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

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March 22, 2006

Keywords: Operational loss events, information spillovers, operational risk, banking, insurance, contagion, event study.

JEL Codes: G21, G22, G14, G28.

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Abstract

This paper conducts an event study analysis of the market value impact of operational loss events on non-announcing firms in the U.S. banking and insurance industries. We seek evidence of negative or positive information spillovers, i.e., that operational risk events have negative effects on stock prices of non-announcing firms or lead to wealth transfers from announcing to non-announcing firms. Three main sectors of the financial services industry are analyzed – commercial banking, investment banking, and insurance – and both intra and inter-sector analyses are conducted. The rationale for anticipating inter-sector spillover effects is the integration of the previously fragmented markets for financial services that has occurred over the past twenty-five years – banks have entered the insurance market and insurers offer wholesale and retail financial products in competition with banks. The results indicate that operational risk events cause strong negative intra and inter-sector spillover effects, i.e., the stock prices of non-announcing firms respond negatively to operational loss announcements. Regression analysis reveals that the negative effect is information-based rather than purely contagious.

1. Introduction

Although financial institutions have been subject to operational risk throughout their history, only during the last decade has operational risk management attracted significant attention among managers, regulators, and investors. Operational risk is defined as “the risk of loss resulting from inadequate or failed internal processes, people, and systems or from external events” (Basel Committee 2003). 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 fines and lawsuits against Prudential Financial for misleading sales presentations. In response to these and other events, the Basel Committee on Banking Supervision has incorporated a new minimum capital charge for operational risk as part of the Basel II Capital Accord (Basel Committee 2001); major financial institutions have been developing sophisticated operational risk management systems; and ratings firms have begun to consider operational risk in assigning corporate financial ratings (Moody’s Investors Service 2003, Fitch Ratings 2004).

Recent research reveals that operational loss events have a strong, statistically significant negative stock price impact on announcing firms (Cummins, Lewis, and Wei 2005; Perry and de Fontnouvelle 2005). Moreover, the market value loss significantly exceeds the amount of the operational loss, 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 a *contagion effect* or positively affecting prices through a *competitive effect*.[1] The objective of this paper is to investigate spillovers by analyzing the impact of

[1] Although the earlier literature has referred to negative information externalities (spillovers) as contagion

operational loss events on the stock prices of non-announcing firms in the U.S. banking and insurance industries. We take advantage of a relatively new database on operational risk events compiled by OpVantage, a subsidiary of Fitch Risk, to conduct an event study of the effects of 247 bank events and 91 insurance events during the period 1985-2003 on the stock prices of 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 (contagion effects) attributable to operational risk events from a few institutions. Such events are hypothesized to cause securities markets to reduce estimates of expected future cash flows at non-announcing institutions, leading to 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). 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

(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., DeBandt and Hartman 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 to use the term negative information externalities or spillovers, we also occasionally use the term contagion as a synonym for informational spillovers for consistency with the existing event study literature (e.g., Lang and Stulz 1992, Fenn and Cole 1994, Docking, et al., 1997, and Slovin, et al. 1999).

competing institutions as buyers 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 competitive and contagion 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 breakdown of regulatory barriers during the 1980s and 1990s. Prior to the 1980s, the Glass-Steagal Act of 1933 prohibited commercial banks from engaging in investment 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;[2] and, beginning in 1985, the Office of the Comptroller of the Currency (OCC) authorized banks to sell certain types of insurance products, including annuities. In 1987, the Federal Reserve authorized commercial banks to engage in securities underwriting through Section 20 subsidiaries.[3] The deregulation culminated in the passage of the Gramm-Leach-Bliley Act (GLB) in 1999. GLB removed most of the remaining barriers to inter-sector competition within the financial services industry and created a new type of financial services firm, the financial holding company (FHC), which can engage in bank and non-bank financial activities through subsidiaries.[4]

[2] The interpretation centered around the "small town" exception to the National Banking Act (Section 92) that allowed national banks to engage in a general insurance business through a subsidiary located in a town where the population is 5,000 or fewer.

[3] In 1987, the revenue from investment banking activities of bank holding companies (BHC) was limited to 5% of their gross revenues. The restriction was gradually lifted; and by 1996, BHCs were permitted to derive up to 25% of their revenues from investment banking (Geyfman 2005).

[4] These activities include securities underwriting and dealing, insurance underwriting, insurance agency

The analysis in this paper considers both intra and inter-sector effects on commercial banks, investment banks, and insurers. Comparing the intra and inter-sector effects provides evidence on the degree of integration that has taken place among sectors 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 Standard Industrial Classification (SIC) System 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 commercial and personal financial intermediation services.

We also distinguish between *pure spillover* 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.[5] 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. If the response is unrelated to event and firm characteristics, 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. The results thus have implications for the significance of operational risk as a determinant of market values for banks and insurers and for the impact of integration on firms in the industry. More generally, our research has

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activities, merchant banking, etc. FHCs are still prohibited from owning shares of non-financial corporations and hence are not true universal banks.

[5] Pure spillover effects impose social costs because they penalize institutions that are not exposed to risks relating to the release of new information on operational and other adverse events. Information-based spillovers generally do not involve social costs but rather reflect the market's ability to correctly identify risks that many firms have in common and thus represents a rational adjustment to a new equilibrium.

implications for the literature on systemic risk. A limitation in the existing literature on systemic risk is the difficulty in determining whether spillover effects represent negative externalities or the consequences of macro-economic shocks affecting many institutions simultaneously (DeBandt and Hartmann 2000). Studying operational loss events provides a solution to this problem because such events tend to be idiosyncratic to the institutions where they occur (Perry and de Fontnouvelle 2005), and thus any measured spillover effects are not likely to reflect unmeasured macro-economic fluctuations. Moreover, because the existence of governmental safety nets has prevented major banking crises in industrialized nations during recent decades, analyses of bank runs have generally focused on historical episodes. Event studies have an important role to play in drawing inferences about investor (and by extension informed-depositor) behavior under modern market conditions and thus have implications for important public policy issues such as the use of market discipline in regulating financial institutions (Flannery 1998).

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 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 existence of information spillover effects has been widely documented for a variety of corporate events in many industries. Bankruptcy announcements have been analyzed by Aharony and Swary (1983, 1996), Lang and Stulz (1992), Akhigbe and Madura (2001), Halstead, Hegde, and Klein (2004), Spiegel and Yamori (2004), and Kabir and Hassan (2005). Dividend reduction announcements are studied in Laux, Starks, and Yoon (1998), Slovin, Sushka, and Polonchek (1999), Bessler and Nohel (2000), and Impson (2000). Other authors have analyzed open market repurchase announcements (Erwin and Miller 1998), earning restatement announcements (Gonen 2003), bank loan-loss reserve announcements (Docking, Hirschey, and Jones 1997), disclosure of supervisory actions (Jordan, Peek, and Rosengren 2000), and asset write-down announcements (Fenn and Cole 1994).

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 is related to the risk of doing business and exists as long as the business exists. However, only during the last decade has operational risk management begun to attract increasing attention following a number of very costly and highly publicized operational risk events. Even though discussions of operational risk began to intensify during the 1990s, a consensus definition of operational risk emerged only recently with the definition of operational risk adopted by the Basel Committee:

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

This definition includes legal risk, but excludes market risk, credit risk, strategic risk, reputational risk, and systemic risk.[6] It is based on underlying causes of operational risk, which are broken down into four categories: people, processes, systems, and external factors. To

[6] See Basel Committee (2001). Legal risk is the risk of loss from possible litigations against an institution. Strategic risk is the risk of loss from wrong decisions or strategies that reach negative results (Cruz, p.316). Reputational risk is the risk of loss from the indirect impact of a direct or “real” loss, i.e. an operational risk loss (Cruz, p.287). Systemic risk is non-diversifiable risk characterized by the breakdown of the entire financial system or major components of the system.

provide guidance to risk managers, the Committee breaks losses into seven event types and further divides the event types into twenty sub-categories. For example, embezzlement is a sub-category under internal fraud, and deceptive sales practices are a sub-categories classified under "clients, products, and business practices" (Basel Committee 2002).[7] The Basel Committee has incorporated a new and separate minimum capital charge for operational risk as part of the revised Basel Capital Accord (Basel Committee 2001).[8]

The increasing attention focused on operational risk over the past several years likely emanates from two key developments: (1) An enhanced emphasis on transparency in firm financial reporting 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 2005).

2.2. Background on Integration. Although inter-sector competition among financial services firm intensified with deregulation beginning in the 1980s, significant competition existed even prior to the deregulatory wave. Insurers and banks competed for the management of public and private 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 both close substitutes for bank certificates of deposit (Todd and Wallace 1992); and banks and insurers competed intensively in the market for commercial mortgage loans (Brewer and Jackson 2002). The development of the

[7] Within each sub-category, several examples are given (Basel Committee 2002). Cummins, Lewis, and Wei (2005) provide detailed statistics on operational losses in the U.S. banking and insurance industries
[8] The new Accord is scheduled to be implemented in 2006/2007, and is based on three complementary pillars: minimum capital requirements (pillar 1), supervisory review process (pillar 2), and market discipline (pillar 3). Minimum capital charges will also be applied to credit risk, which was included in the original 1988 Accord, and market risk, which was introduced in a 1996 amendment to the Accord.

commercial paper market threatened commercial banks' traditional dominance in business lending. On the retail side, securities firms introduced checkable money market mutual funds during the 1970s, providing competition for commercial 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 1985-2004, there were 579 cross-sector mergers and acquisitions (M&As) involving commercial banks, investment banks, insurance firms, and securities firms (Thomson Financial 2005). There were 151 transactions where a commercial bank purchased an investment bank and 229 transactions where a commercial bank purchased an insurer or insurance agency. There were 52 transactions where investment banks acquired commercial banks, and 49 transactions involving investment bank acquisitions of insurance firms. Insurers acquired 22 commercial banks and 76 investment banks during this period. The M&A data thus suggest that commercial banks have expanded significantly into investment banking and insurance but that the retail market expansion of investment banks has been more limited. Although insurers have been less active in the inter-sector M&A market than banks, they offer a broad range of wholesale and retail financial products in competition with both banks. In addition, insurers have introduced innovative investment products such as variable annuities and variable life insurance and have succeeded in selling private label annuities and life insurance through joint ventures with banks.

