Financial Sector Integration and Information Spillovers: Effects of Operational Risk Events on U.S. Banks and Insurers

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ABSTRACT

This paper presents an event study analysis of the market value impact of operational risk events on non-announcing firms in the U.S. banking and insurance industries. We seek evidence of positive or negative intra or inter-sector spillover effects on stock prices in the commercial banking, investment banking, and insurance industries. The rationale for anticipating inter-sector spillovers is the integration of the previously fragmented markets for financial services that has occurred over the past twenty-five years. We find that operational risk events cause significant negative intra and inter-sector spillover effects. Regression analysis reveals that the spillovers are information-based rather than purely contagious.

1. Introduction

Although financial institutions have been subject to operational risk throughout their history, only since the 1990s has operational risk management attracted significant attention among managers, regulators, and investors. Operational risk can be defined theoretically as the firm's residual risk after core risks, such as market risk, credit risk, interest rate risk, and foreign exchange rate risk are taken into account (Allen and Bali 2007). Broadly defined, operational risk includes strategic risk, reputational risk, and other types of business risk. For regulatory purposes, the Basel Committee defines operational risk somewhat more narrowly as "the risk of loss resulting from inadequate or failed internal processes, people, and systems or from external events" (Basel Committee 2006, p. 144).[1] Operational risk is potentially large enough to threaten the existence of financial institutions.[2]

Interest in operational risk has intensified following several highly publicized and costly events in the 1990s and beyond. Examples of operational risk events include the Nasdaq odd-eighths pricing scandal in 1994, the 1995 bankruptcy of Barings Bank due to a rogue trader, the brokerage firm conflict of interest scandal in 2002, and the 1990s lawsuits against Prudential Financial for misleading sales presentations. More recent events include Wachovia's 2008 write-down for misrepresenting its mortgage underwriting standards, and the 2008 implosion of the Madoff Investment Securities, the largest Ponzi scheme in history. The Basel Committee on Banking Supervision has incorporated a minimum capital charges for operational risk in the Basel II Capital Accord (Basel Committee 2006); major financial institutions have been developing sophisticated operational risk management systems; and ratings firms consider

[1] The Basel definition excludes strategic risk, reputational risk, and systemic risk, as well as market and credit risk, from operational risk, even though an argument can be made that strategic and reputational risk should be included.

[2] De Fontnouvelle, et al. (2006) found that the amount of capital held for operational risk can exceed capital held for market risk. Some types of operational risks such as computer systems failures and liability lawsuits are subject to hedging by purchasing insurance. However, Basel II limits the recognition of insurance risk transfer to a maximum of 20 percent of the operational risk capital charge. Among the concerns about the use of insurance are that insurers could withdraw coverage or default on promised insurance claim payments, triggering financial system instability.

operational risk in assigning corporate financial ratings (Moody's 2003, Fitch 2004).

Recent research reveals that operational loss events have a strong, statistically significant negative stock price impact on announcing firms (Perry and de Fontnouvelle 2005; Cummins, et al. 2006; Gillet et al. 2010; Fiordelisi et al. 2011). Moreover, the market value loss significantly exceeds the amount of the operational loss (Cummins et al. 2006), implying that such losses convey adverse information about future cash flows of announcing firms. Operational risk events also may have significant informational externalities or spillover effects on the stocks of non-announcing financial institutions, either adversely affecting prices through *negative spillover* (*contagion) effects* or positively affecting prices through *positive spillover* (*competitive) effects*.[3]

The objective of this paper is to investigate spillovers by analyzing the impact of operational loss events on the stock prices of non-announcing firms in the U.S. banking and insurance industries. We utilize the Algo OpData database on operational risk events provided by Algorithmics to conduct an event study of the effects of 445 bank events and 158 insurance events during the period 1978-2010 on the stock prices of both announcing and non-announcing institutions. Both intra and inter-sector effects are analyzed for three major segments of the financial services industry – commercial banks, investment banks, and insurers.

The principal hypothesis investigated in this study is that non-announcing financial institutions are vulnerable to negative information externalities attributable to operational risk events from announcing institutions. Such events are hypothesized to cause securities markets to reduce estimates of expected future cash flows at non-announcing institutions, leading to

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[3] Although the earlier literature has referred to negative information externalities (spillovers) as contagion (e.g., Lang and Stulz 1992), in the more recent literature the term contagion usually is reserved for more serious episodes, such as shocks that lead to multiple bank failures, currency crises, or stock market crashes, and often refers to a post-event increases in correlations (e.g., De Bandt and Hartmann 2000, Gande and Parsley 2005). The types of spillovers analyzed here are typically milder but do provide evidence of the transmission of information throughout the financial sector. Although we prefer the term negative information externalities or spillovers, we also occasionally use the term contagion to help link our analysis with the earlier event study literature (e.g., Lang and Stulz 1992, Fenn and Cole 1994, Docking, et al. 1997, and Slovin, et al. 1999).

reductions in market values across the industry. Market value losses could arise for several reasons. Operational risk events may reveal information about the potential for the occurrence of similar events affecting non-announcing firms in the future and/or could reflect higher anticipated regulatory costs. Events also could lead to the loss of current or future customers, departure of key managerial personnel, disruptions of relationships with business partners, or higher costs of capital (Perry and de Fontnouvelle 2005).[4] Such events also could lead to disintermediation if they cause customers to become wary of dealing with financial institutions.

The alternative to the negative information externality hypothesis is the competition hypothesis (Lang and Stulz 1992). The latter hypothesis is that adverse events such as operational losses weaken the announcing institutions and lead to market value gains at competing institutions as customers shift their business away from the announcing firms. Because both contagion and competitive effects may be present, the analysis measures the net effect, i.e., the sum of the contagion and competitive effects on the non-announcing firms.

An important rationale for arguing that information spillover effects may exist in the financial services industry is the integration over the past quarter century of the previously fragmented markets for financial services. Significant integration began during the 1970s, with the introduction of checkable money market mutual funds by securities dealers, the expansion of the commercial paper market, and competition among insurers and banks in the commercial mortgage market. Integration accelerated with the gradual deregulation during the 1980s, which permitted banks to sell insurance and annuities and to engage in securities underwriting through Section 20 subsidiaries.[5] Deregulation culminated in the passage of the Gramm-Leach-Bliley Act

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[4] For example, operational risk events might increase an institution's sensitivity to priced factors such as the financial distress factor in the Fama-French three-factor model (Fama and French 1993) or raise the cost of debt capital by increasing the market's valuation of the firm's default risk. The cost of capital also could increase through a Froot-Stein (1998) mechanism if operational risk events raise the probability that the firm will need to raise costly external capital or increase informational asymmetries between the firm and investors.

[5] Prior to the 1980s, the Glass-Steagal Act of 1933 prohibited commercial banks from engaging in investment

(GLB) in 1999. GLB permitted the formation of financial holding companies (FHC), which can engage in bank and non-bank financial activities through subsidiaries.[6]

This paper considers both intra and inter-sector effects of operational loss events on commercial banks, investment banks, and insurers. Comparing the intra and inter-sector effects provides evidence on the degree of integration of the financial services industry. Firms providing products that serve similar economic needs can be expected to react similarly to informational events, regardless of their nominal industrial category. Thus, studying inter-sector spillover effects provides information on the degree to which commercial banks, investment banks, and insurers are competing with each other in the market for wholesale and retail financial services.

We also distinguish between *pure spillover (contagion)* effects such as bank runs, which involve the indiscriminant re-pricing of all shares, and *information-based spillover* effects, which refer to the informed re-pricing of stock. Cross-sectional regression analysis is used to test for the presence of pure versus information-based effects, utilizing several hypotheses about the relationship between firm characteristics and the anticipated stock price response to operational losses. An information-based effect is indicated if the stock price response varies across firms as predicted by the hypotheses; otherwise, it suggests that a pure spillover effect is present.

This is the first paper to analyze the market value effects of operational risk events on non-announcing firms in any industry. It is also the first to investigate the inter-sector effects of operational risk events within the financial services industry. By way of preview, the results provide evidence of strong negative intra and inter-sector spillover effects within the financial services industry. Investment bank events cause negative information spillovers for both

banking and other non-bank financial activities; and the National Banking Act (NBA) of 1916 prohibited banks from selling insurance. However, more liberal interpretations of the NBA enabled national banks to begin selling insurance in the 1980s; and, beginning in 1985, the Office of the Comptroller of the Currency (OCC) authorized banks to sell certain types of insurance products, including annuities (Carow 2001). In 1987, the Federal Reserve authorized commercial banks to engage in securities underwriting through Section 20 subsidiaries (Geyfman 2005).

[6] These activities include securities underwriting and dealing, insurance underwriting and sales, merchant banking, etc. FHCs are prohibited from owning shares of non-financial corporations and hence are not true universal banks.

commercial banks and insurers, and insurance events have a significant negative effect on both types of banks. Commercial bank events have strong intra-industry spillover effects and significant inter-industry effects on both insurers and investment banks. However, the effect on investment banks is smaller and dissipates more rapidly, consistent with competition among commercial banks and insurers in retail financial markets but more limited penetration of investment banks in traditional commercial banking markets.

The remainder of the paper is organized as follows: Section 2 provides a brief background discussion on operational risk and convergence, and section 3 reviews the prior literature and specifies hypotheses to be tested. The database, sample selection, and methodology are discussed in section 4. Section 5 presents the results, and section 6 concludes.

2. Background on Operational Risk and Convergence

2.1. Background on Operational Risk. Operational risk has attracted increasing attention since the 1990s, following a number of very costly and highly publicized operational risk events. Definitions of operational risk have emerged only recently. As mentioned, operational risk can be defined theoretically as the firm's residual risks after accounting for core risks such as market risk, credit risk, interest rate risk, and exchange rate risk (Allen and Bali 2007). Operational risk includes risks that are idiosyncratic and have the potential to reduce firm value and threaten solvency.

The definition of operational risk promulgated by the Basel Committee is also important because it has been developed in considerable detail and has implications for regulation:

> *Operational risk* is the risk of loss resulting from inadequate or failed internal processes, people and systems or from external events (Basel Committee 2006, p. 144).

The Basel definition includes legal risk, but excludes market risk, credit risk, strategic risk, reputational risk, and systemic risk, even though some of the latter risks would be included under

the residual risk definition.[7] The Basel definition is based on underlying causes of operational risk, broken down into four categories: people, processes, systems, and external factors.[8] Operational risk is one of three risks for which the Basel II Capital Accord requires a minimum capital (the other two are market risk and credit risk).[9]

The increasing attention focused on operational risk over the past several years has been influenced by two key developments: (1) An enhanced emphasis on transparency in firm financial reporting has increased the level of sensitivity in reporting material changes in earnings – including losses arising from operational risk. (2) Increasingly complex production technologies used by financial service firms as a result of technological advances, deregulation, and globalization have raised the exposure to operational risk (Cummins, Lewis and Wei 2006).

