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The market value impact of operational loss events for US banks and insurers ☆

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Abstract

This paper conducts an event study analysis of the impact of operational loss events on the market values of banks and insurance companies, using the OpVar database. We focus on financial institutions because of the increased market and regulatory scrutiny of operational losses in these industries. The analysis covers all publicly reported banking and insurance operational risk events affecting publicly traded US institutions from 1978 to 2003 that caused operational losses of at least \$10 million – a total of 403 bank events and 89 insurance company events. The results reveal a strong, statistically significant negative stock price reaction to announcements of operational loss events. On average, the market value response is larger for insurers than for banks. Moreover, the market value loss significantly exceeds the amount of the operational loss reported, implying that such losses convey adverse implications about future cash flows. Losses are proportionately larger for institutions with higher Tobin's Q ratios, implying that operational loss events are more costly in market value terms for firms with strong growth prospects.

JEL classification: G14; G21; G22; G28

Keywords: Operational loss events; Operational risk; Banking; Insurance; Event study

☆ The opinions expressed in this paper are those of the authors and do not necessarily reflect the views of the Wharton School or the Hartford Insurance Group.

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1. Introduction

Although financial institutions have faced operational risks throughout their history, the attention devoted to managing operational risk has increased dramatically in recent years. Managerial and regulatory focus on operational risk has been heightened following a number of very costly and highly publicized operational events. In banking, examples include the infamous bankruptcy of Barings bank in 1995, which was triggered by a \$1.3 billion loss due to a rogue trader, the Allied Irish Bank's loss of \$750 million due to unauthorized trading in 2002 (Ascarelli, 2002), and the \$1.4 billion in fines levied in 2002 against several leading brokerage firms for issuing misleading research reports to investors.[1] Operational loss events for insurance companies have been equally damaging. Prudential Insurance Company of America paid \$2 billion to settle allegations of sales abuses during the late 1990s; and State Farm Insurance paid \$1.2 billion to auto insurance policyholders as the result of a breach of contract lawsuit in 1999, resulting from the use of inferior quality generic replacement parts for damaged cars (Lohse, 1999). Even a cursory review of these events demonstrates the severe impact that operational losses can have on earnings, share price volatility, and potentially even solvency.

The increasing attention focused on operational risk over the past several years likely emanates from two key developments: (1) an enhanced emphasis on transparency in firm financial reporting, and (2) rising levels of exposure to operational risk driven by increasingly complex production technologies used by financial services firms. As the world economy swept into the information age during the 1980s and 1990s, information technology enabled investors to quickly access and analyze large volumes of corporate financial data. A natural outcome of this process was the development of investor advocacy groups demanding increasing levels of transparency in firm financial reporting. Regulatory actions further supported this demand. Bank regulators argue for increased disclosure as a way for the capital markets to police corporate behavior along side the normal bank regulation process. The passage of The Sarbanes-Oxley Act of 2002, following the collapse of Enron and WorldCom, only served to further buttress this call for disclosure. The net result of these developments was to increase the level of sensitivity in reporting material changes in earnings – including losses arising from operational risk.

Other developments in financial markets also have heightened the scrutiny of operational risk. Deregulation, globalization, and advances in technology have led to the creation of new and highly sophisticated production processes and complex products for both wholesale and retail customers. While new technologies often reduce production costs and enhance product value, they also create operational risks. For example, the development of hedging and risk mitigation techniques have enabled institutions to better manage the market and credit risks arising from complex products but, in turn, have created additional operational risk exposures. Greater use of automation in back-office operations can eliminate relatively minor manual processing errors, but increases exposure to larger system-wide failures. The growth of e-banking and e-commerce exposes institutions to new and unknown risks, as well as increasing their exposure to traditional risks such as fraud. Mergers and acquisitions create operational risk arising from the integration of previously separate information technology systems; and the growth in outsourcing and participation in clearing and settlement systems has mitigated some risks while exacerbating others.

[1] "Regulators Announce Settlement with Ten Wall Street Firms", *Wall Street Journal*, April 28, 2003.

These newly emerging risks are difficult to identify, and financial firms generally have made less progress in quantifying operational risks than they have with market and credit risks.

Both the regulatory community and international financial rating organizations have recognized the importance of operational risk management. The Basel Committee on Banking Supervision has incorporated a new minimum capital charge for operational risk as part of the Basel II Capital Accord, scheduled to be implemented in 2006–2007 (Basel Committee, 2001). To encourage better risk management, the Committee has published guiding principles for the management of operational risk (Basel Committee, 2001, 2003a). The major rating firms have published reports discussing operational risk management and analyzing the implications of operational risk for the assignment of financial ratings (e.g., Moody's Investors Service, 2003; Fitch Ratings, 2004).

In spite of the widespread recognition of the importance of operational risk, there is little systematic information on the extent of operational risk, the magnitude of operational loss events, or its impact on the affected financial institutions. The objective of this paper is to remedy this deficiency in the literature by analyzing operational loss events in the US banking and insurance industries. We utilize a relatively new data source, the OpVar database developed by OpVantage, a subsidiary of FitchRisk. OpVar consists of operational loss events from the late 1970s to the present gathered from publicly available data sources. The objective of our study is to analyze the impact of operational loss events on the stock price performance of the affected financial institutions. Specifically, we conduct an event study of 403 operational loss events in the US banking industry and 89 operational loss events in the US insurance industry. The banking industry is broadly defined to include investment banks and investment advisory firms as well as commercial banks. Our study will help to determine whether the current regulatory scrutiny on operational risk is justified on the basis of the impact on shareholder value and will provide information on the efficacy of market discipline in policing operational risk events.

2. Definition of operational risk and event types

When discussions of operational risk began to intensify during the 1990s, the definition of operational risk was far from clear. Financial institutions had devoted considerable resources to measuring and quantifying market and credit risk and some, like Bankers Trust, had devoted considerable attention to the measurement of operational risk (Hoffman, 2002). However, a consensus definition of operational risk emerged only recently with the definition of operational risk adopted by the Basel Committee:

> Operational risk is the risk of loss resulting from inadequate or failed internal processes, people and systems, or from external events (Basel Committee, 2003a, p. 2).

This definition of operational risk is based on underlying hierarchy of operational risk causes that are broken down into four categories: people, processes, systems, and external events. The definition includes legal risk, but excludes strategic, reputational, and systemic risk, as well as market risk and credit risk (Basel Committee, 2001).[2] From a business

[2] Legal risk is the risk of loss from possible litigations against an institution, and strategic risk is the risk of loss from wrong decisions or strategies that reach negative results (Cruz, 2002, p. 316). Reputational risk is the risk of loss from the indirect impact of a direct or "real" loss (Cruz, 2002, p. 287). Systemic risk is non-diversifiable risk characterized by the breakdown of the entire financial system or major components of the system.

perspective, operational risk can be considered as risk created by the production of goods and services for the clients of a financial services firm, i.e., risks arising from breakdowns in the production processes that comprise the institution's value-chain.

To identify the most significant causes of operational losses and to provide guidance on what types of events should be recorded for internal loss data, the Basel Committee breaks operational risk losses into seven event types (Basel Committee, 2002):

- Employment practices and workplace safety: losses arising from acts inconsistent with employment, health or safety laws or agreements, from payment of personal injury claims, or from diversity or discrimination events.
- Internal fraud: losses due to acts of a type intended to defraud, misappropriate property or circumvent regulations, the law or company policy (excluding diversity/discrimination events) which involves at least one internal party.
- External fraud: losses due to acts of a type intended to defraud, misappropriate property or circumvent the law, by a third party.
- Clients, products, and business practices: losses arising from unintentional or negligent failure to meet a professional obligation to specific clients (including fiduciary and suitability requirements), or from the nature or design of a product. Losses in this category include losses due to fiduciary breaches, misuse of confidential customer information, improper trading activities, money laundering, and sale of unauthorized products, etc.
- Damage to physical assets: losses due to loss or damage of physical assets from natural or man-made disasters or other events (e.g., fire, explosion, terrorism, etc.).
- Business disruption and system failures: losses arising from disruption of business or system failures including hardware and software failure, system development, and infrastructure issues. An example is the blackout in New York City and many other US cities that occurred on August 14, 2003.
- Execution, delivery and process management: losses from failed transaction processing or process management or from relations with trade counterparties and vendors.

The Committee believes that every individual event should be reported separately and offers guidance on what constitutes an individual event (Basel Committee, 2002).

To further guide the recording of internal loss data, the Committee also breaks losses into eight standard *business lines* for banks – corporate finance, trading and sales, retail banking, commercial banking, payment and settlement, agency services, asset management, and retail brokerage. Because international insurance regulators have not made as much progress in defining operational risk, standardized business line definitions are not yet available for insurers. However, the event type classification is easily extendible for use by insurers.

Many of the risks encompassed by the Basel Committee's definition of operational risk traditionally have been managed by purchasing insurance. For example, fraud by bank employees has long been insured under the so-called bankers blanket bond, and damage to physical assets has traditionally been covered by property insurance. Insurance also exists to cover information systems failures, although the coverage is often limited. However, for many operational risks, insurance does not exist and probably will not exist for the foreseeable future. In fact, many of the operational loss events that we examine in this paper are more "catastrophic" in nature and arise from uninsured and often uninsurable risks. As such, operational risk management clearly poses significant challenges for financial institutions.