Evidence that banks have achieved considerable success in the annuity market is shown in Table 1. Banks' share of the annuity market has been increasing since the 1980s. In 1987, 11.3% of all individual annuities were purchased through banks (White 1996). By 2004, banks had 35.9% of the total individual fixed annuity market and 13.5% of the total individual variable annuity market. The primary insurance distribution channels for banks are acquired insurance agencies, de novo entry, and joint ventures.[9] Banks have preferred to enter the insurance market as sellers rather than underwriters, marketing policies written by unrelated insurance companies.

3. Literature Review and Research Hypotheses

3.1 Prior Literature. The contagion effect of an event usually refers to "the spillover effects of stocks of one or more firms to others" (Kaufman 1994) and also has been characterized as "the change in the value of a firm that can be attributed to economic events with a clearer and more direct impact on some other firm" (Docking, et al. 1997). Contagion has been studied widely in the theoretical and empirical financial literature (for reviews see Flannery 1998 and DeBandt and Hartmann 2000). Analyses have ranged from strong systemic shocks involving multiple bank failures, currency crises, and market crashes to informational spillover effects that lead to the revaluation of stock prices but not to widespread failures. This paper contributes to the latter body of literature by analyzing the stock price effects of operational loss events on non-announcing financial institutions. This type of informational spillover has 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 reason for the abundance of empirical research on bankruptcy announcements in the banking industry is that bank failure contagion can have a devastating impact on the economy. In fact, preventing contagion is often given as a principal rationale for bank regulation (Meltzer 1967, Kaufman 1994).[10] The pioneering work in contagion event studies is by Aharony and Swary (1983), who find that bank failures caused by firm-specific events such as internal fraud do not induce an industry-wide stock price reaction. However, bank failures due to common

[9] De novo refers to agency originated by the bank without acquisition of a platform agency. Joint venture refers to joint venture or marketing alliance with an insurance agency.
[10] Bank runs are one form of contagion that can disrupt banking and financial markets (Kaufman 1994).

difficulties within the industry cause a negative stock price reaction for non-announcing banks.

Aharony and Swary (1983) were the first to distinguish between *pure contagion* 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 if the cause of an event is correlated across firms, only the correlated firms experience spillover effects, and where investors are able to differentiate among firms with different risk characteristics. Information-based spillovers are viewed as a rational response (Kaufman 1994). Distinguishing between the two contagion effects is non-trivial even though they have completely different implications for public policy. The pure contagion effect imposes social costs, while the information-based contagion effect reflects a justified revaluation based on new information, which generally does not have social costs (Lang and Stulz 1992).

Lang and Stulz (1992) make a significant contribution to the contagion literature by introducing the *competitive effect*. The competitive effect 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. As Lang and Stulz (1992) point out, the competitive effect cannot occur in a completive 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.

Both 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, in studies of spillover effects, the results measure the sum of the competitive and contagion effects and reveal which effect is dominant. Lang and Stulz (1992) find that industries with similar cash flow characteristics tend to exhibit contagion effects and that the competitive effect is more likely to dominate in highly concentrated industries.

These two papers have inspired many studies of information spillovers. Aharony and Swary (1996) provide additional evidence on the information-based contagion effect of bank failures. Analyzing bank loan loss-reserve announcements, Docking, Hirschey, and Jones (1997) find significant negative contagion effects for non-announcing money-center and regional banks following announcements by regional banks, but no significant contagion effects of announcements by money-center 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. Dividend reductions at regional banks have a competitive effect on geographic rivals. 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.

Several studies also document the contagion effect in the insurance industry. Szewczyk, Thomas, and Tsetsekos (1997) find an information-based contagion effect in the life insurance industry after the failure of Mutual Benefit Life Insurance Corporation in 1991. Fenn and Cole (1994) and Cowan and Power (2001) also identify information-based contagion in life insurance industry after the asset write down announcement by First Executive Corporation in 1990.[11] Fields, Klein, and Myskowski (1998) study the contagion effect within the US property-liability insurance industry after Lloyd's of London's financial distress announcement in 1993 and find evidence of negative information spillovers in the global insurance marketplace.

A few papers document inter-industry contagion effects. Slovin, Sushka, and Polonchek

[11] The failure of First Executive was triggered by huge losses from junk-bond and commercial real estate investments (Fenn and Cole 1994, Todd and Wallace 1992). Fenn and Cole (1994) find that the contagion effect was greater for insurers with large holdings of junk bond and commercial mortgage assets, i.e., they provide evidence consistent with an information-based contagion effect.

(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 the inter-industry contagious movement of real estate investment trusts (REITs) and find that announcements of declining real estate values negatively affect the stock prices of firms in both the banking and insurance industries. Brewer and Jackson (2002) investigate the inter-industry effects of adverse information about commercial real estate portfolios between commercial banks and life insurers. They find strong evidence of significant inter-industry shareholder wealth spillover effects.

There are no existing studies of intra or inter-industry contagion between insurance and banking in reaction to operational risk events. This provides the motivation for the present paper, where we analyze the information spillover effects of operational risk events on U.S. commercial banks, investment banks, and insurers.[12]

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, because 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 because event announcements raise suspicion that other companies in the industry confront similar problems, triggering an update of the expected cash flows or capital costs of other firms in the industry (*the negative information externality (contagion) hypothesis)*. This suggests the first null hypothesis.

Null Hypothesis 1: Announcements of operational loss events have no intra-sector effect.

[12] Although the insurance industry 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.

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.

Due to the integration of the financial services industry, 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. This competition intensified beginning in the mid-1980s, when the regulatory barriers keeping commercial banks from participating fully in investment banking and insurance markets were gradually eliminated. To the extent that products offered by the three types of intermediaries can be used to achieve the same financial goals for consumers and business firms, 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 with respect to financial products or leads to general disintermediation by causing customers to become wary of dealing with financial institutions. 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 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. In addition, insurance operational loss events are likely to have stronger spillover effects on commercial banks than on investment banks. As discussed further below, the most important insurance events in our sample period involved deceptive sales practices in the retail market; and commercial banks have achieved greater penetration in retail insurance markets than have investment banks. Hence, the commercial banks may be more likely to be affected by insurance operational loss events than are investment banks. Because insurers offer both wholesale and retail products, however, 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 (contagion) hypotheses. Because there are three types of events (commercial bank, investment bank, and insurance), each of which could have inter-sector effects on two other types of intermediaries, there are six opportunities to reject the null in favor of the alternative hypotheses.

One of the most noticeable patterns of operational loss events during the 1990s is the surge of deceptive sales events incurred by insurers selling annuities and life insurance products.[13] This unprecedented wave of litigation against insurance companies for deceptive sales practices can be traced back to the 1980s and is directly related to the deregulation of the banking industry. Before the 1980s, U.S. life insurers enjoyed a reputation for financial stability and were generally regarded as trustworthy by policyholders. In the early 1980s, high inflation and record-high interest rates triggered a major episode of disintermediation in the industry. Many policyholders borrowed against their policies at low, contractually-guaranteed interest rates to take advantage of higher rates in the market, and some policyholders simply surrendered

[13] The number of the deceptive sales events started to increase in the early 1990s; and by 1997, 64 class action lawsuits had been filed against insurance companies for "vanishing premium" policies whose premium did not vanish as expected because of the prolonged decline in market interest rates (Santomero and Babbel 1997).

their policies altogether. Some insurers experienced net losses on their life insurance operations for the first time since the Depression. Insurers also lost business due to growing interest among retail investors in direct equity investing and mutual funds; and insurers also faced increasing competition from banks, especially after the OCC authorized banks to sell fixed and variable annuities in 1985 and 1990, respectively.[14]

In order to stay competitive, insurers developed innovative products and new marketing approaches, and agents began to place more emphasis on the use of insurance policies as investment vehicles. An unfortunate byproduct of these competitive pressures was the emergence of unethical sales practices (Egler and Malak 1999). Many insurers suffered staggering damages from the ensuing lawsuits, and consumer confidence in the industry was badly shaken.

There are three primary reasons to believe that non-announcing insurers will be negatively affected by deceptive sales events. First, the announcement of such events from a few insurers can be perceived as an indication of a common problem in the industry.[15] This would lead to a new adverse market assessment of the future cash flows to insurers, due to anticipated future operational losses. Second, this type of event undermines the integrity of the industry and destroys consumer confidence and trust. Reputation is a very important intangible asset for financial service firms, and deceptive sales events are likely to cause reputational damage that will reduce future sales.[16] Third, announcements of deceptive sales events can increase regulatory compliance costs for non-announcing firms by inducing more intensive regulatory scrutiny of all insurers. However, it is also possible that non-announcing firms would have a

[14] Carow (2001) shows that these rulings significantly reduced insurance company market values.

[15] According to a poll by *Money* magazine in 1995, deceptive sales practices permeated the life insurance industry. They are not “the acts of a handful of bad agents in a few companies” but rather a systematic pattern in the industry (Updegrave 1995a). The poll results also show that financial illiteracy and too much trust of their own agents make policyholders easy victims of unethical practices (Updegrave 1995b).

