Business Complexity and Risk Management: Evidence from Operational Risk Events in U.S. Bank Holding Companies*

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Abstract

Recent regulatory proposals tie the systemic importance of a financial institution to its complexity. However, we know little about how complexity affects a bank's behavior, including its risk management. Using the gradual deregulation of banks' nonbank activities during 1996–1999 as a natural experiment, we show that the frequency and magnitude of operational risk events in U.S. bank holding companies have increased significantly with their business complexity. This trend is particularly strong for banks that were bound by regulations beforehand, especially for those with an existing Section 20 subsidiary, and weaker for the other banks that were not bound and for nonbank financial institutions that were not subject to the same regulations to begin with. These results reveal the darker side of post-deregulation diversification, which in earlier studies has been shown to lead to improved earnings performance. We use operational risk events as a risk management measure because (i) the timing of the origin of each event is well identified, whereas actual balance sheet losses can take years to materialize, and (ii) the risk events can serve as a direct measure of materialized failures in risk management without being influenced by the confounding factors that drive asset prices, such as implicit government guarantees. Our findings have important implications for the regulation of financial institutions deemed *systemically important*, a designation tied closely to their complexity by the Bank for International Settlements and the Federal Reserve.

Keywords: operational risk, bank holding companies, financial deregulation, Glass-Steagall Act, business complexity.

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"The failure of large, complex, and interconnected financial firms can disrupt the broader financial system and the overall economy, and such firms should be regulated with that fact in mind."

Ben S. Bernanke, former Chairman of the Federal Reserve System, June 16, 2010

1 Introduction

The recent financial crisis has catapulted the regulation of large, complex financial institutions to the center of policy debate. Although regulators have recently proposed complexity as one of the main criteria for the designation of a bank as *systemically important*, we have very little evidence as to how complexity affects risk management in financial institutions. This issue is further complicated by the lack of a clear definition of complexity. In this paper, we follow the guidelines provided by the Bank for International Settlements (BIS), which describe complexity as the activities of banks outside of the traditional business of banking and strictly separate it from other measures such as interconnectedness and size.[1] Based on these guidelines, we use the gradual deregulation of banks' nonbank activities in the United States between 1996 and 1999 as a natural experiment that has led to increased complexity in the banking system. This approach also conforms with the notion that the attempts to work around and relax regulatory restrictions on bank activities have contributed to the creation of complex financial systems of today (Gorton and Metrick, 2013). We use operational risk events as a risk management measure because (i) the timing of the origin of operational risk events is well identified, and (ii) such risk events can serve as a direct measure of materialized failures in the risk management process without being influenced by confounding factors such as implicit government guarantees.

We show that the frequency and magnitude of operational risk events in U.S. bank holding companies (BHCs) have increased significantly with complexity following the deregulation. We find that this trend is particularly strong for banks that had already engaged in regulated activities but were bound by regulations, making them more likely to take advantage of the deregulation by increasing their diversification into previously regulated activities, such as securities underwriting

[1] BIS scores a financial institution's complexity using their notional amount of OTC derivatives, trading and Available for Sale (AFS) securities, and Level 3 assets (`http://www.bis.org/bcbs/publ/d296.pdf`). Recent proposals from the Federal Reserve also follow a similar direction (`http://www.federalreserve.gov/newsevents/press/bcreg/20150720a.htm`).

and dealing, insurance agency and underwriting activities, and merchant banking. This result holds in comparison with both banks that did not engage in regulated activities before the deregulation and with nonbank financial institutions that were never subject to these regulations in the first place. Our results suggest that the increased complexity due to expansion into nonbank business lines leads to a deterioration of banks' risk management and to higher operational risk.

Operational risk is considered an important challenge to banks' risk management.[2] The Basel II Capital Accord mandates that banks quantify and manage their operational risk, which is defined as the risk of loss resulting from inadequate or failed internal processes, people, systems, or external events (BCBS 2001b). Operational risk is diverse in nature with a wide range of causes, including unauthorized transactions, fraud, technology and software failures, flawed financial models and products, poor business practices, natural disasters and terrorism, employment issues and discrimination, and execution and delivery failures. The losses arising from operational risk can be substantial. In a recent example, Deutsche Bank announced a \$7.3 bln loss in January 2016, attributed to its past wrongdoing, which includes colluding with other banks to fix benchmark interest rates and violating international sanctions. The \$6.2 bln trading fiasco from JP Morgan Chase's "London Whale" in 2012, Bernard Madoff's \$50 bln Ponzi scheme in 2008, and the \$7.2 bln trading loss at Société Générale in 2008 are just a few other examples of the devastating nature of operational risk in recent years. De Fontnouvelle et al. (2006) show that the regulatory capital charge of many banks for operational risk can exceed those for market and credit risk.[3] The Basel Accord requires that *"banks should implement policies, procedures and practices to manage operational risk commensurate with their size, complexity, activities and risk exposure."* (BCBS 2014, p. 4). In the United States, the 2010 Dodd-Frank Wall Street Reform and Consumer Protection Act includes operational risk in stress testing through the Comprehensive Capital Analysis and Review (CCAR) framework. In Europe, operational risk has been a mandatory constituent of the United Kingdom's Prudential Regulation Authority and European Banking Authority stress test-

[2] Quoting Thomas J. Curry, the Comptroller of the Currency, *"Given the complexity of today's banking markets [...] the OCC deems operational risk to be high and increasing. [...] this is the first time [OCC supervisors] have seen operational risk eclipse credit risk as a safety and soundness challenge. Rising operational risk concerns them, it concerns me, and it should concern you."* (May 16, 2012, `http://www.occ.gov/news-issuances/speeches/2012/pub-speech-2012-77.pdf`)

[3] De Fontnouvelle et al. (2006) report that banks allocate on average 15 percent of their risk capital to operational risk. By more recent estimates, Ames, Schuermann, and Scott (2015) find that operational risk represents approximately 10–30 percent of the total risk.

ing requirements since 2013 and 2009, respectively.[4] Ratings agencies, such as Moody's Investors Service, Morningstar, and Fitch Ratings, recently also began to incorporate operational risk in assigning corporate financial ratings (Moody's Investors Service 2003; Morningstar 2015; Fitch Ratings 2004).[5] Arguably, operational risk has been at least partially responsible in the flawed business practices that had let to the crisis (Gorton and Metrick 2013). Recent political debates in 2016 have renewed the idea of reinstating the Glass-Steagall Act.

A good illustration of the dangers of business complexity to a bank's operations is the recent operational risk event at Wells Fargo. Following a lawsuit filed in May 2015 by the Los Angeles City Attorney, in September 2016 Wells Fargo was fined $185 million for its aggressive sales practices. Investigation revealed that over five thousand employees were engaged in cross-selling practices involving secretly opening up fake checking and credit card accounts, insurance or retirement plans — a total of over two million accounts — for customers without their consent, in order to reach sales targets set by the bank and to boost bonuses. In November 2016, it was revealed that the customers of the brokerage business of the bank were also affected by the scam. Consumer Financial Protection Bureau's Director Richard Cordray said that these "abusive practices" were made possible largely because "the bank did not monitor the program carefully."[6] During September 2016, Wells Fargo's stock price dropped by nearly 16 percent, 5,300 employees were fired, and on October 12 its CEO and Chairman John Stumpf resigned after a nine-year tenure.

In this study, we perform a difference-in-differences analysis, using as a natural experiment the deregulation in the U.S. banking sector between the end of 1996 and the end of 1999 (the Gramm-Leach-Bliley Act) that gradually relaxed the restrictions imposed under the Glass-Steagall Act of 1933. We investigate the impact of organizational complexity on U.S. BHCs' operational risk by noting that, compared with that of the other BHCs and nonbank financial institutions, the regulatory environment before deregulation was likely to be more restrictive for BHCs that had already diversified into nonbank business lines, especially for those with established Section 20 subsidiaries.[7] We find that the BHCs that are more likely to be constrained by the regulations face

[4] See `http://www.bankofengland.co.uk/pra/Pages/supervision/activities/stresstesting.aspx` and `http://www.eba.europa.eu/risk-analysis-and-data/eu-wide-stress-testing`.

[5] See also `http://businessfinancemag.com/blog/moodys-new-operational-risk-guidelines-will-impact-ratings`.

[6] `http://www.wsj.com/articles/wells-fargo-to-pay-185-million-fine-over-account-openings-1473352548`

[7] In this paper, we use the terms bank, bank holding company, and financial holding company interchangeably. The term financial holding company generally replaced the term bank holding company after the Gramm-Leach-Bliley Act of 1999. See `http://www.federalreserve.gov/boarddocs/rptcongress/glbarptcongress.pdf`.

greater frequency and magnitude of operational risk events following the deregulation. In other words, an increase in a BHC's organizational complexity can increase its exposure to operational risk. Moreover, our results show that the impact of complexity on operational risk remain robust even after controlling for size and other bank-specific attributes and merger activity. Our results are also robust to various model specifications and a comprehensive set of endogeneity tests.

At the heart of the policy debate lies the tradeoff between potential synergies and diversification benefits from a financial institution's involvement in multiple business lines versus the potential risk management weaknesses generated by their increased complexity that can result in losses for both the financial sector and the taxpayers. On the positive side, papers as early as Diamond (1984) and Boyd and Prescott (1986) emphasize that diversified banks benefit from cost efficiencies that can enhance stability. Large financial conglomerates benefit from an implicit extension of "too-big-to-fail" guarantees to their nonbank activities as well as additional opportunities to amass significant market power (Kane 2000; Carow and Heron 2002). Neuhann and Saidi (2016a) showed that the repeal of the Glass-Steagall Act enabled banks to utilize informational economies of scale in monitoring. They find that firms that borrow from universal banks have higher sales growth and stock returns. On the negative side, expansion of scope can hinder the ability of a bank's headquarters to monitor its subsidiaries (for example, Brickley, Linck, and Smith 2003; Berger et al. 2005). The academic literature since the financial crisis also reflects this tension. For example, Goetz, Laeven, and Levine (2013, 2016) find that geographic diversification reduces a bank's valuation as well as its risk. Regarding the diversification of business lines, Neuhann and Saidi (2016a) find that firms that borrow from universal banks have higher productivity growth but riskier cash flows, while Focarelli, Marquez-Ibanez, and Pozzolo (2011) find that these firms are also more likely to default. Gorton and Metrick (2013) and Neuhann and Saidi (2016b) argue that the advent of universal banking has fostered the growth of institutional investors and securitization that is central to the recent financial crisis.

We contribute to this debate by studying the effects of business diversification on operational risk events and comparing them with the effects on traditional performance and risk measures, which include balance-sheet- and market-based measures, such as market-to-book value and the mean and standard deviation of return on assets. While these measures are useful to answer certain questions studied in the literature, their use creates identification problems when it comes to the study of banks' risk management in our context. Balance sheet measures, such as return on assets (ROA), capture the risk after it is realized, whereas our empirical identification requires knowledge of the risk when the risk is actually taken, which may be far in the past, as, for example, has been the case with the mortgage-backed securities in the 2008 financial crisis.[8] Market-based measures, such as bond yields, CDS spreads, and stock returns, are also not suitable for capturing the effect of deregulations on risk management in our study because (a) investors are only partially informed of the risks taken by management due to asymmetric information between managers and investors and (b) these measures are contaminated by other confounding factors, such as implicit government guarantees associated with the systemic importance of financial institutions.[9] To aggravate the problem, the level of these implicit government guarantees is likely to increase as the level of complexity of a bank goes up. Therefore, a more complex bank can appear more profitable and less risky according to balance-sheet and market-based measures because it loads on risks that boost profits today in exchange of losses to be realized far in the future and to be borne by taxpayers. Using operational risk events helps circumvent these issues and thus provides a more suitable laboratory to study the effects of deregulation-induced complexity on banks' risk management.

We show that the operational risk of banks goes up after deregulation especially for banks that were constrained by the financial regulations, which is consistent with the operational risk model described in Basak and Buffa (2016). At the same time, balance-sheet and market-based performance measures typically improve. Thus, our study highlights that traditional performance measures may be insufficient to fully capture the impact of regulations on risk management, and that any apparent performance benefit comes at the expense of increased risk that is not immediately evident. Furthermore, some recent empirical literature highlights potential threats coming from operational risk externalities in the form of intra-industry spillover effects (for example, Cummins, Wei, and Xie 2011; Chernobai, Jorion, and Yu 2007), suggesting a systematic nature of this risk in the financial sector. Because these spillovers are more likely to originate from the BHCs that are more complex, such firms may warrant more stringent regulatory requirements for

[8]See, for example, Kohn (2009). The average difference between the origination and realization date of our BHC operational risk events is about four years, with a standard deviation of around three years.

[9]Acharya, Anginer, and Warburton (2015) show that bond credit spreads are not sensitive to risk for large financial institutions, and that after TARP, larger financial institutions had greater reduction in credit spreads than smaller institutions. Beliaeva, Khaksari, and Tsafack (2015) found that implicit government guarantees reduce CDS spreads by 76 bps for financial institutions.

operational risk.

This paper proceeds as follows. Section 2 reviews the relevant literature. Section 3 offers a review of operational risk and its management principles. Section 4 reviews highlights of the regulatory background of the Glass-Steagall Act and its repeal. Section 5 discusses the development of hypotheses that are then tested in Section 6. Section 7 offers concluding remarks.

2 Literature Review

Our study is closely related to the literature on bank complexity. Extant literature on banks' complexity lacks consensus on the definition of complexity and how it should be measured. One stream of this literature focuses on organizational complexity. In a recent study that is closely related to ours, Cetorelli, McAndrews, and Traina (2014) discuss the benefits and costs of banks' organizational complexity, which they measure by the number and types of a BHC's subsidiaries. They show that BHCs' average complexity increased steadily between 1990 and 2010. Liu, Norden, and Spargoli (2015) examine the complexity of BHCs and find it to be inversely U-shaped in relation to system risk and that increased complexity leads to an improved market-based performance.

Another strand of literature related to complexity focuses on the network of interconnected financial firms. Allen and Gale (2000) develop a theoretical model of financial networks that describes how networks influence systemic risk through financial contagion. In their model, in a more densely interconnected financial network, the impact of negative shocks to individual institutions on the rest of the economy is reduced because the losses of a distressed bank are divided among a larger number of creditors. Similar positive effects of interconnectedness are documented in Freixas, Parigi, and Rochet (2000), and a negative effect from the network of cross exposures is documented in Caballero and Simsek (2013).[10]

Another stream of literature closely related to our paper studies the effects of deregulation and diversification. Ashcraft and Schuermann (2008) document that diversification creates new

[10] Other papers on financial networks and interconnectedness, such as Acemoglu, Ozdaglar, and Tahbaz-Salehi (2015), Vivier-Lirimont (2006), and Leitner (2005), investigated the opposite, adverse effects of network complexity on financial firms and the economy. Gai, Haldane, and Kapadia (2011) studied a network model of interbank lending and showed how greater complexity and concentration in the financial network amplifies systemic risk. Shin (2010) argued that securitization increased the complexity of the financial system by lengthening the intermediation chains, thus deteriorating financial stability.

frictions across the newly established intermediaries. Stiroh and Rumble (2006) document that, between 1997 and 2002, diversified BHCs experienced higher costs of increased exposure to volatile non-interest activities, such as brokerage, advisory services, and underwriting, and may have had a higher probability of default.[11] Cetorelli, McAndrews, and Traina (2014) argue that the practice of cross-selling may expose multiple businesses to the same shocks that propagate across the many affiliates of the same organization, and that possible subsidies from explicit or perceived government guarantees may distort incentives in failure resolution. Loutskina and Strahan (2011) find that concentrated mortgage lenders have higher profits, which vary less systematically, and experienced a smaller drop in stock prices during the financial crisis than their diversified counterparts.

Our study also contributes to the growing body of literature on operational risk. This literature has made remarkable advances in the 15 years since the passage of the Basel II Capital Accord in 2001. First-generation studies on operational risk (around the early 2000s) explore static models and examine actuarial-type modeling of operational risk in light of operational risk capital charge estimation under the Capital Accord: a non-comprehensive list includes Cruz (2002), Chernobai, Rachev, and Fabozzi (2007), Ebnöther et al. (2003), and de Fontnouvelle et al. (2006). Rosenberg and Schuermann (2006) examine the correlation structure between operational, credit, and market risks and emphasize modeling difficulties arising from the heavy-tailed nature of operational risk. Later studies on operational risk in the financial industry focus on the market-value impact and the root causes of operational risk events (for example, Perry and de Fontnouvelle 2005; Cummins, Lewis, and Wei 2006; Gillet, Hübner, and Plunus 2010; Biell and Muller 2013; Barakat, Chernobai, and Wahrenburg 2014). The extant literature points to strong links between operational risk and banks' internal attributes (for example, Chernobai, Jorion, and Yu 2011; Abdymonumov and Mihov 2015; Basak and Buffa 2016; Wang and Hsu 2013) and their external business environment (for example, Chernobai, Jorion, and Yu 2011; Abdymomunov, Curti, and Mihov 2015; Cope, Piche, and Walter 2012).

While the majority of extant empirical studies on operational risk document its effect on the particular bank that experiences operational failures, there is a growing literature on operational risk externalities that suggests a systemic nature of this risk in the financial sector. Our study

[11] In their study, non-interest income includes fiduciary income, fees and service charges, trading revenue, and the non-interest income reported under the 'Others' category.

contributes to this literature by suggesting spillovers arising from the BHCs that are more complex, which can call for regulators to impose more stringent requirements on such firms. Cummins, Wei, and Xie (2011) find evidence that the equity-value effects from operational risk announcements spill over to rival firms operating in the commercial banking, investment banking, and insurance industries. Chernobai, Jorion, and Yu (2007) document that the doubly stochastic Poisson assumption of the joint conditional arrival process of operational risk events industry-wide fails, thus suggesting a systemic nature of operational risk. DTCC (2015) suggests that, due to payment-system dependence, an initial operational risk failure may lead to a cascade of systemwide disruptions and breakdowns. A relevant theoretical framework for illiquidity due to disruptions in the interbank payment system was developed and tested empirically in Bech and Garratt (2012). Jordan, Peek, and Rosengren (2000) showed that announcements of formal supervisory enforcement actions[12] imposed on large BHCs cause spillover effects in other rival banks operating in the same geographical region and having similar portfolio exposures.