2.2. Background on Integration. Although inter-sector competition among financial services firms intensified with deregulation beginning in the 1980s, significant competition existed even prior to the deregulatory wave. Insurers and banks competed for the management of pension plans; and life insurers were major players in the privately placed bond market, in direct competition with the securities underwriting operations of investment banks. During the early 1980s, life insurers introduced single premium deferred annuities (SPDAs) and guaranteed investment contracts (GICs), which are substitutes for bank certificates of deposit; and banks and insurers competed intensively in the commercial mortgage market (Brewer and Jackson 2002). The development of the commercial paper market threatened commercial banks' traditional dominance in business lending. On the retail side, securities firms introduced checkable money

[7] Basel Committee (2006). Legal risk is the risk of loss from litigations, and strategic risk is the risk of loss from decisions or strategies that reach negative results. Reputational risk is the risk of loss from the indirect impact of a direct or "real" loss, i.e. an operational loss (Cruz 2002). Systemic risk is non-diversifiable risk characterized by the break-down of the entire financial system or major components of the system (De Bandt and Hoffmann 2000).

[8] The Committee breaks losses into seven event types and divides the event types into several sub-categories. E.g., embezzlement is a sub-category under internal fraud, and aggressive sales is a sub-category under "clients, products, and business practices" (Basel Committee 2006).

[9] The Accord, which is currently being implemented, is based on three pillars: minimum capital requirements (pillar 1), supervisory review process (pillar 2), and market discipline (pillar 3). See Basel Committee (2006).

market mutual funds during the 1970s, competing with bank demand deposits. Insurers opened their own families of mutual funds beginning in the 1970s, and life insurance and annuities have long competed with retail banking and brokerage accounts as consumer savings vehicles.

An indication of the degree of cross-sector integration that has taken place since deregulation began is provided by data on mergers and acquisitions (M&As). From 1991-2010, there were 487 cross-sector M&As involving commercial banks, investment banks, insurance firms, and securities firms (Thomson ONE Banker 2011). There were 121 transactions where a commercial bank purchased an investment bank and 246 transactions where a commercial bank purchased an insurer or insurance agency. There were 32 transactions where investment banks acquired commercial banks, and 26 transactions involving investment bank acquisitions of insurance firms. Insurers acquired 19 commercial banks and 43 investment banks during this period. Thus, commercial banks have expanded significantly into investment banking and insurance but the retail market expansion of investment banks has been more limited. Insurers have been less active in the M&A market than banks.

Banks have achieved considerable success in the annuity market. In 2009, banks accounted for 28.4% of individual fixed annuity premiums and 10.2% of variable annuity premiums. Banks have preferred to enter the insurance market as sellers rather than underwriters, marketing policies written by unaffiliated insurance companies.[10]

3. Literature Review and Research Hypotheses

3.1 Prior Literature. The negative externality (contagion) effect of an event refers to "the spillover effects of stocks of one or more firms to others" (Kaufman 1994). Contagion has been studied widely in the theoretical and empirical financial literature (for reviews see Flannery 1998 and De Bandt and Hartmann 2000). Analyses have ranged from systemic shocks involving

[10] Based on online data from the Insurance Information Institute (http://www.iii.org).

multiple bank failures, currency crises, and stock market crashes to information spillovers that lead to the revaluation of stock prices but not to widespread failures. Our paper contributes to the latter body of literature. Non-systemic informational spillovers have been analyzed extensively for other types of events. This section discusses the prior papers with the most significant implications for the research presented in this paper.

The pioneering work in contagion event studies is Aharony and Swary (1983), who distinguish between *pure* and *information-based contagion*. Pure contagion is defined as the indiscriminant re-pricing of all shares regardless of the cause of the event or the non-announcing firms' risk characteristics and is generally viewed as an irrational response. Information-based contagion refers to the informed re-pricing of shares, where investors are able to differentiate among firms with different risk characteristics such that only correlated firms experience spillover effects. Pure contagion imposes social costs, while information-based contagion reflects rational revaluation, which generally does not have social costs (Lang and Stulz 1992).

Lang and Stulz (1992) contribute to the spillover literature by introducing the *competitive effect*, which arises if event announcements increase the value of rival firms by redistributing wealth from the announcing firm to its competitors. A competitive effect can occur if customers shift business to rival firms, if the announcing firm is sufficiently weakened due to the event that it cannot respond to predatory moves by competitors, or from other causes.[11] Competitive and contagion effects can be present simultaneously, and the effects are offsetting because the competitive effect is positive and the contagion effect is negative. Thus, the event study results measure the sum of the competitive and contagion effects and reveal which effect is dominant.

These two studies have inspired many studies of information spillovers. Aharony and Swary (1996) provide additional evidence on the information-based contagion effect of bank

[11] The effect cannot occur in a perfectly competitive industry because rival firms will not be able to extract rents under competition. Thus, some degree of market power is needed in order for wealth transfers to rivals to take place.

failures. Docking, Hirschey, and Jones (1997) find significant negative contagion effects for non-announcing money-center and regional banks following loan loss reserve announcements by regional banks. Slovin, Sushka, and Polonchek (1999) show that dividend reductions are negative events for both announcing money-center and regional banks but only reductions at money-center banks have negative contagion effects. Kabir and Hassan (2005) study the near-collapse of Long-Term Capital Management (LTCM) and find that commercial and investment banks with exposure to LTCM lost significant market value around the event.[12]

Several studies also document negative spillover effects in the insurance industry. Fenn and Cole (1994) and Cowan and Power (2001) also identify negative information-based spillovers in the life insurance industry after the asset write down announcement by First Executive Corporation in 1990.[13]

A few papers document inter-industry spillover effects. Slovin, Sushka, and Polonchek (1992) examine share-price reactions to seasoned equity issues of commercial banks and find negative spillover effects on both commercial banks and investment banks. Ghosh, Guttery, and Sirmans (1998) study real estate investment trusts (REITs) and find that REIT stock prices react negatively to announcements of poorly performing real estate portfolios of banks and insurers. Brewer and Jackson (2002) find negative inter-industry spillovers between commercial banks and life insurers in response to adverse information about commercial real estate portfolios.

There are no existing studies of intra or inter-industry spillovers in reaction to operational risk events. This provides the motivation for the present paper, where we analyze information spillovers of operational risk events on U.S. commercial banks, investment banks, and insurers.

[12] Examples of the numerous additional spillover studies include dividend reduction announcements (Bessler and Nohel 2000), open market repurchase announcements (Erwin and Miller 1998), earnings restatements (Gonen 2003), and disclosure of supervisory actions (Jordan, Peek, and Rosengren 2000).

[13] The failure of First Executive was triggered by huge losses from junk-bond and commercial real estate investments (Fenn and Cole 1994). Fenn and Cole (1994) find that the contagion effect was greater for insurers with large holdings of junk bonds, i.e., they provide evidence consistent with information-based spillovers.

3.2. Hypotheses: Intra and Inter-Sector Effects. Informational events can affect non-announcing firms in two ways: (1) stock prices could be positively affected by operational loss events if investors believe that the non-announcing firms are likely to gain at the announcing firms' expense (*the competitive hypothesis*). (2) Stock prices could be negatively affected if event announcements raise suspicion that other firms in the industry confront similar problems, triggering an update of the expected cash flows or capital costs of non-announcing firms (*the negative information externality hypothesis)*. This suggests the first null hypothesis.

Null Hypothesis 1: Announcements of operational loss events have no intra-sector effect. Rejection of the null hypothesis would provide support for either the competitive hypothesis or the negative information externality hypothesis. The intra-industry analysis is conducted separately for the commercial banking, investment banking, and insurance industries.

If the financial services industry is integrated, operational risk events are expected to have cross-sector spillover effects. As discussed above, there has long been competition between commercial banks, investment banks, and insurers in the markets for both wholesale and retail financial services. To the extent that products offered by the three types of intermediaries can be used to achieve the same financial goals, inter-industry information spillover effects are expected. An announcement of operational losses by one type of intermediary could have an adverse impact on other types of intermediaries if the announcement raises suspicions about common practices across sectors or leads to general disintermediation. On the other hand, there also could be a competitive effect if customers shift their business from troubled institutions to other types of intermediaries in response to operational loss announcements.

Although financial sector integration provides a plausible rationale for predicting inter-sector information spillover effects, spillovers between the two types of banks and between banks and insurers will not necessarily be uniform. The regulatory environment and business

models of investment banks continue to differ significantly from those of commercial banks, and most investment banks do not offer traditional commercial banking products such as loans and deposits. Hence, it would not be surprising to observe different inter-sector responses for commercial and investment banks. Because commercial banks have achieved greater penetration in retail insurance markets than have investment banks, commercial banks may be more likely to be affected by insurance operational loss events than investment banks. Because insurers offer both wholesale and retail products, it is not clear whether commercial or investment bank events will have a stronger impact on insurers. This discussion suggests the second null hypothesis:

Null Hypothesis 2: Announcements of operational loss events have no inter-sector effect. The alternative hypotheses are the competitive and the negative information externality hypotheses. Because there are three types of events (commercial bank, investment bank, and insurance), each of which could have inter-sector effects, there are six opportunities to reject the null in favor of the alternative hypotheses.

3.3. Hypotheses: Pure versus Information-Based Effects. Pure spillover effects occur when investors perceive that non-announcing firms are similarly affected regardless of differences in firms' characteristics and the cause of the events. Pure spillovers are more likely when the ability of the market to differentiate among firms is low. Information-based spillovers occur when events affect only firms whose cash flows are highly correlated with those of the announcing firm. Information-based spillovers are more likely when information is accurately and readily available to enable investors to discriminate among the non-announcing firms (Brewer and Jackson 2002). In today's market, vast amounts of information are conveyed to the market in an accurate and timely fashion. Thus, it is reasonable to believe that spillovers to non-announcing firms depend on firm characteristics, implying an information-based spillover effect. We next develop hypotheses to distinguish between pure and information-based spillovers.

If spillover effects are present, the loss amount from the operational loss event can potentially indicate the possible size of the operational risk exposure in non-announcing firms. Large events are also less frequent and hence more likely than smaller events to convey new information to the market. Thus, the larger are the operational loss events, the larger should be the magnitude of the loss in market value for non-announcing firms. If there is a competitive effect, the larger the event, the larger should be the magnitude of the gain in market value for the rival firms. This suggests the following hypothesis:

> **Null Hypothesis 3**: The loss amount or size of the operational loss event has no relationship with the market value impact on non-announcing firms in the industry.

If announcements of operational events convey adverse information about the future cash flows of non-announcing firms, such announcements may lead to increases in the cost of capital and/or reduce the expected value of future internal capital available for investment in new projects. Such effects are especially problematical if external capital is more costly than internal capital (Froot, Scharfstein, and Stein 1993). These effects are expected to have a stronger impact on firms with relatively strong growth prospects because such firms may have to forego positive net present value projects if they are hit by future operational events. Thus, we predict a direct relationship between non-announcing firms' growth prospects and the stock price response to operational loss events and specify the following null hypothesis:

> **Null Hypothesis 4:** The response of non-announcing firms' stock prices to operational losses is independent of the firms' growth prospects.