[16] Previous research has shown that management fraud tends to cause larger equity market losses than other types of events. This has been shown for operational losses by Cummins, Lewis, and Wei (2005) and Perry and de Fontnouvelle (2005), for earnings restatements by Palmrose, Richardson, and Scholz (2004), and for various acts of misconduct by Murphy, Shrieves, and Tibbs (2004).

positive reaction if buyers avoid announcing firms and migrate to their competitors, as suggested by the competition hypothesis. This discussion suggests our third null hypothesis:

> **Null Hypothesis 3**: Non-announcing insurers are not affected by the deceptive sales events of a few insurers.

Another interesting question is how banks were affected by the insurance deceptive sales events. The occurrence of deceptive sales problems of the insurers is at least partly attributable to the intensified competition induced by bank entry into the life insurance and annuity market. Thus, it is reasonable to expect that insurance and annuity-selling banks will benefit from insurers' scandals and further increase their market share, reflecting the competitive effect. On the other hand, it is also possible that these banks are also facing intense competition in the market and are not immune to the deceptive sales problem themselves. Thus, to the extent that insurers' deceptive sales problems damaged the reputations of financial institutions selling insurance products rather than just the reputations of insurers, an inter-sector contagion effect might be expected. This discussion suggests the following null hypothesis:

> **Null Hypothesis 4**: Banks are not differentially affected by insurer deceptive sales events.

3.3. Hypotheses: Pure versus Information-Based Effects. The pure contagion effect happens when investors perceive that non-announcing firms are similarly affected regardless of differences in firms' characteristics and the cause of the events. Pure contagion is more likely to happen when the ability of the market to differentiate among firms is low. An information-based contagion effect occurs when the spillover from an event affects only firms whose cash flows are highly correlated with those of the announcing firm. Information-based contagion is more likely to happen when information is accurately and readily available to enable investors to discriminate among the non-announcing firms by their characteristics (Brewer and Jackson 2002). In today's market, it would appear that vast amounts of information are conveyed to the market in an accurate and timely fashion. Thus, it is reasonable to believe that the degree of contagion of non-announcing firms depends on their financial and/or other characteristics, implying an information-based contagion effect. We next develop hypotheses to distinguish between pure and information-based contagion.

If there is a contagion effect, the loss amount or size of 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 the magnitude of the loss in market value for non-announcing firms. If there is competitive effect, the loss amount indicates the size of the announcing company's damage. Hence, the larger are the events, the larger should be the magnitude of the gain in market value for the rival firms. This suggests the following hypothesis:

> **Null Hypothesis 5**: 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.

Like firms in other industries, banks and insurers differ in terms of their growth opportunities, i.e., the relative importance of growth opportunities and assets in place in determining firm market value. 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. An increase in expected losses due to operational events also may 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 due to informational asymmetries or other market imperfections (Froot, Scharfstein, and Stein 1993). Increases in the cost of capital or reductions in expected availability of internal funds are expected to have a stronger impact on market values for firms with relatively strong growth prospects because these 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 decline in the stock price in response to operational loss events and specify the following null hypothesis:

> **Null Hypothesis 6**: 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 7**: The response of non-announcing firms' stock prices to operational losses is independent of the firms' leverage.

Aharony and Swary (1983) find that bank failures caused by firm-specific factors do not cause negative externalities, whereas bank failures due to common difficulties within the industry do cause adverse effects. It is reasonable to suspect the same would hold for operational loss events. Some event types might influence firm value more than others due to reputational damage that reduces expected future cash flows from new business or leads to disintermediation. As discussed above, deceptive sales problems may have a larger impact than operational events that do not directly affect customer relationships such as employee workplace safety. Because most customers of banks are protected by deposit insurance, Federally-insured banks would seem to be less susceptible to reputational losses with respect to their deposit taking activities, although evidence of fraud and other irregularities could affect relationships with investment clients and commercial borrowers. This discussion suggests the following hypothesis:

> **Null Hypothesis 8**: Operational losses from deceptive sales and operational losses from other type of events do not differentially affect stock prices of non-announcing firms, i.e., deceptive sales losses do not have a disproportionate impact on these firms market value.

Rejection of one or more of these four hypotheses would provide evidence of information-based contagion, with the strength of the evidence directly related to the number and strength of the rejections. If none of the hypotheses is rejected, the results would suggest pure contagion.

4. Database, Sample Selection, and Methodology

4.1. The Database. The data analyzed in this study are from the OpVar operational loss database distributed by OpVantage.[17] The data are collected from public sources worldwide. The OpVar database has historical events from 1978 through 2003 covering a number of industries, including banking and insurance. However, 97% of the events occurred during the period 1985 through 2003, providing the opportunity to investigate the effects on financial firms during the period when financial sector convergence was at its height.

The OpVar database provides event dates as well as descriptive information on the events.[18] Although the database includes losses from countries other than the U.S., two-thirds of the reported losses are from the U.S. Moreover, de Fontnouvelle, et al. (2003) concluded that the non-U.S. losses were significantly different in magnitude and distribution from the U.S. losses. Accordingly, and also because it is likely not advisable to mix event study results from different national stock exchanges, we focus the analysis on the U.S. operational loss events.

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[17] OpVantage is a division of Fitch Risk Management (www.opvantage.com).
[18] The event date in OpVar is the original announcement date, i.e., the earliest announcement of the event. The loss amount is the ultimate settlement amount rather than the originally announced loss amount.

The OpVar database reports all publicly announced losses that exceed a threshold of $1 million. We 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.[19]

4.2. Summary Statistics. Summary statistics on the U.S. operational loss events of at least $50 million are shown in Table 2.[20] There are 247 bank events and 91 insurer events of this magnitude in the database.[21] Among the bank events, 158 events were incurred by commercial banks and 89 by investment banks. Both the mean and the median operational losses of insurers exceed those of banks – the average operational loss for insurers is $224.1 million, compared to $193.2 million for banks, while the medians are $117.8 million for insurers and $101.4 million for banks. The maximum loss is slightly larger for banks than for insurers – $2.5 billion versus $2.3 billion. About 91% of the bank events are concentrated in internal fraud, external fraud, and clients, products, and business practices. Commercial banks have about 30% more internal fraud events and almost three times more external fraud events than investment banks.

Although both banks and insurers have incurred deceptive sales events, the insurance events were both relatively more frequent and more severe. Deceptive sales accounted for 37.4%

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[19] 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.

[20] For a more comprehensive analysis of operational loss events in the OpVar Database, see Cummins, Lewis, and Wei (2005).

[21] The contagion analysis allows the use of a much larger sample than the sample used in Cummins, Lewis, and Wei (2005) 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 contagion 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 traded non-announcing firms with valid data.

of all events for insurers but only 19.8% of events for banks. The mean and median of the insurer deceptive sales events are considerably higher than for comparable bank events – the median deceptive sales loss is $137.6 million for insurers and only $82.3 million for banks. The maximum deceptive sales loss for insurers was $2.3 billion, nearly three times the maximum deceptive sales loss for banks. Thus, among operational risk events, deceptive sales event were far more important and damaging for insurers than for banks, whereas banks have higher exposure to fraud and other types of clients, products, and business practices events.

4.3. Sample Selection. To obtain the sample of operational loss events used in the contagion study, we use all U.S. events of at least $50 million in the OpVar database. We carefully checked the observations in the OpVar database to verify the events, loss amounts, and event dates by searching several different on-line indices of business publications.[22] To study the spillover effect of these events on the U.S. banking and insurance industries, we select all non-announcing banks and insurance companies 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. In addition, the commercial bank category includes bank holding companies (SIC 6711). The investment bank category consists of SIC 6211, Security Brokers, Dealers, and Flotation Companies, as well as those firms in SIC 6282 which provide securities broker-dealer services.[23] The insurance sample consists of (SIC 631, life insurance, and 633, fire, marine, and casualty insurance).[24] That is, health insurers, mono-line specialty insurers such as title insurers,

[22] Four bank events were eliminated because we were unable to verify the event, event date, or loss amount. No insurance events were eliminated.
[23] 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.
[24] All SIC assignments were checked carefully for errors, and misclassified firms were deleted from the sample. E.g., SIC 602 includes some firms that are actually thrift institutions rather than commercial banks, and a few insurance companies and non-financial holding companies appear in 6711.

and insurance agents were excluded from the sample in order to focus the insurance sample on insurance underwriters who perform significant intermediation functions.

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, we utilize the standard market model. To estimate abnormal returns based on the market model, two time series of stock return data are needed for each event. One is for the *estimation* period where the parameters of the market model are estimated. The other is for *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 through time (MacKinlay 1997). The market model is given by the following equation:

$$R_{jt} = \alpha_j + \beta_j R_{mt} + \varepsilon_{jt} \tag{1}$$

where R_{jt} is the return on security j on day t, R_{mt} is the CRSP equally-weighted market return on day t, α_j and β_j are parameters to be estimated, and ε_{jt} is the error term of the regression. Under the assumptions of joint normality and independent and identically distributed returns, the regression error is well–behaved, i.e., E(ε_{jt}) = 0 and Var(ε_{jt}) = $\sigma^2_{\varepsilon_j}$. The estimation period for equation (1) is the 250-day period ending the day before the event windows (defined below).[25]

Using the parameters estimated from the market model, the daily unexpected or abnormal return (AR) is calculated for each event. Abnormal returns are calculated for windows surrounding the event day (day 0). A window is denoted as ($-w_1$,$+w_2$), representing an event window beginning w_1 days prior to the event day and ending w_2 days after the event day. The abnormal return on day t in the event window for stock j can be expressed as the estimated

[25] 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 influence by the event (MacKinlay 1997)

disturbance term of the market model:

$$AR_{jt} = R_{jt} - \hat{\alpha}_j - \hat{\beta}_j R_{mt} \tag{2}$$

where the coefficients of $\hat{\alpha}_j$ and $\hat{\beta}_{\mathrm{j}}$ are ordinary least squares (OLS) estimates of α_j and β_{j}.

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 all insurance events, i.e., the windows for the bank and insurance events are (-10,+10) and (-15,+15), respectively.[26] 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 (2005). 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.