3 Background on Operational Risk Management

Traditionally, it has been a belief that financial services firms face three primary risks: credit risk (or a risk of a counterparty's default on a debt obligation), market risk (or systematic risk, whose components include interest rate risk, equity risk, and commodity risk), and liquidity risk (or the risk of inability to meet short-term obligations). This belief has been shaken by a sharp increase in the incidence of operational risk and its often devastating consequences to a firm and the economy, ranging from large monetary losses and shattered reputations to bankruptcy. Hoffman (2002) reports that publicly announced large operational losses amounted to over $15 bln annually during 1980s and 1990s, and this figure represents only the tip of the iceberg, with the true figure easily being "as high as 10 times this amount," (Hoffman 2002, p. 26) once the losses that are not visible publicly are accounted for.

International banking regulatory standards define operational risk as "the risk of loss resulting from inadequate or failed processes, people and systems, or from external events" (BCBS 2001b).

[12]In their study, formal enforcement actions include cease and desist orders and written agreements issued by the Office of the Comptroller of the Currency, the Federal Reserve System, and the Federal Deposit Insurance Corporation.

This definition reflects the diverse nature of this risk. The Basel Committee classifies operational risk into seven distinct event types:

1. Internal Fraud: Includes events intended to defraud, misappropriate property, or circumvent regulations or company policy, involving at least one internal party, and are categorized into unauthorized activity and internal theft and fraud.

2. External Fraud: Includes events intended to defraud, misappropriate property, or circumvent the law, by a third party, and are categorized into theft, fraud, and breach of system security.

3. Employment Practices and Workplace Safety: Includes events or acts inconsistent with employment, health, or safety laws or agreements, and are categorized into employee relations, safety of the environment, and diversity and discrimination.

4. Clients, Products, and Business Practices: Includes events related to failures to comply with a professional obligation to clients, or arising from the nature or design of a product, including disclosure and fiduciary practices, improper business and market practices, product flaws, and advisory activities.

5. Damage to Physical Assets: Includes events leading to loss or damage to physical assets from natural disasters, such as hurricanes, earthquakes, and floods, or man-made events, such as terrorism and vandalism.

6. Business Disruption and System Failures: Includes events causing disruption of business or system failures, including IT system failures and malfunctions.

7. Execution, Delivery, and Process Management: Includes events related to failed transaction processing or process management occurring from relations with vendors and trade counterparties, and are classified into transaction execution and maintenance, customer intake and documentation, and account management.

The financial industry and regulatory authorities recently recognized operational risk as a major standalone risk posing a serious threat to financial institutions' stability globally (BCBS 2001a; OCC 2007; Curry 2012). The Basel Capital Accord (Basel II)[13] explicitly separated oper-

[13]Basel II was replaced by Basel III in late 2009 (BCBS 2011). Basel III is a comprehensive set of reform measures aimed at strengthening the regulation, supervision, and risk management of the banking sector. Its objective is to enhance the banking sector's ability to absorb shocks arising from financial and economic stress, improve risk management and governance, and improve banks' transparency and disclosures (`http://www.bis.org/bcbs/basel3.htm`). Early versions of the Capital Accord include BCBS (1999 and 2001b). More recent

ational risk from credit risk and market risk and laid out a set of specific regulatory standards. Pillar I of the Accord outlines capital requirements under which banks are mandated to quantify capital reserves at a high confidence level to serve as buffer capital against potential losses due to operational risk on a one-year-ahead horizon. For U.S. banks, only the Advanced Measurement Approach (AMA), which is a bottom-up, risk-sensitive, data-driven approach, is permitted. Pillar II and Pillar III pertain to the supervisory review of capital adequacy and market disclosure principles, respectively. The primary scope of application of the Accord is bank holding companies that are the parent entities within a banking group, internationally active banks, and their subsidiaries, including securities companies.[14] For U.S. banks, the scope of application of the Basel II guidelines is all holding companies that are the parent entities within a banking group and all internationally active banks, with mandatory application to those banks with either consolidated assets of $250 bln or more or total foreign exposure of $10 bln or more on their balance sheets.

The 2010 Dodd-Frank Wall Street Reform and Consumer Protection Act includes operational risk in stress testing through the Comprehensive Capital Analysis and Review (CCAR) framework. The CCAR guidelines were issued by the Federal Reserve System in November 2010 to assess, regulate, and supervise BHCs through a common, conservative approach to ensure that BHCs "hold adequate capital to maintain ready access to funding, continue operations and meet their obligations to creditors and counterparties, and continue to serve as credit intermediators, even under adverse conditions" (BGFRS 2011, p. 2) and that "they have robust, forward-looking capital planning processes that account for their unique risks" (BGFRS 2015, p. 5). Similarly, in Europe, operational risk has been a mandatory constituent of the United Kingdom's Prudential Regulation Authority and European Banking Authority stress testing requirements since 2013 and 2009, respectively.[15] Ratings agencies, such as Moody's Investors Service, Morningstar, and Fitch Ratings, recently also began to incorporate operational risk in assigning corporate financial ratings (Moody's Investors Service 2003; Morningstar 2015; Fitch Ratings 2004).

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guidelines are described in BCBS (2006).

[14] In addition to the Basel requirements for banks, in Europe insurance companies are subject to similar mandates under the Solvency II framework, scheduled for implementation EU-wide since January 2016. In the hedge fund industry, under the new SEC rules, in 2006, U.S. firms operating in the hedge fund industry were required to file due diligence reports (Form ADV) that disclosed information on hedge fund operational risk, including information on inadequate or failed internal processes, factual misrepresentations, and inconsistencies in statements and materials provided by hedge fund managers; see Brown et al. (2008), which studies the value of such disclosures.

[15] See `http://www.bankofengland.co.uk/pra/Pages/supervision/activities/stresstesting.aspx` and `http://www.eba.europa.eu/risk-analysis-and-data/eu-wide-stress-testing`.

Unlike the credit and market risks, which have been shown in academic literature to be closely linked to the macroeconomic environment, operational risk is of a more idiosyncratic nature (for example, Chernobai, Jorion, and Yu 2011) and should therefore be more closely dependent on (or be a consequence of) a firm's internal environment, including the strength of governance (for example, Perry and de Fontnouvelle 2005; Wang and Hsu 2013) and the quality of its risk management (for example, Barakat, Chernobai, and Wahrenburg 2014; Abdymomunov and Mihov 2015).

Yet, some anecdotal evidence suggests that failures in one type of operational risk are indicative of broader weaknesses in other areas. Although the academic literature on the internal drivers of operational risk is still sparse, existing studies support the view that the same idiosyncratic metrics affect various types of operational risk similarly. For example, Chernobai, Jorion, and Yu (2011) develop an econometric framework to examine the effects of internal factors on the incidence of operational risk, and their results hold uniformly across different operational risk event types, consistent with the theory that lack of internal control is the common root cause of various operational risk events. According to Kieran Poynter, former U.K. chairman of PriceWaterhouse-Coopers, "Organizations with weak data security are generally also weak in terms of wider risk management and governance." (Poynter 2008) In another piece of anecdotal evidence, the 2012 $6.2 bln trading loss of JP Morgan in the London Whale case has revealed significant deficiencies in the bank's overall risk management (Zeissler and Metrick 2014).

Among the seven event types, this paper focuses on four types that we believe are particularly connected to failures in risk management that likely resulted from increased complexity. We illustrate these event types with corresponding examples:[16]

Internal Fraud: A former vice president in Citibank's private-banking section was charged in 1998 with defrauding the bank out of more than $10 million in 1993 by creating phony bank accounts and using them to obtain loans. In another example, on June 23, 2010, subsidiaries of Fidelity National Financial were ordered to pay $5.7 million in compensation for the role employees played in a $30 million mortgage fraud scam.

External Fraud: In 1997, the Citibank unit of Citigroup discovered that it had been the victim of loan fraud and had lost between $8 and $9 million. In another example, Allied Irish Bank sued

[16] We also check the robustness of our results using all event types, see Tables A1–A3.

Bank of America and Citibank, alleging that they had provided John Rusnak with $200 million through prime brokerage accounts, enabling him to engage in unauthorized trading, in an incident that surfaced in February 2002.

Clients, Products, and Business Practices: Bank of America agreed to pay $460.5 million on March 3, 2005, in settlement of a shareholder lawsuit that claims the third largest bank in the United States failed to conduct proper due diligence when it underwrote securities for WorldCom. In another example, on October 25, 2013, the U.S. Federal Housing Finance Agency reached a $5.1 bln settlement with JP Morgan, which allegedly overstated borrowers' capacity to repay loans underlying more than $33 bln of residential mortgage-backed securities that were sold to Fannie Mae and Freddie Mac between 2005 and 2007.

Execution Delivery and Process Management: On May 23, 2008, clients of People's United Bank, based in Bridgeport, Connecticut, filed a class action lawsuit in New Haven Superior Court against Bank of New York Mellon, related to a data breach that occurred on February 27, 2008. In August 2008, BNY Mellon disclosed in a regulatory filing that it was notifying 12 million customers about the security breach and would set aside $22 million for credit monitoring. In another example, in June 2005 Bank of America reached a $1.5 million settlement for failing to ensure proper storage of employee email correspondence related to its brokerage business.

These four event types are among those with the highest percentage of event counts with "managerial action/inaction" and "lack of internal control" cited in our operational risk database as the key contributing factors to operational failure (see Chernobai, Jorion, and Yu (2007) for the detailed breakdown of contributing factors by event type). In the examples above, clearly not every event is directly related to investment banking or occurred within the deregulated business lines. However, our goal in this study is to capture any weakness in risk management that can arise from weakening of managerial focus following the deregulation of the late 1990s. Since these weaknesses can reveal themselves in any part of the business, we do not limit our attention to the events that originated in the deregulated business lines.

4 Regulatory Background

The Glass-Steagall Act (GSA) of 1933 prohibited commercial banks from having securities affiliates, thus separating commercial and securities activities. It made it unlawful for commercial banks to be affiliated with any company that is "engaged principally" in underwriting or dealing in securities. The Act also prohibited securities firms from accepting deposits and from creating interlocks of officers, directors, or employees between a commercial bank and any company "primarily engaged" in securities underwriting or dealing. Certain securities were exempt from the restrictions and were called "bank-eligible securities"; such securities included general obligation bonds, U.S. government bonds, and real estate bonds (Lown et al. 2000).

In the years leading up to 1999 when the Act was repealed, its provisions were gradually relaxed.[17] The terms "engaged principally" and "primarily engaged" were not clearly defined in the GSA. Because of this, in April 1987, the Federal Reserve allowed U.S. bank holding companies to establish Section 20 investment banking subsidiaries that were allowed to underwrite certain "bank-ineligible securities": mortgage-related securities, municipal revenue bonds, and commercial paper. Not all banks were eligible to set up such subsidiaries; special permission was granted by the Federal Reserve on a case-by-case basis under Section 20 of the GSA. Such securities affiliates were therefore termed "Section 20 subsidiaries." In the beginning, the revenues from bank-ineligible securities were capped at 5 percent of a Section 20 subsidiary's gross revenue. This cap was raised to 10 percent in September 1989, and then to 25 percent in December 1996. Lown et al. (2000) show that in the six years between 1993 and 1998, bank holding companies increased their share of the securities industry's total revenue from 9 percent to more than 25 percent.

On November 12, 1999, the Gramm-Leach-Bliley Act (GLBA) was passed, repealing the GSA and lifting the 25 percent cap.[18] In addition to dissolving the boundaries between commercial banking and investment banking, the GLBA also repealed the parts of the Bank Holding Company

[17] See Table 2 in Lown et al. (2000) for an overview of the dates of important deregulatory actions between 1987 and 1998.

[18] Barth, Brumbaugh, and Wilcox (2000) offer three reasons for the repeal of the GSA. First, empirical research had found that the securities activities of commercial banks bore little responsibility for the banking failures around the Great Depression. Second, since the Federal Reserve had permitted the establishment of Section 20 investment banking subsidiaries in the late 1990s, there was insufficient evidence that banking problems in subsequent years were attributable to the wider range of permitted activities. Third, technological advances reduced the costs of sharing data from one business with another, raising the expected profitability of cross-selling insurance and securities products to customers.

Act of 1956 that separated commercial banking from the insurance business. Lown et al. (2000) show that, in the five years between 1995 and 1999, bank holding companies increased their annuity sales from around \$10 bln to over \$21 bln, accounting for roughly 15 percent of total annuity sales nationwide during the same period (Association of Banks-In-Insurance 1999). In sum, since the passage of the GLBA, bank holding companies have been able to engage in a wide range of activities, including securities underwriting and dealing, insurance agency and underwriting activities, and merchant banking.

5 Hypotheses Development

More-complex organizations may face challenges in providing effective oversight. According to Ashcraft and Schuermann (2008), diversification creates new frictions across the newly established intermediaries. Stiroh and Rumble (2006) document that between 1997 and 2002, higher risk-adjusted profits arising from revenue diversification in BHCs are typically offset by the costs of increased exposure to volatile non-interest activities and may potentially increase the probability of default. Specifically, the practice of cross-selling may expose multiple businesses to the same shocks that propagate across the many affiliates of the same organization (Cetorelli, McAndrews, and Traina 2014). When bank holding companies act as equity holders they have the incentive to take risk beyond what is optimal, and this trend can be exacerbated by implicit government guarantees, especially for banks perceived as too big to fail. The financial crisis of 2007–2009 has vividly demonstrated that possible subsidies from explicit or perceived government guarantees may distort incentives in failure resolution (Cetorelli, McAndrews, and Traina 2014).[19] Loutskina and Strahan (2011) find that concentrated mortgage lenders have higher profits, which vary less systemically and experienced a smaller drop in stock prices during the financial crisis than their diversified counterparts. In sum, existing literature documents a greater exposure to systemic and idiosyncratic financial risk of more-diversified financial institutions. Extending this discussion to operational risk, we expect operational risk in BHCs to increase with the greater complexity that

[19] Empirical literature suggests that bank holding companies may have motives other than profit maximization in expanding into new activities. These include empire-building, over-diversification to protect firm-specific human capital, corporate control problems, or managerial hubris and self-interest (Berger, Demsetz, and Strahan 1999; Milbourn, Boot, and Thakor 1999; Bliss and Rosen 2001; Houston, James, and Ryngaert 2001; Aggarwal and Samwick 2003).

comes from increased diversification.

The measurement of complexity and finding an exogenous variation thereof is the main challenge in our paper. BIS describes complexity as the activities of banks outside of traditional banking business, such as OTC derivatives, trading and AFS securities, and Level 3 assets, and strictly separates this concept from the other measures, such as interconnectedness and size. However, the data for most of these variables are unavailable for our sample period. In particular, information on trading assets (Schedule HC-D), such as U.S. Treasury securities, U.S. government agency obligations (exclude mortgage-backed securities), securities issued by states and political subdivisions in the U.S., derivatives with a positive fair value, and other trading assets, were not included in FR Y-9C reports until 1995, which is the middle of our pre-deregulation period. Similarly, OTC derivatives (Schedule HC-L) were not included in FR Y9-C reports until 2009. Likewise, other items, such as mortgage-backed securities, were not available until 2009. With regard to AFS securities (Schedule HC-B), there exist items, such as other debt securities, that were added in 2001. In sum, regulatory filings do not provide us with the means of computing a continuous time series variable to measure complexity that would also agree with the BIS definition.

To address this challenge, we note that the gradual repeal of Glass-Steagall Act over the period from 1996 to 1999 has opened up new possibilities for banks to expand into the previously restricted non-bank business lines, leading to their increased complexity. As such, we identify those BHCs that are more likely to be affected by the deregulations and distinguish them from the rest. Although the repeal of the Glass-Steagall Act as a whole was a gradual process, consisting of a series of deregulations that applied to all U.S. BHCs, we argue that the pre-1996 regulations were more binding on those BHCs that were already diversified into nonbank activities before the 1996–1999 deregulations. This is so because they were more likely to have had a stronger motivation to expand further into nonbank business lines based on the investments they had already made after the early deregulations in the late 1980s but had been unable to do so under the then-existing restrictions until the end of 1996. This consideration allows us to sort BHCs into two distinct groups. The treatment group consists of pre-diversified BHCs and the control group consists of BHCs that did not diversify before the end of 1996 but were otherwise similar to those in the treatment group, conditional on other bank-specific controls.

In order to form treatment and control groups for the difference-in-differences analysis, we examine the distribution of the Herfindahl-Hirschman Index (HHI) of BHCs' industrial concentration developed in Cetorelli, McAndrews, and Traina (2014) — our measure of organizational diversity. The HHI is designed to measure industry concentration of an ultimate parent throughout the time using subsidiary merger and acquisition information in each year. It is a count-based index, taking a value of 1 if the BHC has only commercial banks and values smaller than 1 if the BHC acquires nonbank subsidiaries operating in the remaining nine financial industries.[20] For each family tree i and year t, the HHI is computed as follows:

$$HHI_{it} = \sum_{j=1}^{10} \left(\frac{n_{it,j}}{N_{it}} \right)^2, \tag{1}$$

where n_j is the number of subsidiaries of type j, $j = 1, ..., 10$, and N is the total number of subsidiaries.

