdic.gov).
DUM_POST2001	Dummy variable equal to 1 for the post-February 2001 sample period.
Year fixed effects	Dummy variables for years 1980–2005.

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