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

$$\overline{AR}_t = \frac{1}{N}\sum_{j=1}^{N} AR_{jt} \, , \tag{3}$$

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

$$CAR_{T_1 T_2, j} = \sum_{t=T_1}^{T_2} AR_{jt} \, . \tag{4}$$

[26] 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.

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

$$\overline{CAR}_{T_1T_2,j} = \frac{1}{N}\sum_{j=1}^{N} CAR_{T_1T_2,j} = \frac{1}{N}\sum_{j=1}^{N}\sum_{t=T_1}^{T_2} AR_{jt} \ , \tag{5}$$

Many prior studies have documented the possible bias caused by cross-sectional dependence (e.g., Collins and Dent 1984; Bernard 1987; Chandra, Moriarity, and Willinger 1990). This may arise when the event window overlaps so that stock returns of different companies respond to some underlying factors in the same way, and these factors are not explicitly controlled for in estimating parameters in the 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.[27] 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. This means that 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.

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

[27] 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.

$$CAR^{i}_{T_1T_2} = \frac{\sum_{All\ j \in Portolio\ i} CAR_{T_1T_2,j}}{N_i} \tag{6}$$

where $CAR^{i}_{T_1T_2}$ is the CAR for firm j affected by event i and N_i is the number of firms in portfolio i. A portfolio standard deviation $\widehat{SD}\left(CAR^{i}_{T_1T_2}\right)$ is estimated from the time series of portfolio abnormal returns in the estimation period and used to standardize the portfolio return:

$$SCAR^{i}_{T_1T_2} = \frac{CAR^{i}_{T_1T_2}}{\widehat{SD}\left(CAR_{T_1T_2}\right)} \tag{7}$$

where $SCAR^{i}_{T_1T_2}$ is the standardized cumulative abnormal return. Thus, under the null hypothesis that stock prices do not respond to event announcements, the $SCAR^{i}_{T_1T_2}$ is distributed $N\left(0,1\right)$. The mean SCAR across all portfolios is:

$$\overline{SCAR_{T_1T_2}} = \frac{1}{M}\sum_{i=1}^{M} SCAR^{i}_{T_1T_2} \tag{8}$$

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

$$t = \frac{\overline{SCAR^{i}_{T_1T_2}}}{\frac{1}{\sqrt{M}}} = \sqrt{M}\cdot\overline{SCAR^{i}_{T_1T_2}}\ . \tag{9}$$

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. The results are also tested for statistical significance using the variance-adjusted Z-statistic developed by Boehmer, Musumeci, and Poulsen (1991).[28]

5. Event Study Results

This section first presents the results with respect to the intra-industry effects of banking events on the banking industry and insurance events on the insurance industry and then 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 3 presents the mean and median cumulative abnormal returns (CAR) for the effects of commercial bank events on all non-announcing commercial banks (Panel A.1) and all 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 most of the discussion on the mean CARs. Three significance tests of the mean CARs are reported: the variance adjusted z-statistic, calendar time t-test, and the (non-parametric) generalized sign z-test.

Panel A.1 of Table 3 shows that the commercial bank operational loss events have a significant negative contagion 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 -0.05%, 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 -0.51% for (-10, +10) window, both of which are statistically significant based on all 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 -0.12%, suggesting some information leakage before

[28] This statistic 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 (Boehmer, Musumeci, and Poulsen 1991).

the event day. The cumulative abnormal returns for (-1, +10) window is -0.38%, significant based on all three tests. Thus, significant information also "trickles out" after the event day.

Panel A.2 of Table 3 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 in these windows is larger than for the commercial banks (-0.12% and -0.23%, respectively, compared to -0.05% and -0.06% 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 insignificant and are sometimes positive. 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 3 shows that the investment bank events have a strong and significant contagion effect on both non-announcing commercial banks and non-announcing investment banks. Not surprisingly, 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 -0.20% for non-announcing investment banks, and the CAR in the (-1,+10) window is -0.86% for commercial banks and -1.45% for investment banks. These CARs are statistically significant according to at least two of the three test statistics. There is no significant information leakage during the pre-event period.

These results reject Null Hypothesis 1 for 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 reject Null Hypothesis 2. There is an inter-sector effect from investment to commercial banks and from commercial to investment banks.

Comparing Panels A and B of Table 3, it is clear that commercial bank events primarily affect non-announcing commercial banks in the wider windows (beyond (-1,+1)), while the investment bank events have an adverse impact on both non-announcing commercial banks and investment banks for both the narrow and wide windows. We suggest two main explanations for this pattern. First, many commercial banks offer investment banking products through investment subsidiaries, whereas most investment banks do not provide traditional commercial banking depository and lending services. For example, Salomon Brothers Asset Management is a fully-owned subsidiary of Citigroup, which is classified as a commercial bank by SIC code. Thus, investment bank events are likely to affect numerous commercial banks with investment or security units, but many operational loss events incurred by commercial banks are less applicable or inapplicable 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 Office of the Comptroller of the Currency (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 than commercial banks. 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, and regulatory attention can increase compliance costs for non-announcing firms. 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 information spillovers because investors are able to differentiate non-announcing firms' exposure across sectors.

Based on a weighted average (not shown) of the commercial and investment bank response to all bank events, the impact of bank events jointly on all non-announcing banks is -

0.47% for (-10, +10) window. According to Cummins, Lewis, and Wei (2005), the mean CAR for the announcing banks during (-10, +10) window is -1.27%. Thus, the contagion effect of the operational loss bank events is about 37% of the impact that these events have on the announcing banks during the same window around the events.

5.1.2. Effect of insurance operational loss events on non-announcing insurers. Panel A of Table 4 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 the insurance industry. On the event day, the mean CAR is -0.06%, which is weakly significant by the variance adjusted z and non-parametric (generalized sign z) tests. The abnormal return continues to increase in magnitude following the event day, and the mean CAR for (-1, +15) is -1.02%, statistically significant at 0.1% by all three tests. The mean CARs in the other (-1,+x) windows also are statistically significant by at least two tests. According to Cummins, Lewis and Wei (2005), the average cumulative abnormal return of announcing insurers from these events for the (-1,+15) window using the market model is -3.88%. The average contagion effect on the industry during the same window is thus about 26% of the impact on the announcing insurers.

Panel B of Table 4 presents the CARs of non-announcing insurers in reaction to the deceptive sales events of announcing insurers. It shows a strong contagion effect for the wider windows and suggests rejection of Hypothesis 3. There is not much leakage before the events, confirming that these deceptive sales events took the market by surprise. The mean CAR for (-1,+15) is -1.27%, which is statistically significant by all three tests. The importance of the deceptive sales events for insurers is reinforced by Panel C of Table 4, which presents the cumulative abnormal returns of non-announcing insurers in reaction to the non-deceptive sales events of announcing insurers. This panel shows that the market reaction to non-deceptive sales events was smaller than for deceptive sales events. For (-1, +15) window, the mean CAR is -0.88%, which is about 70% of the CAR for deceptive sales events.

The development of the cumulative abnormal returns for insurers is shown clearly in Figure 1, which reinforces the conclusion that the operational loss events of a few insurers triggered a substantial reduction in market expectations of future cash flows for other insurers in the industry. Figure 1 also reinforces the conclusion that deceptive sales events have a more damaging effect on insurers than other types of events and suggests that the arrival of new information occurs over a longer period following the event day for deceptive sales events than for other types of events. This could be attributable to many factors, including the slow discovery process of the true magnitude of these events. Because the occurrence of deceptive sales events is a relatively new phenomenon for insurers, the market needed time to evaluate the situation based on the newly emerging information.

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 contagion would suggest a high degree of integration between the banking and insurance components of the financial services industry.

5.2.1. Effect of bank operational loss events on insurers. Table 5 shows that commercial and investment bank operational loss events have significant negative information spillover effects on the market value of insurers. Panel A of Table 5 shows the impact of commercial bank events on insurers. The mean CAR on the event day is -0.05%, 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., -0.39% for (-10, +10) window, which is statistically significant by two of three tests. Panel B of Table 5 shows the impact of investment bank events on insurers. The mean CAR is -0.07% for the event day and -0.23% for the (-10, +10) window, and both are statistically significant by all three tests.

As noted, although most insurers do not have Federally insured banking subsidiaries, many insurers do have investment banking, mutual fund, and securities dealing operations. In addition, insurers compete directly with both commercial and investment banks for a wide-range of personal and commercial financial products; and bank operational loss events could impact insurance companies because of their competition with banks in these financial product markets. 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.

The results in Table 5 suggest a high degree of financial sector integration. In fact, the effects of commercial bank events on insurers are similar to their effects on commercial banks (Table 3, Panel A.1). In the (0,0) and (-1,+10) windows, commercial bank events lead to mean CARs of -0.05% and -0.38%, respectively, for non-announcing commercial banks and -0.05% and -0.37%, respectively, for insurers. However, investment bank events have a stronger impact on other investment banks than on insurers. For the (0,0) and (-1,+10) windows, investment bank events result in a mean CARs of -0.20% and -1.45%, respectively for non-announcing investment banks, compared to -0.07% and -0.76%, respectively, for insurers. This provides evidence that financial sector integration is more pronounced for commercial banks and insurers than for investment banks and insurers, although the effects are significant for both comparisons.

Interestingly, commercial bank events have a significant contagion effect on insurers in the wider windows, whereas these events generally do not have a significant contagion effect on investment banks, beyond the (-1,+1) window. Thus, the cross-sector spillovers from commercial banks to insurers are stronger than from commercial banks to investment banks, providing further evidence that commercial banks and insurers compete intensively in the market for retail financial services and in business-oriented products such as GICs.