As shown in Figure 1, while we observe a continuous decline in the mean value of the HHI, indicating a continuous expansion of our sample BHCs into the nonbank industries, the median BHC in our sample did not start to diversify until after the deregulations at the end of 1996. This gives us a natural definition of the treatment group as those BHCs that had an average HHI less than 1 before the end of 1996. We therefore formulate our first hypothesis as follows:

Hypothesis H1: *Following the deregulations from the end of 1996 to the end of 1999, pre-diversified BHCs observed a greater increase in their operational risk than BHCs that did not diversify.*

One potential problem with this specification is that a BHC can have an HHI smaller than 1 before 1997 only by having subsidiaries in the industry type of savings banks and thrifts, as these are not among the business lines affected by the deregulations of 1996–1999. In other words, since

[20] The remaining nine industry types are: asset manager, broker-dealer, financial technology, insurance broker, insurance underwriter, investment company, real estate, savings bank/thrift/mutual, and specialty lender. Cetorelli, McAndrews, and Traina (2014) use the HHI as a measure of complexity. In their study, complexity is measured by the degree of business diversification. In our study, we refrain from using the HHI as a direct measure of complexity for the following reason: Because the HHI is based on an equal-weighted, rather than a value-weighted, subsidiary count, in our study, the HHI only is a measure of diversification. In our sample, following the repeal of the GSA, many nonbank subsidiaries became larger in size and revenue volume, thereby increasing the complexity of the parent, but their count, and therefore the HHI of the parent, remained the same. As a result, while a lower HHI gives rise to greater complexity, the converse is not always true. For this reason, we use the HHI as a preliminary indicator of complexity in initial models, while in our subsequent models we zoom in on Section 20 subsidiary holders, which identify a complex institution more precisely.

BHCs' activities as savings bank and thrift organizations were largely allowed in the pre-1997 regulatory environment, the BHCs in our current treatment group were not necessarily bound by the regulations before the deregulations, and this can potentially bias our estimation results. Therefore, we enhance our treatment group by separating it into two subgroups: a group of BHCs that had a Section 20 subsidiary before the repeal of the Glass-Steagall Act at the end of 1999 and a group of BHCs that contains the remaining high holders (that is, ultimate parents) in our treatment group.[21] According to Geyfman (2005), BHCs that did not participate in Section 20 activities exhibited lower market risk than BHCs with Section 20 subsidiaries although systemic risk rose for all BHCs in the late 1980s and during the 1990s. Furthermore, Liu, Norden, and Spargoli (2015) document that BHCs with Section 20 subsidiaries are more complex than BHCs without such subsidiaries; in particular, their complexity increases post repeal of the GSA, while the complexity of BHCs without such subsidiaries decreases. Consistent with the findings of Liu, Norden, and Spargoli (2015), Lown et al. (2000) record that BHCs, through their Section 20 subsidiaries, increased their share of the securities industry's total revenue from about 17 percent to 27 percent and their share in underwriting business from about 5 percent to about 15 percent between 1996 and 1998, when Section 20 subsidiaries made significant inroads in underwriting, thanks to the 1996 loosening of the "ineligible" underwriting revenue restriction. In addition, according to testimony by Federal Reserve Governor Susan M. Phillips on March 20, 1997, "existing Section 20 subsidiaries have indicated that they have been able to expand their activities given the added flexibility with respect to both staffing and revenue."[22]

We collect information on Section 20 subsidiary owners by first following the Appendix in Cornett, Ors, and Tehranian (2002). We then check the complete merger and acquisition history of these BHCs by hand through their records at the National Information Center (NIC) to identify whether any of these BHCs had their Section 20 subsidiary acquired by the end of 1999 by another high holder that did not own a Section 20 subsidiary beforehand.[23]

[21] Restricting Section 20 ownership to before 1996 does not change the results.

[22] Consistent with this evidence, we find that the nonbank asset ratio (BHCP4778/BHCK2170) has increased from about 5.6 percent to around 8.8 percent for the Section 20 owners, whereas the remaining BHCs experienced a decrease from 2.3 percent to 1.9 percent in our regression sample. Similarly, non-interest income ratio (BHCK4079/(BHCK4079+BHCK4107)) has increased from 22 percent to 32 percent for Section 20 owners whereas the remaining BHCs experienced an increase from 12 percent to 15 percent. While these measures are noisy proxies for the BIS definition, it is reassuring that they move in the direction we expected.

[23] The situation in which a BHC acquires only a Section 20 subsidiary of another BHC, instead of the whole high holder, is extremely rare.

Because the 1996–1999 deregulations significantly relaxed the restrictions on Section 20 subsidiaries' activities, we expect that those BHCs that owned a Section 20 subsidiary would have a much greater increase in their complexity due to their binding position before and during the 1996–1999 deregulations and, therefore, would experience greater levels of operational risk. This leads us to the following second hypothesis:

Hypothesis H2: *The increase in operational risk post-deregulation is more pronounced for pre-diversified BHCs with Section 20 subsidiaries prior to 1999 than for pre-diversified BHCs with other types of subsidiaries.*

Empirical evidence documents positive equity market reaction to the passage of the Gramm-Leach-Bliley Act in 1999: shareholders viewed the continuation of BHC expansion into nonbank financial products and financial consolidation favorably, especially for BHCs with Section 20 subsidiaries (Lown et al. 2000). Dismantling of the Glass-Steagall Act allowed banks to achieve economies of scale associated with the fixed costs of collecting, processing, and assessing proprietary information (Narayanan, Rangan, and Rangan 2004) as well as distributing a wide range of financial services at relatively low marginal costs, thereby increasing the profit margin. A comprehensive review of the literature on an increase in revenues due to diversification is provided in Saunders and Cornett (2003). Stiroh and Rumble (2006) document that between 1997 and 2002, revenue diversification was associated with higher risk-adjusted profits for bank holding companies. Cornett, Ors, and Tehranian (2002) examine the performance of 40 BHCs that set up Section 20 subsidiaries between 1987 and 1997 and show that, based on accounting measures, their increase in performance is attributable to increased revenue from the new line of business in the three years following the establishment of the Section 20 subsidiary.

Additionally, as a result of the benefits of diversification, a broad banking company[24] may experience lower profit variance than a traditional banking company (Barth, Brumbaugh, and Wilcox 2000). In particular, broad banking companies' decline in lending activity can be offset by an increase in their securities activity if the correlation of profits between different financial activities is low. Furthermore, a reduction in the variance of profits decreases the likelihood of default (Kwan and Laderman 1999), and so a more diversified banking company may pay lower

[24]In literature, the term "broad banking" refers to the activities of bank holding companies outside of the banking businesses, as a result of the enactment of the Gramm-Leach-Bliley Act. See, for example, Barth et al. (2000). Therefore, the terms broad banking company and bank holding company are frequently used interchangeably.

interest rates on its funds that are not covered by the federal safety net (Barth, Brumbaugh, and Wilcox 2000). Gande, Puri, and Saunders (1999) also show that, consistent with increased competition, a bank's entry into a nonbank business improves information flow and results in a significant reduction of underwriter spreads and ex ante yield spreads.

Alternatively, BHCs can experience a significant improvement in their balance sheet performance as they become more complex, even as their risk management suffers significantly. This is because while the gains of increased complexity, such as cross-selling of investment and commercial banking services, are realized immediately, the losses associated with weaknesses in risk management will take significant time to show up on balance sheet. For example, Jin and Myers (2006) argue that senior management can close their eyes to internal control failures when firms are profitable and financially unconstrained. In sum, the increased risk-taking resulting from an increase in a BHC's organizational complexity can, in fact, be overlooked if one focuses only on the BHC's balance sheet performance.

Following prior literature (for example, Santos 2011 and Cornett, Ors, and Tehranian 2002), we use the return on assets (ROA), market-to-book ratio, Z-score, and volatility of the ROA as accounting-based and market-based performance and risk indicators for our sample of high holders (see Table 1 for the definitions and construction of these variables). We formulate our third hypothesis as follows:

Hypothesis H3: *The increase (decrease) in accounting-based and market-based performance (risk) measures post-deregulation is more pronounced for pre-diversified BHCs and BHCs with Section 20 subsidiaries prior to 1999 than for non-diversified BHCs or pre-diversified BHCs with other types of subsidiaries.*

6 Empirical Results

6.1 Data and Sample Construction

In order to identify an *exogenous* variation in bank complexity, we take advantage of the changes in the regulatory environment in the U.S. banking industry. We focus our analysis on U.S. bank holding companies.

To construct our sample, we first follow the footsteps of Cetorelli, McAndrews, and Traina (2014). For each of the U.S. publicly traded BHCs identified as an ultimate parent, Cetorelli, McAndrews, and Traina's method develops a complete family tree by taking an intersection of the market data from four sources: the Center for Research in Security Prices (CRSP) U.S. Stock Database, the regulatory accounting data from the Board of Governors of the Federal Reserve System, Consolidated Financial Statements for Bank Holding Companies (FR Y-9C), and financial institutions' merger and acquisition (M&A) activity data from the SNL DataSource compiled by SNL Financial. The family tree is constructed by accounting for the subsidiaries acquired over time among 10 financial industries: bank, asset manager, broker-dealer, financial technology, insurance broker, insurance underwriter, investment company, real estate, savings bank/thrift/mutual, and specialty lender.

Second, this family tree can be then traced through time in order to calculate the Herfindahl-Hirschman Index (HHI) of BHCs' industrial concentration. We described the construction of this variable in Section 5. We remind the reader that lower values of the HHI indicate a more diversified firm, with HHI=1 being the least diversified BHC with only banking subsidiaries. Using the HHI for our BHCs, we narrow down our sample to U.S. publicly traded BHCs that are high holders and that have engaged in at least one M&A activity between 1988:Q1 and 2012:Q4, as recorded in the SNL M&A database. This step yields a total of 1,059 BHCs with 42,053 bank-quarter observations during 1988:Q1–2012:Q4. Here, two important aspects of our data are noteworthy. First, we focus our analysis on high holders because we assume that strategic business decisions are made at the parent level instead of at the subsidiary level. In addition, we exclude high holders that have no documented M&A activity in any of the 10 financial industries until the end of our sample period because a) the M&A database is necessary to construct a family tree and b) those high holders are likely to be the BHCs that never diversified into nonbank business lines before or after the 1996–1999 deregulations, for certain endogenous reasons. Hence, adding such BHCs into our control group would make our treatment and control group endogenously different from each other.

Third, we obtain operational risk information for our sample of high holders from the Financial Institutions Risk Scenario Trends (IBM Algo FIRST) operational risk database marketed by IBM. The database contains several decades of data collected worldwide on over 10,000 public operational risk events, with the bulk of the data coming from after 1980. The majority of data are from the United States, with about three-quarters coming from financial institutions. The database includes information on the dates of the occurrence of each event, along with its public disclosure and settlement, the dollar impact of loss, event type, business line, contributory factors, and a narrative of event details. The format of the data conforms to the Basel Accord's definitions of event types and business lines. The availability of the precise timing of an event's origination date is a key advantage of using the IBM Algo FIRST database for our analysis.[25] Although the database is restricted to those events that are made public, rather than being a repository of all internal operational events of financial services firms, we believe that the database is a fair representation of the loss population and is appropriate for our study for the following reasons: First, as explained in Chernobai, Jorion, and Yu (2011), there is a large variance in loss amounts, with many losses being small in magnitude—some as small as $1, and the loss distribution is similar to that typically observed for losses in banks' internal databases (for example, lognormal), thus reducing concerns about an upward bias of recorded losses. Second, in most cases the source of the data is a third party (for example, a regulatory agency such as the SEC, FINRA, NASD, NYSE, or FDIC, court decisions, affected customers, business partners, and shareholders) rather than the firms themselves, thus mitigating concerns over self-selection bias.[26]

In the fourth step, we match the firms in the IBM Algo FIRST database with those in the Compustat database by assigning an appropriate GVKEY to each operational risk event, following Chernobai, Jorion, and Yu (2011). Specifically, we assign the historical GVKEY to each firm-event around the event's occurrence date in order to capture the actual timing of an operational failure that has taken place.[27] In total, our initial sample consists of 505 financial firms (including

[25] The primary clientele of the IBM Algo FIRST database are risk management professionals, auditors, compliance personnel, and senior executives. Currently, around 100 financial institutions subscribe to the database. The data were previously used in Barakat, Chernobai, and Wahrenburg (2014), Chernobai, Jorion, and Yu (2011), Cummins, Lewis, and Wei (2006), Dahen and Dionne (2010), De Fontnouvelle et al. (2006), Gillet, Hübner, and Plunus (2010), Rosenberg and Schuermann (2006), and Wang and Hsu (2013). Other studies (for example, Dutta and Perry 2006) used operational risk data collected from a Loss Data Collection Exercise (LDCE) conducted by the U.S. banking regulatory agencies (the Federal Reserve, the OCC, the FDIC, and the Office of Thrift Supervision); however, the data are limited to very few contributing institutions. Abdymomunov and Mihov (2015) used supervisory operational loss data from FR Y-14-Q filings; however, reporting institutions are limited to BHCs with $50 bln or more in total consolidated assets. Others (for example, Cope, Piche, and Walter 2012) used the ORX Global Loss Database; the data period begins in 2002 and is contributed by around 50 member institutions worldwide.

[26] Dyck, Morse, and Zingales (2014) examine occurrences of accounting fraud and argue that the probability of getting caught is the same for all firms, conditional on engaging in fraud.

[27] The information on the individual firms experiencing operational risk events is already provided in the IBM Algo FIRST database. Unfortunately, the IBM Algo FIRST database does not keep track of the ultimate parent

both banks and nonbank firms) with 4,407 operational risk events that occurred from 1988:Q1 to 2012:Q4.

In the fifth step, we begin to construct the operational risk event sample for U.S. BHCs. We start by linking each GVKEY to the corresponding identifier PERMCO within the CRSP/Compustat Merged Database. Then, we obtain each PERMCO's high holder RSSD ID by first mapping each PERMCO to the corresponding RSSD ID through the PERMCO-RSSD ID links provided by the Federal Reserve Bank of New York and then obtaining each RSSD ID's high holder RSSD ID through FR Y-9C filings and the Call Reports. This mapping process helps us locate 1,173 operational risk events under U.S. BHCs. For the GVKEYs with a missing high holder RSSD ID, we manually go through the IBM Algo FIRST database to match the events with their historical high holder at the event's occurrence date for our BHC sample. This exercise increases our sample to 1,257 operational risk events.

In the sixth step, we merge the operational risk data with our complete BHC sample from FR Y-9C filings. For a bank-quarter observation that does not have a publicly available operational risk event recorded in IBM Algo FIRST, we treat this observation as having a zero event count and loss, following Chernobai, Jorion, and Yu (2011). Of the 1,257 operational risk events in our sample, 424 of them have their loss missing, with about 97 percent of these having their missing losses marked as "unreported" in the database. In order to maximize the operational risk information in our econometric models, we try to fill these missing values with the bank's annual median loss whenever possible from the operational risk events where the loss is available. If the loss amount is still missing after this filling process, we then replace the missing values with zeros so that we will at most underestimate the impact of these events. As a result of this procedure, we successfully filled 324 of 424 missing losses with the available annual median values.[28]

Finally, our data of realized operational risk events end in 2012, but we truncate our sample earlier, as not all risks taken by 2012 would have materialized by the end of our sample period. By doing so, we acknowledge the delays between the time a risk is taken and the time it materializes. In particular, we include only events that originated before the end of 2005. Following Chernobai, Jorion, and Yu (2011), this truncation reduces concerns over downward bias in event counts during

firms back in history; in addition to individual firm names, it provides only the names of their current parent firms, which are updated regularly to account for any merger or acquisition activity.

[28]We also estimate our models without replacing the zeros with median values by keeping them as zeros instead. The results of our study are practically unchanged.

the last several years of our sample period. IBM Algo FIRST codes the origination date of an event as having occurred in the first quarter of a year if the information about the exact origination date is uncertain. Therefore, we consolidate our quarterly data to an annual basis to remove spurious spikes in the data in the first quarter of each year. This step yields our final sample of 8,745 bank-year observations within 968 high-holder BHCs over the sample period 1988–2005, of which 5,115 bank-year observations from 347 high holders have observations available before the end of 1996 and after 1999.

Figures 2 and 3 describe the distribution of annual event count and average loss, respectively, using all BHCs available in our data. As illustrated in Figure 2, we observe that a pronounced increase in operational risk frequency coincides with the deregulation period starting in 1996, with some leveling after 2001. Figure 3 shows spikes in the average loss amount per event, following the major deregulations at the end of 1996 and 1999. These findings are consistent with our idea that there is an increase in operational risk resulting from the growing complexity enabled by the 1996–1999 deregulations. To ensure that these trends are not driven by the number of BHCs in our sample, we plot the frequency and severity of operational risk against the time series of high holder count, as shown in Figures 2 and 3.

6.2 Econometric Framework: Difference-in-Differences Estimator

Our identification strategy exploits the 1996-1999 deregulations as a shock to banks' propensity to diversify into nonbank activities and thereby grow in complexity. In order to empirically assess the impact of the *exogenous* change in organizational complexity on BHCs' operational risk and balance sheet performance, we rely on a difference-in-differences estimator that uses the 1996–1999 deregulations as a natural experiment.[29] For each BHC, we specify our baseline model as follows:

$$\begin{aligned} Oprisk_{it} &= \alpha + \beta\ After_{it} + \gamma\ Diversified_{it} \\ &+\lambda\ After_{it} \times Diversified_{it} \\ &+ \textstyle\sum_{k=1}^{K} \delta_k\ Control_{k,it} + \phi\ Bank\_FE_i + \epsilon_{it}, \end{aligned} \tag{2}$$

[29]Recent studies by Neuhann and Saidi (2016a, 2016b) also used the deregulations as a natural experiment. In their studies, they examined the effects of the gradual repeal of the Glass-Steagall Act on banks' idiosyncratic risk and participation in the market for syndicated loans.

where α is the intercept term, $After$ is a dichotomous variable taking a value of 1 post-deregulation, $Diversified$ is also a dichotomous variable equal to 1 for diversified banks, the set $Control$ is a set of bank-level control variables described next, $Bank\_FE$ consists of bank fixed effects, ϵ is the residual term, and subscripts i and t refer to bank and time index. The dependent variable $Oprisk$ is a measure of operational risk — either operational risk frequency count ($Count$) or the severity amount (either annual total loss $LnLoss$ or average loss per event $LnAvgLoss$).[30] In all models, monetary values are adjusted for inflation using 2005 CPI.