The relationship between operational loss events and the wealth effect on non-announcing firms is also likely to depend on leverage. On the one hand, announcements are predicted to have more damaging effects on firms with relatively high leverage (low equity-to-assets ratios) because firms with low equity-to-assets ratios are more likely to encounter financial distress when hit by events of similar magnitude. On the other hand, the "deep-pocket" theory of

liability implies that richer firms with higher equity-to-assets ratios are more likely to become targets of lawsuits, which would increase the likelihood of a loss. Option-pricing theory also predicts that a firm's stock price is more sensitive to new information if it has a high equity-to-assets ratio. Thus, financial distress theory predicts an inverse relationship between the equity-to-assets ratio and the wealth response, while deep-pockets and option-pricing theory predict the opposite. The empirical analysis measures the net effect and thus can determine which prediction dominates. This discussion suggests the following hypotheses:

> **Null Hypothesis 5**: The response of non-announcing firms' stock prices to operational losses is independent of the firms' leverage.

Rejection of one or more of the last three hypotheses would provide evidence of information-based spillovers, with the strength of the evidence related to the number and strength of the rejections. If none of the hypotheses is rejected, the results would suggest pure spillover effects.

4. Database, Sample Selection, and Methodology

4.1. The Database. This study utilizes operational loss events from the Algo OpData database compiled by Algorithmics. The data are collected from public sources worldwide. OpData provides event dates as well as descriptive information on the events.[14] The version of OpData used in this study has historical events from 1978 through 2010.[15] Although the database includes losses from other countries, two-thirds of the reported losses are from the U.S. Moreover, de Fontnouvelle, et al. (2006) concluded that the non-U.S. losses are significantly different in magnitude and distribution from the U.S. losses. Accordingly, we focus on the U.S. operational loss events.

OpData reports all publicly announced losses that exceed a threshold of $1 million. We

[14] The event date in OpVar is the original announcement date, i.e., the earliest announcement of the event. The loss amount is the originally announced loss amount rather than the ultimate settlement amount. Although OpData includes losses for various industries, we focus on the bank and insurance events.
[15] However, 97% of the events occurred during the period 1985 through 2010, providing the opportunity to investigate the effects on financial firms during the period when financial sector integration was at its height. I.e., all of the events from 1978-2010 were used in the study but 97% occurred from 1985-2010.

chose to conduct the event study using relatively large losses, defined as losses of at least $50 million, because relatively large losses are more likely to be considered "material" under accounting standards and therefore more likely to affect stock prices. Such losses are also more likely to have an impact on the value of non-announcing firms than smaller losses because high frequency, low severity losses to a large extent are anticipated events that are already incorporated in a firm's expense budget and therefore embedded in current stock prices.[16]

4.2. Summary Statistics. Summary statistics on the U.S. operational loss events of at least $50 million are shown in Table 1.[17] There are 445 bank events and 158 insurer events of this magnitude in the database.[18] Among the bank events, 290 events were incurred by commercial banks and 155 by investment banks. The average operational loss for banks is $450.5 million, compared to $324.8 million for insurers, while the medians are $112.7 million for banks and $123.7 million for insurers. The maximum loss for banks is $55.0 billion (the Madoff Ponzi scheme), and the maximum loss for insurers is $9.5 billion (The AIG credit default swap write-down).

Table 1 classifies operational losses by event type, using the Basel II category definitions. Internal and external fraud represent 40.6% of the operational loss events for commercial banks but only 21.3% for investment banks and 9.5% for insurers. Clients, products, and business practices also generate a substantial number of operational loss events for financial institutions, representing 51.7% of events for commercial banks, 71.6% for investment banks, and 78.5% for insurers. Deceptive sales practices account for 24.7% of events for insurers and 21.3% for

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[16]As a robustness check, we also conducted the analysis for all events of $10 million or larger. As expected, the average magnitude of the event study results is smaller compared to analysis using only events of $50 million and above. However, the analysis supports similar conclusions.

[17] For a more comprehensive analysis of the loss events in OpVar, see Cummins, Lewis, and Wei (2006).

[18] The spillover analysis allows the use of a much larger sample than the sample used in Cummins, Lewis, and Wei (2006) or Perry and de Fontnouvelle (2005). Many of the banking and insurance operational loss events in the OpVar database were incurred by non-traded stock firms and mutuals. In the spillover analysis, we not only capture more events, because the events affecting non-traded announcing firms can be included, but the sample of firms on which the analysis is conducted is also much larger because it consists of all non-announcing firms with valid data.

investment banks but represent only 7.6% of events for commercial banks. This perhaps reflects the relatively less complex products offered by commercial banks to consumers. At the median, insurer deceptive sales events are larger than for either type of bank.

4.3. Sample Selection. The sample of operational loss events used in this study consists of all U.S. events of at least $50 million in the OpData database.[19] To study the spillover effect of these events, we select all non-announcing banks and insurers around the time of each event that were traded on the NYSE, AMEX, or Nasdaq. The commercial banking sample includes firms categorized as SIC 6021, 6022, and 6029, i.e., commercial banks were included but thrifts and credit unions were excluded.[20] The commercial bank category also includes bank holding companies (SIC 6710, 6711, and 6712). The investment bank category consists of SIC 6211, Security Brokers, Dealers, and Flotation Companies, as well as firms in SIC 6282 which provide securities broker-dealer services.[21] The insurance sample consists of SIC 631, life insurance, and 633, fire, marine, and casualty insurance.[22] That is, health insurers, mono-line specialty insurers such as title insurers, and insurance agents were excluded from the sample in order to focus on insurance underwriters who perform significant intermediation functions.[23]

4.4. Methodology. The event-study analysis seeks to assess the market reaction of non-announcing firms to operational loss events of announcing firms. To measure abnormal returns,

[19] We carefully checked the observations in the database to verify the events, loss amounts, and event dates by searching several different on-line indices of business and financial publications. Four bank events were eliminated because we were unable to verify the event, event date, or loss amount. No insurance events were eliminated.

[20] The results of robustness tests on savings and loans (S&Ls) and other non-bank and non-insurance financial institutions are discussed following the presentation of the main results.

[21] We use the term "investment banks" to apply to all firms selected from SIC 6211 and 6282, primarily for convenience, even though there is considerable heterogeneity in the range of services provided by these firms. Oil and gas lease brokers were excluded from SIC 6211, and firms that exclusively provide investment advice rather than serving as broker-dealers were excluded from SIC 6282.

[22] All SIC assignments were checked carefully for errors, and misclassified firms were reclassified or deleted from the sample. E.g., SIC 602 includes some firms that are actually thrift institutions rather than commercial banks, and some insurance companies and non-financial holding companies appear in 6711.

[23] Although the insurer sample is nominally segmented into life-health (L-H) and property-liability (P-L) insurance, nearly all of the traded insurers that constitute our sample are active in both industry segments. In extensive preliminary analysis, we did not find statistically significant differences between firms that were nominally classified as L-H (SIC 631) versus P-L (SIC 633) insurers. Accordingly, we do not distinguish between the two categories of insurers in the results presented in the paper.

we conduct a standard event study utilizing the market model. We also conducted robustness tests by estimating the model using GARCH. Because the event-study methodology is well-known, it is briefly sketched here, with details provided in the Appendix. The following discussion focuses primarily on a specific estimation issue encountered in this study.

To estimate abnormal returns for an event, data are collected 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 market model is given by the following equation:

$$R_{ijt} = \alpha_{ij} + \beta_{ij} R_{mt} + \varepsilon_{ijt} \tag{1}$$

where R_{ijt} is the return on security i for event j on day t, R_{mt} is the CRSP equally-weighted market return on day t, α_{ij} and β_{ij} are parameters to be estimated, and ε_{ijt} is the error term of the regression. The estimation period for equation (1) is the 250-day period ending the day before the event windows (defined below).[24]

Using the parameters estimated from the market model, the daily abnormal returns (AR) are calculated for each event 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. The abnormal return on day t in the event window for stock j is the estimated disturbance term of the market model. The average abnormal returns and cumulative abnormal returns are calculated in the usual way (see Appendix).

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 10 trading days prior to each event and extending 10 trading days after for all bank events and in a window beginning 15 trading days prior to each event and extending 15 trading days after for all insurance events, i.e., the windows for the bank and insurance events are

[24] The estimation period used in this paper is the standard length in the event study literature (Binder 1985).

(-10,+10) and (-15,+15), respectively. A longer window was used for the insurance events because preliminary analysis revealed a longer post-event response period for insurance events than for bank events, consistent with Cummins, Lewis, and Wei (2006). 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 ±10 and ±15 day windows.

An important estimation issue encountered in this study is *event clustering*. There are two sources of clustering: (1) Some events are announced on the same day; and (2) since we pair each event with all traded non-announcing firms that are not directly affected by that event, there is clustering within each event in the sample.[25] Accordingly, we employ significance tests that are robust to event clustering. The first test is Jaffe's (1974) *calendar time t-test,* which corrects for the cross-sectional dependence caused by clustering. The abnormal returns of non-announcing firms are placed into portfolios according to event date, i.e., all events that occurred on the same day are grouped into one portfolio. Thus, the calendar time t-test controls for both sources of cross-sectional correlation. The test does not change the mean but only the standard deviation of the average cumulative abnormal returns. The second test used to control for clustering is the variance-adjusted Z-statistic, which controls for the possibility of event-induced variance increases around event days and also has been shown to have good properties when clustering exists in the sample (Boehmer, Musumeci, and Poulsen 1991).

A nonparametric test, Cowan's (1992) generalized sign test, is also conducted to ensure that the parametric test results are not driven by outliers. This test is also well-specified when the variance of stock returns increases around the event day and when there is event-clustering.

5. Event Study Results

This section first presents the intra-industry results for banks and insurers and then

[25] Of the 247 bank events, 84 are announced on the same days as one or more other bank events. Among the 91 insurance events, 20 are announced on the same days with one or more other insurance events.

discusses the inter-industry impact of bank events on insurers and insurance events on banks.

5.1. Intra-Industry Event Study Results

5.1.1. Effect of bank operational loss events on non-announcing banks. Panel A of Table 2 presents the mean and median cumulative abnormal returns (CAR) for the effects of commercial bank events on non-announcing commercial banks (Panel A.1) and non-announcing investment banks (Panel A.2); and Panel B presents the CARs for the effects of the investment bank events on non-announcing commercial banks (Panel B.1) and non-announcing investment banks (Panel B.2). We focus the discussion on the mean CARs.

Panel A.1 of Table 2 shows that the commercial bank operational loss events have a significant negative effect on the market values of non-announcing commercial banks and thus support the hypothesis of negative information spillovers. The mean CAR on the event day is -0.04%, which is statistically significant based on all three tests. The cumulative abnormal returns are larger in absolute value for the wider windows, -0.24% for the (-5, +5) window and -0.39% for (-10, +10) window, both of which are statistically significant based on at least two of the three tests.