5.2.2. Effect of insurance operational loss events on banks. Panel A of Table 6 presents the CARs for the impact of all insurance events on commercial banks. The results show strong and significant negative CARs, supportive of an inter-industry contagion effect, and the findings thus reject Null Hypothesis 2 of no inter-industry effect. The mean CAR for the event day is -0.06%, significant by the variance adjusted z test. The mean CAR continues to grow following the event day and -1.21% for the (-1, +15) window, which significant by all three tests. Comparing Panel A of Table 6 with that of Table 4, 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 significant financial sector integration.

Panel B of Table 6 shows the CARs for the impact of insurance events on investment banks. The mean CARs are -0.32% for the event day, which is significant by two of three tests. Although the CARs are also negative for the (-1,+10) and (-1,+15) windows, the significance levels are lower. Thus, for the wider windows, most of the adverse effects of insurer event announcements are absorbed by the commercial banks. This pattern is expected and consistent with information-based contagion because commercial banks have expanded more widely into the insurance industry than investment banks. The somewhat asymmetrical response between insurers and investment banks, i.e., investment bank events significantly affect insurers (Table 5), but insurance events have less significant effects on investment banks (Table 6), may be due to the fact that the most important insurance events involve deceptive sales in the retail market, where many investment banks do not have a strong presence, whereas insurers do provide wholesale financial services such as investment management.

Table 7 presents the cumulative abnormal returns for the impact of insurance deceptive sales events on non-announcing banks. Panel A shows that the effect of insurance deceptive sales events on commercial banks is strongly significant and similar to the effect on non-announcing insurers (Table 4, Panel B). As in Table 4, Panel B, there is virtually no response on the event day, but the wider window results show a large, statistically significant negative impact. Insurance deceptive sales events are associated with a mean CAR for commercial banks in the (-1, +15) window is -1.89%, which is statistically significant by all three tests and actually somewhat stronger than the impact on non-announcing insurers, -1.27%. There is some leakage before the event day, but most of the reaction comes after the events, providing further evidence that the deceptive sales events were truly unexpected. The results reveal that the deceptive sales events of a few insurers produce widespread damage to both non-announcing insurers and commercial banks, rejecting Null Hypothesis 4. Insurance deceptive sales events also have a significant negative effect on investment banks on day zero (by one test) and in the (-1,+10) and (-1,+15) windows (by two tests), perhaps suggesting adverse reputational effects for the financial sector as a whole and/or adverse effects on retail operations such as mutual funds and brokerage.

The primary distribution channels for banks' insurance products are acquired agencies, de novo entry, and joint ventures. In order to market insurance products, bankers need to be licensed as insurance agents; and many bank sales employees have previous experience in the insurance industry (White 1996, Insurance Information Institute 2005). Bank sales employees are exposed to significant competition. The licensed bankers have sales goals and incentive sales compensation in more than 90% of bank sales programs, and about two-thirds of banks will no longer maintain the license of a banker that is not selling successfully (Kehrer and Spadafora 2003). Many large insurers such as Hartford, Nationwide, and New York Life market products through banks and other financial institutions. The overlap of sales forces between the banking and insurance industries and the competition faced by the licensed bankers make bank sales employees vulnerable to deceptive sales practices. This helps to explain the strong contagion effect of insurer deceptive sales events on commercial banks.

In sum, the results reject null hypotheses 1 to 4 and provide significant evidence for both intra and inter-industry contagion 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 effects. Next we conduct multiple regression analysis to further provide evidence regarding information-based spillover effects.

5.3. Testing For Pure Versus Information-Based Spillovers. We estimate regression models to test Hypotheses 5, 6, 7, and 8. 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, and that there is no significant difference between the impact of deceptive sales events and other types of events. To be consistent with the information-based spillover effects, the stock price response of non-announcing firms should be correlated with some of the event and firm characteristics specified in the hypotheses. A finding of no relationship between stock prices and any of the event or firm characteristics would provide evidence of pure rather than information based contagion.

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 also are conducted for the commercial and investment bank events. The CARs in the (-10, +10) window are used as the dependent variables in the bank regressions, while the CARs in the (-15, +15) window are the dependent variables in the insurance regressions, reflecting the longer post-event response time of insurer stocks to the operational risk events, especially the deceptive sales events.[29] Weighted least squares estimation is used to control for heteroskedasticity.[30]

The independent variable to test Hypothesis 5 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 5. 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 6 is the firm's Tobin's Q ratio, derived from Compustat data. 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. Using the book value of assets is appropriate in the case of 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. Q is viewed as a proxy for the firm's growth opportunities – firms with relatively strong growth opportunities tend to have higher Q values. A significant coefficient on Q would reject Hypothesis 6, and 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.

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[29] Regressions based on other windows such as (-1,+10) and (-1,+15) produced similar results.

[30] 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.

The variable used to test Hypothesis 7 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 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 coefficient on the equity-to-assets ratio would imply rejection of Hypothesis 7, and a significant positive coefficient 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 that deceptive sales events do not differentially affect value, Hypothesis 8, a dummy variable is included in the regressions, set equal to 1 for deceptive sales events and to 0 otherwise. To analyze separately the effects of commercial bank and investment bank deceptive sales events, this variable appears in some regressions interacted with a dummy variable for investment bank events. A significant coefficient on this variable would imply rejection of Hypothesis 8, and a significant negative coefficient would imply that the market believes that deceptive sales problems reduce expected future cash flows more than other types of events. A significant positive coefficient would imply that deceptive sales events are less problematic for the non-announcing firms than other types of events, potentially due to competitive effects.

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 on commercial and investment banks.[31] Dummy variables set equal to 1 for commercial and investment banks,

[31] ComEvtComBank = 1 if CAR is a commercial bank response to a commercial bank event, 0 otherwise;

respectively, and to zero otherwise, also are included to test whether the intra-sector effect is larger than the inter-sector effect. The insurance regressions include a dummy variable for life insurers in order to test if there is a differential reaction of operational loss events between life and P-L insurers. It is equal to one for insurers with SIC code 6311 (life insurance) and zero for insurers with SIC code 6331 (P-L insurance). For the effect of insurance events on banks, we include a dummy to formally 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.

The regression results appear in Table 8, 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 5 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, 3, and 4, and positive but insignificant in panel 2. Thus, larger announced bank losses produce significantly less negative stock returns for non-announcing banks and insurers after controlling for other factors, with the exception of commercial bank events on non-announcing banks (panel 2), where the effect is insignificant. This may provide some evidence of a competitive effect (Table 4). By contrast, the coefficient of the log of loss amount for insurance events has a significant negative effect on both non-announcing insurers and banks (Panels 5 and 6), implying that larger announced insurer losses result in more negative returns for non-announcing firms. Thus, the loss amount variable reinforces the inference that insurance losses cause negative

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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.

information spillovers for both insurers and banks.

Null Hypothesis 6 is rejected in all panels: the coefficients of the Q ratio variable are statistically significant at the 1% level and negative 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 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.[32]

Hypothesis 7 is rejected since the coefficients of the equity-to-assets ratio variables are positive and statistically significant the 10% level or better in all regressions, i.e., non-announcing firms with high equity-to-assets ratio are less negatively affected by operational loss events. Thus, operational loss events have more severe contagion effects on firms with higher insolvency risk, consistent with the view that such firms have higher risk of financial distress.

Null Hypothesis 8 is rejected with regard to the impact of insurance deceptive sales events on insurers. The insurance deceptive sales event have a significantly larger negative impact on non-announcing insurers than other types of operational loss events (Panel 5 of Table 8), confirming that insurance deceptive sales events affect stock prices of non-announcing insurers differently from other types of events. On average, for the (-15,+15) window, the contagion effect of insurance deceptive sales events on non-announcing insurers is -1.10% more

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[32] According to Fama and French (1993), book to market equity is a risk factor, which has a positive correlation with 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 would 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, further supporting the adverse effect of operational loss events on non-announcing firms with strong growth prospects.

than that of other events, controlling for other variables in the equation. The insurance deceptive sales variable also has a negative coefficient in the regression measuring the effect of insurance deceptive sales on banks, but this effect is not statistically significant. Thus, Hypothesis 8 is not rejected with respect to the effect of insurance deceptive sales events on banks.

Based on panels 1 and 2 of Table 8, commercial bank deceptive sales events have a small negative effect on non-announcing banks; and based on panel 4, commercial bank deceptive sale events have no significant differential effect on insurers. Also recall that banks do not respond significantly to insurer deceptive sales events, after controlling for the other variables in the regression. The lack of a differential inter-sector response to deceptive sales events between insurers and commercial banks suggests that such events are not more damaging to other types of institutions than non-deceptive sales events. Thus, the differential impact of insurance deceptive sales events is confined to the insurance industry, suggesting that the commercial bank distribution channel is perhaps less vulnerable to deceptive sales.

Contrary to commercial bank deceptive sales events, investment bank deceptive sales events have significant positive coefficients for investment banks, commercial banks, and insurers, implying that (other things equal) investment bank deceptive sales events are associated with lower market value losses. This is suggestive of a possible competitive effect at the margin, whereby 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 database, 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 more adverse impacts 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 also negative and statistically significant, implying that investment bank events have more adverse impacts on non-announcing investment banks than on commercial banks. These results show that the intra-sector contagion effect is stronger than inter-sector contagion effect within the banking industry.

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 a stronger contagion effect 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 contagion effect on commercial banks than on investment banks. This asymmetrical response reflects market realities. Because most insurers do not offer traditional commercial banking products such as loans and deposits, they are not exposed to many of the commercial bank events; whereas insurers are heavily involved in wholesale financial services such as investment management. 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 contagion 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 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 all six regressions, implying that larger firms have a stronger market value loss in percentage terms than smaller firms. 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.

Overall, the regression analysis reveals significant correlation between the independent variables studied and the percentage change in market value of firms in the sample. The results thus support the argument that the contagion effect identified by the event study is, in fact, an information-based contagion effect, as oppose to a pure contagion effect. The market is able to distinguish among different financial characteristics of the firms and different types of events in a way that makes sense in terms of economic hypotheses.