We use market data from CRSP and regulatory accounting data from FR Y-9C to construct bank-specific controls that are deemed to be important determinants of operational risk events, following Chernobai, Jorion, and Yu (2011). These control variables include bank size ($LnTA$), the cash-to-assets ratio ($CashToTA$), the Tier 1 ratio ($Tier1R$), profitability (ROE), an excessive growth dummy ($ExcessiveGrowth$), and a dummy for a high dividend payout ratio ($HighDividend$). Excessive growth is measured by excessive growth in liabilities: Moody's Investors Service (2002) and OCC (2001) show that aggressive growth strategies, especially growth in liabilities, often accompany risk management deficiencies and management's inability to effectively sustain exceptional growth. A high dividends payout ratio is used to capture "troubled banks." Dividend payout may be restricted by the Office of the Comptroller of the Currency (OCC) for banks experiencing large losses and identified by regulators as problem banks (OCC 2001; Collier et al. 2003). Table 1 details the definition of variables we use in our difference-in-differences econometric models.

Our main difference-in-differences analysis uses sample periods 1994–1996 and 2000–2002 for pre- and post-regulation periods to effectively capture the impact of deregulations that became effective between the end of 1996 and the end of 1999. To address the serial correlation problem of performing difference-in-differences estimation directly on time series information, we follow Bertrand, Duflo, and Mullainathan (2004) and average our sample during before (1994–1996) and after (2000–2002) periods using the set of pre- and post-regulation periods in the main analysis. We also present various robustness checks and falsification tests in the end to verify our main specification and study results.

[30] As was explained at the end of Section 3, in our main models we omit operational risk events of types Employment Practices and Workplace Safety, Damage to Physical Assets, and Business Disruption and System Failures. These events are unlikely to be directly affected by the failure in risk management due to increased complexity.

6.3 Sample Descriptive Statistics

Table 2 summarizes sample descriptive statistics of our key variables. An average BHC in our sample has \$1.31 bln in total assets with a market-to-book ratio of around 1.7. There is a wide variability in the cash-to-assets ratio and Tier 1 ratio, ranging from around 0.02 to 0.28 and from 0.04 to 0.29. In addition, 39 percent of the banks have excessive growth in liabilities, and 56 percent have an above the industry's median dividend payout ratio relative to other BHCs within the previous year.

Table 3 provides univariate mean differences and difference-in-differences in operational risk (frequency and severity) for the treatment and control groups, along with their market and accounting risk and performance measures (ROA, ROA volatility, market-to-book ratio, and Z-score). As the table suggests, our operational risk measures are higher for the pre-diversified BHCs than for the control group. ROA decreases slightly post-deregulation but the decrease is smaller for the treatment group. The market-to-book ratio that serves as a proxy for bank growth opportunities and the Z-score are higher on average for the pre-diversified BHCs, whereas volatility in ROA does not show a particular consistent trend. Nevertheless, the difference-in-differences for the market-to-book ratio, Z-score and volatility in ROA are all positive. Overall, these univariate tests suggest that, while the pre-diversified BHCs seem better off on their balance-sheet and market-based metrics in terms of higher growth opportunities and lower risk, this comes at the expense of significantly higher operational risk.

6.4 Complexity and Operational Risk

Our main results are based on sample periods 1994–1996 and 2000–2002. Our difference-in-differences analysis investigates the impact of the 1996–1999 deregulations on the number of operational risk events that occurred in our sample high holders, by comparing the average values from 1994–1996 and 2000–2002 to control for the serial correlation of error terms, as in Bertrand, Duflo, and Mullainathan (2004). The results are summarized in Table 4. We begin with an unconditional difference-in-differences regression with our treatment group defined by the BHCs that have an average HHI less than 1 ($Pre96HHI < 1$) before the end of 1996 (Table 4, Model (1)). The difference-in-differences interaction term enters our regression with a positive sign (0.243) and is statistically significant at the 1 percent level. BHCs that made a move to enter into a nonbank industry through M&A activity before 1996 experienced, on average, a 0.243 greater increase in their event count than other BHCs, which experienced only a modest increase of 0.01 in their event count. This increased likelihood of operational risk events for the pre-diversified BHCs is robust to inclusion of the bank size ($LnTA$) variable in Model (2) and other bank-specific controls in Model (3). The results thus lend support to our Hypothesis H1.

As discussed in Section 5, classifying firms as pre-diversified based on the HHI can have problems that cause an underestimation of the true effect of deregulation. The first issue is that the HHI is based on merger and acquisition activities and therefore does not capture diversification to other industries through organic growth. Second, some of the BHCs have diversified into the business line of savings bank/thrift/mutual fund, whose activities were largely allowed before the end of 1996. If such pre-deregulation diversification was the case, then BHCs may not have been bound by the regulatory restriction before the end of 1996 and, therefore, may not have responded to the 1996–1999 deregulations by subsequently increasing their complexity. By including these BHCs in our treatment group, we may have introduced a downward bias into our DID estimates. To address this concern, as per Hypothesis H2 we conduct a similar difference-in-differences analysis but refine our previous treatment group into two subgroups according to whether a BHC owned a Section 20 subsidiary prior to the end of 1999 ($Section20$) or not ($Non20HHI < 1$). This refinement is motivated by the fact that the Gramm-Leach-Bliley Act of December 1999, the climax of the deregulations, effectively lifted the revenue cap restrictions on nonbank activities of Section 20 subsidiaries.

As shown in Models (4)–(6) of Table 4, the impact of deregulation is indeed much higher for the Section 20 owners once we single them out, as is evidenced by the greater magnitude and statistical significance of the coefficients of the *Section20* variable than of the *Non20HHI<1* variable. Specifically, the increase in annual operational risk frequency for the Section 20 owners on average is 1.5 times the increase for the control group. Moreover, the event count increase of the remaining (non-Section 20) pre-diversified banks differs much less from the increase for the banks that were not diversified before 1996, compared with the results we obtained in the earlier models (about 0.24 vs. 0.05), although the difference is still statistically significant. When we add the full set of bank-specific controls, as indicated by Model (6), the relative effect on pre-diversified non-Section 20 BHCs becomes slightly higher (0.06 vs. 0.05), but it also loses its statistical significance. The relative effect on Section 20 owners remains very similar in magnitude and statistical significance.

Previous models used the annual count of operational risk events as the dependent variable. We now turn to examining the dollar loss amount of operational risk events of our sample high holders to see whether similar findings persist. We do so by estimating equivalent difference-in-differences models to those in Table 4 but replacing our dependent variable with the annual total loss (Table 5, Panel A) and annual average loss per event (Table 5, Panel B).

The results in Table 5 echo those from our frequency models. The columns are arranged in the same manner as those in Table 4. The results from the loss amounts can be considered as consistent with those we see from the event count. In particular, Table 5, Panel A, shows that the pre-diversified banks (i.e., HHI<1) observe an about 65 percent ($exp(0.5) = 1.65$) greater increase in their total loss. Moreover, Models (4)–(6) show that, as before, most of the effect comes from Section 20 owners. Table 5, Panel B, confirms these results for average loss per event in a given year for each BHC.

Summarizing our key findings, based on our hypothesis that the Section 20 owners are most likely to be those that increased their organizational complexity and expanded into the newly allowed nonbank business lines during the deregulations due to their earlier, binding position at the end of 1996 (Hypotheses H1 and H2), the "treatment effects" we observed in Tables 3–5 offer compelling evidence that an increase in a BHC's organizational complexity can increase its taking on operational risk. Moreover, our results show that the impact of complexity on operational risk we have observed so far cannot be captured by considering bank size or other confounding factors, as the deregulation effects remain robust even after controlling for size and other bank-specific variables.

6.5 Complexity and Performance Measures

As it may take many years for operational risk to materialize — from its origin until discovery by management and settlement — a BHC can potentially improve its balance sheet performance and its performance in the eyes of investors as it becomes more complex or diversified, while the associated risks remain hidden. Thus, an interesting and important research question is whether the increased operational risk-taking arising from greater organizational complexity can potentially be concealed by a BHC's balance sheet performance.

To shed light on this question, we repeat our analysis using several performance measures for BHCs, including their return on assets, market-to-book ratio, Z-score, and the standard deviation of return on assets. The results of these estimations are shown in Table 6.

Results in Table 6, Panels A and B, reveal a positive and statistically significant impact of the deregulations on BHCs' return on assets (ROA) and market-to-book ratio for the pre-diversified BHCs as well as for the Section 20 owners, especially after controlling for the full set of bank-specific characteristics (Models (3) and (6)). While the standard deviation of ROA increases somewhat more for the firms in our treatment group, this difference is insignificant (and even negative) after introducing controls (Panel C, Models (3) and (6)). When we compare the increase in the level and standard deviation in ROA using BHCs' Z-score, the treatment effect is statistically insignificant after introducing controls, but it always goes in the same direction as ROA (Panel D).

These results imply that BHCs can indeed experience a significant improvement in their balance sheet performance without a significant increase in their balance sheet riskiness as they become more complex, even as their risk management suffers significantly. These findings support our Hypothesis H3. The results are consistent with Jin and Myers (2006), who argue that senior management can close their eyes to internal control failures when firms are profitable and financially unconstrained. In sum, we conclude that the increased risk-taking resulting from an increase in a BHC's organizational complexity can, in fact, be overlooked if one focuses only on the BHC's balance sheet performance.

6.6 Robustness Tests

6.6.1 Results with Extended Sample Period 1988–2005

We use this section to present various robustness checks and falsification tests to verify our results from the main analysis. To begin with, instead of using the sample of 1994–1996 vs. 2000–2002, we use the full sample of 1988–1996 vs. 1997–2005 to construct the before and after periods and perform a similar difference-in-differences estimation. The results are summarized in Tables

7–9. Table 7 focuses on operational risk frequency, while Table 8 focuses on annual total loss (Panel A) and annual average loss (Panel B). The results in these tables demonstrate that our earlier findings remain consistent for the most part. We note that, in most models, the R-squared has dropped. Also, the key coefficients of the dummy variables and the interaction terms have dropped in magnitude and significance, as expected. The results for performance measures — ROA, volatility in ROA, market-to-book ratio, and Z-score — also remain qualitatively similar, as depicted in Table 9.

6.6.2 Placebo Tests with Alternative Pre- and Post-Deregulation Periods

As a next step, we conduct two placebo tests for our difference-in-differences analysis by using the same definitions of the treatment and control groups, but with different sample periods. Specifically, we use the periods of 1991–1993 vs. 1994–1996 for the first placebo test and the periods of 2000–2002 vs. 2003–2005 for the second one. The key idea is to check whether our results from the DID analysis capture some forms of nonparallel time trend caused by omitted time-variant variables, the Achilles heel of DID regression. If our findings are in fact driven by such a time trend during our sample period, it is likely that a similar trend also exists right before and after our regression periods. If this is the case, then our placebo tests should generate results similar to those produced by our main difference-in-differences models described in Sections 6.4 and 6.5.[31]

The results from our placebo tests are shown in Tables 10–12 and Tables 13–15; Tables 10–12 display the results of our first placebo test (1991–1996), and Tables 13–15 display the results of the second one (2000–2005). From the first placebo test, we pick up no significant results in any of the re-specified models, thus mitigating endogeneity concerns over the interpretation of our earlier difference-in-differences analysis. From the second placebo test, we observe a small decline in operational risk events for all banks. This result is likely driven by the announcement of the Basel II Capital Accord in February 2001 and the passage of the Sarbanes-Oxley Act in July 2002, both of which are geared toward improved risk management. Moreover, we observe some (economically, but not statistically) significant decline in the operational risk of pre-diversified banks and Section

[31] Of the two placebo tests, the test of 1991–1993 vs. 1994–1996 is particularly interesting, as the year 1994 coincides with the passage of the Riegle-Neal Interstate Banking and Branching Efficiency Act. We also provide a more detailed analysis of the potential impact of the Riegle-Neal Act on our DID estimation in Section 6.6.4.

20 owners relative to other banks, which suggests that the effect of increased complexity due to the deregulations was temporary, possibly because of the new regulations mentioned above and/or because these BHCs may have learned how to manage their increased complexity. Overall, the results of our placebo tests help to mitigate concerns over endogeneity. In addition, they can serve as effective robustness tests in support of our main findings on the impacts of the 1996–1999 deregulations.

6.6.3 Banks versus Nonbanks

In addition to our analysis among the high holders, we also re-estimate our key equations to make a comparison between high holder bank holding companies and U.S. nonbank financial firms. This analysis serves two purposes. First, since the nonbank financial companies were never subject to banking regulations, their complexity would not have been affected by the deregulations, which means they can serve as an alternative control group to test our main hypothesis. Second, this analysis addresses the potential concern that the increase in operational risk we observed among the high holder BHCs is simply a by-product of the nature of nonbank business lines. For example, because securities activities are inherently riskier than commercial banking activities (Boyd and Graham 1986; Boyd, Graham, and Hewitt 1993), bank holding companies may elevate their risk without experiencing a significant increase in their complexity by expanding into this line of business.

Because our analysis so far has been based on RSSD IDs from FR Y-9C, which are not available for the nonbank financial firms, we re-map the RSSD IDs of our sample high holders back to their GVKEYs and construct the equivalent firm-specific controls for both the high holders and nonbank financial firms, using Compustat. The definitions of the newly constructed variables are included in Table 1. To further address the concern that different nonbank business lines can have different risk levels by nature and that not all of the business lines were affected equally by the deregulations, we restrict our nonbank control group to the securities firms (SIC codes 62xx) and add a dummy variable for each of the remaining nonbank financial business lines: non-depository credit institutions (SIC codes 61xx), insurance carriers (SIC codes 63xx), insurance agents, brokers and services (SIC codes 64xx), real estate firms (SIC codes 65xx), and other investment offices (SIC codes 67xx excluding 671x). We then include interaction terms for each of these nonbank business line indicators with the $After$ dummy term in our difference-in-differences regressions.

Tables 16–18 summarize the main findings. The key result here is that BHCs that are Section 20 subsidiary owners ($Section20 = 1$) experienced a substantially greater increase in operational risk than their nonbank counterparts ($SIC62 = 1$, the control group), while changes in operational risk for the non-Section 20 high holders ($Non20BHC = 1$) are similar to those of the nonbanks (Tables 16 and 17). This finding reinforces our main argument about the increased operational risk caused by the 1996–1999 deregulations by using an alternative control group, the nonbank financial firms, that is not targeted by the banking deregulations. Perhaps more importantly, it points to a higher level of operational risk stemming from increased complexity after the banking and nonbank activities are combined, as shown by the significant increase in operational risk of the Section 20 subsidiary owners and the insignificant results from the non-Section 20 high holders, compared with their nonbank counterparts. In addition to the finding above, the coefficients of the nonbank business lines with SIC codes 63xx and above are not significantly different from those of the SIC 62xx control group in Tables 16 and 17.

6.6.4 Merger and Acquisition Activities with a Matched Sample by Size

Our robustness tests so far have left us with a remaining concern: the possibility that our findings might be biased by certain time-variant unobservables residing within the period of our main DID analysis (1994–1996 vs. 2000–2002) and cannot be detected by the two placebo tests. The most likely case of such concern is the Riegle-Neal Interstate Banking and Branching Efficiency Act, which was signed in 1994 and became fully effective in June 1997. The purpose of the Riegle-Neal Act was to relax geographic limits on banks by allowing them to open branches and/or merge with banks across state lines. Merger activity surged in the banking sector following the Act, as BHCs began to consolidate their no-longer-necessary banking subsidiaries across state borders. An increase in banks' efficiency and performance was observed at the same time, as documented in Jayaratne and Strahan (1997). Although our first placebo test of 1991–1993 vs. 1994–1996 addresses the potential endogeneity coinciding with the passage of the Riegle-Neal Act, the effective date of the Act overlaps with our main regression period. Therefore, a likely criticism of our research could be that, to the extent that Section 20 subsidiary owners are substantially larger in asset size than the other high holders, they also engage in significantly more and larger

M&A activities than the other banks. If this is the case, then the increase in operational risk during the post-deregulation period we have captured may simply be attributable to the heightened M&A activities in the banking sector allowed by the Riegle-Neal Act, instead of to the increased business complexity enabled by the 1996–1999 deregulations, as we have argued.

To address this concern, we plot the M&A activities of our sample high holders in the banking sector over the period of 1988–2005 using the Mergers and Acquisitions data provided by the Federal Reserve Bank of Chicago. The Chicago Fed's data set contains the complete banking sector M&A records of our sample high holders since 1976 for all the acquirers existing in the FR Y-9C data or Call Reports. In addition, it provides us the top holding company of the acquirer for each M&A deal, along with the total assets of the acquirer and the target. For a few cases where the total assets of the target are missing because the target did not report FR Y-9C or Call Report information at the time of the M&A (for example, the target is a savings and loan association), we estimated the total assets by using the change from the previous quarter in the total assets of the acquirer. We then calculated an annual target assets ratio for each of our sample high holders to measure the size of its banking sector M&A activities. This ratio is defined as the sum of the assets of all targets from M&As in the current year divided by the total assets of the high holder in the previous year. Figure 4 illustrates the banking sector M&A activities for all the high holders in our main, balanced DID regression sample. Panel A shows the average number of M&As per high holder, whereas Panel B describes the average target assets ratio.

As shown in Figure 4, we can see that there is indeed a surge of M&A activities that coincides with the passage and effective dates of the Riegle-Neal Act around 1994 and 1997. However, comparing the post-deregulation period (2000–2002) in our main DID analysis with the pre-deregulation period (1994–1996), the banking sector M&A activities among the Section 20 owners, on average, seem to decrease, whereas the average banking sector M&A activities seem to increase slightly for the non-Section 20 high-holder group. Therefore, it is unlikely that the increased operational risk we have captured from the Section 20 owners in the post-deregulation period is attributable to the banking sector M&A activities at that time. If anything, the omitted M&A activities seem to bias our main results downward.

To make sure we do not omit any time-variant characteristics associated with the M&A activities, we add the number of banking sector M&As in each year as well as the corresponding target assets ratio as two additional bank-specific controls. We also obtain the number of non-bank M&As for each of our sample high holders from Thomson Reuters SDC Platinum to further control for the potential impacts of nonbank M&As. We construct the number of nonbank M&As by counting each high holder's completed M&A deals in a given year in which a target is a U.S. financial firm whose primary business line is not classified as commercial banks or bank holding companies. We choose not to include the nonbank target assets ratio in our regressions because over 50 percent of the M&As in our SDC sample have missing information on the total assets of the target.