3. Literature review and research hypotheses

3.1. Prior literature

To our knowledge, this is the first paper to provide a comprehensive analysis of the market value impact of operational loss events in the US banking and insurance industries. A previous study by de Fontnouvelle et al. (2003) analyzes both the OpVar database and a similar database from a competing vendor, OpRisk Analytics.[3] Their primary objective is to quantify operational risk and to provide guidance to managers and regulators about the magnitude of operational risk capital in the banking industry. They find that operational losses are an important source of risk for large, internationally active banks, and that the capital charge for operational risk will often exceed the charge for market risk. de Fontnouvelle et al. (2003) do not consider the impact of operational losses on bank market values and do not analyze operational losses in the insurance industry.

The Basel Committee has conducted two surveys of operational loss events, in 2001 and 2002 (Basel Committee, 2003b). The surveys covered banks in several countries and report data on the number and amount of operational loss events by type. The surveys are not useful for an event study, however, because neither the names of the banks nor the dates of the losses are identified. In addition, the Basel Committee data are not as representative as the OpVar data due to the small number of banks included in the surveys and the absence of insurance companies.

There have been prior event studies analyzing the wealth effects of individual operational loss events, although few of these studies focus specifically on banking or insurance. For example, Palmrose et al. (2004) study the impact of earnings restatements on the stock prices of firms in financial and non-financial industries. They find significant negative stock price reaction to earnings restatements, which are relatively large for restatements involving fraud. Bizjak and Coles (1995) study the impact of private antitrust litigation on a broad sample of firms, and Bhagat et al. (1994) analyze the impact of inter-firm lawsuits, including operational loss events such as breach of contract and patent infringement.

Fields et al. (1990) and Grace et al. (1995) study the wealth effects of a voter initiative, California's Proposition 103, which was approved in 1988 in an attempt to regulate insurance premium rates,[4] and find that the proposition had a negative impact on the stock prices of affected insurers. Additional analyses of insurance stocks include Lamb (1995), who analyzes the effect of Hurricane Andrew, and Cummins and Lewis (2003), who study the effect of the terrorist attacks of September 11, 2001. Both studies find significant negative stock price reactions around the event day. Our paper differs from these prior studies in analyzing operational loss events more broadly defined.

3.2. Hypotheses

The inclusion of operational risk within the Basel II capital formula was controversial. Most participants in the debate would acknowledge that the value of a firm represents the

[3] Because their analysis shows that the two databases are remarkably similar (de Fontnouvelle et al., 2003, p. 8), we consider it appropriate to focus only on the OpVar database in the present study.

[4] A loss due to a new regulation is defined as operational loss under the Basel Committee's definition of operational risk. It is categorized under improper business or market practices.

present value of its future cash flows adjusted for risk and that operational risk is a major source of cash flow risk for financial institutions (King, 2001). However, opponents of the new charge argued that operational risk was not a "balance sheet" risk, but simply earnings "noise" that can be diversified away by shareholders. According to this interpretation, the rationale for managing operational risk is not compelling if idiosyncratic or unsystematic risk can be dealt with by investors through holding diversified portfolios.

Operational risk, however, differs from most other risks faced by financial institutions in that it is asymmetric, causing losses and not gains. Hence, to the extent that operational losses have a negative mean, it makes sense for financial institutions to make expenditures on managing operational risk at least to the point where the marginal expenditure equals the marginal reduction in expected losses from operational events. Thus, by managing operational risk, financial institutions can maximize future expected cash flows by reducing the expected costs of operational loss events. Financial firms such as insurers and banks also are motivated to manage operational losses because their customers are particularly sensitive to insolvency risk (Merton and Perold, 1993), which can be exacerbated by large operational losses. This motivation is likely accentuated by the recent rating agency focus on operational risk.

Froot et al. (1993) argue that informational asymmetries between firms and investors imply that external capital is likely to be more costly than internal capital. Thus, if a firm suffers shocks to its internal capital due to unsystematic risk events, it may have to forego positive net present value projects because of the need to raise external capital. This rationale is likely to be particularly applicable to banks, which tend to have much more information about the quality of bank loan portfolios than do investors, and also to insurers, where the principal information asymmetry involves the adequacy of prices and loss reserves. Thus, to the extent that operational losses deplete internal capital, it may be optimal to engage in risk management expenditures beyond the point implied by the expected value of the loss events themselves.

With these theoretical arguments providing the backdrop, this paper examines whether the announcement of large operational loss events has an empirical impact on the market value of a firm. Consistent with most of the event study literature, we assume that securities markets are efficient in the sense that all publicly available information is priced into the firm's stock. If the announcement of an operational loss event conveys negative and unexpected information, the institution's stock price will be adversely affected. In an efficient capital market, announcements of operational loss events are said to be informative if they lead to a change in investors' assessments of the companies' future cash flows. Otherwise, the announcements are said to be non-informative. This discussion suggests the following hypothesis:

Null Hypothesis 1. Operational loss events do not significantly change the stock prices of affected companies. That is, the announcement of operational loss event is non-informative.

The alternative hypothesis is that such announcements are informative and, more specifically, convey negative information about the value of the firm.

If, as opponents of the new operational risk capital charge contend, investors diversify away operational loss events by holding diversified portfolios, the announcement of an operational loss should not have an impact on the value of a financial institution beyond the monetary value of the loss. However, if the announcement conveys adverse information that affects investors' expectations about future cash flows, then the market value loss may be larger than the operational loss. There are several reasons why this could occur: (1) The loss may cause market participants to revise upward their expectations regarding the probability and severity of future loss events, particularly if the loss conveys significant new information about the nature and magnitude of potential operational losses. (2) The loss may trigger further costly events such as management reorganization, regulatory or prosecutorial investigations, and lawsuits. The loss also could damage the firm's reputation with regulators, increasing the frequency or stringency of *future* regulatory actions unrelated to the loss event. (3) The loss could damage the firm's reputation with customers, reducing future operating cash flows as customers transfer their business to competitors. (4) The loss may induce downward stock price pressure as seller-initiated trades increase. For example, some institutional investors may not want to report the bank or insurer as being among their holdings. (5) The loss may serve as a signal of poor managerial controls or other management defects, causing the market to revise downward expected future cash flows, and (6) the loss may cause the firm to forego attractive projects because of the depletion of internal capital. This discussion suggests the following hypothesis:

Null Hypothesis 2. Operational loss events convey no information about the firm's *future* cash flows and therefore have no effect on firm value beyond the amount of the loss itself.

The alternative to Hypothesis 2 is that the loss conveys adverse information about expected future cash flows that causes firm value to decline by more than the amount of the loss.

Like firms in most industries, firms within the banking and insurance industries differ in terms of their growth opportunities, i.e., the relative importance of growth opportunities and assets in place in determining firm market value. Differences can arise due to product line specialization, because some product segments grow faster than others, geographical focus, or advantages in product development, distribution networks, customer service, or technology that enable some firms to generate larger numbers of attractive investment opportunities than others. Operational losses that lead to internal capital depletion are likely to be more severe for firms with strong growth prospects than for those whose market value is more dependent on assets in place because having capital for new investments is more important for growth-oriented firms. Thus, there may be a direct relationship between the firm's growth prospects prior to the loss and the amount of the decline in the stock price, suggesting the following hypothesis:

Null Hypothesis 3. The response of a firm's stock to operational losses is independent of the firm's growth prospects.

The alternative hypothesis is that the loss in firm value is positively related to growth prospects.

For financial institutions, the trust of clients is an important asset that can be significantly shaken by some types of operational loss events (Merton, 1995). Thus, events such as market conduct problems that damage an institution's reputation with its customers may reduce expected future cash flows more than events that do not directly affect customers, such as employee workplace safety. Market-conduct events may be especially important for customers purchasing long-term contracts such as life insurance and annuities.[5] This suggests the following hypothesis:

Null Hypothesis 4. Operational losses from market-conduct problems and operational losses from other type of events have the same effect on stock prices, i.e., market-conduct losses do not have a disproportionate impact on firm market value.

The alternative to Hypothesis 4 is that market-conduct events have a stronger effect on stock prices than events that do not directly affect the relationship of the institution to its customers.

4. The database, summary statistics, and operational loss trends

4.1. The database

The data analyzed in this study are from the OpVar operational loss database distributed by OpVantage, a division of Fitch Risk Management. The database consists of publicly reported operational loss events worldwide from 1978 through the present covering a number of industries, including banking and insurance. The bank and insurance losses are categorized according to the Basel Committee's definition of operational risk event types, and the bank losses are further categorized according to the Committee's business lines hierarchy. The database provides descriptive information on the events and event dates. Two-thirds of the reported losses in OpVar are from the US. Moreover, de Fontnouvelle et al. (2003) concluded that the non-US losses are significantly different in magnitude and distribution from the US losses. Accordingly, and also because it is likely not advisable to mix event study results from different national stock exchanges, we focus our analysis on the US operational loss data.

The OpVar database reports all publicly announced losses that exceed a threshold of $1 million. However, in this study, we chose to investigate the market value impact of relatively large losses, defined as losses of at least $10 million. The primary rationale is that relatively large losses are more likely to affect stock prices due to their size and more likely to be considered "material" from an accounting perspective. Moreover, high frequency, low severity losses to some extent are anticipated events that are already incorporated in a firm's expense budget and therefore embedded in current stock prices.