5.4. Robustness Tests: Effects on Firms in Other Industries. To test the robustness of the results and to provide support for the interpretation of the findings in terms of contagion and convergence, we conducted two robustness tests. The first test involved an event study of the effects of the bank and insurer operational losses on firms in financial industries other than banking and insurance, i.e., firms in the finance, insurance, and real estate industry with SIC codes other than those included in the commercial bank, investment bank, and insurer samples. This category includes firms such as thrift institutions, real estate firms, and commodity dealers. Because most insurers and banks generally do not compete directly with such firms, there is no reason to expect spillover effects from banking and insurance operational loss events. The second test consisted of an event study of 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. 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 other financial firms or industrials, supporting the interpretation of the main results of the study as providing evidence of contagion and convergence in the banking and insurance industries.

6. Conclusions

This paper presents an intra and inter-industry analysis of 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 banking and insurance industries that began in the 1970s and accelerated with deregulation beginning in the mid-1980s. Financial services companies 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 in competition with banks. The two principal hypotheses investigated in the study are the *negative information externality hypothesis*, i.e., that operational risk events have a negative effect on stock prices of non-announcing firms, and the *competition hypothesis*, i.e., that operational events lead to wealth transfers between announcing and 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 a relatively new database, the OpVar database distributed by Fitch. The study focuses on relatively large events defined as events causing losses of at least $50 million, and the analysis includes 247 bank events and 91 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 contagion and competitive effects.

The results imply that operational loss events have strong negative intra and inter-industry spillover effects, that is, non-announcing firms 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 services firms that cause markets to revise downward estimates of future cash flows for financial firms in general rather than creating wealth transfers from announcing to non-announcing firms.

The mean CAR of bank events on non-announcing banks in the (-10, +10) window is -0.47%, which is 37% of the impact of these events on the announcing banks. We also investigate the effect of commercial bank and investment banks events separately and find that the intra-sector contagion effect is stronger than the inter-sector contagion. Investment bank events have an adverse effect on both non-announcing investment banks and commercial banks, which persists through the (-1,+10) widow. Commercial bank events have a significant impact on investment banks on the event day and in the (-1,+1) window but the effect dissipates rapidly and is not present in the wider windows. This result is expected because many commercial banks have investment banking operations, whereas investment banks typically 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. The CAR for (-1,+15) window for non-announcing insurers is -1.02%, which is 26% of the impact on the announcing insurers. The insurance events have a significant negative impact on both commercial and investment banks, and bank events have a significant negative impact on insurers. Thus, the results provide evidence of both negative spillovers and integration.

Insurance deceptive sales events are associated with especially large market value losses, but this differential effect is mostly confined to the insurance industry. During the (-15,+15) window, insurance deceptive sales events are associated with an additional market value change of -1.10% for non-announcing insurers, in comparison with other types of operational loss events. Thus, the deceptive sales events of a few insurers triggered a substantial downward revision of expected future cash flows for both insurers and commercial banks. The occurrence of deceptive sales problems among insurers is a direct response to the intensified competition resulting from bank entry into insurance markets. However, there is no significant differential effect of deceptive sales events between insurance and commercial banking. Investment bank deceptive sales events tend to be associated with lower market value losses for both insurers and banks, perhaps suggesting a marginal competitive effect.

Regression analysis provides evidence that the negative information externalities identified by the event study are information-based contagion rather than purely contagious. 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 or pay higher costs of capital for future projects following potential future operational losses. The negative response is also larger for firms with lower capital-to-asset ratios, implying that such firms exposed to higher insolvency risk are more sensitive to 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.

Figure 1: Impact on non-announcing insurers around operational loss announcements by insurers

Mean cumulative abnormal returns (CAR), in percentage terms, of non-announcing insurers during the period starting 30 days before the operational loss announcements by other insurers and ending 30 days after the announcements. Day 0 is the first public announcement of an operational loss event. The impact of deceptive sales and non-deceptive sales events are shown separately.

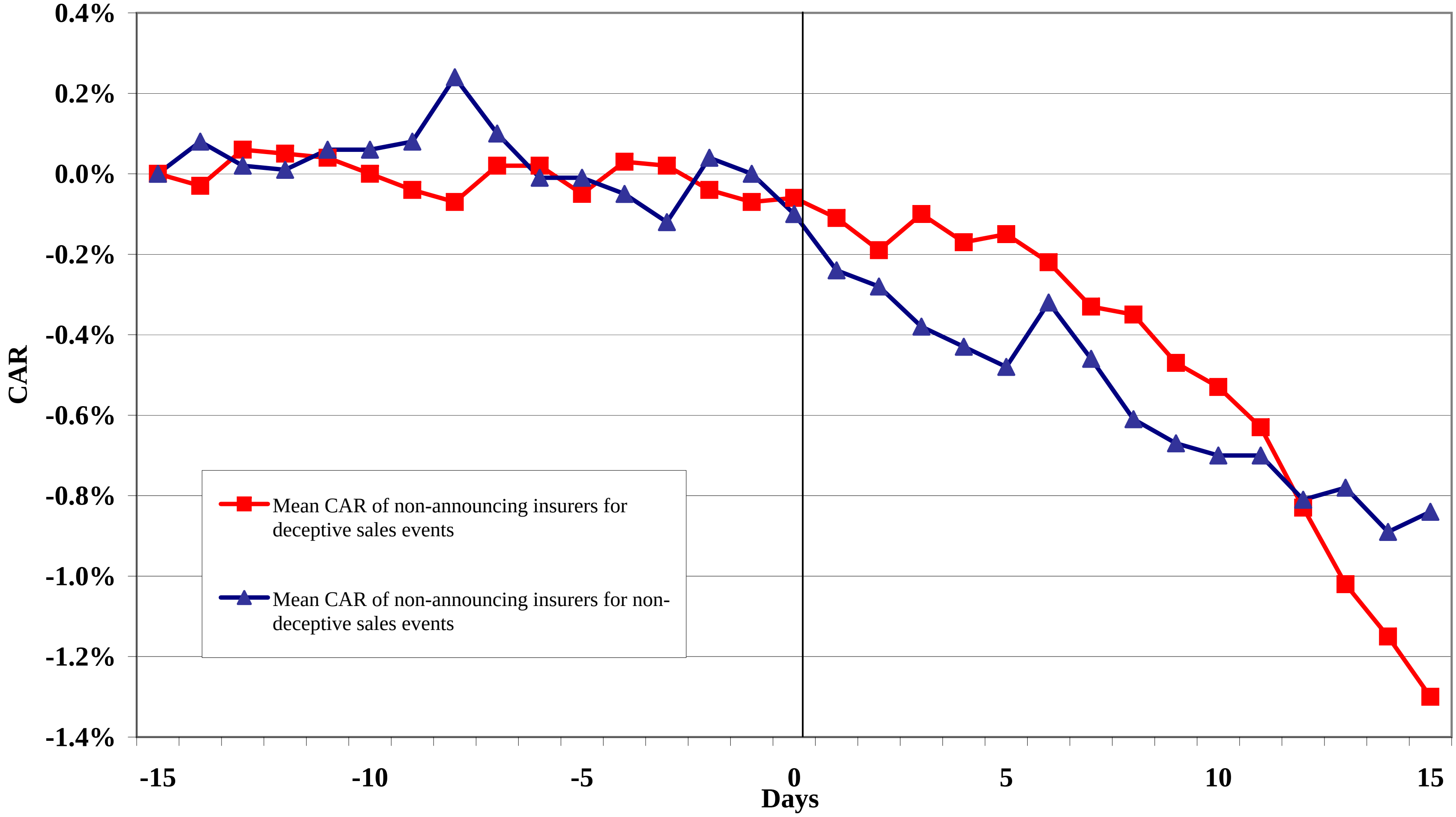

Table 1: Bank share of annuity premiums ($ billions), 1995-2004

This table reports banks' share of total individual annuity premium from 1995 to 2004, and it also reports their share of individual fixed and variable annuity premium separately. The data are obtained from the Insurance Information Institute. Premiums are in billions of dollars.

	Individual fixed annuity premium			Individual variable annuity premium			Individual annuity premium		
Year	Total ($B)	Bank ($B)	Bank share (%)	Total ($B)	Bank ($B)	Bank share (%)	Total ($B)	Bank ($B)	Bank share (%)
1995	49.4	10.7	21.7%	49.3	3.5	7.1%	98.7	14.2	14.4%
1996	38.9	10.3	26.5%	72.5	6.9	9.5%	111.4	17.2	15.4%
1997	38.2	10.0	26.2%	87.9	9.3	10.6%	126.1	19.3	15.3%
1998	32.9	8.5	25.8%	98.6	11.2	11.4%	131.5	19.7	15.0%
1999	42.1	12.5	29.7%	114.4	13.9	12.2%	156.5	26.4	16.9%
2000	52.8	15.4	29.2%	137.7	15.6	11.3%	190.5	31.0	16.3%
2001	71.5	27.4	38.3%	112.8	10.9	9.7%	184.3	38.3	20.8%
2002	98.6	36.4	36.9%	119.3	12.5	10.5%	217.9	48.9	22.4%
2003	81.6	32.0	39.2%	129.2	18.1	14.0%	210.8	50.1	23.8%
2004	84.4	30.3	35.9%	133.5	18.0	13.5%	217.9	48.3	22.2%

Table 2: Descriptive statistics for operational loss events studied by event types ($ millions), from 1978-2003