Most of the action in terms of the mean CAR takes place after the event day. The mean CAR for the pre-event (-10, -1) window is -0.04%, suggesting some information leakage before the event day. The cumulative abnormal returns for (-1, +10) window is -0.30%, significant based on all three tests. Thus, significant information also "trickles out" after the event day.

Panel A.2 of Table 2 shows the effects of the commercial bank events on non-announcing investment banks. The event day and (-1,+1) CARs are negative and significant by all three tests, and the reaction for both windows is larger than for the commercial banks (-0.09% and -0.17%, respectively, versus -0.04% and -0.02% for the commercial banks). However, unlike the commercial bank reaction, the investment bank response dissipates rapidly, and the CARs for the

wider windows tend to be mostly insignificant. Thus, the commercial bank events have negative spillover effects for both commercial banks and investment banks, but the investment banks tend to recover more rapidly.

Panel B of Table 2 shows that the investment bank events have strong and significant negative spillover effects on both non-announcing commercial banks and non-announcing investment banks. For the event day and the (-1,+1) window, the effect on investment banks is stronger than the effect on commercial banks, but both types of banks exhibit negative information externalities. The mean CAR for the event day is -0.04% for non-announcing commercial banks and -0.12% for non-announcing investment banks, and the CAR in the (-1,+1) window is -0.12% for commercial banks and -0.35% for investment banks. These CARs are statistically significant according to at least two of the three test statistics. Interestingly, there seems to be some positive information leakage prior to the event date. In the (-10,-1) window, the impact on commercial banks is 0.24% and the impact on investment banks is 0.37%, perhaps providing some evidence of a competitive effect, such that the net effect in the widest window (-10,+10) is a small positive percentage which is only weakly significant.

These results reject Null Hypothesis 1 for the commercial banking and investment banking sectors within the banking industry, i.e., there is evidence of a significant intra-sector effect in banking. The results also generally reject Null Hypothesis 2. There is an inter-sector effect from investment to commercial banks and from commercial to investment banks. For the commercial bank events, the inter-sector spillovers are predominantly negative, whereas there is some evidence of positive spillovers prior to the event day for the investment bank events.

Table 2 shows that the effect of commercial bank events on investment banks dies out quickly, whereas the investment bank events significantly affect both commercial and investment banks in both the narrow and wider windows. We suggest two main explanations for this pattern.

First, many commercial banks offer investment banking products through investment banking subsidiaries, whereas most investment banks do not provide traditional commercial banking depository and lending services. Thus, investment bank events are likely to affect numerous commercial banks with investment units, but many operational loss events incurred by commercial banks are less applicable to investment banks (e.g., embezzlement, loan fraud).

Second, commercial banks and investment banks operate under very different regulatory environments. National commercial banks are regulated by the Federal Reserve and the OCC, and state chartered banks are regulated by state banking authorities. Nearly all commercial banks are federally insured and hence regulated by the Federal Deposit Insurance Corporation (FDIC). Investment banks, on the other hand, are primarily regulated by the Securities and Exchange Commission and thus are generally subject to less stringent regulatory scrutiny. Thus, a given operational loss event might induce more regulatory attention if it is incurred by a commercial bank as opposed to an investment bank. Hence, both commercial and investment bank stocks respond negatively to commercial bank events, but the effects are more long-lasting for non-announcing commercial banks. This pattern is consistent with information-based spillovers because investors are able to differentiate non-announcing firms' exposure across sectors.

5.1.2. Effect of insurance operational loss events on non-announcing insurers. Panel A of Table 3 presents the CARs in response to insurance events for all non-announcing insurers. The table shows that operational loss events have a strong negative spillover effect on the market value of the non-announcing insurers, rejecting Null Hypothesis 1 for insurers. The CAR on the event day is near zero and not statistically significant. However, in the (-1,+1) and most of the wider windows, the CARs are negative and statistically significant. The CAR in the (-1,+1) window is -0.14%, and the CAR in the (-15,+15) window is -0.58%, most of which is generated in the period (-1,+15). Hence, there is little evidence of leakage for the insurance events.

5.2. Inter-Industry Event Study Results

In this section, we present event study results for inter-industry effects of bank events on insurers and insurance events on banks. A finding of strong inter-industry spillovers would provide evidence of integration between the banking and insurance components of the financial services industry.

5.2.1. Effect of insurance operational loss events on banks. The CARs for the impact of insurance events on commercial banks are shown in Panel B of Table 3. There is a small positive CAR on the event day, but the CARs are negative for the wider windows. The CAR for the (-1,+1) window is -0.08, significant by the variance adjusted z-statistic. The CARs for the wider windows are larger, e.g., for (-15,+15) the CAR is -.83%, significant by two out of three tests. There is significant information leakage prior to the event day. E.g., the CAR from (-15,-1) is -0.33, and the CAR from (-1,+15) is -0.53. The findings are supportive of negative intra-industry spillovers and thus reject Null Hypothesis 2. Comparing Panels A and B of Table 3, the impact of insurance events on commercial banks is similar in pattern and magnitude to their impact on non-announcing insurers, providing further evidence of financial sector integration.

Panel C of Table 3 shows the CARs for the impact of insurance events on investment banks. The mean CAR is -0.19% for the event day, which is significant by two of three tests. The mean CAR for (-1,+1) is similar (-0.20%), also significant by two of three tests. However, for the wider windows the CARs are smaller in absolute value and often insignificant. The CAR for (-10,+10) is even positive, primarily due to information leakage during (-10,-1). Therefore, on balance the impact of insurance events on investment banks provides evidence of negative information spillovers, but there is also some evidence of a competitive effect.

For the wider windows, insurance events have more impact on commercial than on investment banks. This pattern is expected and consistent with information-based contagion

because commercial banks have expanded more widely into insurance than investment banks.

5.2.2. Effect of bank operational loss events on insurers. Panels A and B of Table 4 present CARs measuring the impact of commercial and investment bank events on non-announcing insurers. The results reveal that both commercial and investment bank operational loss events have significant negative information spillover effects on the market value of insurers and that the magnitudes of the CARs from the two types of bank events are similar. The mean CAR on the event day is -0.03% for both commercial and investment bank events, significant by the variance adjusted z and non-parametric tests. The cumulative abnormal returns are larger in absolute value for the wider windows, e.g., in the (-1, +10) window, the CAR is -0.34% for commercial bank events and -0.32% for investment bank events. The former is significant by the variance adjusted Z-statistic and the calendar time t-test, and the latter is significant by all three tests. The (-1,+10) CARs for the bank events on insurers are almost identical to the CARs in the same window for the insurance events (-0.35%, Panel A of Table 3), implying that insurer stocks respond similarly to bank and insurance announcements and suggesting a high degree of integration in the financial sector. Reinforcing this inference, the impact of commercial bank events on commercial banks and the impact of investment bank event on investment banks (Table 2) are similar in magnitude to the impact of bank events on insurers (Table 4).

Although most insurers do not have federally insured banking subsidiaries, many insurers do have investment banking, mutual fund, and securities dealing operations. In addition, as mentioned, insurers compete directly with both commercial and investment banks for a wide-range of personal and commercial financial products. Although this might suggest a competitive effect, bank events could signal problems with financial institutions in general, triggering disintermediation. The negative net effect suggests that adverse reputational damage to the sector in general dominates any competitive effects that may be present. Thus, the results reject Null

Hypothesis 2 with respect to the impact of bank events on insurers – there are significant negative inter-industry spillovers from banks to insurers.

5.2.3. Summary. In summary, the results reject null Hypotheses 1 and 2 and provide significant evidence of both intra and inter-industry negative information spillover effects caused by operational loss events in the U.S. banking and insurance industries. Some of the patterns in the inter-industry spillovers provide evidence consistent with information-based spillover effects. Next we conduct multiple regression analysis to provide further evidence on whether the observed effects represent pure or information-based spillovers.

5.3. Testing For Pure Versus Information-Based Spillovers

We estimate regression models to test Hypotheses 3, 4, and 5. Briefly, these hypotheses are, respectively, that the size of operational loss events, a firm's growth opportunities, and a firm's equity-to-assets ratio are unrelated to the stock price reaction of non-announcing firms. In addition to variables specifically designed to test the hypotheses, the regressions also include several variables to control for other firm and event characteristics such as size and whether the events represent deceptive sales practices. To be consistent with information-based spillover effects, the stock price response of non-announcing firms should be correlated with some of the event and firm characteristics. A finding of no relationship with any event or firm characteristics would provide evidence of pure rather than information-based spillovers.

The dependent variable in the regressions is the percentage change in equity value, i.e., the cumulative abnormal returns (CARs) for the non-announcing firms. Separate cross-sectional regressions are conducted for insurers and banks, and separate regressions are conducted for the commercial and investment bank events. The CARs in the (-10, +10) window are the dependent variables for the bank events, while the CARs in the (-15, +15) window are the dependent variables for the insurance events, reflecting the longer post-event response time to the insurance

operational risk events.[26] Weighted least squares is used to control for heteroskedasticity.[27]

The independent variable to test Hypothesis 3 is the log of the loss amount. A statistically significant coefficient on this variable would imply that operational losses of announcing firms convey information about possible exposure to similar events for other firms and lead to the rejection of Hypothesis 3. A significant negative coefficient would imply that larger operational loss events induce higher revisions of future expected losses for non-announcing firms, and a significant positive coefficient would imply that there is a competitive effect.

The measure of growth opportunities to test Hypothesis 4 is the firm's Tobin's Q ratio, derived from Compustat data. Firms with relatively strong growth opportunities tend to have higher Q values. Our proxy for Q is the market value of equity plus the book value of liabilities, divided by the book value of assets in the quarter preceding the event.[28] A significant negative coefficient on Q would imply that operational loss events have more severe effects for non-announcing firms with relatively strong growth prospects. Such firms may have to forgo profitable projects or pay higher costs of capital to raise funds externally in the event of future operational losses, thus reducing firm value.

The variable used to test Hypothesis 5 is the equity-to-assets ratio, defined as the book value of equity divided by the book value of assets in the quarter prior to the event, from Compustat. The equity-to-assets ratio is a proxy for the firm's insolvency risk. Recall that the expected sign of this variable is ambiguous. Financial distress theory predicts that stock prices of

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[26] Regressions based on CARs for other windows produced similar results.
[27] Since there is event clustering in our sample, cross-sectional dependence can potentially bias the standard errors. Karafiath (1994) utilizes simulations to show that correcting the least squares estimator to account for heteroskedasticity and cross-sectional correlation seems to have no marginal benefit relative to the OLS covariance matrix. The author shows that for a sufficiently large sample, there is no advantage to using the more complex estimators, e.g., the feasible generalized least squares (FGLS) estimator, as oppose to the ordinary least squares estimator. Furthermore, even when the FGLS estimator is well specified, it is not more powerful than the simple weighted least squares estimator.
[28] Using the book value of assets is appropriate for financial institutions because the carrying value of their assets is a much closer approximation to the replacement cost than would be the case for industrial firms; and, in any event, other proxies for replacement costs are not available.

firms with higher equity-to-assets ratios should be less sensitive to operational loss events, while "deep pockets" liability and option-pricing arguments suggest that firms with higher ratios will be more sensitive. A significant positive coefficient on the equity-to-assets ratio would imply that operational loss events have a more damaging effect on firms with low equity-to-assets ratios, consistent with financial distress theory. A significant negative coefficient would suggest that the deep-pockets liability and option-theory explanations dominate financial distress.