In addition to the M&A controls, we further construct a matched sample in order to address the remaining endogeneity concern associated with the substantially larger size of the Section 20 owners even after controlling for our full set of bank-specific characteristics. We create such matched sample by restricting the BHCs in our non-Section 20 group to those whose average total assets over the pre-deregulation years (1994–1996) is greater than the minimum average assets of the Section 20 group during the same period. This exercise yields a sample of 64 non-Section 20 high holders vs. 18 Section 20 owners. The minimum and median averaged assets for the non-Section 20 group are \$1.930 and \$4.891 bln over the pre-deregulation years. The equivalent minimum and median period averaged assets for the Section 20 owners are \$1.920 and \$59.865 bln. [32]

The matched sample results are summarized in Tables A4–A6, Models (1)–(8).[33] To begin with, Models (1), (2), (4), and (5) of Tables A4 and A5 show that our results on operational risk remain very similar in the matched sample analysis. For example, the pre-diversified high holders in the matched sample have about 0.4 more events per year than the other high holders, whereas this number for the Section 20 owners is about 1.4. In comparison, the corresponding numbers from our original sample without matching are about 0.25 and 1.5. These results help alleviate the

[32] We also tried alternative methods to form our matched sample, by using the 10 smallest Section 20 owners in the pre-deregulation period and the 64 non-Section 20 high holders as described above, and by matching the 18 largest non-Section 20 high holders in the pre-deregulation period with the 18 BHCs in our Section 20 group. The median averaged assets comparison for the 10 Section 20 and 64 non-Section 20 sample is \$18.239 and \$4.891 bln over the pre-deregulation period. The median assets comparison for the 18 Section 20 and 18 non-Section 20 sample is \$59.865 and \$14.193 bln. The regression results obtained from our alternative matched samples are highly consistent with those we obtained from the original samples. We choose to report the results from our original matched sample because it maximizes the number of observations in our regressions.

[33] We also conduct the same analysis using our original, balanced DID sample for all the matched sample regressions and obtain consistent results with our main findings. We choose to skip these result tables for brevity, but they are available upon request.

concern that the increase in operational risk experienced by the Section 20 BHCs is driven by their size, rather than their increased complexity. When adding in the full set of bank-specific controls, including the newly introduced variables on M&A activities, our results on operational risk stay robust and the estimated coefficients on the M&A controls remain statistically insignificant (Tables A4 and A5, Models (3) and (6)). In addition, R^2 values generally improve with the number of controls included in the analysis as expected. In order to control for the potential affiliate mergers caused by the Riegle-Neal Act as well as for the accumulated effects of M&As, we also conduct alternative M&A analysis by excluding affiliate mergers in the banking sector and counting the accumulated M&As for both banks and nonbanks during the previous three years (for each year t, we accumulated the M&A information from year t-3 to year t-1). As shown by Models (7) and (8) of Tables A4 and A5, our main conclusions on operational risk remain consistent even when we observe certain significant impacts from M&As after controlling for the affiliate mergers in the banking sector (Tables A4 and A5, Model (7)). Together, these results further reinforce our main findings on operational risk and relieve the potential endogeneity concern of our DID analysis. Compared with the results on performance measures from our original DID analysis, however, we notice that the matched sample regressions fail to provide evidence of an improved performance from the deregulations (Table A6, Panels A–D). Therefore, we should treat the argument of improved bank performance from the growing complexity enabled by the 1996–1999 deregulations with caution, even without taking the increased operational risk into consideration.

6.6.5 Media Coverage

Asides from the potential endogeneity related with size, another concern of our study lies in the relation between median attention and operational risk event disclosure. In particular, Section 20 owners, being substantially large in size and usually deemed as *systemically important* by the regulators, can naturally draw more attention from the public. This can in turn increase the chance of their operational risk events being publicized. If there is a sudden increase of media attention paid to the Section 20 owners during the 1996-1999 deregulations, it is possible that our findings on operational risk can be driven by the disproportional change in media interest, instead of an increase in complexity. However, given that the data source of the IBM Algo First database relies heavily on regulatory reports and court resolutions, we do not expect a significant bias in our study caused by potential changes in media attention. To address the remaining concerns regarding an increasing public attention paid to the Section 20 BHCs, we introduce an additional media attention control for a formal robustness check.

We construct our media attention variable by counting the number of news articles in the Factiva business news database, where the headline or the first paragraph of the news mentions the names of our sample high holders. To maximize our data quality, we manually search the Factiva database using the historically accurate as well as multiple alternative names of a BHC for each year, starting at the beginning of the pre-deregulation period (1994). Figure 5 illustrates the annual median news count for each of the Section 20 and non-Section 20 group. We notice that, in general, the Section 20 owners indeed attract more public attention compared to the non-Section 20 BHCs, as indicated by their consistently higher level of news count. However, the news number of the Section 20 owners does not seem to have a significant trend throughout the time compared to the number of the other group. This situation holds even after we extend the news count sample to right before the 2008 crisis. As a result, the median attention paid to the Section 20 and non-Section 20 groups seems to satisfy the parallel trend assumption of the DID estimator.

In addition to this evidence, we further include the news count as an additional control variable into our DID regressions based on the matched sample for a formal robustness test. We note that the inclusion of the news variable will likely introduce a downward bias to our estimates because an increase in the number of public operational risk events can mechanically increase the news count by construction. Therefore, the estimation results after controlling for the media attention should be considered as a lower bound of the effects of complexity on operational risk.

The econometric results are depicted in Tables A4–A6, Model (9), in which the M&A controls are the original ones we use in Model (6). As the tables suggest, while we observe a positive and marginally statistically significant effect of the news count on the frequency of operational risk events, in addition to the significant coefficients of the M&A activities, the economic and statistical significance of our key DID estimates stay consistent (Table A4, Model (9)). In terms of the total and average annual loss of operational risk, we find no significant impact coming from the additional news and M&A controls and no qualitative change in our main findings (Table A5, Model (9)). Our results on the performance measures from Section 6.6.4 also remain robust to the inclusion of the media attention control (Table A6, Panels A–D). In sum, these findings reconcile concerns over potential media reporting bias in our DID results.

6.6.6 Non-Section 20 Diversification and Insurance Deregulations

We use this section to study how our results are affected by the non-Section 20 BHCs that entered the business of securities underwriting and dealing after the repeal of GSA as well as by the insurance deregulations that occurred at the same time during our sample period. If a BHC from the non-Section 20 group entered a deregulated industry during our post-deregulation period (2000–2002), this BHC may have experienced a sudden increase in its complexity, which could increase its operational risk and bias our results downward from the DID estimations. Therefore, it is interesting for us to see whether this is indeed the case and, if so, to what degree our main estimation results change.

National banks were allowed to sell insurance from small towns with a population of fewer than 5,000 people in 1993, following an argument proposed by the Office of the Comptroller of the Currency back in 1986. In 1995, national banks were allowed to sell annuities. In 1996, both national and state-chartered banks were allowed to sell insurance through subsidiaries or directly through bank branches. Compared with the regulatory changes on securities, the insurance regulations never involved anything similar to a Section 20 subsidiary. Therefore, BHCs in both our Section 20 and non-Section 20 groups were able to expand their insurance activities following a corresponding deregulation. In addition, if such an expansion was conducted by obtaining nonbank subsidiaries through M&As, it can be captured by our HHI-based treatment group as well as by the additional M&A controls described in the previous section. Nevertheless, given that the BHCs in our Section 20 group were larger and more diversified in general, it is possible that they were more likely to develop their insurance business than were the high holders in our non-Section 20 group. If this is the case, then part of the treatment effects we captured from the 1996–1999 deregulations among our Section 20 BHCs may have been contributed by their increased complexity through nonbank expansion into insurance, instead of through nonbank expansion into securities underwriting and dealing. Although this scenario does not change our conclusion that an increase in bank complexity leads to an increase in operational risk, it matters regarding whether we reached the conclusion in the way we intended. Therefore, it is important for us to see to what extent our main results change after controlling for BHCs' insurance activities.

In order to address the questions described above, we take advantage of the fact that BHCs are required to report their income from investment banking, advisory, brokerage and underwriting, and insurance since 2001 in FR Y-9C. This enables us to approximate whether a non-Section 20 BHC decided to make a significant expansion into securities underwriting and dealing after 1999 and whether a BHC has an active business line in insurance.[34] Specifically, to control for the non-Section 20 BHCs that began to expand into securities underwriting and dealing after 1999, we drop any non-Section 20 BHC that had more than 1 percent of its total annual income from securities underwriting and dealing in either 2001 or 2002, before re-estimating our main DID model based on our original, balanced sample. This exercise yields a sample of 18 Section 20 high holders vs. 255, instead of 329, non-Section 20 BHCs. To control for any BHC with an active business line in insurance, we conduct a similar but separate robustness check by dropping any BHC that had more than 1 percent of its total annual income from insurance commissions and fees in either 2001 or 2002. This gives us a sample of 11 Section 20 high holders vs. 262 non-Section 20 BHCs. Our choice of the 1 percent threshold is guided by the general disclosure threshold of FR Y-9C in those years, when a BHC was required to report any source of income that made up more than 1 percent of its total annual income under the category of other income for a given year if that income source was not specifically requested elsewhere in that year's FR Y-9C.

The results of our robustness checks are reported in Table A7. Compared with the main results from our original analysis, as shown in Models (1), (4), and (7), the impact of the deregulations on both operational risk frequency and severity increases after controlling for the non-Section 20 BHCs that began to expand into securities underwriting and dealing after 1999, as shown by Models (2), (5), and (8). In comparison, Models (3), (6), and (9) show that the impact of the deregulations on operational risk losses decreases, whereas the effect on operational risk event frequency sharply increases after controlling for BHCs' insurance activities, as shown in Models (3), (6), and (9). Overall, the impacts of the deregulations remain substantial and statistically significant. In short, the results of our robustness checks are consistent with those we obtained from the main DID analysis.

[34] A BHC's income from investment banking, advisory, brokerage and underwriting commissions and fees is reported in variable BHCKB490. A BHC's income from insurance commissions and fees is reported in BHCKB494. These two variables are not available before 2001.

6.6.7 Subgroup Analysis of Banking and Nonbanking Events with Growth Matching

Until now, we have been focusing on the overall impact of complexity on the operational risk of U.S. BHCs. This section investigates whether the changes in complexity caused by the banking sector deregulations have a different impact on the operational risk events originated in the banking business lines, compared to those originated in the nonbanking business lines.

One potential concern in our analysis so far was the possibility that Section 20 owners, compared to the other BHCs, can elevate their risk when they expand into securities underwriting simply because securities activities are inherently riskier than the traditional commercial banking business. This concern was addressed by the comparison of banks vs. nonbanks in Section 6.6.3, where we found a significant increase in the operational risk events for Section 20 owners even in comparison with the nonbank underwriting firms. However, compared to the non-Section 20 BHCs, one remaining concern is whether the increased operational risk among the Section 20 owners is driven by the events from the nonbanking business lines alone. If it is the case that the increase in operational risk stems mostly from the nonbanking sector, then the elevated complexity caused by the deregulation may be less of a concern for the banking sector activities of U.S. BHCs. If, on the other hand, a significant portion of the increased operational risk indeed originates from the banking sector, the negative effects of greater complexity may point to a greater systemic risk, with significant ramifications for the regulation of complexity.

The separation of banking and nonbanking events helps us answer this question by providing us with an opportunity to perform a DID analysis between the Section 20 owners and the non-Section 20 BHCs, using only their banking events. We utilize the BIS business line classification provided by the IBM Algo FIRST database for each event to separate the banking and nonbanking events in our sample. Following the event classification by the Basel II Capital Accord, we define an operational risk event as a banking event if the business line of the event is one of Retail Banking, Commercial Banking, Payment and Settlement, or Agency Services, and we define an event as a nonbanking event if the business line is one of Asset Management, Corporate Finance, Retail Brokerage, Trading and Sales, or Insurance. Among the 1,047 events we have for the U.S. BHCs in the IBM Algo FIRST database, 598 of them fall under our banking event definition and 411 of them are classified as nonbanking events. We exclude the remaining 38 events with an associated business line labeled as “Others” in the IBM Algo FIRST database. Of the 265 events originated before the complete repeal of the GSA in 1999, 157 are banking events, of which 83 come from Section 20 high holders. Of the 108 nonbanking events originated before the repeal of the GSA, 71 come from Section 20 high holders. Among the 441 banking and 303 nonbanking events originated after 1999 and before the end of our sample period in 2012, the number of banking and nonbanking events occurred in a Section 20 holder is 232 and 159.

Since this exercise requires the separation of banking and nonbanking activities, we measure the banking assets of a BHC as its total assets minus the assets of its nonbank subsidiaries (item BHCP4778 from FR Y-9L filings). We then match the Section 20 owners and the non-Section 20 BHCs by the growth of their average banking assets from the pre-deregulation period (1994–1996) to the post-deregulation period (2000–2002). We construct our matched sample based on the asset growth. This approach roduces closer matches than the matching approach based on the size of the assets because Section 20 owners are substantially larger than the non-Section 20 BHCs not only in terms of either total assets but also in terms of banking assets. More importantly, the relevant endogeneity issue related with size is not that the Section 20 owners were larger to begin with but that the deregulation might have caused them to grow significantly in a rather short period of time and that this burst in asset growth led to the growth of operational risk for reasons unrelated to complexity. Matching by asset growth addresses this problem more directly.

Based on the banking asset growth, we select the top three non-Section 20 BHCs for each of the Section 20 owners with the shortest Mahalanobis distance in order to ensure a sufficiently large sample size for our matched sample. To improve the matching quality, we perform the growth matching with replacement, i.e., we require that the selection of the non-Section 20 BHCs for different Section 20 owners is independent of each other. Following this matching procedure, we end up with a sample of 18 Section 20 vs. 47 non-Section 20 BHCs. The mean and median growth rates of the Section 20 owners are 69.77% and 86.3%, with a standard deviation of 61.35%. The mean and median growth rates of the non-Section 20 BHCs are 81.15% and 95.56%, with a standard deviation of 54.93%. We then perform a DID estimation based on the matched sample using only the banking events.

The results of the matched sample analysis are presented in Table A8, Models (1), (2), and (3). We include the complete set of control variables that we use in the main analysis, which can be seen in Tables 4 and 5. Compared with the main results in Tables 4 and 5, we find that the coefficients of interest remain quite similar. In particular, the coefficient of the Section 20 interaction term is 1.569 (Table 4, Model (6)) vs. 0.871 (Table A8, Panel A, Model (3)) for the annual operation risk event frequency, 2.102 (Table 4, Panel A, Model (6)) vs. 2.325 (Table A8, Panel B, Model (3)) for the total annual operational loss, and 1.822 (Table 4, Panel B, Model (6)) vs. 2.131 (Table A8, Panel C, Model (3)) for the average annual operational loss. Therefore, the results from our banking event estimation demonstrate that the elevation in operational risk among the Section 20 owners following the banking sector deregulations is not solely driven by their nonbanking events. In fact, the exogenous increase in complexity caused by a rapid diversification into the nonbanking business lines has a substantial impact on the operational risk from the banking sector activities of U.S. BHCs.

We extend this robustness test to further compare the impact of deregulation on the operational risk originated in the banking business lines with those originated in the nonbanking business lines, and conduct another analysis with only the nonbanking events. For this purpose, we use the Section 20 owners as the treatment group and the nonbank underwriting firms (SIC code 62xx) as the control group, following our practice in Section 6.6.3. We apply the same matching mechanism described in the banking event analysis and create a matched sample between the Section 20 owners and the nonbank securities firms according to their nonbanking asset growth. The nonbanking assets of the Section 20 group are measured by the assets of its nonbank subsidiaries (item BHCP4778 from FR Y-9L filings). We treat the total assets of the nonbank underwriting firms as their nonbanking assets for the purpose of this analysis.

Following an equivalent matching procedure, we end up with a sample of 18 Section 20 owners vs. 18 underwriting firms. The mean and median growth rates of the nonbanking assets of the Section 20 owners are 168.20% and 158.29%, with a standard deviation of 80.48%. The mean and median growth rates of the underwriting firms are 149.41% and 131.06%, with a standard deviation of 91.15%. Based on this matched sample, we conduct a DID estimation using only the nonbanking events. We choose to include the complete set of controls we use in the banks vs. nonbanks robustness check described in section 6.6.3. The list of control variables are shown in Tables 16 and 17.

The estimation results of the nonbanking event analysis are presented in Table A8, Models (4), (5), and (6). Compared with the coefficients of the Section 20 interaction terms from the banks vs. nonbanks robustness check (Section 6.6.3), where the DID estimates for the annual operation risk event frequency, total annual operational loss, and average annual operational loss are 1.072, 1.647, and 1.462 (Table 16, Model (6) and Table 17, Panels A and B, Model (6)), the estimates from the nonbanking event analysis remain highly consistent despite a much smaller sample size. In particular, the coefficients of the Section 20 interaction terms from the nonbanking event analysis on the operational risk frequency, total operational loss, and average operational loss are 1.159, 1.759, and 1.393 (Table A8, Panels A, B, and C, Model (6)). The estimates of our nonbanking event analysis have a weaker statistical significance due to the limited size of our matched sample caused by a smaller pool of comparable nonbank underwriting firms.

In conclusion, both of the banking and nonbanking events analyses confirm that the escalated complexity caused by the banking sector deregulations had a substantial impact on operational risk of U.S. BHCs, particularly of the Section 20 owners. These results put to rest concerns that a rapid expansion into the nonbanking business lines caused an increase in operational risk only from the nonbanking activities, and provide compelling evidence that increased operational risk is driven by both the events from the banking and nonbanking business lines.