This table shows sample mean, median, standard deviation, minimum, and maximum for all operational loss events studied by event types from 1978 to 2003. The descriptive data on operational loss events of all banks, commercial banks, investment banks, and all insurers are shown in Panel A, B, C, and D, respectively. The data are obtained from the OpVar operational loss database distributed by OpVantage, which is a division of Fitch Risk Management. All summary statistics are in millions of constant 2002 dollars based on Consumer Price Index. N is the number of events. % total N is the number of events from a specific 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	196.32	172.19	115.37	205.60	156.51	232.63	123.29	171.85	143.13	193.20
Median	109.70	102.39	133.54	97.07	82.28	105.69	112.05	171.85	78.42	101.35
Std Dev	254.84	193.55	43.99	319.91	150.96	380.55	44.10	116.43	119.94	277.90
Min	50.28	51.33	65.21	50.38	51.02	50.38	84.86	89.53	50.20	50.20
Max	1,557.88	972.21	147.37	2,532.39	774.54	2,532.39	184.22	254.18	409.34	2,532.39
N	56	30	3	138	49	89	4	2	14	247
% total N	22.7%	12.1%	1.2%	55.9%	19.8%	36.0%	1.6%	0.8%	5.7%	100.0%
Panel B: All commercial bank events										
Mean	173.00	169.91	115.37	244.74	165.41	267.22	123.29	89.53	164.88	204.16
Median	86.07	96.92	133.54	95.38	79.34	123.57	112.05	89.53	98.26	94.23
Std Dev	268.14	204.34	43.99	409.45	188.33	451.67	44.10		134.26	328.32
Min	50.28	51.33	65.21	51.33	58.67	51.33	84.86	89.53	50.20	50.20
Max	1,557.88	972.21	147.37	2,532.39	774.54	2,532.39	184.22	89.53	409.34	2,532.39
N	39	26	3	77	17	60	4	1	8	158
% total N	24.7%	16.5%	1.9%	48.7%	10.8%	38.0%	2.5%	0.6%	5.1%	100.0%
Panel C: All investment bank events										
Mean	249.81	186.98		156.19	151.79	161.06		254.18	114.14	173.73
Median	206.64	199.83		99.09	97.78	101.35		254.18	77.13	109.70
Std Dev	219.35	117.74		129.94	130.05	131.94			101.99	151.59
Min	51.56	60.67		50.38	51.02	50.38		254.18	52.55	50.38
Max	969.88	287.57		479.39	479.39	452.52		254.18	318.19	969.88
N	17	4		61	32	29		1	6	89
% total N	19.1%	4.5%		68.5%	36.0%	32.6%		1.1%	6.7%	100.0%
Panel D: All insurance events										
Mean	200.55	94.48	101.76	239.70	340.55	156.07	201.68	335.52	94.41	224.14
Median	160.25	94.48	78.97	119.73	137.61	110.11	201.68	335.52	90.48	117.80
Std Dev	139.77	32.39	66.92	411.98	572.64	166.31			27.16	377.60
Min	76.00	71.58	50.16	52.72	52.72	55.82	201.68	335.52	69.42	50.16
Max	411.89	117.39	198.93	2,256.75	2,256.75	1,071.45	201.68	335.52	123.32	2,256.75
N	5	2	4	75	34	41	1	1	3	91
% total N	5.5%	2.2%	4.4%	82.4%	37.4%	45.1%	1.1%	1.1%	3.3%	100.0%

Table 3: Impact of commercial and investment bank operational loss events on non-announcing commercial and investment banks

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. On average, there are approximately 318 non-announcing commercial banks and 39 non-announcing investment banks.

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)	158	-0.05%	-0.14%	-8.663 ***	-2.257 *	-10.742 ***
(-1,+1)	158	-0.06%	-0.27%	-12.275 ***	-1.784 $	-5.727 ***
(-5,+5)	158	-0.24%	-0.54%	-10.650 ***	-1.775 $	-1.762 *
(-10,+10)	158	-0.51%	-0.85%	-14.402 ***	-1.745 $	-4.518 ***
(-5,-1)	158	0.02%	-0.20%	2.435 **	0.041	5.362 ***
(-10,-1)	158	-0.12%	-0.34%	-1.988 *	-0.191	4.250 ***
(-1,+5)	158	-0.25%	-0.48%	-16.197 ***	-2.324 *	-5.309 ***
(-1,+10)	158	-0.38%	-0.71%	-18.233 ***	-2.382 *	-7.678 ***

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)	158	-0.12%	-0.17%	-2.965 **	-1.859 $	-2.691 **
(-1,+1)	158	-0.23%	-0.43%	-3.674 ***	-2.036 *	-3.565 ***
(-5,+5)	158	-0.14%	-0.57%	-0.943	-0.448	-0.328
(-10,+10)	158	0.06%	-0.49%	0.537	0.187	1.980 *
(-5,-1)	158	-0.13%	-0.38%	-0.284	-0.447	-0.710
(-10,-1)	158	0.04%	-0.36%	1.317 $	0.319	1.751 *
(-1,+5)	158	-0.08%	-0.42%	-1.412 $	-0.427	0.306
(-1,+10)	158	-0.06%	-0.52%	-0.940	-0.173	0.661

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)	89	-0.04%	-0.12%	-6.007 ***	-1.160	-4.627 ***
(-1,+1)	89	-0.16%	-0.27%	-9.318 ***	-1.301	-3.128 ***
(-5,+5)	89	-0.51%	-0.75%	-14.089 ***	-1.332	-7.758 ***
(-10,+10)	89	-0.49%	-0.84%	-10.603 ***	-0.815	-2.614 **
(-5,-1)	89	0.03%	-0.12%	3.411 ***	0.404	7.666 ***
(-10,-1)	89	0.36%	-0.01%	12.967 ***	1.377	13.765 ***
(-1,+5)	89	-0.53%	-0.62%	-18.821 ***	-1.816 $	-8.967 ***
(-1,+10)	89	-0.86%	-0.93%	-23.899 ***	-2.007 *	-10.925 ***

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)	89	-0.20%	-0.28%	-5.022 ***	-0.538	-3.757 ***
(-1,+1)	89	-0.59%	-0.55%	-8.512 ***	-1.354	-5.098 ***
(-5,+5)	89	-0.92%	-1.14%	-6.822 ***	-1.155	-4.931 ***
(-10,+10)	89	-0.68%	-1.16%	-3.772 ***	-0.462	-1.492 $
(-5,-1)	89	-0.08%	-0.35%	-0.462	-0.817	-0.269
(-10,-1)	89	0.62%	-0.04%	3.744 ***	0.804	4.325 ***
(-1,+5)	89	-0.98%	-1.01%	-9.221 ***	-1.006	-4.662 ***
(-1,+10)	89	-1.45%	-1.31%	-9.844 ***	-1.169	-5.683 ***

Table 4: Impact of insurance operational loss events on non-announcing insurers

This table shows market model mean and median cumulative abnormal returns (CAR), in percentage terms, of non-announcing insurers for various windows around operational loss announcements by other insurers. The impact of all insurance events is shown in Panel A. The impact of deceptive sales events and non-deceptive sales events 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. On average, there are approximately 133 non-announcing insurers around each event.

Days	N	Mean CAR	Median CAR	Variance adjusted z-stat	Calendar time t-test	Generalized sign z-test
Panel A: Impact of all insurance events on all non-announcing insurers						
(0,0)	91	-0.06%	-0.09%	-2.134 *	-0.322	-1.317 $
(-1,+1)	91	-0.20%	-0.25%	-3.981 ***	-1.561	-4.212 ***
(-5,+5)	91	-0.36%	-0.53%	-3.601 ***	-1.916 $	-2.519 **
(-10,+10)	91	-0.68%	-0.60%	-3.902 ***	-2.080 *	0.012
(-15,+15)	91	-0.96%	-0.86%	-4.480 ***	-2.194 *	-0.443
(-10,-1)	91	-0.08%	-0.35%	-0.126	-0.423	0.231
(-15,-1)	91	0.03%	-0.31%	0.616	0.449	2.944 **
(-1,+5)	91	-0.37%	-0.45%	-4.697 ***	-2.280 *	-2.956 **
(-1,+10)	91	-0.64%	-0.60%	-6.384 ***	-2.600 *	-1.535 $
(-1,+15)	91	-1.02%	-0.91%	-7.393 ***	-3.536 ***	-5.304 ***
Panel B: Impact of all deceptive sales insurance events on all non-announcing insurers						
(0,0)	34	0.01%	-0.08%	-1.282 $	0.078	-0.173
(-1,+1)	34	-0.07%	-0.22%	-2.010 *	-0.726	-1.839 *
(-5,+5)	34	-0.17%	-0.43%	-3.005 **	-0.880	-1.096
(-10,+10)	34	-0.56%	-0.90%	-5.709 ***	-1.562	-2.315 *
(-15,+15)	34	-1.23%	-1.38%	-8.582 ***	-2.133 *	-3.059 **
(-10,-1)	34	-0.10%	-0.40%	-1.286 $	-0.713	-0.322
(-15,-1)	34	0.00%	-0.23%	-0.494	-0.487	1.998*
(-1,+5)	34	-0.11%	-0.44%	-2.601 **	-0.730	-2.167 *
(-1,+10)	34	-0.49%	-0.84%	-6.397 ***	-1.488	-3.357 ***
(-1,+15)	34	-1.27%	-1.42%	-10.931 ***	-2.577 *	-6.837 ***
Panel C: Impact of all non-deceptive sales insurance events on all non-announcing insurers						
(0,0)	57	-0.10%	-0.09%	-1.716 *	-0.690	-1.531 $
(-1,+1)	57	-0.27%	-0.26%	-3.477 ***	-1.805 $	-3.902 ***
(-5,+5)	57	-0.47%	-0.59%	-2.481 **	-1.827 $	-2.337 **
(-10,+10)	57	-0.76%	-0.41%	-2.029 *	-1.689 $	1.807 *
(-15,+15)	57	-0.79%	-0.55%	-1.302 $	-1.582	1.807 *
(-10,-1)	57	-0.06%	-0.31%	0.285	0.087	0.541
(-15,-1)	57	0.05%	-0.36%	0.871	0.779	2.176*
(-1,+5)	57	-0.52%	-0.46%	-3.911 ***	-2.621 *	-2.061 *
(-1,+10)	57	-0.73%	-0.41%	-3.802 ***	-2.525 *	0.656
(-1,+15)	57	-0.88%	-0.60%	-2.760 **	-2.955 **	-1.416 $

Table 5: Impact of commercial and investment bank operational loss events on insurers

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. On average, there are approximately 137 insurers around each event.