An additional reason for focusing on the larger losses is that smaller losses are less likely to be reported and less likely to be identified by the database vendors if they are reported (de Fontnouvelle et al., 2003). However, non-reporting is a less serious problem for an event study than for studies attempting to measure the probability distribution of operational losses. It is only necessary when drawing conclusions to recognize that any inferences from the analysis apply to *relatively large, publicly-reported* operational losses. Nevertheless, given that relatively small losses tend to be anticipated as a normal aspect of doing business, their value-relevance is likely to lie more in their frequency of occurrence

[5] Indeed, the announcement of operational loss events can have reputational spill-over effects on other firms who have not experienced such events. For example, Cowan and Power (2001) show that the announcement of an accounting charge related to market losses on junk bonds by First Executive Corporation in 1990 caused an adverse stock price reaction for other life insurers. The reaction was stronger for insurers with higher portfolio holdings of junk bonds and more dependence on retail business.

than in their existence or severity. Hence, we consider our focus on relatively large events appropriate for the purposes of the present study.

4.2. Summary statistics and operational loss trends

The focus of this paper is on the relationship between operational losses and market values in the US banking and insurance industries. However, because there is not much quantitative information in the literature on operational losses, an overview of the data for both industries can provide new knowledge on the operational risk exposure of both industries. Thus, we begin by reporting some overview information of the operational loss experience of US banks and insurers. The present section discusses all operational loss events of at least $10 million reported in OpVar, while the following section discusses the subset of events utilized in the event study.

Summary statistics on all banking and insurance operational loss events of at least $10 million are shown in the first row of Table 1. There are 691 bank events and 241 insurer events. Both the mean and median operational losses of insurers exceed those of banks – the average operational loss for insurers is $99.8 million, compared to $84.4 million for banks, while the medians are $33.6 million for insurers and $32.3 million for banks. The maximum loss is slightly larger for banks than for insurers – $2.532 billion versus $2.257 billion.

As the means and medians suggest, the severity distribution of operational loss events is significantly skewed to the right. For losses of at least $10 million, approximately 60% of the losses fall between $10 and $50 million for both banks and insurers, and roughly 80% fall between $10 and $100 million. The skewnesses of the operational losses are indeed relatively high, 7.25 for banks and 6.90 for insurers. Figs. 1 and 2 show the number of events and aggregate loss amounts by year for banks and insurers, respectively.[6] The number of reported loss events increased substantially in the latter part of the sample period.[7] For the US banking industry (Fig. 1), the number of losses greater than $10 million first exceeded 20 in 1987, and there were at least 20 reported operational loss events each year from 1990 to 2002, peaking at 72 events in 1997. The US insurance industry (Fig. 2) experienced few losses until the early 1990s with fewer than 5 losses per year until 1992. However, there were at least 10 events per year from 1994 to 2002, with a maximum of 30 in 1998.

A few years are particularly noteworthy. In 1997 and 2002, major banking institutions were confronted by law suits and regulatory investigations, leading to massive settlements. In 1997, thirty-seven brokerage firms agreed to pay approximately $1 billion to end an antitrust lawsuit alleging that brokers had colluded between 1989 and 1994 to manipulate

[6] Because the version of the OpVar database available for this study ended in April 2003, Figs. 1 and 2 include only the period for which complete years' data were available. Since the focus of this analysis is on conducting an event study, the date (and hence year) of each loss event is the first date that the loss amount became public.

[7] Although OpVantage indicates that it has made a thorough effort to track reported operational loss events during the sample period, it is possible that some proportion of the increase in the number of events during the sample period is due to reporting differences rather than actual increases in operational losses. Among other factors, regulators and investors have become more sensitive both to transparency issues and operational loss events in recent years, perhaps leading to increased media coverage of such events. In addition, the electronic publications utilized by OpVantage in compiling their database are likely to be more complete for more recent years. Nevertheless, the upward trends are consistent with the emergence of operational loss events such as rogue traders and derivatives problems in banking and market-conduct problems in insurance, which were relatively rare in earlier years.

Table 1
Summary statistics for the overall and event study samples

Statistic	Banks						Insurers				
	Mean	Median	Std Dev.	Min	Max		Mean	Median	Std Dev.	Min	Max
All operational losses	84.40	32.33	184.93	9.76	2532.39	***	99.75	33.63	250.93	9.80	2256.75
Number of observations	691						241				
Summary statistics for event study samples											
Operational losses	69.53	32.33	101.78	9.76	774.54		73.54	37.03	76.89	9.82	335.52
Market capitalization	29,469	11,818	45,113	4	269,022	**	20,064	7552	38,841	67	228,955
Book value of equity	12,115	6150	14,459	14	84,106		10,241	5184	14,290	55	79,059
Book value of assets	208,253	133,381	221,220	64	1,063,572	***	111,140	54,384	175,532	626	1,077,236
Book value of liabilities	196,138	127,976	207,902	38	979,467	***	101,607	38,183	166,662	277	998,177
Q ratio	1.111	1.049	0.382	0.519	7.191	*	1.218	1.061	0.520	0.881	4.928
BV liabilities/BV assets (%)	92.1	93.7	8.2	22.4	97.9	***	83.0	85.9	14.4	37.1	97.6
BV equity/BV assets (%)	7.9	6.3	8.2	2.1	77.6	***	17.0	14.1	14.4	2.4	62.9
Operational loss/MktCap (%)	4.3	0.6	10.8	0.0	94.5		3.6	0.8	9.9	0.0	71.2
Number of observations	403						89				

Note: Summary statistics are in millions of constant 2002 dollars based on the consumer price index.
Sources: OpVantage for operational losses, compustat for financial summary statistics.
Stars indicate significance level of two-sided t-test on differences between bank and insurance mean values.
[*] Significant at the 10% level.
[**] Significant at the 5% level.
[***] Significant at the 1% level.

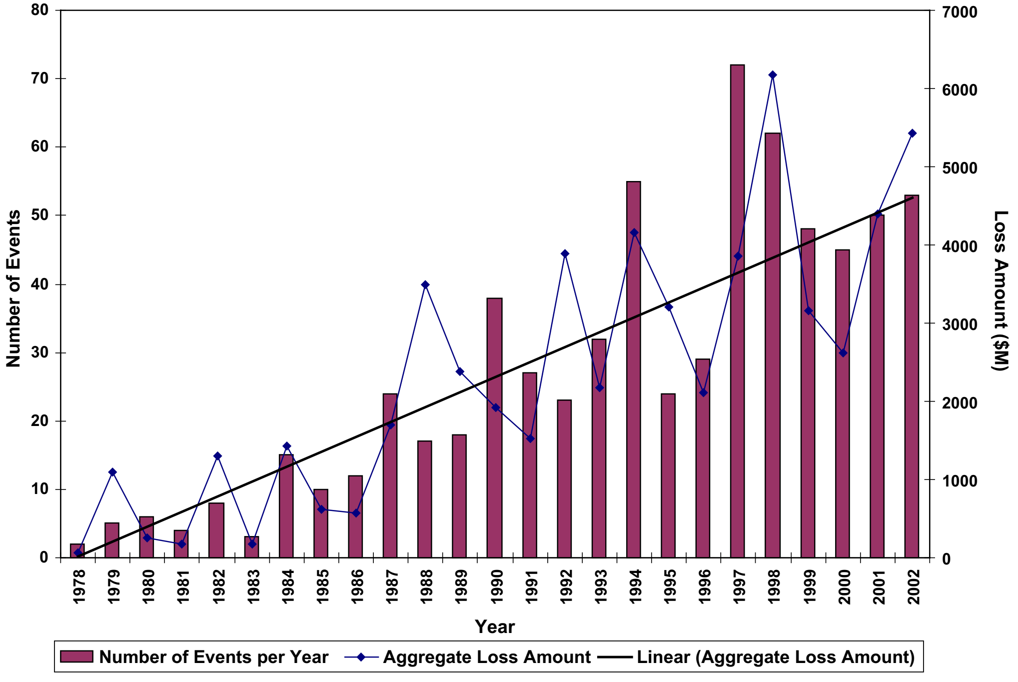

Fig. 1. All operational loss events of at least $10 million by year: US banks.

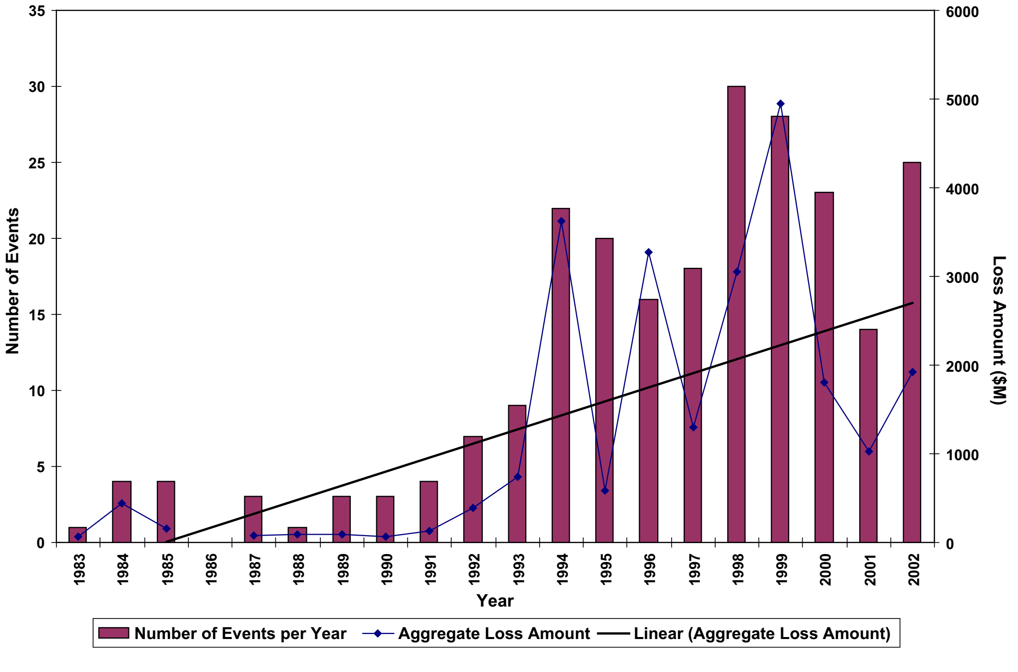

Fig. 2. All operational loss events of at least $10 million by year: US insurance companies.

prices on Nasdaq.[8] Twenty firm-events relating to this market manipulation are included in our sample. Major Wall Street scandals also erupted in 2002, beginning with the Justice Department's investigation of the Enron collapse. In February, brokerage firms including Merrill Lynch and JP Morgan Chase agreed to pay more than $100 million each to settle Securities and Exchange Commission (SEC) allegations that they helped Enron fraudulently overstate its income. An SEC investigation of conflicts of interests by Wall Street analysts also revealed that the brokers' investment advice was biased by the desire to aid their own investment banking business. In late 2002, ten large securities firms agreed to pay about $1.4 billion to settle the investigation. All ten of the investment-advice operational losses are included in our sample.