To test whether deceptive sales events differentially affect value, a dummy variable is utilized, set equal to 1 for deceptive sales events and to 0 otherwise. To analyze separately the effects of commercial and investment bank deceptive sales events, this variable appears in some regressions interacted with a dummy variable for investment bank events. A significant negative (positive) coefficient on this variable would imply that the market believes that deceptive sales events reduce expected future cash flows more (less) than other events.

To measure the intra-industry effect of bank events, three dummy variables are included to capture the differential effect of commercial bank and investment bank events.[29] Dummy variables set equal to 1 for commercial and investment banks, respectively, and to 0 otherwise, also are included to test the intra-sector effect vs. the inter-sector effect. The insurance regressions include a dummy variable for life insurers to test for a differential reaction of operational loss events between life and property-liability (P-L) insurers. It is equal to 1 for insurers with SIC code 6311 (life insurers) and 0 for insurers with SIC code 6331 (P-L insurers). For the effect of insurance events on banks, we include a dummy to test whether commercial banks are significantly more adversely affected compared with investment banks. Finally, the natural log of the market value of equity is included as a control variable to represent firm size.

[29] ComEvtComBank = 1 if CAR is a commercial bank response to a commercial bank event, 0 otherwise; InvEvtComBank = 1 if CAR is a commercial bank response to an investment bank event, 0 otherwise; InvEvtInvBank = 1 if CAR is an investment bank response to an investment bank event.

The regression results appear in Table 5, where Panels 1 to 4, respectively, show the impact of all bank events on all non-announcing banks, the impact of commercial bank events on all non-announcing banks, the impact of investment bank events on all non-announcing banks, and the impact of bank events on insurers. Panels 5 and 6, respectively, show the regression results for the impact of insurance events on non-announcing insurers and banks.

The findings reject Null Hypothesis 3 for both the bank and the insurance events. The coefficient on the log of loss amount for bank events is positive and significant in Panels 1 through 4. The coefficient of the log of loss amount is also positive and significant in Panel 6, showing the effect of insurance events on banks. Thus, larger announced bank losses produce significantly less negative stock returns for non-announcing banks and insurers after controlling for other factors, and the effect of insurance events on banks is similar. The results thus provide significant evidence of a competitive intra and inter-industry effect for bank events and a competitive inter-industry effect for the insurance events. By contrast, the log of loss amount in the regression for the effect of insurance events on insurers (Panel 5) is negative and significant. Thus, larger announced insurer losses result in more negative returns for non-announcing insurers, reinforcing the inference that insurance losses cause negative intra-industry spillovers.

Null Hypothesis 4 is rejected in all panels: the coefficients of the Q ratio variable are negative and statistically significant at the 1% level for all bank events and insurance events, implying that non-announcing firms with higher Q-ratios are more adversely affected by operational loss events. Thus, operational loss events of announcing firms have a greater adverse impact on the market value of non-announcing firms with strong growth prospects. This is consistent with the view that such firms may have to forego attractive projects or pay higher capital costs to finance new projects following potential future operational loss events.[30]

[30] According to Fama and French (1993), book to market equity is a risk factor, which has a positive correlation with

Null Hypothesis 5 is rejected for banks but not for insurers. The coefficients of the equity-to-assets ratio variables are positive and statistically significant at the 10% level or better in Panels 1, 2, 3, and 6. Thus, non-announcing banks with high equity-to-assets ratios are less negatively affected by operational loss events, consistent with larger negative information spillovers for firms with higher default risk, supporting the financial distress hypothesis. The equity-to-assets ratio is statistically insignificant in the regressions for the effect of bank events on insurers and for insurance events on insurers. Thus, neither the financial distress nor the deep pockets/option pricing hypothesis is supported for insurers.

Insurance deceptive sales events have a significantly larger negative impact on non-announcing insurers than other types of operational loss events (Panel 5 of Table 5). This supports the inference that insurance deceptive sales events affect stock prices of non-announcing insurers differently from other types of events. The coefficient of the deceptive sales dummy implies that the market value loss for non-announcing insurers due to insurance deceptive sales events is 2.0% greater than the loss from other events, controlling for other variables in the equation. The insurance deceptive sales variable also has a significant negative coefficient in the regression measuring the effect of insurance deceptive sales on banks, implying market value losses 1.3% greater than for other types of events. Thus, insurance deceptive sales events have significant adverse effects on both insurers and banks.

Commercial bank deceptive sales events have a significant negative effect on non-announcing banks (panel 2), and bank deceptive sales events have a significant negative effect on insurers (Panel 4); but the implied effects are much smaller than for the insurance deceptive

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equity returns. Firms with low book to market equity will have high Q ratios. The abnormal returns in this paper are the excess returns from a market model which does not take into account book to market equity as a risk factor. Thus, under the market model, firms with low book to market equity would have higher predicted returns than if the risk factor were considered, which would lead to abnormal returns with higher magnitude. This could induce a spurious negative relation between the Q ratio and the CARs. As a robustness check, the regression model was also estimated with CARs from the Fama-French three-factor model, which produces excess returns net of the book to market equity factor. The results provide qualitatively similar results on the Q ratio variable.

sales events. Investment bank deceptive sales events have a significant positive effect on non-announcing banks. Moreover, the interaction between the investment bank event and deceptive sales dummy variable in Panels 1 and 4 implies that investment bank events have a net positive impact in these regressions. Therefore, there is evidence of positive information spillovers from investment bank deceptive sales events, implying the existence of a competitive effect. Thus, investment bank deceptive sales events may cause buyers to shift business to competing institutions. The investment advice conflict of interest scandal of 2002, which is included in our sample, is an example of an event that may have had such an effect.

For the impact of commercial bank events on non-announcing banks in Panel 2, the commercial bank dummy has a statistically significant negative coefficient, implying that commercial bank events have a more adverse impact on non-announcing commercial banks than on investment banks. For the impact of investment bank events on non-announcing banks in Panel 3, the investment bank dummy is statistically insignificant, implying that investment bank events do not affect non-announcing investment banks more than commercial banks. These results provide evidence that the intra-sector spillover effect is stronger than the inter-sector spillover effect for commercial banks but not for investment banks.

The investment bank event dummy variable is statistically significant and negative in the regression for the insurer reaction to bank operational loss events (Panel 4), suggesting that investment bank events have stronger spillover effects on insurers than commercial bank events. However, in the regression for the impact of insurance events on banks (Panel 6), the commercial bank dummy is negative and significant, providing evidence that insurance events have a stronger negative spillover effect on commercial banks than on investment banks. This asymmetrical response reflects market realities. Because most insurers do not offer traditional commercial banking products, they are not exposed to many commercial bank events; whereas

insurers are heavily involved in wholesale financial services. On the other hand, commercial banks rather than investment banks are the major players in bank expansion into retail insurance markets and thus are affected more strongly by insurance events. These results provide evidence of information-based spillovers because they suggest that investors are able to differentiate the varying degrees of exposure of banks and insurers to different types of operational losses.

The life insurer dummies in the regressions for the impact of bank events and insurance events on non-announcing insurers in Panels 4 and 5 are not statistically significant, implying that life and P-L insurers do not have a differential reaction to operational loss events. Finally, the log of the market value of equity is negative and significant in Panels 3 through 6, negative but insignificant in Panel 1, and positive and significant in Panel 2. This implies that larger firms have a stronger market value loss in percentage terms than smaller firms, except for commercial bank events, where larger firms have smaller losses. This is consistent with the argument that large organizations tend to be relatively complex and hence are more susceptible to operational risk events than smaller, less complex organizations. The commercial bank event result (Panel 2) perhaps indicates that many commercial bank events carry stronger implications for smaller firms, perhaps given the relatively smaller size of many commercial banks.

The regressions reveal the existence of significant relationships between the independent variables and the market value response of firms to operational loss events. The results thus support the argument that the spillover effects identified by the event study have significant information-based components, as opposed to being pure spillover effects. The market is able to distinguish among firms and events in a way that makes sense in terms of economic hypotheses.

5.4. Robustness Tests

To test the robustness of the results and to provide support for the interpretation of the findings in terms of spillovers and integration, we conducted several robustness tests. This

section briefly discusses the results of these tests.

The first robustness test involved an event study of the effects of the bank and insurer operational losses on firms in financial industries other than commercial banking, investment banking, insurance, and thrift institutions. This category includes firms such as real estate firms, non-depository credit institutions, mortgage bankers, commodity dealers, and exchanges. Because most insurers and banks compete less directly with such firms, there is no reason to expect spillover effects from bank and insurance operational loss events. The second robustness test analyzed the effects of bank and insurance operational loss events on industrial firms. The sample of industrials consisted of all firms outside of the finance, insurance, and real estate sector (SIC categories other than groups 61 through 65 and 67). Again, there is no reason to expect spillover effects from the bank and insurance events into the industrial sector of the economy. This expectation was borne out in both robustness checks – the bank and insurance operational loss events have no significant spillover effects on non-bank and non-insurance financial firms or industrials, supporting the interpretation of the main results of the study as providing evidence of spillovers and integration in the banking and insurance industries.

The third set of robustness tests provided a more detailed analysis of the effect of the operational loss events on non-announcing firms in different size categories. Even though there are some very small firms in the announcing firm sample, many of the announcing firms are relatively large, i.e., above the seventy-fifth size percentile in market capitalization. Because our objective is to focus on the effects of operational loss events on non-announcing firms in the financial services sector, broadly defined, we have reported the results from our overall sample of non-announcing firms in Tables 2 through 5. However, in view of the regression finding that the market value losses to non-announcing firms are directly related to firm size, we conducted additional robustness checks based on firm size. Specifically, we reran all of the event study

tests on two additional samples – the top 50% and top 25% of non-announcing firms.

The results of the size robustness checks can be easily summarized – consistent with the regression finding with respect to size, the mean CARs tended to become somewhat larger as the smaller firms are eliminated from the sample, i.e., the mean CARs are smallest for the full sample and largest for the non-announcing firms in the top size quartile.[31] However, size stratified results have the sample implications as the full sample results in terms of the overall conclusions to be drawn from the analysis.

The fourth set of robustness checks reestimated all of the event study models using the GARCH specification. These results support are very similar in terms of CARs and statistical significance levels to the results shown in Tables 2 through 5.