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)	158	-0.05%	-0.11%	-4.435 ***	-1.492	-4.770 ***
(-1,+1)	158	-0.07%	-0.19%	-3.996 ***	-1.013	-0.509
(-5,+5)	158	-0.11%	-0.38%	-2.300 *	-1.060	1.683 *
(-10,+10)	158	-0.39%	-0.64%	-6.077 ***	-1.713 $	0.761
(-5,-1)	158	0.17%	-0.09%	5.264 ***	0.859	6.739 ***
(-10,-1)	158	0.06%	-0.21%	0.999	-0.315	5.032 ***
(-1,+2)	158	-0.07%	-0.23%	-3.542 ***	-0.680	-0.240
(-1,+3)	158	-0.13%	-0.28%	-4.810 ***	-1.238	-0.202
(-1,+5)	158	-0.20%	-0.35%	-5.914 ***	-1.633	-0.877
(-1,+10)	158	-0.37%	-0.51%	-8.068 ***	-1.929 $	-1.276
Panel B: Impact of investment banks events						
(0,0)	89	-0.07%	-0.12%	-3.986 ***	-1.681 $	-3.032 **
(-1,+1)	89	-0.15%	-0.21%	-6.016 ***	-2.339 *	0.178
(-5,+5)	89	-0.18%	-0.53%	-7.505 ***	-2.160 *	-1.185
(-10,+10)	89	-0.23%	-0.55%	-5.336 ***	-1.812 $	2.005 *
(-5,-1)	89	0.29%	-0.08%	4.431 ***	0.076	6.088 ***
(-10,-1)	89	0.60%	0.11%	9.476 ***	0.847	10.771 ***
(-1,+2)	89	-0.24%	-0.32%	-8.285 ***	-2.940 **	-2.117 *
(-1,+3)	89	-0.27%	-0.40%	-9.682 ***	-2.832 **	-3.471 ***
(-1,+5)	89	-0.41%	-0.58%	-12.096 ***	-2.967 **	-4.707 ***
(-1,+10)	89	-0.76%	-0.82%	-14.988 ***	-3.141 **	-5.758 ***

Table 6: Impact of insurance operational loss events on commercial and investment banks

This table shows market model mean and median cumulative abnormal returns (CAR), in percentage terms, of banks for various windows around operational loss announcements by insurers. The impact of all insurance events on commercial banks is shown in Panel A. Panel B shows the impact of all insurance events on 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. On average, there are approximately 323 commercial banks and 45 investment banks around each event.

Days	N	Mean CAR	Median CAR	Variance adjusted z-stat	Calendar time t-test	Generalized sign z-test
Panel A: Impact on commercial banks						
(0,0)	91	-0.06%	-0.08%	-4.656 ***	-0.522	0.836
(-1,+1)	91	-0.12%	-0.19%	-4.471 ***	-1.109	-0.100
(-5,+5)	91	-0.46%	-0.65%	-10.412 ***	-0.927	-7.301 ***
(-10,+10)	91	-1.11%	-1.26%	-19.161 ***	-1.916 $	-12.242 ***
(-15,+15)	91	-1.52%	-1.51%	-21.884 ***	-1.900 $	-10.490 ***
(-10,-1)	91	-0.37%	-0.50%	-8.031 ***	-0.077	-2.939 **
(-15,-1)	91	-0.33%	-0.46%	-6.383 ***	0.268	0.673
(-1,+5)	91	-0.35%	-0.44%	-9.980 ***	-1.688 $	-5.525 ***
(-1,+10)	91	-0.76%	-0.70%	-18.074 ***	-2.463 *	-7.845 ***
(-1,+15)	91	-1.21%	-1.04%	-23.760 ***	-2.852 **	-11.771 ***
Panel B: Impact on investment banks						
(0,0)	91	-0.32%	-0.21%	-2.539 **	-1.330	-3.188 ***
(-1,+1)	91	-0.18%	-0.33%	-1.898 *	0.327	-2.136 *
(-5,+5)	91	0.04%	-0.39%	0.995	1.061	1.803 *
(-10,+10)	91	0.06%	-0.73%	0.309	0.756	0.485
(-15,+15)	91	-0.15%	-0.60%	0.261	0.751	1.771 *
(-10,-1)	91	0.63%	-0.17%	2.572 **	1.714 $	2.399 **
(-15,-1)	91	0.75%	-0.23%	3.342 ***	1.940 $	3.057 **
(-1,+5)	91	-0.22%	-0.63%	-1.136	0.394	-1.209
(-1,+10)	91	-0.36%	-0.77%	-1.570 $	-0.284	-2.338 **
(-1,+15)	91	-0.69%	-0.96%	-2.564 **	-0.400	-1.021

Table 7: Impact of insurer deceptive sales events on commercial and investment banks

This table shows market model mean and median cumulative abnormal returns (CAR), in percentage terms, of banks for various windows around insurance deceptive sales events. The impact of insurance deceptive sales events on commercial and investment banks 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. On average, there are approximately 323 commercial banks and 45 investment banks around each event.

Days	N	Mean CAR	Median CAR	Variance adjusted z-stat	Calendar time t-test	Generalized sign z-test
Panel A: Impact on commercial banks						
(0,0)	34	0.00%	-0.07%	-1.147	-0.202	1.512 $
(-1,+1)	34	-0.20%	-0.21%	-5.32 ***	-1.312	-1.251
(-5,+5)	34	-0.38%	-0.55%	-5.057 ***	-0.975	-2.833 **
(-10,+10)	34	-1.19%	-1.25%	-11.146 ***	-1.498	-7.318 ***
(-15,+15)	34	-2.04%	-1.92%	-15.808 ***	-1.809 $	-9.221 ***
(-10,-1)	34	-0.18%	-0.28%	-1.313 $	-0.330	1.412 $
(-15,-1)	34	-0.21%	-0.33%	-1.616 $	-0.367	2.273 *
(-1,+5)	34	-0.38%	-0.47%	-6.797 ***	-1.290	-4.315 ***
(-1,+10)	34	-1.06%	-0.96%	-14.288 ***	-2.073 *	-9.821 ***
(-1,+15)	34	-1.89%	-1.74%	-20.787 ***	-2.574 *	-14.947 ***
Panel B: Impact on investment banks						
(0,0)	34	-0.31%	-0.21%	-0.781	-0.727	-1.880 *
(-1,+1)	34	-0.40%	-0.44%	-1.652 *	-0.484	-1.372 $
(-5,+5)	34	-0.36%	-0.79%	-0.039	0.051	-0.304
(-10,+10)	34	-0.18%	-1.14%	0.125	0.494	0.001
(-15,+15)	34	-1.02%	-1.42%	-0.999	0.216	0.052
(-10,-1)	34	0.87%	-0.31%	2.009 *	1.089	1.373 $
(-15,-1)	34	0.71%	-0.55%	1.798 *	1.095	0.560
(-1,+5)	34	-0.50%	-0.75%	-1.058	-0.130	-0.812
(-1,+10)	34	-1.02%	-1.37%	-1.588 $	-0.621	-3.303 ***
(-1,+15)	34	-1.70%	-1.82%	-3.121 ***	-1.032	-3.557 ***

Table 8: Regression results for operational loss announcements by both banks and insurers

This table reports multivariate OLS regression 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,+y), which is the cumulative abnormal return from an event in a window w days before the event date to y 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 with a head SIC code 602, 0 otherwise; InvBank = 1 if the bank is a investment bank with SIC code 6211, 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 a investment bank event, 0 otherwise; InvEvtInvBank = 1 if CAR is from a investment bank for a investment bank event; Life = 1 if the insurer is a life insurer with 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 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)	0.00101	-0.00191	0.00250	-0.00320	0.01237	-0.00229	0.02477	-0.00417	-0.01193	-0.01780	0.009	69.03	247
	0.33	-10.06	6.42	-4.46	2.37	-1.85	15.30	-2.20	-6.06	-7.16		***	
		***	***	***	**	*	***	**	***	***			

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)	0.00398	-0.00124	0.00072	-0.00290	0.01574	-0.00269	-0.00371	0.002	10.98	158
	1.1	-4.98	1.52	-3.32	2.33	-2.11	-1.72		***	
		***		***	**	**	*			

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)	-0.02493	-0.00285	0.00681	-0.00387	0.01451	0.02314	-0.00765	0.028	112.65	89
	-6.24	-9.54	9.91	-3.01	1.72	23.05	-2.72		***	
	***	***	***	***	*	***	***			

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)	0.01064	-0.00175	0.00189	-0.01234	0.00651	-0.00127	-0.00620	0.01529	0.00163	0.007	23.54	247
	2.65	-6.22	3.07	-7.29	1.76	-0.64	-5.12	5.88	1.45		***	
	***	***	***	***	*		***	***				

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)	0.07942	-0.00395	-0.00722	-0.02328	0.01615	-0.01101	0.00052	0.015	29.7	91
	9.25	-6.67	-5.66	-5.83	2.14	-4.97	0.12		***	
	***	***	***	***	**	***				

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)	0.11271	-0.00198	-0.00753	-0.05951	0.05367	-0.00066	-0.01716	-0.00108	0.015	63.57	91
	16.64	-5.16	-9.93	-12.41	5.92	-0.15	-5.16	-0.23		***	
	***	***	***	***	***		***				

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