For the insurance industry, 8 out of 22 reported events in 1994 are related to California's Proposition 103, which mandated premium rollbacks for California policyholders in 1989. On November 28, 1994, many insurers that had not paid the refund received an order from the insurance commissioner of California requiring them to pay refunds to their policyholders plus interest since May 1989. A surge of deceptive sales events explains the peak in 1998 for the insurance industry. Thirteen of the 30 events reported in that year involved deceptive sales practices. The number of deceptive sales events started to increase in the early 1990s; and by 1997, 64 class action lawsuits had been filed against life insurance companies for "vanishing premium" policies whose premiums did not vanish as expected because of the prolonged decline in market interest rates (Santomero and Babbel, 1997).

This unprecedented wave of litigation against life insurers for deceptive sales practices in the 1990s can be traced back to the 1980s. Before the 1980s, US life insurers enjoyed reputations for financial stability and were generally regarded as trustworthy by policyholders. However, in the early 1980s, record-high interest rates triggered a major episode of disintermediation in the industry. Many policyholders borrowed against their policies at low, contractually-guaranteed interest rates to take advantage of higher rates in the market, and some policyholders simply surrendered their policies altogether. Life insurers also faced increasing competition from stockbrokers offering mutual funds to individuals who had not previously invested in stocks as well as competition from banks, especially after Federal regulators gave national banks the right to sell fixed and variable annuities in 1985 and 1990, respectively (Carow, 2001; Cowan et al., 2002). Insurers developed new products and marketing approaches to stay competitive and placed more emphasis on life insurance policies as investment vehicles. An unfortunate byproduct of these competitive pressures was the emergence of unethical sales practices (Egler and Malak, 1999).[9] Many insurers suffered staggering damages from the ensuing lawsuits, and consumer confidence in the industry was badly shaken. Although insurers and regulators have taken steps to prevent unethical market practices (Wincuinas, 2000), exposure to market conduct risk continues to be important for life insurers.

The operational loss events for the banking industry are classified by event type and business line in Tables 2 and 3. Table 2 summarizes the number of loss events, and Table 3

[8] The lawsuit was influenced by a paper by Christie and Schultz (1994), which reported that odd-eighth quotes virtually did not exist for a large number of actively traded securities on Nasdaq, implying that the inside spread was at least $0.25 and suggesting that Nasdaq market makers colluded to inflate profits.

[9] A poll by *Money* magazine in 1995 found that deceptive sales practices permeated the life insurance industry. They are not "the acts of a handful of bad agents in a few companies" but more like a systematic pattern in the industry (Updegrave, 1995).

Table 2
Number of individual loss events from US banks per business line and event type

Business units	Business lines	Internal fraud	External fraud	Employment practices and workplace safety	Clients, products and business practices	Damage to physical assets	Business disruption and system failure	Execution, delivery and process management	Total across event types
Investment banking	Corporate finance	1.45%			3.91%			0.14%	5.50%
	Trading and sales	2.60%	0.14%		3.47%	0.14%	0.14%	0.43%	6.95%
	No information	0.58%		0.14%	1.16%				1.88%
Banking	Retail banking	9.12%	4.20%	1.45%	12.74%			1.16%	28.65%
	Commercial banking	3.47%	6.08%	0.72%	7.38%	0.43%	0.29%	0.58%	18.96%
	Payment and settlement	0.29%	0.14%		0.29%	0.29%		0.14%	1.16%
	Agency Services	0.87%	0.29%		2.60%			0.43%	4.20%
Others	Asset management	1.88%	1.01%	0.14%	4.78%			0.72%	8.54%
	Retail brokerage	2.46%	0.72%	0.72%	14.62%		0.14%		18.67%
	Institutional brokerage	0.29%			4.05%			0.72%	5.07%
	No information	0.14%						0.29%	0.43%
Total number of events		160	87	22	380	6	4	32	691
Total across business lines		23.15%	12.59%	3.18%	54.99%	0.87%	0.58%	4.63%	100.00%

Note: Results are for losses of at least $10 million for the time period 1978 through April 2003.

Table 3
Total gross loss amounts ($M) of individual loss events for US banks by business line and event type

Business units	Business lines	Internal fraud	External fraud	Employment practices and workplace safety	Clients, products and business practices	Damage to physical assets	Business disruption and system failure	Execution, delivery and process management	Total across event types
Investment banking	Corporate finance	2.55%			2.53%			0.06%	5.14%
	Trading and sales	4.80%	0.03%		3.97%	0.15%	0.44%	0.11%	9.49%
	No information	0.09%		0.03%	0.88%				0.99%
Banking	Retail banking	8.19%	3.20%	0.66%	21.61%			0.49%	34.15%
	Commercial banking	3.63%	4.72%	0.44%	6.90%	0.52%	0.21%	0.77%	17.18%
	Payment and settlement	0.09%	0.05%		0.42%	0.24%		0.70%	1.50%
	Agency services	0.54%	1.21%		1.68%			0.63%	4.05%
Others	Asset management	1.83%	0.81%	0.05%	5.31%			0.85%	8.85%
	Retail brokerage	1.19%	1.25%	0.24%	12.45%		0.02%		15.15%
	Institutional brokerage	0.16%			2.64%			0.40%	3.21%
	No information	0.02%						0.27%	0.29%
Total gross loss amounts ($M)		13,463	6566	824	34,044	528	391	2497	58,312
Total across business lines		23.09%	11.26%	1.41%	58.38%	0.91%	0.67%	4.28%	100.00%

Note: Monetary variables are in millions of constant 2002 dollars, based on the consumer price index.
In this table, there are nine business lines rather than the eight defined by the Basel Committee because OpVantage added a ninth business line, institutional brokerage. Results are for losses of at least $10 million for the time period 1978 through April 2003.

Table 4
Distribution of loss events and loss amounts for US insurers by event type

Level 1	Level 2	Level 3	Number of events and % frequency			Gross loss amount ($M) and % severity		
			All	L&H	P&L	All	L&H	P&L
Employment practices and workplace safety	Diversity and discrimination	Discrimination	1.7%	0.7%	3.1%	1.1%	0.1%	3.6%
	Employee relations	Compensation and benefits	0.8%	0.7%	1.0%	0.7%	0.4%	1.3%
		Wrongful termination	1.2%	1.4%	1.0%	0.4%	0.4%	0.3%
Internal fraud	Theft and fraud (internal)	Embezzlement	7.9%	7.6%	8.3%	4.3%	2.5%	8.9%
		Bribes and kickbacks	1.2%		3.1%	0.2%		0.7%
		All other fraud (internal)	0.4%	0.7%		0.3%	0.4%	
	Unauthorized activity	Unauthorized trading	0.8%	0.7%	1.0%	1.2%	0.1%	3.9%
External fraud	Theft and fraud (external)	All other fraud (external)	2.5%	3.4%	1.0%	1.2%	1.3%	1.1%
		Loan fraud	0.4%	0.7%		0.0%	0.1%	
Damage to physical assets	Disasters and other events	Terrorism	0.4%		1.0%	0.8%		3.0%
Clients, products and business practices	Improper business or market practices	Antitrust	1.2%	2.1%		0.4%	0.5%	
		Breach of contract	18.7%	13.1%	27.1%	12.2%	4.0%	33.1%
		Current interpretation of Law	0.8%	0.7%	1.0%	0.6%	0.7%	0.4%
		Discrimination	3.3%	3.4%	3.1%	3.0%	3.8%	0.8%
		Failure to supervise	0.4%	0.7%		0.2%	0.2%	
		Mergers and acquisitions	0.4%	0.7%		0.2%	0.3%	
		New law/regulation	6.6%	0.7%	15.6%	4.9%	0.2%	17.0%
		Overcharging	10.4%	9.0%	12.5%	4.2%	3.0%	7.4%
		Taxation	0.8%	1.4%		1.0%	1.4%	
		All other mismanagement	0.4%		1.0%	0.2%		0.7%
	Suitability, disclosure and fiduciary	Breach of fiduciary duty	2.9%	2.8%	3.1%	1.1%	0.7%	2.2%
		Churning	0.8%	1.4%		2.1%	3.0%	
		Deceptive sales practices	22.4%	33.1%	6.3%	50.4%	66.1%	10.5%
		Failure to disclose	5.4%	5.5%	5.2%	4.3%	5.2%	1.8%
		Inadequate due diligence	2.9%	3.4%	2.1%	1.6%	1.9%	0.8%
Business disruption and system failures	System	Systems development	0.4%	0.7%		1.4%	1.9%	
Execution, delivery and process management	Monitoring and reporting	Compliance	2.5%	2.8%	2.1%	1.3%	1.2%	1.6%
	Transaction capture, execution and maintenance	Erroneous data entry	0.4%		1.0%	0.3%		1.0%
		Flawed process	1.7%	2.8%		0.4%	0.6%	
Total number of events and gross loss amount ($M)			241	145	96	24,040	17,274	6766
			100.0%	100.0%	100.0%	100.0%	100.0%	100.0%

Note: Monetary variables are in millions of constant 2002 dollars, based on the consumer price index. Results are for losses of at least $10 million for the time period 1978 through April 2003.

reports the total loss amounts. The number of events tends to cluster in three of the nine business lines (Table 2) – retail banking accounts for 28.7% of the events, commercial banking for 19.0%, and retail brokerage for 18.7%. Other lines accounting for significant numbers of events include asset management (8.5%), trading and sales (7.0%), and corporate finance (5.5%). Clustering also appears across event types. Clients, products and business practices accounts for 55.0% of the total events, internal fraud accounts for 23.2%, and external fraud accounts for 12.6%.