6. Conclusions

This paper analyzes the market value effects of operational loss events on non-announcing firms in the U.S. banking and insurance industries. The paper is motivated by increasing attention devoted to operational risk by managers, regulators, shareholders, and rating agencies. Bank and insurance events are expected to have intra and inter-industry spillover effects on other financial services firms because of the integration of the previously fragmented segments of the financial sector that began in the 1970s and accelerated with deregulation in the 1980s and 1990s. Financial services firms now do business across sectors – commercial banks have entered the investment banking and insurance markets, and insurers offer a variety of wholesale and retail financial products. The two principal hypotheses investigated in the study are the *negative information externality hypothesis*, i.e., that operational risk events have a negative spillover effect on stock prices of non-announcing firms, and the *competition hypothesis*,

[31] We also conducted the analysis for the smallest 50% of non-announcing firms. The results confirm that the effect of the operational loss announcements is statistically significant but somewhat smaller for this group of firms than for firms above the median.

i.e., that operational events lead to wealth transfers from announcing to non-announcing firms.

We analyze spillovers by conducting an event study of the impact of operational loss events on non-announcing banks and insurers. The study exploits the OpData database compiled by Algorithmics. The study focuses on large events, defined as events causing losses of at least $50 million; and the analysis includes 445 bank events and 158 insurance events. Because both positive and negative spillovers may be present, the results show the net effect on non-announcing firms, i.e., the sum of negative externality and competitive effects.

The results imply that operational loss events have strong negative intra and inter-industry spillover effects, that is, non-announcing banks and insurers within and across the financial industry are negatively affected by operational loss events. Thus, the operational loss events convey new information about risks to financial firms that cause markets to revise downward estimates of future cash flows for financial firms in general rather than creating net wealth transfers from announcing to non-announcing firms.

There is significant evidence of inter-sector effects of operational loss events for commercial and investment banks. For the commercial bank events, the inter-sector spillovers are predominantly negative, whereas there is some evidence of positive spillovers prior to the event day for the investment bank events. Investment bank events have significant negative spillovers for both commercial and investment banks in both the narrow and wider event windows. However, for the commercial bank events the intra-sector effect on investment bank dissipates rapidly, and the CARs for the wider windows tend to be insignificant. The strong effect of investment bank events on commercial banks compared to the relatively weak effect of commercial bank events on investment banks likely occurs because many commercial banks have investment banking operations, whereas most investment banks do not offer traditional commercial banking products such as loans and deposits.

Insurance operational loss events have a strongly significant effect on non-announcing insurers, supporting the hypothesis that operational loss events create negative externalities in the insurance industry. The (-1,+10) CARs for the bank events on insurers are almost identical to the CARs in the same window for the insurance events, suggesting a high degree of financial sector integration. The impact of commercial bank events on commercial banks and the impact of investment bank events on investment banks are similar in magnitude to the intra-sector effect for insurers, reinforcing the conclusion about integration. Moreover, the impact of insurance events on commercial banks is similar in magnitude and pattern to their impact on non-announcing insurers. In general, the impact of insurance events on investment bank provides evidence of negative externalities, but there is also some evidence of a competitive effect. For the wider windows, the insurance events have more impact on the commercial banks than on the investment banks. This pattern is consistent with information-based contagion because commercial banks have expanded more widely into insurance than have the investment banks. Overall, the results provide strong evidence of negative spillovers and financial sector integration.

Regression analysis and inter-industry results provide evidence that the negative information externalities identified by the event study are information-based rather than pure spillovers. The market is able to distinguish among financial characteristics of the firms and different types of events. The negative stock price response is larger for firms with higher Tobin's Q ratios, implying that such firms may have to forego attractive projects following potential future operational losses. The negative response is also larger for banks with lower capital-to-asset ratios, implying that banks exposed to higher insolvency risk are more sensitive to operational losses and supporting the financial distress hypothesis for banks. However, the equity-to-assets ratio is not significantly related to the CARs for insurers.

Insurance deceptive sales affects have significantly larger adverse effects on both banks

and insurers than other types of events, but the intra-sector effect is stronger than the inter-sector effect. Investment bank deceptive sales events have a significant positive effect on non-announcing banks, providing evidence of a competitive effect for these events. Within the banking sector, the intra-sector spillover effect is stronger for commercial banks but not for investment banks. Investment bank events have stronger negative spillover effects on investment banks than on commercial banks, but the insurance events have a stronger spillover effect on commercial banks than on investment banks. This asymmetrical response likely occurs because insurers do not offer traditional commercial banking products but are heavily involved in wholesale financial services. Overall, the results provide evidence of information-based spillovers because they suggest that investors are able to differentiate the varying degrees of exposure of banks and insurers to different types of operational losses.

While previous research suggested that operational loss events have a strong, statistically significant negative stock price effect on announcing firms, the present study shows that such events also have strong negative intra and inter-industry spillover effects on non-announcing firms. This study further supports the regulatory view that operational risk posses a significant threat to the market value of both banks and insurers, providing a rationale for firms to manage operational risks, even though such risks tend to be non-systematic. The study also provides strong quantitative evidence that the integration of the U.S. financial services industry has progressed further and is much more profound than previous evidence would indicate. Finally, the results imply that bank regulators are on the right track in terms of relying on market discipline as one of the regulatory pillars in the Basel II capital accord – the market clearly penalizes financial firms for operational risk management failures.

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Appendix

Event Study Methodology

The event-study analysis seeks to assess the market reaction of non-announcing firms to operational loss events of announcing firms. To measure abnormal returns, we utilize the standard market model. To estimate abnormal returns for an event, data are collected 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 distributions of stock returns are assumed to be jointly multivariate normal and independently and identically-distributed (iid) through time (MacKinlay 1997). The market model is given by the following equation:

$$R_{ijt} = \alpha_{ij} + \beta_{ij} R_{mt} + \varepsilon_{ijt} \tag{1}$$

where R_{ijt} is the return on security i for event j on day t, R_{mt} is the CRSP equally-weighted market return on day t, α_{ij} and β_{ij} are parameters to be estimated, and ε_{ijt} is the error term of the regression. Under the assumptions of joint normality and iid returns, the regression error is well–behaved, i.e., E(ε_{ijt}) = 0 and Var(ε_{ijt}) = $\sigma^2_{\varepsilon_{ij}}$. The estimation period for equation (1) is the 250-day period ending the day before the event windows (defined below).[1]

Using the parameters estimated from the market model, the daily abnormal returns (AR) are calculated for each event 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. The abnormal return on day t in the event window for stock j can be expressed as the estimated disturbance term of the market model:

$$AR_{ijt} = R_{ijt} - \hat{\alpha}_{ij} - \hat{\beta}_{ij} R_{mt} \tag{2}$$

where the coefficients of $\hat{\alpha}_{ij}$ and $\hat{\beta}_{ij}$ are ordinary least squares (OLS) estimates of α_{ij} and β_{ij}.

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 10 trading days prior to each event and extending 10 trading days after for all bank events and in a window beginning 15 trading days prior to each event and extending 15 trading days after for all insurance events, i.e., the windows for the bank and insurance events are (-10,+10) and (-15,+15), respectively.[2] A longer window was used for the insurance events because preliminary analysis revealed a longer post-event response period for insurance events than for bank events, consistent with Cummins, Lewis, and Wei (2006). To provide information on the responsiveness of stocks to event announcements, we also tabulate returns for windows of

[1] 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)

[2] Since many of these events have not been studied before, a longer event period can provide a better idea of the impact of the events over time.

various lengths that are subsets of the overall ±10 and ±15 day windows.

Under the assumption that the conditional abnormal returns are independent and identically distributed, we can aggregate the abnormal returns across securities for each event day. The average abnormal return across all securities for event j at day t is computed as follows:

$$\overline{AR}_{jt} = \frac{1}{M_j}\sum_{i=1}^{M_j} AR_{ijt} \;, \tag{3}$$

where M_j is the number of stocks for event j. 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 as:

$$CAR_{T_1T_2,ij} = \sum_{t=T_1}^{T_2} AR_{ijt} \;. \tag{4}$$

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

$$\overline{CAR}_{T_1T_2} = \frac{1}{N}\sum_{j=1}^{N}\frac{1}{M_j}\sum_{i=1}^{M_j} CAR_{T_1T_2,ij} = \frac{1}{N}\sum_{j=1}^{N}\frac{1}{M_j}\sum_{i=1}^{M_j}\;\sum_{t=T_1}^{T_2} AR_{ijt} \;, \tag{5}$$

Many prior studies have documented the possible bias caused by cross-sectional dependence (e.g., Collins and Dent 1984, Bernard 1987, Chandra, et al. 1990). This can 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 normal return generating process. Thus, the error terms are often 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 (Bernard 1987; MacKinlay 1997).

In this study, there are two sources of clustering: (1) some events are announced on the same day, and (2) since we pair each event with all traded non-announcing firms that are not directly affected by that event, there is clustering within each event in the sample.[3] Accordingly, to test for statistical significance of CARs in this study, we adopt Jaffe's (1974) *calendar time t-test*, which corrects for the cross sectional dependence caused by clustering. The abnormal returns of non-announcing firms are placed into portfolios according to event date, i.e., all events that occurred on the same day are grouped into one portfolio. Thus, Jaffe's calendar time t-test controls for both sources of cross sectional correlation; the test does not change the mean but only the standard deviation of the average cumulative abnormal returns.

For the case where there is only one event on a given day, we compute the cumulative abnormal return (CAR) for a portfolio as:

[3] Of the 247 bank events, 84 are announced on the same days as one or more other bank events. Among the 91 insurance events, 20 are announced on the same days with one or more other insurance events.

$$CAR_{T_1T_2,j} = \frac{\sum_{All \ \mathrm{i} \in Portolio \ \mathrm{j}} CAR_{T_1T_2,ij}}{M_j} \qquad (6)$$

where $CAR_{T_1T_2,j}$ is the CAR for portfolio (event) j and M_j is the number of firms in portfolio j.[4] A portfolio standard deviation $\widehat{SD}\left(CAR_{T_1T_2,j}\right)$ is estimated from the time series of portfolio abnormal returns in the estimation period and used to standardize the portfolio return:

$$SCAR_{T_1T_2,j} = \frac{CAR_{T_1T_2,j}}{\widehat{SD}\left(CAR_{T_1T_2,j}\right)} \qquad (7)$$

where $SCAR_{T_1T_2,j}$ is the standardized cumulative abnormal return for portfolio j. Thus, under the null hypothesis that stock prices do not respond to event announcements, the $SCAR_{T_1T_2,j}$ is distributed $N(0,1)$. The mean SCAR across all portfolios is:

$$\overline{SCAR_{T_1T_2}} = \frac{1}{N_p} \sum_{j=1}^{N_p} SCAR_{T_1T_2,j} \qquad (8)$$

where N_p is the number of portfolios. Finally, a cross sectional t-test is performed on $\overline{SCAR_{T_1T_2}}$:

$$t = \frac{\overline{SCAR_{T_1T_2}}}{\frac{1}{\sqrt{N_p}}} = \sqrt{N_p} \cdot \overline{SCAR_{T_1T_2}} . \qquad (9)$$

The results are also tested for statistical significance using the variance-adjusted Z-statistic developed by Boehmer, Musumeci, and Poulsen (1991). The Boehmer, Musumeci, and Poulsen (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.