7 Conclusion

Using the repeal of the Glass-Steagall Act during 1996–1999 as a natural experiment, we show that the frequency and magnitude of operational risk events have increased significantly with bank complexity. This trend has been particularly strong for bank holding companies that were constrained by the regulations restricting their securities underwriting and dealing activities, especially those with existing Section 20 subsidiaries, while weaker for the other banks that did not engage in extensive securities underwriting and dealing activities and for nonbank financial institutions that were not subject to the same regulations.

Our findings underscore that business complexity is a two-faced by-product of the banking sector's financial deregulation. On the one hand, we show that traditional market- and balance-sheet-based performance measures typically improved following deregulations for the banks that had been the most constrained by financial regulations. On the other hand, their operational risk increased. Tail events (such as JP Morgan Chase's "London Whale" or the recent malpractices at

Wells Fargo) are likely unanticipated by the management and shareholders. Additionally, some recent studies document negative externalities of operational risk events to other financial firms (e.g., Cummins, Wei, and Xie 2011; Chernobai, Jorion, and Yu 2007). Therefore, even if higher levels operational risk were optimal for an individual bank, they are likely not socially optimal.

One limitation of our findings is that we are unable to separate between operational risk events that arise from increased moral hazard (due to increased government guarantees) and events associated with shortcomings in managerial oversight. For example, an ongoing settlement with the U.S. Department of Justice in connection with an investigation into residential mortgage-backed securities at Deutsche Bank has reduced the bank's initial fine from $14 bln to roughly $7.2 bln due to the fear that the impact could extend beyond Deutsche Bank and its capital position.[35] If implicit government guarantees do extend to the amount of operational loss as in this example, this would mean that our findings are a lower bound on the effect of complexity on operational risk severity. We hope that this study would jump-start new scholarly research on the interaction between complexity and risk-taking in the financial sector.

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Figure 1: Distribution of Herfindahl-Hirschman Index (HHI) of Industry Concentration during 1988–2005

This figure illustrates the Herfindahl-Hirschman Index (HHI) of industry concentration for the bank holding companies in our sample. Descriptive statistics (mean, median, 25th, and 75th percentiles) are based on the annual sample of 1988–2005 for bank holding companies with available HHI data before and after 1996.

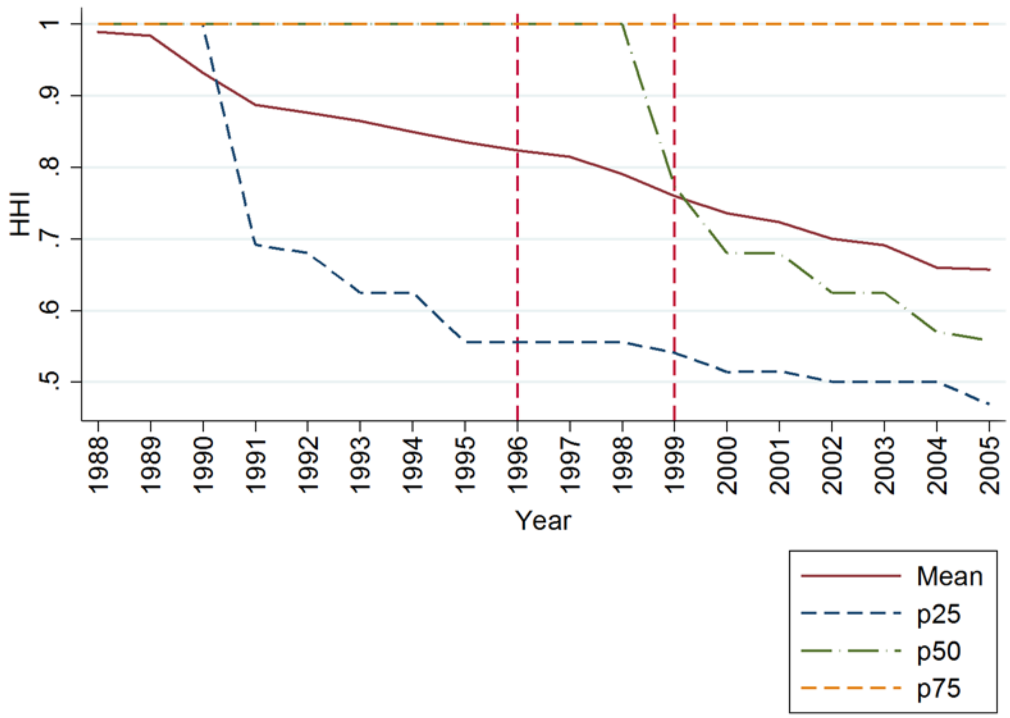


Figure 2: Number of Operational Risk Events during 1988–2005

This figure illustrates the annual count of operational risk events, along with the number of bank holding companies, in our sample over the period of 1988–2005. The dashed lines around 1996 and 1999 indicate the timing of deregulations.

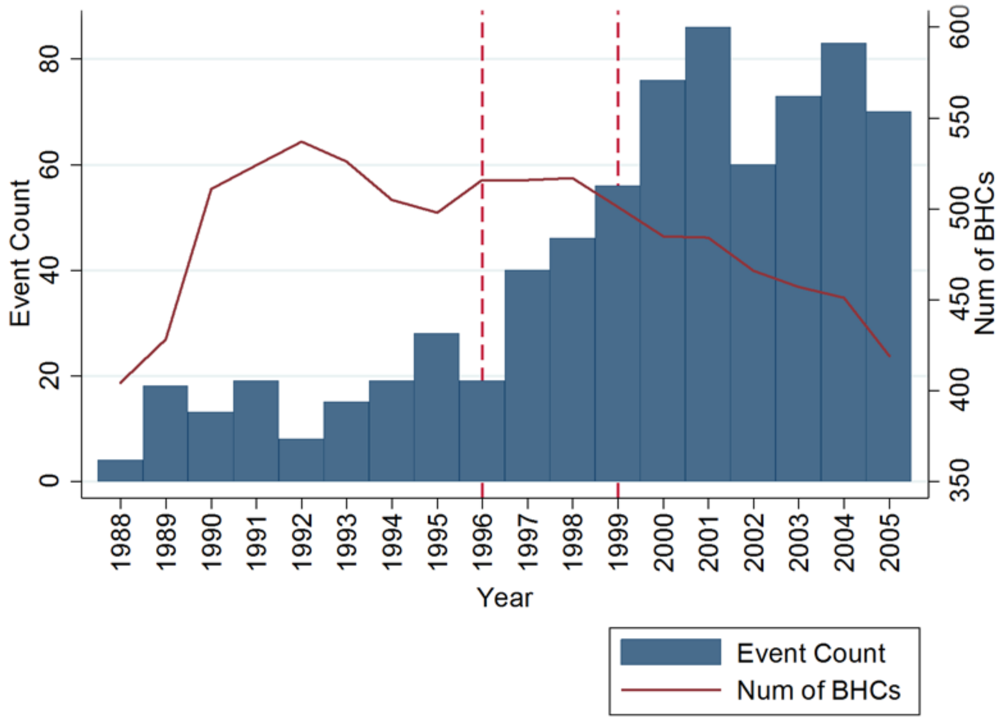


Figure 3: Average Loss of Operational Risk Events during 1988–2005

This figure illustrates the average loss of operational risk events (USD millions per event), along with the number of bank holding companies, in our sample over the period of 1988–2005. The dashed lines around 1996 and 1999 indicate the timing of deregulations.

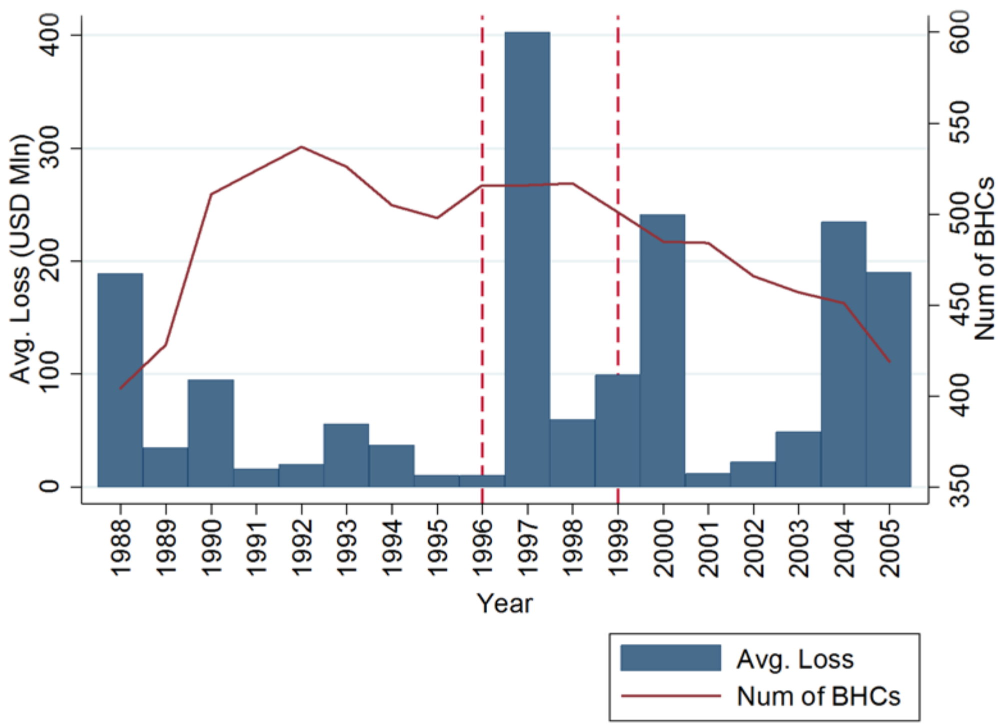
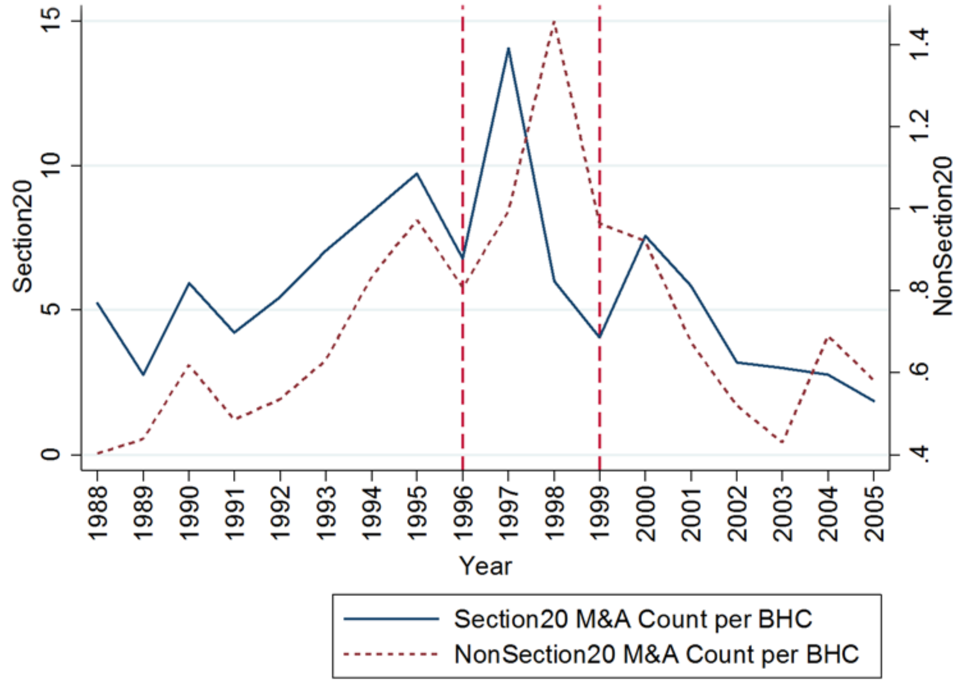


Figure 4: Banking Sector M&A Activities during 1988–2005

This figure illustrates the banking sector M&A activities of our sample high holders included in the difference-in-differences analysis over the period of 1988–2005. The dashed lines around 1996 and 1999 indicate the timing of deregulations.

Panel A: Average Number of M&As per High Holder



Panel B: Average Target Assets Ratio per High Holder

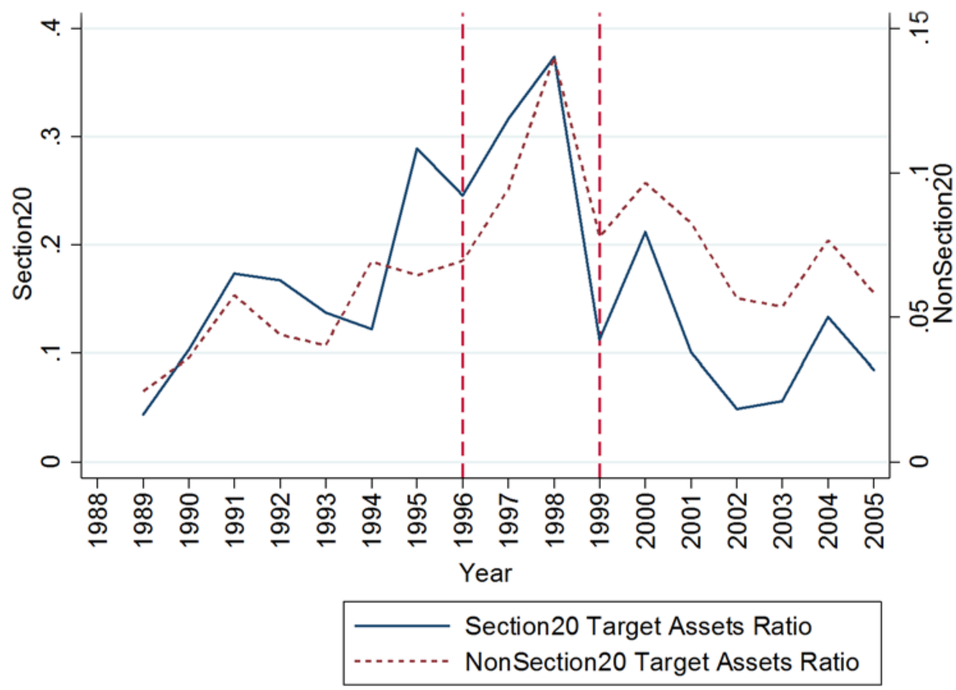


Figure 5: Numbers of News Articles during 1994-2011

This figure illustrates the median number of news articles from Factiva for the Section 20 subsidiary owners and non-Section 20 high holders included in our main difference-in-differences analysis over the period of 1994-2011. The dashed lines around 1996 and 1999 indicate the timings of deregulations.

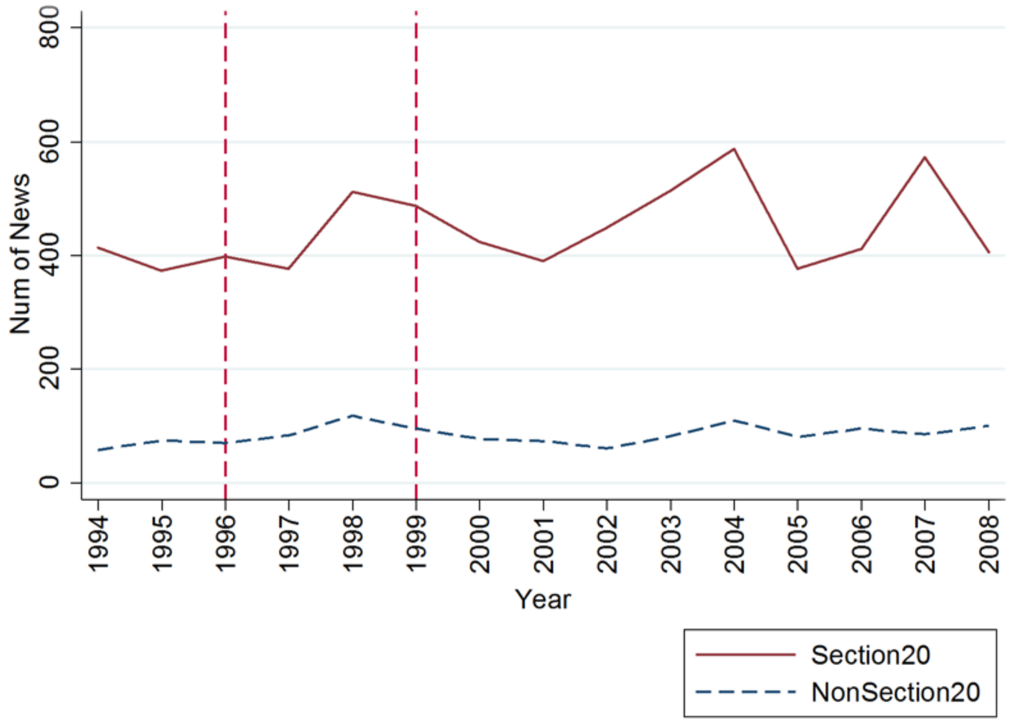


Table 1: Variable Definitions and Sources of Data Used in the Study

This table summarizes the variable definitions and sources of data used in our study.