Table 3 shows that the aggregate loss amounts also exhibit a pattern of clustering across business lines and event types. Retail banking accounts for 34.2% of the total loss amount, commercial banking accounts for 17.2%, retail brokerage accounts for 15.2%, and trading and sales accounts for 9.5%. Across event type, clients-products-business practices, internal fraud, and external fraud together account for 92.7% of the total loss amount.

The database also categorizes the events further by breaking down each event type into specific events. This tabulation shows that embezzlement accounts for 17.2% of the banking events, and deceptive sales practices and concealment account for another 17.2%. However, these events account for only 28% of the total aggregate loss amount. In contrast, insider trading and unauthorized trading are infrequent events but have much larger average losses.

Table 4 presents the distribution of the number of losses and gross loss amounts by event types for the insurance industry. There are 241 insurance events – 145 for life and health (L&H) insurers and 96 for property-liability (P&L) insurers. The total aggregate loss amount is \$24.0 billion – \$17.3 billion for L&H insurers and \$6.8 billion for P&L insurers. For both types of insurers, the most important type of event was clients, products, and business practices, accounting for 77.6% of events and 86.4% of the gross loss amount. Within the business practices category, deceptive sales events were most important for L&H insurers, accounting for 33.1% of the events and 66.1% of the gross loss amount. For P&L insurers, the largest number of events are generated by breach of contract (27.1%), new laws or regulations (15.6%), and overcharging (12.5%); while the largest loss amount categories are breach of contract (33.1%), new laws or regulations (17.0%), deceptive sales (10.5%), and embezzlement (8.9%). Clearly the operational risk exposure has been distributed differently between the two major segments of the insurance industry, reflecting differences in marketing practices and insurance coverages.

In summary, the operational risk exposure for both banks and insurers was significant during the 1990s. Clients, products, and business practices is the most important type of operational loss event for both banks and insurers. Within this category, deceptive sales events were the predominant type of loss for life insurers, while other types of client, product, and business practices were also important for banks and P&L insurers. Internal and external fraud are much more important sources of loss for banks than for insurers.

5. Sample selection and estimation methods

5.1. Sample selection

To obtain the sample of operational loss events used in the event study, we begin with the total number of US losses of at least \$10 million in the OpVar database. To conduct the event study on a given event, both the event date and stock prices are required. We carefully checked the observations in the OpVar database to verify the events, loss amounts, and event dates. Fifteen bank events were dropped from the sample because the event or event date could not be verified, but no insurance events were eliminated by this criterion. The second criterion for inclusion in the event study is that the affected firms have to be publicly traded at the time of the event on the NYSE, AMEX, or Nasdaq. This criterion eliminated a significant number of both banking and insurance observations, primarily because they affected closely held stock companies or mutuals, with closely held stocks predominating in the bank sample and mutuals in the insurance sample. As a result of these sampling criteria, the event study sample includes 403 bank events and 89 insurance events. Daily stock returns for the event study were obtained from the Center for Research in Security Prices (CRSP) database.

Table 1 provides summary statistics on the event study sample. The criterion that all firms be publicly-traded at the time of loss eliminated several of the largest events. As a result, the mean loss in the event study sample is lower than the overall mean for both banks and insurers. However, the medians are about the same in the overall and event study samples.

Table 1 also shows that the banks in the event study sample are larger on average than the insurers – the average bank has market capitalization of $29.5 billion and assets of $208.2 billion, compared to $20.1 billion market capitalization and $111.1 billion in assets for the average insurer. The equity capital-to-assets ratios of banks also are significantly smaller than for both L&H and P&L the insurers – 7.9% versus 13.8 and 20.2, respectively. Finally, the median ratios of operational losses to equity capital tend to be relatively small – 0.6% for banks and 0.8% for insurers – but the means are considerably larger, reflecting some very large loss events.

5.2. Estimation methods

Because banks and insurers may react differently to operational loss events, the wealth effects in the two industries are analyzed separately. To measure abnormal returns in our event study analysis, we utilize a *three-factor return generating model* as our primary benchmark. In addition to the standard market factor, the three-factor model also includes an industry factor in order to isolate the effect of operational loss events on a particular stock beyond any overall movements in banking or insurance industry stocks on the same day. Because financial institutions are especially sensitive to interest rates and changing investment opportunity sets, we also include an interest rate factor in the model. As a robustness check, we also conduct the analysis using the standard *market model*. The market model results, which support the same conclusions as the three-factor model, are reported in an appendix available from the authors.

More specifically, the three-factor model is specified as follows:

$$R_{jt} = \alpha_j + \beta_j R_{mt} + s_j R_{\mathrm{IND}t} + h_j I_t + \varepsilon_{jt}, E(\varepsilon_{jt}) = 0 \quad \text{and} \quad \mathrm{var}(\varepsilon_{jt}) = \sigma^2_{\varepsilon_j},\ j = 1 \ldots N_{\mathrm{IND}}, \tag{1}$$

where R_{jt} is the holding period return of the affected company of event j on day t, R_{mt} is the CRSP equally-weighted market return on day t, $R_{\mathrm{IND}t}$ is the return of the industry index on day t, where $\mathrm{IND} = B$ for the banking industry, and $\mathrm{IND} = I$ for the insurance industry, and N_{IND} = the number of events in the bank and insurance samples, respectively. The banking industry index is an equally-weighted average of the returns of all commercial banks (SIC 602×) and all investment banks and brokerage firms (SIC 6211) from CRSP; and the insurance industry index is an equally-weighted average of the returns of all life insurers (SIC 631×), health insurers (SIC 632×), and property-liability insurers (SIC 633×) from CRSP. I_t is the change in the interest rate on day t for the one-year constant-maturity treasury bill from the Board of Governors of the Federal Reserve System H.15 Report. Finally, ε_{jt} is the zero mean disturbance term; and α_j, β_j, s_j, h_j and $\sigma^2_{\varepsilon_j}$ are the parameters of the 3-factor model.

To estimate abnormal returns, two time series of stock return data are needed for each event – for the *estimation period*, where the parameters of the market model are estimated, and for the *event period* where the abnormal returns are calculated. The three-factor model is estimated using ordinary least squares (OLS) over an estimation period of 250 trading days ending 21 days prior to the event day (day 0).[10] Using the estimated parameters and the movement of the three factors during the event period, the abnormal return (AR) for each event during the event period is then computed as follows:

$$\mathrm{AR}_{jt} = R_{jt} - \hat{\alpha}_j - \hat{\beta}_j R_{mt} - \hat{s}_j R_{\mathrm{IND}t} - \hat{h}_j I_t, \tag{2}$$

where the coefficients $\hat{\alpha}_j$, $\hat{\beta}_j$, $\hat{s}_j$ and $\hat{h}_j$ are the OLS estimates of α_j, β_j, s_j, and h_j. Abnormal returns are calculated for windows surrounding the event day (day 0). A window is denoted as $(-w_1,+w_2)$, representing an event window beginning w_1 days prior to the event day and ending w_2 days after the event day.

In order to allow for the possibility of information leakage prior to the loss events and to allow sufficient time for the market to fully respond after an event, we calculate abnormal returns in a window beginning 20 trading days prior to each event and extending 20 trading days after the event for both the bank and insurance samples, i.e., the window is $(-20,+20)$. To provide information on the responsiveness of stocks to event announcements, we also tabulate returns for windows of various lengths that are subsets of the overall $(-20,+20)$ window.

Under the assumption that the conditional abnormal returns are independent and identically distributed, we can aggregate the abnormal returns across events within any given time period. The average abnormal return across all events at day t in the event period is computed as follows:

$$\overline{\mathrm{AR}}_t = \frac{1}{N}\sum_{j=1}^{N} \mathrm{AR}_{jt}. \tag{3}$$

We compute the cumulative abnormal return (CAR) over a time period of two or more trading days beginning with day T_1 and ending with day T_2 for event j as

$$\mathrm{CAR}_{T_1 j, T_2 j} = \sum_{t=T_1 j}^{T_2 j} \mathrm{AR}_{jt}. \tag{4}$$

The mean cumulative abnormal returns (mean CAR), also called cumulative average abnormal returns, across the N events is obtained as follows:

[10] The estimation period used in this paper is the standard length in the event study literature (Binder, 1985). In general, the estimation period and the event period do not overlap so that the parameters of normal return model are not influenced by the event (MacKinlay, 1997).

$$\overline{\mathrm{CAR}}_{T_1j,T_2j} = \frac{1}{N}\sum_{j=1}^{N}\mathrm{CAR}_{T_1j,T_2j} = \frac{1}{N}\sum_{j=1}^{N}\sum_{t=T_1j}^{T_2j}\mathrm{AR}_{jt}. \tag{5}$$

Many prior studies have documented the possible bias in standard errors caused by cross-sectional dependence (e.g., Bernard, 1987; Collins and Dent, 1984; Chandra et al., 1990). This may arise when the event window overlaps so that stock returns of different companies respond to some underlying factors in the same way, and these factors are not explicitly controlled for in estimating parameters in the return generating process. Thus, the error terms are correlated across securities, instead of being independent. When clustering occurs, it can be accommodated by aggregating abnormal returns into a portfolio dated using the event date (MacKinlay, 1997; Bernard, 1987).