It is also customary to report a nonparametric 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 and when there is event-clustering.

[4] An analogous but slightly more complicated formula is used when there is more than one event on a given day.

Table 1: Descriptive statistics for operational loss events studied by event types ($ millions), from 1978-2010

This table shows sample mean, median, standard deviation, minimum, and maximum for all operational loss events or at least $50 million by event types from 1978 to 2010. Descriptive data on operational loss events of all banks, commercial banks, investment banks, and all insurers are shown in Panels A, B, C, and D, respectively. The data are obtained from the Algo OpData Database compiled by Algorithmics. Monetary valued data are in millions of constant 2002 dollars based on the Consumer Price Index. N is the number of events. % total N is the number of events of a given event type as a percentage of total number of events.

	Internal fraud	External fraud	Employment practices & workplace safety	Clients, products, & business practices			Damage to physical assets	Business disruption & system failure	Execution, delivery & process management	All event types
				All	Deceptive sales	Others				
Panel A: All bank events										
Mean	753.71	354.10	94.24	377.85	308.81	396.29	123.29	180.76	180.45	450.46
Median	117.04	107.76	84.07	119.62	96.47	131.48	112.05	198.57	78.42	112.68
Std Dev	5283.70	957.57	38.19	903.45	927.33	898.37	44.10	83.76	189.53	2706.84
Min	50.28	51.33	51.18	50.38	51.02	50.38	84.86	89.53	50.20	50.20
Max	55017.06	6100.97	147.37	6903.28	6903.28	6902.27	184.22	254.18	699.39	55017.06
N	108	43	6	261	55	206	4	3	20	445
% total N	24.3%	9.7%	1.3%	58.7%	12.4%	46.3%	0.9%	0.7%	4.5%	100.0%
Panel B: All commercial bank events										
Mean	913.53	371.24	102.85	424.35	519.74	407.95	123.29	144.05	137.13	527.94
Median	109.70	106.92	87.45	128.92	87.25	134.83	112.05	144.05	71.43	110.73
Std Dev	6171.85	1004.56	35.60	994.23	1447.45	900.80	44.10	77.11	122.02	3314.43
Min	50.28	51.33	65.21	50.87	58.67	50.87	84.86	89.53	50.20	50.20
Max	55017.06	6100.97	147.37	6903.28	6903.28	6902.27	184.22	198.57	409.34	55017.06
N	79	39	5	150	22	128	4	2	11	290
% total N	27.2%	13.4%	1.7%	51.7%	7.6%	44.1%	1.4%	0.7%	3.8%	100.0%
Panel C: All investment bank events										
Mean	318.35	186.98	51.18	315.02	168.19	377.14		254.18	233.39	305.50
Median	161.64	199.83	51.18	112.00	99.09	121.90		254.18	107.29	119.34
Std Dev	551.18	117.74	.	763.78	158.93	899.84		.	246.93	690.33
Min	51.56	60.67	51.18	50.38	51.02	50.38		254.18	52.55	50.38
Max	2999.64	287.57	51.18	6833.22	692.96	6833.22		254.18	699.39	6833.22
N	29	4	1	111	33	78		1	9	155
% total N	18.7%	2.6%		71.6%	21.3%	50.3%		0.6%	5.8%	100.0%
Panel D: All insurance events										
Mean	279.01	994.05	107.41	266.57	314.17	244.73	169.04	209.25	1295.47	324.81
Median	169.18	117.39	100.46	127.18	126.16	128.20	201.68	209.25	91.01	123.66
Std Dev	316.60	1558.26	52.87	403.61	539.47	324.89	85.36	178.57	3299.04	844.43
Min	74.00	71.58	50.16	50.89	52.72	50.89	72.17	82.98	55.44	50.16
Max	1211.55	2793.17	198.93	2256.75	2256.75	2108.09	233.25	335.52	9455.09	9455.09
N	12	3	6	124	39	85	3	2	8	158
% total N	7.6%	1.9%	3.8%	78.5%	24.7%	53.8%	1.9%	1.3%	5.1%	100.0%

Table 2: Impact of commercial and investment bank operational loss events on non-announcing commercial and investment banks, 1978-2010

This table shows market model mean and median cumulative abnormal returns (CAR), in percentage terms, of non-announcing banks for various windows around commercial and investment banks' operational loss announcements. The impact of commercial bank events on non-announcing commercial and investment banks is shown in Panel A. Panel B shows the impact of investment bank events on non-announcing commercial and investment banks. Day 0 is the first public announcement of an operational loss event. Abnormal returns are calculated as the difference between realized returns, and expected returns obtained from the market model estimated over a 250-day pre-event period ending the day before the event window. Two parametric significance tests of the mean CAR are reported: the variance adjusted z-statistic (Boehmer, Musumeci, and Poulsen 1991) and the calendar time t-test (Jaffe 1974). The non-parametric generalized sign z-test (Cowan 1992) is also reported. Statistical significance is indicated by ***, significant at the 0.1% level; **, significant at the 1% level; *, significant at the 5% level; and $, significant at 10% level.

N is the number of events.

Panel A: Commercial bank events

Panel A.1: Impact on all non-announcing commercial banks

Days	N	Mean CAR	Median CAR	Variance adjusted z-stat	Calendar time t-test	Generalized sign z-test
(0,0)	290	-0.04%	-0.13%	-6.814 ***	-1.562 $	-12.078 ***
(-1,+1)	290	-0.02%	-0.23%	-5.742 ***	-1.035	-5.720 ***
(-5,+5)	290	-0.24%	-0.49%	-8.085 ***	-1.328 $	-3.876 ***
(-10,+10)	290	-0.39%	-0.72%	-6.175 ***	-0.975	-3.859 ***
(-5,-1)	290	0.06%	-0.18%	6.521 ***	0.578	5.497 ***
(-10,-1)	290	-0.04%	-0.31%	2.870 **	0.110	4.057 ***
(-1,+5)	290	-0.25%	-0.44%	-14.539 ***	-1.962 *	-8.098 ***
(-1,+10)	290	-0.30%	-0.57%	-10.195 ***	-1.363 $	-6.258 ***

Note: The average number of non-announcing firms per event is 295

Panel A.2: Impact on all non-announcing investment banks

Days	N	Mean CAR	Median CAR	Variance adjusted z-stat	Calendar time t-test	Generalized sign z-test
(0,0)	290	-0.09%	-0.15%	-2.667 **	-1.544 $	-2.284 *
(-1,+1)	290	-0.17%	-0.30%	-2.813 **	-1.454 $	-2.877 **
(-5,+5)	290	-0.23%	-0.36%	-0.571	-0.316	1.513 $
(-10,+10)	290	0.06%	-0.13%	3.329 ***	0.879	5.055 ***
(-5,-1)	290	-0.15%	-0.24%	0.449	-0.114	0.275
(-10,-1)	290	0.06%	-0.17%	3.446 ***	0.892	3.699 ***
(-1,+5)	290	-0.16%	-0.27%	-1.810 *	-0.481	1.496 $
(-1,+10)	290	-0.08%	-0.19%	0.736	0.293	3.835 ***

Note: The average number of non-announcing firms per event is 48

Panel B: Investment bank events

Panel B.1: Impact on all non-announcing commercial banks

Days	N	Mean CAR	Median CAR	Variance adjusted z-stat	Calendar time t-test	Generalized sign z-test
(0,0)	155	-0.04%	-0.11%	-5.126 ***	-0.511	-3.663 ***
(-1,+1)	155	-0.12%	-0.26%	-10.252 ***	-1.111	-6.002 ***
(-5,+5)	155	-0.22%	-0.52%	-8.126 ***	-0.645	-4.418 ***
(-10,+10)	155	0.01%	-0.49%	-2.323 *	0.090	2.345 **
(-5,-1)	155	0.24%	-0.07%	9.502 ***	1.425 $	10.559 ***
(-10,-1)	155	0.49%	-0.01%	14.778 ***	1.681 *	14.143 ***
(-1,+5)	155	-0.41%	-0.52%	-17.359 ***	-1.707 *	-9.114 ***
(-1,+10)	155	-0.44%	-0.64%	-16.159 ***	-1.224	-6.587 ***

Note: The average number of non-announcing firms per event is 291

Panel B.2: Impact on all non-announcing investment banks

Days	N	Mean CAR	Median CAR	Variance adjusted z-stat	Calendar time t-test	Generalized sign z-test
(0,0)	155	-0.12%	-0.16%	-3.362 ***	-0.516	-2.166 *
(-1,+1)	155	-0.35%	-0.38%	-7.210 ***	-1.393 $	-4.262 ***
(-5,+5)	155	-0.25%	-0.46%	-3.253 ***	-0.118	-0.582
(-10,+10)	155	0.12%	-0.24%	-0.086	1.044	2.959 **
(-5,-1)	155	0.10%	-0.18%	0.984	0.208	1.934 *
(-10,-1)	155	0.37%	-0.07%	2.766 **	0.941	4.077 ***
(-1,+5)	155	-0.39%	-0.47%	-6.000 ***	-0.426	-1.397 $
(-1,+10)	155	-0.29%	-0.48%	-3.511 ***	0.362	-0.488

Note: The average number of non-announcing firms per event is 48

Table 3: Impact of insurance operational loss events on non-announcing insurers and banks, 1978-2010

This table shows market model mean and median cumulative abnormal returns (CAR), in percentage terms, of non-announcing insurers and banks in response to operational loss announcements by insurers. The impact of insurance events on insurers is shown in Panel A. The impact of insurance events on commercial and investment banks are shown in Panel B and C, respectively. Day 0 is the first public announcement of an operational loss event. Abnormal returns are calculated as the difference between realized returns, and expected returns obtained from the market model estimated over a 250-day pre-event period ending the day before the event window. Two parametric significance tests of the mean CAR are reported: the variance adjusted z-statistic (Boehmer, Musumeci, and Poulsen 1991) and the calendar time t-test (Jaffe 1974). The non-parametric generalized sign z-test (Cowan 1992) is also reported. Statistical significance is indicated by ***, significant at the 0.1% level; **, significant at the 1% level; *, significant at the 5% level; and $, significant at 10% level.
N is the number of events.