Variables	Definition
Treatment Group Indicators (1988–2005)	
Pre96HHI<1	Pre96HHI<1 indicator equals 1 if the average HHI of a BHC is smaller than 1 before the end of 1996.
Section20	Section20 indicator equals 1 if a BHC owned a Section 20 subsidiary before the end of 1999.
Non20HHI<1	Non20HHI<1 indicator equals 1 if a BHC did not own a Section 20 subsidiary before the end of 1999 but has an average HHI smaller than 1 before the end of 1996.
BHC	BHC indicator equals 1 if the financial institution is a BHC.
Non20BHC	Non20BHC indicator equals 1 if a BHC did not own a Section 20 subsidiary before the end of 1999.
After=1	After=1 indicator equals 1 for the post-deregulation period.
Operational Risk Variables (1988–2005)	
Count	Annual number of operational risk events, from the IBM Algo FIRST database.
LnLoss	Annual total operational risk loss amount, from the IBM Algo FIRST database. Measurement units: natural logarithm of USD millions.
LnAvgLoss	Annual average operational risk loss amount, from the IBM Algo FIRST database. Measurement units: natural logarithm of USD millions.
Bank Level Characteristics (1988–2005)	
LnTA	Total assets is a proxy for bank size. It is measured by quarterly BHCK2170 from FR Y-9C or by quarterly ATQ from CRSP and Compustat Merged (CCM). The variable is consolidated to the annual level as a state variable. Measurement units: natural logarithm of USD millions.
ROA%	Return on assets is a proxy for bank profitability. It is estimated as net income divided by total assets: quarterly (BHCK4340/BHCK2170)*100% from FR Y-9C or quarterly (OIBDPQ/ATQ)*100% from CCM. The variable is consolidated to the annual level as a flow variable.
MarketToBook	Market-to-book ratio is a proxy for bank growth opportunities and is inversely related to default risk (Fama and French 1992). It is estimated as the ratio of MVE to book equity. MVE is estimated by monthly PRC * SHROUT from CRSP and then summed to the quarterly level or by quarterly CSHOQ * PRCCQ from CCM. Book equity is estimated by quarterly BHCK3230 + BHCK3240 + BHCK3247 – BHCK3153 from FR Y-9C or by quarterly CEQQ from CCM. The variable is consolidated to the annual level as a state variable.
SD ROA%	Standard deviation of return on assets is a proxy for bank riskiness behavior. It is estimated as the standard deviation of the quarterly return on assets in a given year. The variable is calculated at the annual level.
Z-Score	Z-score is a proxy for bank stability. It is estimated as return on assets plus equity-to-asset ratio, scaled by the standard deviation of return on assets, where equity-to-asset ratio is estimated by (book equity)/(total assets). The variable is calculated at the annual level, with the return on assets and equity-to-asset ratio consolidated to the annual level as a flow and state variables.
CashToTA	Ratio of cash and short-term investments to assets is used in this study as a proxy for "problem banks" (Acharya, Davydenko, and Strebulaev 2012). It is estimated as quarterly (BHCK0081 + BHCK0395 + BHCK0397 + BHCK0383)/BHCK2170 from FR Y-9C or as quarterly CHEQ/ATQ from CCM. The variable is consolidated to the annual level as a state variable.
Tier1R	Tier 1 ratio is the ratio of regulatory Tier 1 capital to risk-weighted assets. The Basel Capital Accord requires financial institutions to hold regulatory Tier 1 capital as a protection mechanism against financial risks. It is estimated as quarterly (BHCK3210 + BHCK3247)/BHCK2170 from FR Y-9C or as quarterly (TEQQ + REQ)/ATQ from CCM. The variable is consolidated to the annual level as a state variable. To maximize available observations on TEQQ, we replaced the missing TEQQ first by quarterly CEQQ + PSTKQ, then by quarterly ATQ – LTQ from CCM, following the practice of Davis, Fama, and French (2000).
ROE	Return on equity is an additional control for bank profitability. It is estimated as net income divided by book equity. The variable is consolidated to the annual level as a flow variable. The variable is winsorized at 2% and 98% for the CCM measure to avoid extreme values from nonbank financial firms.
ExcessiveGrowth	Excessive growth in liabilities is a proxy for bank aggressive growth. Aggressive growth strategies, especially growth in liabilities, often accompany risk management deficiencies and management's inability to effectively sustain exceptional growth (Moody's 2002; OCC 2001). The variable is expressed as an indicator equal to 1 if a bank experienced a positive growth of liabilities and assets in the previous year and the growth of liabilities exceeded the growth of assets. Liabilities and assets are measured by quarterly BHCK2948 and BHCK2170 from FR Y-9C or by quarterly LTQ and ATQ from CCM. The variable is calculated at the annual level, with liabilities and assets consolidated to the annual level as state variables.
HighDividend	High dividends payout ratio is used to capture "troubled banks." Dividend payout may be restricted by the Office of the Comptroller of the Currency (OCC) for banks experiencing large losses and identified by regulators as problem banks (OCC 2001; Collier et al. 2003). The variable is expressed as an indicator equal to 1 if a bank's dividend payout ratio during the previous year exceeded the annual median across all sample BHCs. Dividend-to-assets ratio is measured by quarterly (BHCK4460 + BHCK4598)/BHCK2170 from FR Y-9C or by annual DVT/quarterly ATQ from CCM. The variable is calculated at the annual level, with BHCK4460 and BHCK4598 consolidated to the annual level as flow variables and BHCK2170 and ATQ consolidated to the annual level as state variables.

Table 2: Summary Statistics of Key Bank-Level Characteristics

This table summarizes the sample statistics of key bank-level characteristics from FR Y-9C used in our study. Summary statistics are based on the annual sample of 1994–1996 and 2000–2002 for bank holding companies with available HHI data before and after 1996.

	Percentile							
	1th	25th	50th	75th	99th	Mean	SD	Num Obs
LnTA	5.064	6.015	6.725	7.953	12.311	7.177	1.613	2,257
MarketToBook	0.543	1.241	1.558	1.960	4.686	1.699	0.866	1,816
CashToTA	0.020	0.050	0.075	0.108	0.282	0.086	0.053	2,257
Tier1R	0.042	0.107	0.132	0.158	0.288	0.137	0.059	2,257
ROE (%)	-4.323	6.445	7.934	9.457	16.058	7.650	4.872	1,762
ExcessiveGrowth	0	0	0	1	1	0.386	0.487	2,075
HighDividend	0	0	1	1	1	0.563	0.496	2,254

Table 3: Nonparametric Difference-in-Differences Analysis

This table summarizes the mean differences and univariate difference-in-differences analysis of operational risk and performance measurements between the treatment and control groups based on the annual balanced sample of 1994–1996 (pre-deregulation) and 2000–2002 (post-deregulation). The before period is defined as the bank-level time average between 1994 and 1996. The after period is defined as the bank-level time average between 2000 and 2002.

	Before	After	After − Before	Diff-In-Diff
Count				
Pre96HHI<1	0.116	0.370	0.254	0.243
Section20	0.685	2.222	1.537	1.526
Non20HHI<1	0.031	0.092	0.061	0.050
Control	0.006	0.017	0.011	
LnLoss				
Pre96HHI<1	-4.254	-3.820	0.434	0.384
Section20	-2.721	-0.752	1.969	1.919
Non20HHI<1	-4.483	-4.280	0.203	0.153
Control	-4.569	-4.519	0.050	
LnAvgLoss				
Pre96HHI<1	-4.279	-3.886	0.393	0.342
Section20	-2.902	-1.207	1.695	1.644
Non20HHI<1	-4.485	-4.288	0.197	0.146
Control	-4.570	-4.519	0.051	
ROA%				
Pre96HHI<1	0.669	0.655	-0.014	0.083
Section20	0.723	0.678	-0.045	0.052
Non20HHI<1	0.661	0.652	-0.009	0.088
Control	0.765	0.668	-0.097	
MarketToBook				
Pre96HHI<1	1.669	2.068	0.399	0.253
Section20	1.783	2.215	0.432	0.286
Non20HHI<1	1.648	2.041	0.393	0.247
Control	1.578	1.724	0.146	
SD ROA%				
Pre96HHI<1	0.351	0.369	0.018	0.047
Section20	0.370	0.354	-0.016	0.013
Non20HHI<1	0.348	0.372	0.024	0.053
Control	0.397	0.368	-0.029	
Z-Score				
Pre96HHI<1	2.263	2.314	0.051	0.376
Section20	2.173	2.437	0.264	0.589
Non20HHI<1	2.277	2.295	0.018	0.343
Control	2.601	2.276	-0.325	

Table 4: Difference-in-Differences Analysis of Annual Operational Risk Event Frequency

This table presents the results of the OLS models for our difference-in-differences analysis. The dependent variable is annual operational risk event frequency (*Count*). All data are averaged over 1994–1996 (pre-deregulation) and 2000–2002 (post-deregulation) sample periods. *t*-statistics reported in parentheses are based on robust standard errors clustered at the bank holding company level. Superscripts ***, **, and * indicate statistical significance at 1%, 5%, and 10% levels.

	(1) Count	(2) Count	(3) Count	(4) Count	(5) Count	(6) Count
After=1	0.010*	-0.125**	-0.224*	0.010*	-0.135**	-0.282**
	(1.950)	(-1.984)	(-1.871)	(1.949)	(-2.322)	(-2.388)
After=1 × Pre96HHI<1=1	0.243***	0.243***	0.282**			
	(2.856)	(2.882)	(2.525)			
After=1 × Section20=1				1.527***	1.533***	1.569***
				(2.807)	(2.853)	(2.787)
After=1 × Non20HHI<1=1				0.051**	0.050**	0.061
				(2.151)	(2.140)	(1.555)
LnTA		0.171**	0.316**		0.184**	0.337***
		(2.143)	(2.190)		(2.490)	(2.614)
MarketToBook			0.012			-0.057
			(0.234)			(-0.875)
CashToTA			-0.082			-1.383
			(-0.086)			(-1.191)
Tier1R			3.105**			2.694**
			(2.096)			(2.434)
ROE			-0.010			0.011
			(-0.775)			(0.861)
ExcessiveGrowth			0.011			0.080
			(0.119)			(1.002)
HighDividend			-0.188			-0.141
			(-1.244)			(-1.071)
Constant	0.050***	-1.106**	-2.492**	0.050***	-1.194**	-2.561**
	(2.942)	(-1.999)	(-2.058)	(3.388)	(-2.340)	(-2.432)
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Num Observations	694	694	412	694	694	412
R-squared	0.061	0.075	0.118	0.293	0.309	0.336

Table 5: Difference-in-Differences Analysis of Operational Risk Event Severity

This table presents the results of the OLS models for our difference-in-differences analysis. The dependent variable is operational risk event severity: total annual loss (*LnLoss*) in Panel A and average annual loss (*LnAvgLoss*) in Panel B, in logarithmic form. All data are averaged over 1994–1996 (pre-deregulation) and 2000–2002 (post-deregulation) sample periods. *t*-statistics reported in parentheses are based on robust standard errors clustered at the bank holding company level. Superscripts ***, **, and * indicate statistical significance at 1%, 5%, and 10% levels.

Panel A: Total Annual Operational Loss

	(1) LnLoss	(2) LnLoss	(3) LnLoss	(4) LnLoss	(5) LnLoss	(6) LnLoss
After=1	0.051	-0.136	-0.283	0.051	-0.149	-0.356**
	(1.279)	(-1.210)	(-1.404)	(1.278)	(-1.466)	(-2.011)
After=1 × Pre96HHI<1=1	0.383***	0.383***	0.501***			
	(3.080)	(3.105)	(3.458)			
After=1 × Section20=1				1.918***	1.927***	2.102***
				(3.436)	(3.474)	(4.091)
After=1 × Non20HHI<1=1				0.152	0.151	0.227*
				(1.559)	(1.576)	(1.831)
LnTA		0.237*	0.401*		0.252**	0.426**
		(1.776)	(1.796)		(2.139)	(2.144)
MarketToBook			-0.124			-0.210
			(-0.688)			(-1.163)
CashToTA			-3.298			-4.916**
			(-1.518)			(-2.478)
Tier1R			4.628			4.116
			(1.506)			(1.542)
ROE			0.026			0.052
			(0.734)			(1.579)
ExcessiveGrowth			-0.153			-0.068
			(-0.836)			(-0.419)
HighDividend			-0.304			-0.246
			(-1.490)			(-1.215)
Constant	-4.444***	-6.041***	-7.369***	-4.444***	-6.147***	-7.455***
	(-169.014)	(-6.713)	(-3.916)	(-182.909)	(-7.707)	(-4.404)
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Num Observations	694	694	412	694	694	412
R-squared	0.074	0.085	0.145	0.211	0.223	0.294

Panel B: Average Annual Operational Loss

	(1) LnAvgLoss	(2) LnAvgLoss	(3) LnAvgLoss	(4) LnAvgLoss	(5) LnAvgLoss	(6) LnAvgLoss
After=1	0.052	-0.111	-0.236	0.052	-0.121	-0.298*
	(1.315)	(-1.048)	(-1.250)	(1.314)	(-1.253)	(-1.756)
After=1 × Pre96HHI<1=1	0.341***	0.341***	0.452***			
	(2.914)	(2.935)	(3.304)			
After=1 × Section20=1				1.643***	1.651***	1.822***
				(3.150)	(3.172)	(3.746)
After=1 × Non20HHI<1=1				0.146	0.145	0.217*
				(1.528)	(1.543)	(1.805)
LnTA		0.206*	0.344*		0.219**	0.365*
		(1.667)	(1.673)		(1.970)	(1.955)
MarketToBook			-0.131			-0.204
			(-0.738)			(-1.156)
CashToTA			-3.350			-4.735**
			(-1.581)			(-2.430)
Tier1R			4.133			3.695
			(1.470)			(1.492)
ROE			0.031			0.053
			(0.903)			(1.645)
ExcessiveGrowth			-0.163			-0.091
			(-0.993)			(-0.600)
HighDividend			-0.276			-0.226
			(-1.430)			(-1.176)
Constant	-4.454***	-5.845***	-6.930***	-4.454***	-5.935***	-7.004***
	(-178.836)	(-7.007)	(-4.010)	(-190.296)	(-7.887)	(-4.404)
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Num Observations	694	694	412	694	694	412
R-squared	0.068	0.078	0.137	0.179	0.189	0.261

Table 6: Difference-in-Differences Analysis of Performance Measures

This table presents the results of the OLS models for our difference-in-differences analysis. The dependent variable is a metric of performance. All data are averaged over 1994–1996 (pre-deregulation) and 2000–2002 (post-deregulation) sample periods. *t*-statistics reported in parentheses are based on robust standard errors clustered at the bank holding company level. Superscripts ***, **, and * indicate statistical significance at 1%, 5%, and 10% levels.

Panel A: Return on Assets (%)

	(1) ROA%	(2) ROA%	(3) ROA%	(4) ROA%	(5) ROA%	(6) ROA%
After=1	-0.097***	-0.084*	-0.007	-0.097***	-0.084*	-0.008
	(-4.117)	(-1.838)	(-0.393)	(-4.114)	(-1.829)	(-0.472)
After=1 × Pre96HHI<1=1	0.083**	0.083**	0.028**			
	(2.427)	(2.426)	(1.985)			
After=1 × Section20=1				0.052	0.051	0.057**
				(0.902)	(0.893)	(2.041)
After=1 × Non20HHI<1=1				0.087**	0.087**	0.023
				(2.427)	(2.419)	(1.651)
LnTA		-0.016	-0.001		-0.016	-0.001
		(-0.295)	(-0.071)		(-0.301)	(-0.049)
Other Control Variables	No	No	Yes	No	No	Yes
Constant	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Num Observations	694	694	412	694	694	412
R-squared	0.053	0.053	0.855	0.053	0.054	0.856

Panel B: Market-to-Book Ratio

	(1) M/B	(2) M/B	(3) M/B	(4) M/B	(5) M/B	(6) M/B
After=1	0.146**	0.042	0.192*	0.146**	0.042	0.182*
	(2.061)	(0.401)	(1.958)	(2.059)	(0.394)	(1.879)
After=1 × Pre96HHI<1=1	0.253**	0.252**	0.251***			
	(2.357)	(2.342)	(3.219)			
After=1 × Section20=1				0.286	0.292	0.430***
				(1.568)	(1.642)	(2.763)
After=1 × Non20HHI<1=1				0.246**	0.244**	0.217***
				(2.152)	(2.114)	(2.622)
LnTA		0.130	0.037		0.131	0.040
		(0.896)	(0.396)		(0.898)	(0.424)
Other Control Variables	No	No	Yes	No	No	Yes
Constant	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Num Observations	482	482	412	482	482	412
R-squared	0.115	0.120	0.328	0.115	0.120	0.334

Panel C: Standard Deviation of Return on Assets (%)

	(1) SD ROA%	(2) SD ROA%	(3) SD ROA%	(4) SD ROA%	(5) SD ROA%	(6) SD ROA%
After=1	-0.029**	-0.018	-0.004	-0.029**	-0.018	-0.003
	(-2.089)	(-0.712)	(-0.270)	(-2.088)	(-0.701)	(-0.183)
After=1 × Pre96HHI<1=1	0.047***	0.047***	0.015			
	(2.610)	(2.617)	(1.171)			
After=1 × Section20=1				0.013	0.013	-0.014
				(0.385)	(0.373)	(-0.519)
After=1 × Non20HHI<1=1				0.052***	0.052***	0.020
				(2.816)	(2.823)	(1.487)
LnTA		-0.014	-0.017		-0.014	-0.018
		(-0.503)	(-0.991)		(-0.518)	(-1.025)
Other Control Variables	No	No	Yes	No	No	Yes
Constant	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Num Observations	660	660	408	660	660	408
R-squared	0.021	0.022	0.420	0.023	0.025	0.426

Panel D: Z-Score

	(1) Z-Score	(2) Z-Score	(3) Z-Score	(4) Z-Score	(5) Z-Score	(6) Z-Score
After=1	-0.325*	-0.391	0.044	-0.325*	-0.393	0.031
	(-1.880)	(-1.575)	(0.480)	(-1.878)	(-1.582)	(0.326)
After=1 × Pre96HHI<1=1	0.375*	0.375*	0.009			
	(1.926)	(1.925)	(0.087)			
After=1 × Section20=1				0.589**	0.593**	0.298
				(2.298)	(2.297)	(1.268)
After=1 × Non20HHI<1=1				0.342*	0.342*	-0.039
				(1.715)	(1.715)	(-0.385)
LnTA		0.083	0.037		0.086	0.042
		(0.536)	(0.461)		(0.550)	(0.532)
Other Control Variables	No	No	Yes	No	No	Yes
Constant	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Num Observations	660	660	408	660	660	408
R-squared	0.016	0.016	0.082	0.017	0.017	0.101

Table 7: Difference-in-Differences Analysis of Annual Operational Risk Event Frequency: Robustness Test Using 1988–2005 Data

This table presents the results of the OLS models for the robustness test of our difference-in-differences analysis. Instead of using the sample of 1994–1996 vs. 2000–2002 (Tables 4–6), we use the full sample of 1988–1996 vs. 1997–2005 to construct the before (pre-deregulation) and after (post-deregulation) periods. The dependent variable is annual operational risk event frequency (*Count*). All data are averaged over 1988–1996 (pre-deregulation) and 1997–2005 (post-deregulation) sample periods. *t*-statistics reported in parentheses are based on robust standard errors clustered at the bank holding company level. Superscripts ***, **, and * indicate statistical significance at 1%, 5%, and 10% levels.