Our banking sample is affected by clustering of events, particularly the Nasdaq odd-eighths price manipulation in 1997 and the brokerage firm conflict of interest event in 2002. Accordingly, to test for statistical significance of CARs in this study, we adopted Jaffe's (1974) *calendar time t-test,* which corrects for the cross-sectional dependence caused by clustering. Although the insurance events are not affected by clustering, to use a consistent approach throughout the study, we also conducted the calendar time t-test for the insurance sample.

To conduct the calendar time t-tests, clustered events are formed into portfolios according to event date, i.e., events that occurred on the same day are grouped into one portfolio, and events with unique event days form single stock portfolios. We compute the cumulative abnormal return ($\mathrm{CAR}^i_{T_1,T_2}$) for portfolio i over a time period of two or more trading days beginning with day T_1 and ending with day T_2 as

$$\mathrm{CAR}^i_{T_1,T_2} = \frac{\sum_{\mathrm{All}\, j\in \mathrm{Portfolio}\, i}\mathrm{CAR}^i_{T_1j,T_2j}}{N_i}, \tag{6}$$

where $\mathrm{CAR}^i_{T_1j,T_2j}$ is the CAR for firm j affected by event i and N_i is the number of events in portfolio i. A portfolio standard deviation $\mathrm{SD}(\mathrm{CAR}^i_{T_1,T_2})$ is estimated from the time series of portfolio abnormal returns in the estimation period and used to standardize the portfolio return:

$$\mathrm{SCAR}^i_{T_1,T_2} = \frac{\mathrm{CAR}^i_{T_1,T_2}}{\mathrm{SD}\left(\mathrm{CAR}^i_{T_1,T_2}\right)}. \tag{7}$$

Thus, under the null hypothesis that stock prices do not respond to event announcements, the $\mathrm{SCAR}^i_{T_1,T_2}$ is distributed $N(0,1)$. The mean SCAR across all portfolios is

$$\overline{\mathrm{SCAR}}_{T_1,T_2} = \frac{1}{M}\sum_{i=1}^{M}\mathrm{SCAR}^i_{T_1,T_2}, \tag{8}$$

where M is the number of portfolios. Finally, a cross-sectional t-test is performed on the average standardized portfolio abnormal returns:

$$t = \frac{\overline{\mathrm{SCAR}^i_{T_1,T_2}}}{\frac{1}{\sqrt{M}}} = \sqrt{M}\cdot\overline{\mathrm{SCAR}^i_{T_1,T_2}}. \tag{9}$$

It is also customary to report a non-parametric test in addition to parametric tests in event studies to ensure that the results of the parametric tests are not driven by outliers.

In this study, Cowan's (1992) generalized sign test is employed. It compares the proportion of positive abnormal returns around an event day to the proportion from the estimation period. This test is also well-specified when the variance of stock returns increases around the event day. As a robustness check, we also tested the banking and insurance results for statistical significance using the variance-adjusted Z-statistic developed by Boehmer et al. (1991).[11]

6. Event study results

This section discusses the event study results based on the three-factor model for the bank and insurance samples. We first discuss the two samples separately and then compare the results.

6.1. Event study results for the banking sample

Section A of Table 5 presents the cumulative average abnormal returns (CAR) for all 403 events in the banking sample for several event windows. Column 3 of the Table 5, section A, presents the mean CAR, and column 4 presents the median CAR. We focus most of the discussion on the mean CARs. Three significance tests of the mean CAR are reported, the variance-adjusted Z-statistic, the calendar time t-test, and the generalized sign Z-statistic. Because we consider the calendar time t-test and the generalized sign Z-statistic to be somewhat more appropriate due to the clustering of some events in the banking sample, we focus the discussion on the results of these tests.

Table 5 shows that the operational loss events had a significant negative impact on the market values of affected banks. The mean CAR on the event day is −0.30%, which is statistically significant based on the variance adjusted and generalized sign Z-statistics. The cumulative abnormal returns are larger in absolute value for the wider windows, e.g., the mean CAR is −1.07% for the (−2, +2) window, −1.10% for the (−3, +3) window, and −1.12% for the (−5, +5) window, all of which are statistically significant based on all three test statistics. The mean CAR for the (−20, +20) window is −1.97%, which is significant based on the variance adjusted and generalized sign Z-statistics.

Most of the action in terms of the mean CAR takes place within a relatively narrow window around the event day. For example, of the mean CAR of −1.1% for (−3, +3) window, more than half (−0.67%) takes place in the (−3, −1) window, −0.30% occurs on the event day, and only −0.14% occurs in the (+1, +3) window. The breakdown is similar for most of the other windows. Thus, significant information apparently "trickles out" in advance with respect to operational loss events involving the banking industry, and little new information appears to arrive following the event date. This suggests a reasonably high degree of market efficiency in processing information about bank operational loss events.

[11] The Boehmer et al. (1991) procedure adjusts for the possibility of event-induced variance increases around event days. However, the test also has good properties when there is no event-related variance increase and when clustering exists in the sample.

Table 5
Cumulative abnormal returns for all bank and insurance events of at least \$10 million three-factor models

Window	A. Bank events						B. Insurance events					
	N	Mean CAR (%)	Median CAR (%)	Variance adjusted *Z*	Calendar time *t*	Generalized sign *Z*	*N*	Mean CAR (%)	Median CAR (%)	Variance adjusted *Z*	Calendar time *t*	Generalized sign *Z*
(0, 0)	403	−0.30	−0.53	-1.756^{**}	−0.858	-5.530^{***}	89	−1.10	−0.35	$-1.578^{\$}$	$-1.805^{\$}$	−0.902
(−1, +1)	403	−0.60	−0.94	-3.901^{***}	-2.331^{*}	-3.835^{***}	89	−1.22	−0.39	$-1.638^{\$}$	−1.578	−0.69
(−2, +2)	403	−1.07	−1.30	-5.283^{***}	-3.875^{***}	-3.835^{***}	89	−1.44	−0.38	-1.72^{**}	−1.454	−0.266
(−3, +3)	403	−1.10	−1.10	-4.399^{***}	-2.964^{**}	-3.138^{***}	89	−2.01	−0.56	-2.024^{**}	$-1.848^{\$}$	−0.478
(−5, +5)	403	−1.12	−0.85	-3.406^{***}	-2.743^{**}	-1.742^{*}	89	−1.85	−0.63	$-1.382^{\$}$	−1.294	−0.266
(−10, +10)	403	−0.85	−0.42	-1.86^{**}	−0.779	−0.147	89	−2.27	−0.63	−1.252	−1.209	−0.266
(−15, +15)	403	−1.20	−1.62	$-1.398^{\$}$	−0.169	−0.845	89	−2.62	−1.46	−1.214	−1.113	−0.69
(−20, +20)	403	−1.97	−1.77	-2.081^{**}	−0.665	-2.141^{*}	89	−3.88	−2.37	$-1.546^{\$}$	−1.592	−1.114
(−1, +2)	403	−0.66	−1.02	-3.975^{***}	-2.983^{**}	-3.935^{***}	89	−1.23	−0.11	$-1.566^{\$}$	−1.356	0.158
(−1, +3)	403	−0.60	−1.05	-3.488^{***}	-2.562^{*}	-2.540^{**}	89	−1.66	−0.65	-2.032^{**}	$-1.905^{\$}$	$-1.539^{\$}$
(−1, +5)	403	−0.39	−0.60	-2.06^{**}	-2.057^{*}	-1.942^{*}	89	−1.74	−0.56	-1.645^{**}	$-1.724^{\$}$	−0.69
(−1, +10)	403	−0.53	−0.29	$-1.506^{\$}$	−1.035	−0.347	89	−2.35	−0.69	-1.794^{**}	$-1.789^{\$}$	−0.69
(−1, +15)	403	−0.73	−1.12	$-1.583^{\$}$	−0.449	−0.945	89	−3.27	−1.77	-2.359^{***}	-2.314^{*}	$-1.327^{\$}$
(−1, +20)	403	−1.14	−0.73	-2.132^{**}	−0.911	−0.646	89	−4.12	−1.14	-2.645^{***}	-2.700^{**}	$-1.327^{\$}$

Note: For the banking industry, the three factors are: (1) The equally weighted market index (including NYSE, AMEX, and Nasdaq stocks); (2) a banking industry index, which is an equally weighted average of all commercial bank (SIC 602) and investment bank and brokerage (SIC 6211) stocks; and (3) the change in the 1-year constant maturity T-bill rate. For the insurance industry, the banking industry index is replaced by an insurance industry index, which is an equally weighted average of all life insurers (SIC 631), health insurers (SIC 632), and property-liability insurers (SIC 633).

* Significant at the 5% level.

** Significant at the 1% level.

*** Significant at the 0.1% level.

\$ Significant at 10% level.