Days	N	Mean CAR	Median CAR	Variance adjusted z-stat	Calendar time t-test	Generalized sign z-test
Panel A: Impact of insurance events on all non-announcing insurers						
(0,0)	158	-0.02%	-0.07%	-1.011	0.040	-0.016
(-1,+1)	158	-0.14%	-0.19%	-4.166 ***	-1.529 $	-2.982 **
(-5,+5)	158	-0.21%	-0.32%	-2.703 **	-1.479 $	0.726
(-10,+10)	158	-0.38%	-0.21%	-2.051 *	-1.197	4.562 ***
(-15,+15)	158	-0.58%	-0.29%	-2.579 **	-1.432 $	3.706 ***
(-10,-1)	158	-0.08%	-0.25%	-0.628	-0.398	1.524 $
(-15,-1)	158	-0.08%	-0.29%	-0.432	0.210	2.908 **
(-1,+5)	158	-0.21%	-0.24%	-2.844 **	-1.701 *	0.583
(-1,+10)	158	-0.35%	-0.23%	-3.120 ***	-1.600 $	2.722 **
(-1,+15)	158	-0.56%	-0.37%	-3.903 ***	-2.360 **	0.312
Note: The average number of non-announcing firms per event is 125						
Panel B: Impact of insurance events on commercial banks						
(0,0)	158	0.00%	-0.06%	-2.045 *	-0.025	2.595 **
(-1,+1)	158	-0.08%	-0.16%	-3.735 ***	-0.921	-0.161
(-5,+5)	158	-0.20%	-0.43%	-3.601 ***	-0.506	-4.204 ***
(-10,+10)	158	-0.58%	-0.66%	-8.021 ***	-0.921	-5.281 ***
(-15,+15)	158	-0.83%	-0.76%	-8.821 ***	-1.007	-2.323 *
(-10,-1)	158	-0.30%	-0.38%	-7.515 ***	-0.296	-2.370 **
(-15,-1)	158	-0.33%	-0.35%	-5.066 ***	0.117	0.990
(-1,+5)	158	-0.15%	-0.25%	-2.415 **	-0.949	-0.563
(-1,+10)	158	-0.31%	-0.31%	-4.402 ***	-1.264	0.569
(-1,+15)	158	-0.53%	-0.61%	-7.651 ***	-1.652 $	-6.058 ***
Note: The average number of non-announcing firms per event is 290						
Panel C: Impact of insurance events on investment banks						
(0,0)	158	-0.19%	-0.14%	-2.752 **	-1.197	-2.212 *
(-1,+1)	158	-0.20%	-0.29%	-3.322 ***	-0.305	-2.939 **
(-5,+5)	158	-0.03%	-0.11%	1.290 $	0.953	3.899 ***
(-10,+10)	158	0.06%	-0.19%	1.571 $	1.439 $	3.490 ***
(-15,+15)	158	-0.04%	-0.12%	1.904 *	1.449 $	3.854 ***
(-10,-1)	158	0.31%	-0.12%	3.262 ***	1.869 *	3.399 ***
(-15,-1)	158	0.36%	0.01%	4.267 ***	2.210 *	4.990 ***
(-1,+5)	158	-0.17%	-0.35%	-1.155	0.436	0.264
(-1,+10)	158	-0.15%	-0.27%	-0.455	0.572	1.150
(-1,+15)	158	-0.30%	-0.28%	-1.068	0.333	2.195 *
Note: The average number of non-announcing firms per event is 49						

Table 4: Impact of commercial and investment bank operational loss events on insurers, 1978-2010

This table shows market model mean and median cumulative abnormal returns (CAR), in percentage terms, of insurers for various windows around operational loss announcements by banks. The impact of commercial and investment bank events on insurers are shown in Panel A and B, respectively. Day 0 is the first public announcement of an operational loss event. Abnormal returns are calculated as the difference between realized returns, and expected returns obtained from the market model estimated over a 250-day pre-event period ending the day before the event window. Two parametric significance tests of the mean CAR are reported: the variance adjusted z-statistic (Boehmer, Musumeci, and Poulsen 1991) and the calendar time t-test (Jaffe 1974). The non-parametric generalized sign z-test (Cowan 1992) is also reported. Statistical significance is indicated by ***, significant at the 0.1% level; **, significant at the 1% level; *, significant at the 5% level; and $, significant at 10% level.
N is the number of events.

Days	N	Mean CAR	Median CAR	Variance adjusted z-stat	Calendar time t-test	Generalized sign z-test
Panel A: Impact of commercial banks events						
(0,0)	290	-0.03%	-0.10%	-2.774 **	-0.849	-4.094 ***
(-1,+1)	290	-0.08%	-0.17%	-3.282 ***	-0.790	-0.713
(-5,+5)	290	-0.13%	-0.32%	-2.575 **	-0.851	1.121
(-10,+10)	290	-0.35%	-0.46%	-5.009 ***	-1.315 $	1.821 *
(-5,-1)	290	0.11%	-0.10%	4.872 ***	1.082	5.827 ***
(-10,-1)	290	0.04%	-0.23%	1.046	-0.086	3.495 ***
(-1,+5)	290	-0.20%	-0.29%	-6.210 ***	-1.540 $	-0.988
(-1,+10)	290	-0.34%	-0.38%	-6.724 ***	-1.506 $	-0.077

Note: The average number of non-announcing firms per event is 123

Days	N	Mean CAR	Median CAR	Variance adjusted z-stat	Calendar time t-test	Generalized sign z-test
Panel B: Impact of investment banks events						
(0,0)	155	-0.03%	-0.09%	-2.305 *	-0.925	-2.068 *
(-1,+1)	155	-0.05%	-0.16%	-3.583 ***	-1.334 $	0.516
(-5,+5)	155	0.00%	-0.32%	-3.199 ***	-0.896	1.426 $
(-10,+10)	155	-0.05%	-0.29%	-2.179 *	-0.887	4.068 ***
(-5,-1)	155	0.22%	-0.07%	4.327 ***	0.497	6.306 ***
(-10,-1)	155	0.29%	-0.05%	6.179 ***	0.341	7.764 ***
(-1,+5)	155	-0.20%	-0.38%	-7.995 ***	-1.841 *	-2.848 **
(-1,+10)	155	-0.32%	-0.43%	-8.589 ***	-1.641 $	-1.418 $

Note: The average number of non-announcing firms per event is 124

Table 5: Regression results for operational loss announcements by both banks and insurers, 1978-2010

This table reports multivariate regressions for bank and insurance events. Panels 1 through 4 show the results for bank events, and Panels 5 and 6 show the results for insurance events. The dependent variable is CAR($-w_1$,$+w_2$), which is the cumulative abnormal return from an event in a window w_1 days before the event date to w_2 days after the event date; LogMve = log of market value of equity; Log loss amount = log of 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; Equity-to-assets ratio = book value of equity/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; ComBank = 1 if the bank is a commercial bank, 0 otherwise; InvBank = 1 if the bank is an investment bank, 0 otherwise; IBankEvt = 1if the event is an investment bank event, 0 otherwise; ComEvtComBank = 1 if CAR is from a commercial bank for a commercial bank event, 0 otherwise; InvEvtComBank = 1 if CAR is from a commercial bank for an investment bank event, 0 otherwise; InvEvtInvBank = 1 if CAR is from an investment bank for an investment bank event; Life = 1 if the insurer is a life insurer (SIC code 6311), 0 otherwise; Deceptive*IBankEvt is the interaction of deceptive sales event and investment bank event dummies; Deceptive*ComBank is the interaction of deceptive sales event and commercial bank dummy. 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. The weight variable is the reciprocal of the standard deviation of the cumulative abnormal return. The upper entry in each panel is the coefficient, and the middle entry is the t-statistic. Statistical significance is indicated by ***, significant at the 1% level; **, significant at the 5% level; and *, significant at 10% level. N is the number of events. Missing value of Compustat variables resulted in the elimination of less than 20% of the observations.

Bank Events:

Panel 1: Non-Announcing Banks Response to All Bank Events:

Dependent variable	Intercept	LogMve	Log Loss amount	Q ratio	Equity-to-assets ratio	Deceptive sales	Deceptive* IBankEvt	ComEvt ComBank	InvEvt ComBank	InvEvt InvBank	Adj R^2	F stat	N
CAR(-10,10)	-0.00643	-0.00015	0.00251	-0.00192	0.01008	-0.00507	0.01516	-0.00331	-0.00713	-0.00705	0.002	29.75	445
	-3.21	-1.18	10.23	-4.26	3.8	-4.36	9.86	-2.71	-5.64	-4.64		***	
	***		***	***	***	***	***	***	***	***			

Panel 2: Non-Announcing Banks Response to Commercial Bank Events:

Dependent variable	Intercept	LogMve	Log Loss amount	Q ratio	Equity-to-assets ratio	Deceptive sales	ComBank	Adj R^2	F stat	N
CAR(-10,10)	-0.00521	0.00035	0.00129	-0.00164	0.01175	-0.00490	-0.00251	0.008	12.52	290
	-2.12	2.15	4.08	-2.91	3.47	-4.12	-1.83		***	
	**	**	***	***	***	***	*			

Panel 3: Non-Announcing Banks Response to Investment Bank Events:

Dependent variable	Intercept	LogMve	Log Loss amount	Q ratio	Equity-to-assets ratio	Deceptive sales	InvBank	Adj R^2	F stat	N
CAR(-10,10)	-0.01708	-0.0009917	0.00454	-0.00244	0.00735	0.01036	0.00147	0.006	44.06	155
	-7.00	-4.90	11.77	-3.28	1.73	10.68	0.85		***	
	***	***	***	***	*	***				

Panel 4: Insurers Response to Bank Events:

Dependent variable	Intercept	LogMve	Log Loss amount	Q ratio	Equity-to-assets ratio	Deceptive sales	IBankEvt	Deceptive* IBankEvt	Life	Adj R^2	F stat	N
CAR(-10,10)	0.00029	-0.00091	0.00217	-0.00430	-0.00091	-0.00545	-0.00203	0.01109	0.00088	0.002	13.07	445
	0.11	-4.76	6.09	-5.09	-0.35	-3.19	-2.51	4.87	1.01		***	
		***	***	***		***	**	***				

Insurance Events:

Panel 5: Non-Announcing Insurers Response to All Insurance Events:

Dependent variable	Intercept	LogMve	Log Loss amount	Q ratio	Equity-to-assets ratio	Deceptive sales	Life	Adj R^2	F stat	N
CAR(-15,15)	0.04892	-0.00146	-0.00197	-0.02352	0.00397	-0.01975	0.00252	0.0106	34.11	158
	8.24	-3.76	-2.68	-6.75	0.71	-11.55	1.44		***	
	***	***	***	***		***				

Panel 6: Banks Response to All Insurance Events:

Dependent variable	Intercept	LogMve	Log Loss amount	Q ratio	Equity-to-assets ratio	Deceptive sales	ComBank	Deceptive* ComBank	Adj R^2	F stat	N
CAR(-15,15)	0.00645	-0.00051	0.00202	-0.00543	0.02130	-0.01260	-0.00753	-0.00088	0.005	36.96	158
	1.69	-2.14	4.38	-5.75	4.28	-3.71	-3.56	-0.25		***	
	*	**	***	***	***	***	***				