6.2. Event study results for the insurance sample

Section B of Table 5 presents the cumulative abnormal returns for the 89 insurance events in the sample. The operational loss events had a strong negative impact on the market values of affected insurers. There is -1.10% mean CAR on the event day, which is weakly statistically significant based on the calendar time *t*-test and the variance adjusted Z. The abnormal return continues to grow during the period following the event day, and the CAR for the $(-1,+20)$ window is -4.12%, which is statistically significant at the 1% level based on the calendar time *t*-test and at the 0.1% level based on the variance adjusted Z. The mean CARs in most of the other $(-1,+x)$ windows also are statistically significant as are the mean CARs for the $(0,+x)$ windows (not shown). Thus, the insurance events tend to generate a substantially stronger stock price reaction on average than the bank events, even though the mean and median operational loss amounts are about the same for the two samples. In addition, the arrival of new information appears to occur over a much longer period following the event day for insurers than for banks, and there is no significant leakage of information prior to the event day for the insurers. The larger magnitude of the insurance stock price effect is consistent with the observation that events such as deceptive sales are a relatively new phenomenon for insurers. The lack of information leakage suggests that the announcement of many of the insurance events was truly unexpected by the market.

6.3. Comparing the effect on bank and insurance stocks

Fig. 3 shows the development of mean CAR from 20 trading days before the event to 20 trading days after the event day for the bank and insurance stocks. The graph clearly shows that information leakage is more significant for the bank events than for the insurance events and reinforces the conclusion that the stock price reaction is considerably stronger for the insurance stocks than for the bank stocks. Based on Table 5 and Fig. 3, it is clear that we can reject Hypothesis 1: Operational loss events have a statistically significant negative effect on both bank and insurance stock prices.

The greater sensitivity of insurance stocks to operational losses is something of a puzzle, especially in view of the fact that the bank and insurance operational losses are roughly comparable in size. In relative terms, the (unweighted) average ratio of loss amount to market capitalization is 4.3% for banks and 3.5% for insurers (Table 1). Nevertheless, the eventual mean and median market value response to operational events is larger for insurers than for banks.

We offer three possible explanations for the differential relationship of operational losses and stock prices between banks and insurers. The first explanation is related to the banks' risk management processes. Even though operational risk has not yet been included as a separate category in allocating capital reserves by regulatory bodies, many banks, especially big banks, have modified their risk management models to incorporate operational risk. The insurance industry reserves for insured losses but has not made much progress in modeling or reserving for operational losses, apart from insured property catastrophes. In part, this is due to the fact that insurance regulators have paid much less attention to operational risk than have bank regulators. Thus, many of the events and the event magnitudes for the banks might have been somewhat expected by the market. Recall that many bank events involve internal and external fraud, which have long been present

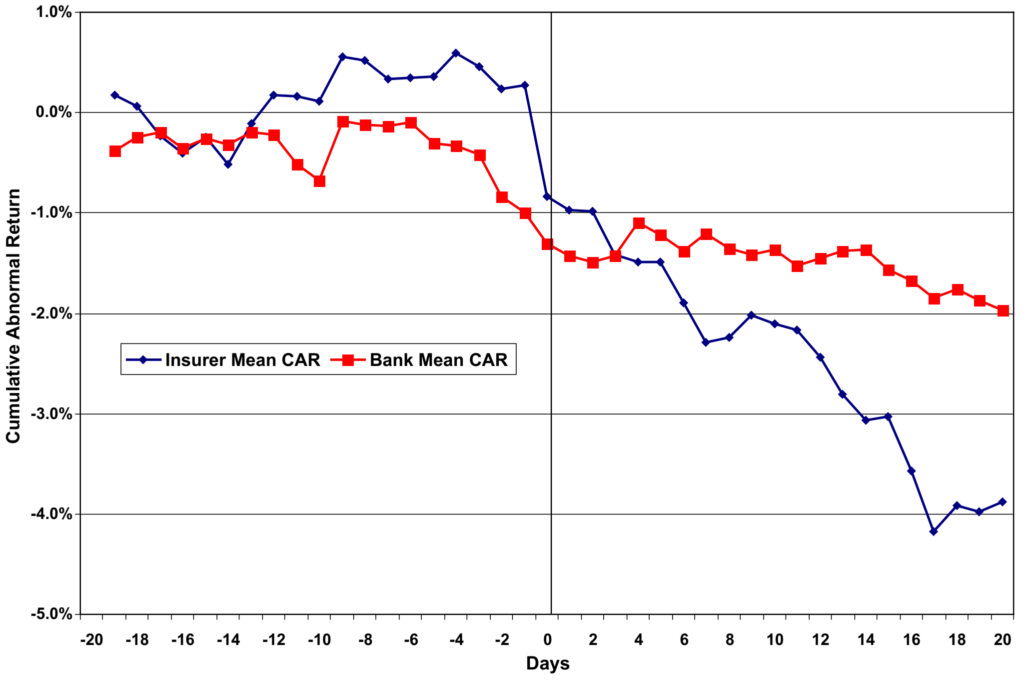

Fig. 3. Cumulative abnormal returns of banks and insurers: three-factor models.

in the banking industry. The most important insurance events, on the other hand, involve market-conduct problems, which were rare in the insurance industry prior to the 1990s. Thus, it is likely that the surge in insurer market-conduct losses took the stock market by surprise. Since the market only reacts to the unexpected portion of operational losses, this could partly explain the differences between the mean CARs for banks and insurers.

The second explanation we offer has to do with bank deposit guarantees and product complexity. Retail bank customers in the US are protected by Federal deposit insurance. By contrast, insurance customers are protected against insolvency by state guaranty funds that are funded by the insurance industry, with no government backing. Insurance guaranty fund coverage is generally much less complete than bank deposit insurance. In addition, retail banking products such as demand deposits and money market funds are relatively uncomplicated compared to insurance policies. Hence, the degree of trust required to maintain a retail banking relationship is likely to be less than for retail insurance relationships. The insurance industry's market-conduct problems and other loss events are likely to have shaken the confidence of the public and may have led consumers to switch their savings dollars to competing institutions such as banks and brokerage firms, helping to explain the stronger reaction of insurance stock prices.

The third explanation relates to option theory. This argument is based on the insurance guaranty fund and bank deposit insurance literature (e.g., Cummins, 1988; Merton, 1978), which interprets the firm's equity value as a call option on the firm's assets with strike price equal to liabilities. In a Black-Scholes context, the option can be equivalently written as a call option on the firm's asset-to-liability ratio with a strike price of 1. Because the call is convex in the asset-to-liability ratio (equivalent to the value of the share price in the

Black-Scholes formula), the market equity (call option values) of firms with higher values of the asset-to-liability ratio will be more sensitive to changes in the ratio than the market equity of firms with lower asset-to-liability ratios, other things equal. The asset-to-liability ratios for the banks, life-health insurers, and property-liability insurers in the event study samples are 1.24, 1.57, and 1.68, respectively.[12] Thus, option convexity may provide an explanation for the greater sensitivity of insurance stocks to operational loss events.

6.4. Testing Hypotheses 2–4

Regression models are estimated to test Hypotheses 2–4. Briefly, these hypotheses are, respectively, that operational loss events convey no information about future cash flows and therefore have no impact on firm value beyond the amount of the loss, that the stock price reaction is unrelated to a firm's growth opportunities, and that there is no significant difference between market-conduct events and other types of events.

We specify regression models to test the hypotheses, with the amount of the market value response as the dependent variable, i.e., the product of the CAR and the market value of firm equity on the day preceding the event window. The independent variable to test Hypothesis 2 is the loss amount. A statistically significant negative coefficient on this variable would imply that the market value loss to the firm is positively correlated with the amount of the operational loss. A coefficient with an absolute value of 1.0 would indicate a one-for-one response of firm market value to the operational event, i.e., that the event announcement conveys no information about future firm cash flows. A negative coefficient with an absolute value greater than 1.0 would imply that the event announcement conveys significant adverse information about the firm's future prospects beyond the loss itself and thus would lead to the rejection of Hypothesis 2.

Hypothesis 3 is tested using Tobin's Q ratio, based on Compustat data. The Q ratio is a commonly used proxy for a firm's growth opportunities (e.g., Shin and Stulz, 2000). The Q ratio is defined as the market value of a firm's assets to the replacement cost of the firm's assets. Because the replacement cost of assets generally is not available, proxies for Q generally are used in the literature. We adopt the standard approach of proxying Q by the ratio of the market value of equity plus the book value of liabilities divided by the book value of assets (e.g., Allen and Rai, 1996; Shin and Stulz, 2000). The book value of assets is likely to be a better proxy for replacement cost for financial institutions than for industrial firms, because the loans and financial assets owned by institutions are generally closer to replacement cost than the plant and equipment that constitutes most of the assets of industrials. In the regressions, Q is measured in the quarter preceding the event window.

The average Q ratios for the banks and insurers in our sample are 1.11 and 1.22, respectively (Table 1). However, the reader is cautioned against interpreting these statistics as implying that insurers have more growth opportunities than banks. Both the assets and the liabilities of the two industries differ significantly, making any such comparison potentially misleading and providing a rationale for using separate regressions for the banks and insurers in testing Hypotheses 2–4.

[12] The ratios are calculated based on data from Compustat. Specifically, the asset-to-liability ratios reported here are equal to the market value of equity plus the book value of liabilities divided by the book value of liabilities. This is a standard definition in the literature. Insurers are also better capitalized than banks based on other definitions such as the ratio of market equity to the book value of liabilities, etc.

Because firms with relatively strong growth opportunities tend to have higher Q values, a significant negative coefficient on Q in the regressions would reject Hypothesis 3 and imply that operational loss events are more costly for firms with better growth prospects. This would be consistent with the argument that such firms may have to forego profitable projects or pay higher costs of capital to raise funds externally following an operational loss, thus degrading firm value.

To test Hypothesis 4 we include a dummy variable in the regressions set equal to 1 for deceptive sales events and 0 otherwise. A significant negative coefficient on this variable would imply that deceptive sales events lead to larger market value losses than other types of events. We also tested dummy variables for two more broadly defined categories of customer-related events – improper business or market practices, and "suitability, disclosure, and fiduciary".[13]

As a control variable, we include a measure of firm size in some specifications, where size is measured by the book value of assets. An additional variable tested in the bank regressions is a dummy variable set equal to 1 for federally insured banks and set equal to zero for other firms such as securities dealers that are not covered by federal deposit insurance. In the insurance regressions, we also tested a dummy variable set equal to 1 for life-health insurers to test for any differential response by type of insurer. Finally, we include a time trend in the regressions equal to the value of the event day, where days are numbered beginning on 1/1/1900.

The regression results are presented in Table 6. Two equations are shown for both banks and insurers, with and without the size variable. The value loss in the $(-5,+5)$ window is used as the dependent variable for banks, and value loss in the $(-20,+20)$ window is the dependent variable for insurers, reflecting the longer response time of insurer stocks to the operational risk events. Regressions using other windows produced similar results.

Hypothesis 2 is rejected for both banks and insurers; the coefficient of the loss amount is statistically significant at the 5% level in three equations and at the 10% level in the fourth equation. Moreover, the coefficient of the loss amount variable is substantially greater than 1 in absolute value in all four equations, implying that operational loss events convey information about future cash flows beyond the amount of the loss itself. Thus, operational losses are costly for both banks and insurers, providing a rationale for incurring costs to manage this type of risk. Somewhat surprisingly, the coefficients of the loss amount variable are larger in the bank equations than in the insurance equations, seemingly contrary to the results presented in Table 5 and Fig. 3. We attribute this result to the fact that the regressions control for other variables, whereas the Table 5 and Fig. 3 results are based on averages. In addition, the insurance data are noisier in a regression context than the bank data because of the much smaller sample size.

Hypothesis 3 is also rejected for both the bank and insurance samples – the coefficients of the Q ratio variables are statistically significant at the 5% level or better in all four equations. Moreover, the Q ratio coefficients have negative signs, implying that operational loss

[13] In the Basel classification, "improper business or market practices" includes conduct relating to antitrust, breach of contract, copyright infringement, discrimination, failure to supervise, inherited liability, mergers and acquisitions, money laundering, new law or regulation, overcharging, patent infringement, polluting, taxation, and all other management. The category "suitability, disclosure, and fiduciary" includes breach of fiduciary duty, churning, deceptive sales, failure to disclose, inadequate due diligence, lender liability, and overstepping authority (Basel Committee, 2001).

Table 6
Regression results loss of market value of equity from operational risk events

Dependent variable	Intercept	Loss amount	Q ratio	Deceptive sales	Assets	Time trend	Adj R^2	N
Banks								
MV loss (−5, +5)[a]	9093.963	−5.337	−1772.715	486. 469		−0.217	0.0449	382
	2.705***	−2.516**	−2.368**	0.968		−2.185**		
MV loss (−5, +5)[a]	−2163.728	−3.597	−2769.244	458.795	−0.006601	0.168	0.1445	382
	−0.593	−1.767*	−3.304***	0.969	−6.758***	1.508		
Insurers								
MV loss (−20, +20)[b]	2480.184	−2.666	−672.128	−1.676		−0.046	0. 0734	81
	2.424**	−2.039**	−3.007***	−0.030		−1.760*		
MV loss (−20, +20)[b]	2945.665	−2.694	−653.166	33.330	0.000117	−0.061	0.0689	81
	2.149**	−2.080**	−2.838***	0.406	0.817	−1.597		

Note: Upper entry in each equation is the coefficient, and the lower entry is the z-statistic. MV Loss($-w,+w$) = the loss in market value of equity from an event in a window extending w days before the event date to w days after the event date; Loss amount = gross loss amount; Q Ratio = market value of equity plus book value of liabilities/book value of assets in the quarter prior to the event date; Deceptive sales = 1 if the event was a deceptive sales event, 0 otherwise; Assets = book value of assets in the quarter prior to the event date; Time trend = number of days from 1/1/1900 to the event date. Monetary values are in millions of constant 2002 dollars based on the consumer price index. Estimation is conducted utilizing weighted least squares to control for heteroskedasticity. White heteroskedasticity consistent standard errors are used to compute the z-statistics for the coefficients.

[a] Missing values of Q resulted in the elimination of 19 observations and 2 outliers were deleted.

[b] Missing values of Q resulted in the deletion of 6 observations and 2 outliers were deleted.

* Significant at the 10% level.

** Significant at the 5% level.

*** Significant at the 1% level.

events are more costly for firms with strong growth prospects, consistent with the view that such firms may have to forego attractive projects following an operational loss event.

The size variable is statistically significant in the bank equation but not in the insurance equation. The negative coefficient on the size variable in the bank equation implies that larger banks suffer larger market value losses from operational events, controlling for event size and the other variables in the regression. This may reflect greater exposure to operational events at large banks due to their complexity.

The deceptive sales dummy variable was never significant in any of the models tested. Consequently, we do not find evidence to support the rejection of Hypothesis 4 – deceptive sales events do not appear to affect financial institutions' stock prices differently from other types of events. In addition, the other dummy variables tested for event types were never statistically significant and were excluded from the final version of the regressions.

The federal deposit insurance dummy variable was not statistically significant in any of the bank models tested. Hence, we do not find evidence that banks with deposit insurance protection react differently from other banking firms. The life-health insurer dummy variable also was statistically insignificant, thus providing no evidence that life-health and property-liability insurers respond differently to operational losses. Finally, the time trend variables are statistically significant and negative when size is excluded from the equations but become insignificant when size is included as a regressor. Hence, we do not find strong evidence of a time trend in the loss amounts, after controlling for the other variables included in the regressions.

7. Conclusions

This paper analyzes operational loss events in the US banking and insurance industries for the period 1978–2003 using the OpVar database. We review operational loss trends in the industries over the study period and conduct an event study analysis of the market value impact of the operational loss events on bank and insurance stocks. The study focuses on operational loss events where the reported loss amount is at least \$10 million – 691 bank events and 241 insurance events. The event study is based on a subset of these events affecting firms that were publicly traded at the time of the event for which we could verify the event date – 403 bank events and 89 insurance events.

In the US banking industry, there were at least 20 operational loss events per year of \$10 million or more aggregating to \$3.4 billion per year from 1990 to 2002 and at least 10 events per year aggregating to \$2.2 billion per year in the US insurance industry from 1994 to 2002. The most important type of operational loss events for both banks and insurers were those involving "clients, products, and business practices". However, internal and external fraud were much more important sources of loss for banks than for insurers.

The event study analysis reveals a significant negative stock price response to operational events for both banks and insurers. For banks, most of the action occurs in the window $(-5,+5)$, with the majority of the market value loss occurring in the $(-5, -1)$ window, indicating significant information leakage prior to the event announcement and a relatively quick response following the announcement. The mean cumulative abnormal return (CAR) for banks in the $(-5,+5)$ window is -1.12% and the median CAR is -0.85%. For insurers, the market value response is much stronger than for the banks on average, and significant abnormal returns continue to accumulate for a considerable period following the event. There is no significant information leakage for insurers prior to the event. The mean CAR in the $(-1,+15)$ window for insurers is -3.27% and the median is -1.77%, indicating stronger and a more prolonged response than for the banks. Thus, the surprise factor for the insurance events appears to be greater than for the bank events, consistent with the argument that insurance-related events were relatively rare prior to the 1990s, whereas banks have long been affected by events such as internal and external fraud.

We propose three possible explanations for the stronger stock price reaction of insurers relative to banks: (1) In response to regulatory and market pressures, many banks have begun to incorporate operational losses into their risk management models, whereas insurers and their regulators have been slow to respond to this type of risk. (2) Retail bank depositors are protected by federal deposit insurance, whereas insurance customers are protected by the much weaker state guaranty fund system. Hence, a higher level of trust may be required in insurance relationships. (3) Insurers tend to be more highly capitalized than banks, leading to the option-theoretic prediction that insurance stock prices will respond more strongly to loss events.

Regression analysis with the market value loss due to operational events as the dependent variable reveals that the response of stock values to operational losses is substantially greater than one-for-one, implying that such events convey adverse information about future cash flows that extends beyond the amount of the operational losses themselves. In addition, the stock price response is larger for firms with higher Tobin's Q ratios, implying that such firms may have to forego attractive projects following operational losses. The results do not support the view that deceptive sales events cause larger losses than other types of events, after controlling for the other variables in the regressions. In addition, the regressions do not support the argument that federally insured banks respond less strongly to operational loss events than do uninsured banks.

Overall, the results strongly support the regulatory view that operational risk poses a significant threat to the market value of both banks and insurers, providing a rationale for firms to manage operational risks. The stock market reaction to operational loss announcements also supports the view that market discipline can serve as a powerful tool for regulators in policing the management of operational risk. Finally, this analysis demonstrates that investors "price" operational risk into their views on the future profitability of a firm, supporting the contention that the management of operational risk is a core competency for financial institutions.

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