	(1) Count	(2) Count	(3) Count	(4) Count	(5) Count	(6) Count
After=1	0.008*	-0.142**	-0.247**	0.008*	-0.132**	-0.207**
	(1.893)	(-2.194)	(-2.147)	(1.892)	(-2.391)	(-2.191)
After=1 × Pre96HHI<1=1	0.185***	0.162***	0.177***			
	(2.711)	(2.766)	(2.655)			
After=1 × Section20=1				1.031**	1.000**	1.010**
				(2.515)	(2.550)	(2.533)
After=1 × Non20HHI<1=1				0.034**	0.015	0.010
				(2.363)	(0.940)	(0.405)
LnTA		0.194**	0.316**		0.181**	0.278***
		(2.318)	(2.413)		(2.536)	(2.606)
MarketToBook			-0.008			-0.036
			(-0.321)			(-0.916)
CashToTA			0.802			0.199
			(1.336)			(0.337)
Tier1R			3.200**			2.301**
			(2.340)			(2.360)
ROE			0.002			0.004
			(0.497)			(0.904)
ExcessiveGrowth			0.093			0.064
			(1.450)			(1.227)
HighDividend			-0.134			-0.043
			(-1.539)			(-0.563)
Constant	0.032**	-1.243**	-2.605**	0.032**	-1.158**	-2.171**
	(2.348)	(-2.212)	(-2.415)	(2.534)	(-2.417)	(-2.588)
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Num Observations	968	968	638	968	968	638
R-squared	0.040	0.066	0.100	0.177	0.200	0.224

Table 8: Difference-in-Differences Analysis of Operational Risk Event Severity: Robustness Test Using 1988–2005 Data

This table presents the results of the OLS models for the robustness test of our difference-in-differences analysis. Instead of using the sample of 1994–1996 vs. 2000–2002 (Tables 4–6), we use the full sample of 1988–1996 vs. 1997–2005 to construct the before (pre-deregulation) and after (post-deregulation) periods. The dependent variable is operational risk event severity: total annual loss (*LnLoss*) in Panel A and average annual loss (*LnAvgLoss*) in Panel B, in logarithmic form. All data are averaged over 1988–1996 (pre-deregulation) and 1997–2005 (post-deregulation) sample periods. *t*-statistics reported in parentheses are based on robust standard errors clustered at the bank holding company level. Superscripts ***, **, and * indicate statistical significance at 1%, 5%, and 10% levels.

Panel A: Total Annual Operational Loss

	(1) LnLoss	(2) LnLoss	(3) LnLoss	(4) LnLoss	(5) LnLoss	(6) LnLoss
After=1	0.022	-0.213***	-0.250**	0.022	-0.202***	-0.205**
	(1.305)	(-3.398)	(-2.251)	(1.304)	(-3.599)	(-1.969)
After=1 × Pre96HHI<1=1	0.265***	0.230***	0.284***			
	(3.338)	(3.077)	(3.187)			
After=1 × Section20=1				1.210***	1.161***	1.211***
				(2.989)	(2.938)	(3.063)
After=1 × Non20HHI<1=1				0.096**	0.066	0.098*
				(2.017)	(1.492)	(1.773)
LnTA		0.304***	0.422***		0.290***	0.379***
		(3.854)	(3.755)		(4.138)	(3.841)
MarketToBook			-0.093			-0.125*
			(-1.609)			(-1.797)
CashToTA			1.049			0.378
			(0.866)			(0.359)
Tier1R			3.316**			2.315*
			(2.098)			(1.942)
ROE			0.009			0.011
			(1.316)			(1.648)
ExcessiveGrowth			0.130			0.097
			(0.909)			(0.780)
HighDividend			-0.222**			-0.120
			(-2.569)			(-1.319)
Constant	-4.483***	-6.480***	-7.748***	-4.483***	-6.385***	-7.265***
	(-277.075)	(-12.371)	(-8.350)	(-296.063)	(-13.797)	(-9.231)
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Num Observations	968	968	638	968	968	638
R-squared	0.061	0.105	0.147	0.179	0.219	0.259

Panel B: Average Annual Operational Loss

	(1) LnAvgLoss	(2) LnAvgLoss	(3) LnAvgLoss	(4) LnAvgLoss	(5) LnAvgLoss	(6) LnAvgLoss
After=1	0.022	-0.184***	-0.197**	0.022	-0.176***	-0.162*
	(1.312)	(-3.484)	(-2.087)	(1.312)	(-3.600)	(-1.778)
After=1 × Pre96HHI<1=1	0.223***	0.192***	0.241***			
	(3.234)	(2.923)	(3.068)			
After=1 × Section20=1				0.966***	0.922***	0.966***
				(2.826)	(2.747)	(2.877)
After=1 × Non20HHI<1=1				0.091**	0.064	0.095*
				(1.986)	(1.510)	(1.814)
LnTA		0.267***	0.359***		0.256***	0.325***
		(4.071)	(3.954)		(4.268)	(3.930)
MarketToBook			-0.095*			-0.120*
			(-1.728)			(-1.889)
CashToTA			0.808			0.283
			(0.744)			(0.294)
Tier1R			2.751**			1.968*
			(2.006)			(1.843)
ROE			0.008			0.010*
			(1.379)			(1.658)
ExcessiveGrowth			0.109			0.083
			(0.863)			(0.747)
HighDividend			-0.197***			-0.118
			(-2.604)			(-1.465)
Constant	-4.490***	-6.241***	-7.219***	-4.490***	-6.166***	-6.841***
	(-316.870)	(-14.388)	(-9.656)	(-333.960)	(-15.629)	(-10.375)
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Num Observations	968	968	638	968	968	638
R-squared	0.058	0.103	0.144	0.153	0.194	0.236

Table 9: Difference-in-Differences Analysis of Performance Measures: Robustness Test Using 1988–2005 Data

This table presents the results of the OLS models for the robustness test of our difference-in-differences analysis. Instead of using the sample of 1994–1996 vs. 2000–2002 (Tables 4–6), we use the full sample of 1988–1996 vs. 1997–2005 to construct the before (pre-deregulation) and after (post-deregulation) periods. The dependent variable is a metric of performance. All data are averaged over 1988–1996 (pre-deregulation) and 1997–2005 (post-deregulation) sample periods. *t*-statistics reported in parentheses are based on robust standard errors clustered at the bank holding company level. Superscripts ***, **, and * indicate statistical significance at 1%, 5%, and 10% levels.

Panel A: Return on Assets (%)

	(1) ROA%	(2) ROA%	(3) ROA%	(4) ROA%	(5) ROA%	(6) ROA%
After=1	0.002	-0.026	-0.064***	0.002	-0.025	-0.062***
	(0.108)	(-0.757)	(-3.285)	(0.108)	(-0.742)	(-3.210)
After=1 × Pre96HHI<1=1	0.069**	0.065**	0.024**			
	(2.554)	(2.380)	(2.033)			
After=1 × Section20=1				0.114**	0.108**	0.051**
				(2.312)	(2.197)	(2.349)
After=1 × Non20HHI<1=1				0.061**	0.058**	0.019
				(2.145)	(2.001)	(1.531)
LnTA		0.036	0.039***		0.035	0.038***
		(1.184)	(3.168)		(1.165)	(3.026)
Other Control Variables	No	No	Yes	No	No	Yes
Constant	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Num Observations	968	968	638	968	968	638
R-squared	0.022	0.025	0.877	0.023	0.027	0.878

Panel B: Market-to-Book Ratio

	(1) M/B	(2) M/B	(3) M/B	(4) M/B	(5) M/B	(6) M/B
After=1	0.737***	0.845***	0.904***	0.737***	0.847***	0.906***
	(13.986)	(11.751)	(11.015)	(13.977)	(11.811)	(11.093)
After=1 × Pre96HHI<1=1	0.208***	0.229***	0.312***			
	(2.797)	(2.990)	(4.497)			
After=1 × Section20=1				0.359**	0.388**	0.446***
				(2.257)	(2.457)	(2.932)
After=1 × Non20HHI<1=1				0.177**	0.196**	0.283***
				(2.326)	(2.519)	(4.045)
LnTA		-0.145**	-0.149**		-0.148**	-0.154**
		(-2.129)	(-2.280)		(-2.182)	(-2.368)
Other Control Variables	No	No	Yes	No	No	Yes
Constant	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Num Observations	730	730	638	730	730	638
R-squared	0.584	0.589	0.674	0.586	0.591	0.676

Panel C: Standard Deviation of Return on Assets (%)

	(1) SD ROA%	(2) SD ROA%	(3) SD ROA%	(4) SD ROA%	(5) SD ROA%	(6) SD ROA%
After=1	-0.002	-0.022	-0.066***	-0.002	-0.022	-0.066***
	(-0.184)	(-1.244)	(-3.574)	(-0.184)	(-1.243)	(-3.554)
After=1 × Pre96HHI<1=1	0.035***	0.032***	0.006			
	(2.864)	(2.610)	(0.529)			
After=1 × Section20=1				0.035	0.031	0.010
				(1.400)	(1.233)	(0.403)
After=1 × Non20HHI<1=1				0.034***	0.032**	0.006
				(2.808)	(2.580)	(0.467)
LnTA		0.026	0.023*		0.026	0.023*
		(1.586)	(1.871)		(1.584)	(1.832)
Other Control Variables	No	No	Yes	No	No	Yes
Constant	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Num Observations	918	918	616	918	918	616
R-squared	0.023	0.032	0.404	0.023	0.032	0.404

Panel D: Z-Score

	(1) Z-Score	(2) Z-Score	(3) Z-Score	(4) Z-Score	(5) Z-Score	(6) Z-Score
After=1	-0.228*	-0.309	-0.105	-0.228*	-0.307	-0.103
	(-1.675)	(-1.471)	(-0.971)	(-1.674)	(-1.463)	(-0.944)
After=1 × Pre96HHI<1=1	0.284*	0.273*	-0.018			
	(1.945)	(1.959)	(-0.267)			
After=1 × Section20=1				0.438**	0.423**	0.054
				(2.568)	(2.568)	(0.421)
After=1 × Non20HHI<1=1				0.255*	0.245*	-0.033
				(1.719)	(1.724)	(-0.481)
LnTA		0.102	0.103		0.100	0.100
		(0.813)	(1.434)		(0.800)	(1.380)
Other Control Variables	No	No	Yes	No	No	Yes
Constant	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Num Observations	918	918	616	918	918	616
R-squared	0.010	0.011	0.437	0.010	0.011	0.438

Table 10: Difference-in-Differences Analysis of Annual Operational Risk Event Frequency: First Placebo Test Using 1991–1993 vs. 1994–1996 Data

This table presents the results of the OLS models for the first placebo test of our difference-in-differences analysis. Instead of using the sample of 1994–1996 vs. 2000–2002 (Tables 4–6), we use the sample of 1991–1993 vs. 1994–1996 to construct the before and after periods. The dependent variable is annual operational risk event frequency (*Count*). All data are averaged over 1991–1993 and 1994–1996 sample periods. *t*-statistics reported in parentheses are based on robust standard errors clustered at the bank holding company level. Superscripts ***, **, and * indicate statistical significance at 1%, 5%, and 10% levels.

	(1) Count	(2) Count	(3) Count	(4) Count	(5) Count	(6) Count
After=1	0.011*	0.010	0.000	0.011*	0.012	0.004
	(1.816)	(1.148)	(0.001)	(1.815)	(1.281)	(0.176)
After=1 × Pre96HHI<1=1	0.025	0.025	0.026			
	(0.911)	(0.904)	(0.730)			
After=1 × Section20=1				0.104	0.105	0.097
				(0.708)	(0.707)	(0.617)
After=1 × Non20HHI<1=1				0.009	0.009	0.008
				(0.732)	(0.720)	(0.381)
LnTA		0.003	-0.002		-0.003	-0.012
		(0.129)	(-0.032)		(-0.091)	(-0.199)
MarketToBook			0.071			0.071
			(0.966)			(0.956)
CashToTA			-0.395			-0.394
			(-1.314)			(-1.314)
Tier1R			-0.107			-0.214
			(-0.173)			(-0.310)
ROE			-0.001			-0.001
			(-0.575)			(-0.585)
ExcessiveGrowth			-0.007			-0.019
			(-0.202)			(-0.444)
HighDividend			-0.082			-0.074
			(-0.941)			(-0.755)
Constant	0.032***	0.009	0.095	0.032***	0.050	0.179
	(5.261)	(0.052)	(0.190)	(5.284)	(0.262)	(0.388)
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Num Observations	764	764	470	764	764	470
R-squared	0.011	0.011	0.026	0.021	0.021	0.034

Table 11: Difference-in-Differences Analysis of Operational Risk Event Severity: First Placebo Test Using 1991–1993 vs. 1994–1996 Data

This table presents the results of the OLS models for the first placebo test of our difference-in-differences analysis. Instead of using the sample of 1994–1996 vs. 2000–2002 (Tables 4–6), we use the sample of 1991–1993 vs. 1994–1996 to construct the before and after periods. The dependent variable is operational risk event severity: total annual loss (*LnLoss*) in Panel A and average annual loss (*LnAvgLoss*) in Panel B, in logarithmic form. All data are averaged over 1991–1993 and 1994–1996 sample periods. *t*-statistics reported in parentheses are based on robust standard errors clustered at the bank holding company level. Superscripts ***, **, and * indicate statistical significance at 1%, 5%, and 10% levels.

Panel A: Total Annual Operational Loss

	(1) LnLoss	(2) LnLoss	(3) LnLoss	(4) LnLoss	(5) LnLoss	(6) LnLoss
After=1	0.049**	0.077	0.075	0.049**	0.075	0.065
	(1.988)	(1.612)	(0.642)	(1.987)	(1.574)	(0.600)
After=1 × Pre96HHI<1=1	0.008	0.019	0.026			
	(0.125)	(0.267)	(0.247)			
After=1 × Section20=1				-0.104	-0.089	-0.127
				(-0.350)	(-0.298)	(-0.404)
After=1 × Non20HHI<1=1				0.032	0.041	0.065
				(0.631)	(0.740)	(0.765)
LnTA		-0.105	-0.238		-0.096	-0.217
		(-0.707)	(-0.797)		(-0.658)	(-0.742)
MarketToBook			0.135			0.135
			(0.548)			(0.545)
CashToTA			-0.823			-0.826
			(-0.833)			(-0.829)
Tier1R			0.650			0.884
			(0.277)			(0.397)
ROE			0.008			0.008
			(0.576)			(0.588)
ExcessiveGrowth			0.069			0.095
			(0.548)			(0.803)
HighDividend			-0.395**			-0.412**
			(-2.020)			(-2.065)
Constant	-4.475***	-3.770***	-2.608	-4.475***	-3.825***	-2.792
	(-289.746)	(-3.796)	(-1.148)	(-290.018)	(-3.889)	(-1.283)
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Num Observations	764	764	470	764	764	470
R-squared	0.008	0.009	0.044	0.011	0.012	0.050

Panel B: Average Annual Operational Loss

	(1) LnAvgLoss	(2) LnAvgLoss	(3) LnAvgLoss	(4) LnAvgLoss	(5) LnAvgLoss	(6) LnAvgLoss
After=1	0.048**	0.078	0.082	0.048**	0.076	0.072
	(1.986)	(1.643)	(0.725)	(1.985)	(1.607)	(0.680)
After=1 × Pre96HHI<1=1	0.005	0.016	0.021			
	(0.076)	(0.238)	(0.213)			
After=1 × Section20=1				-0.121	-0.106	-0.142
				(-0.436)	(-0.378)	(-0.484)
After=1 × Non20HHI<1=1				0.032	0.041	0.063
				(0.629)	(0.752)	(0.760)
LnTA		-0.112	-0.243		-0.102	-0.220
		(-0.770)	(-0.826)		(-0.719)	(-0.769)
MarketToBook			0.110			0.109
			(0.466)			(0.463)
CashToTA			-0.782			-0.786
			(-0.799)			(-0.795)
Tier1R			0.548			0.796
			(0.240)			(0.367)
ROE			0.008			0.009
			(0.644)			(0.658)
ExcessiveGrowth			0.065			0.092
			(0.530)			(0.807)
HighDividend			-0.359*			-0.377**
			(-1.950)			(-2.029)
Constant	-4.483***	-3.731***	-2.572	-4.483***	-3.792***	-2.768
	(-302.492)	(-3.829)	(-1.151)	(-302.956)	(-3.962)	(-1.298)
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Num Observations	764	764	470	764	764	470
R-squared	0.007	0.010	0.043	0.012	0.014	0.050

Table 12: Difference-in-Differences Analysis of Performance Measures: First Placebo Test Using 1991–1993 vs. 1994–1996 Data

This table presents the results of the OLS models for the first placebo test of our difference-in-differences analysis. Instead of using the sample of 1994–1996 vs. 2000–2002 (Tables 4–6), we use the sample of 1991–1993 vs. 1994–1996 to construct the before and after periods. The dependent variable is a metric of performance. All data are averaged over 1991–1993 and 1994–1996 sample periods. *t*-statistics reported in parentheses are based on robust standard errors clustered at the bank holding company level. Superscripts ***, **, and * indicate statistical significance at 1%, 5%, and 10% levels.

Panel A: Return on Assets (%)

	(1) ROA%	(2) ROA%	(3) ROA%	(4) ROA%	(5) ROA%	(6) ROA%
After=1	0.152***	0.202***	0.056**	0.152***	0.203***	0.057**
	(5.401)	(3.647)	(2.318)	(5.397)	(3.640)	(2.362)
After=1 × Pre96HHI<1=1	-0.034	-0.016	-0.012			
	(-0.949)	(-0.477)	(-0.850)			
After=1 × Section20=1				-0.033	-0.005	0.007
				(-0.649)	(-0.113)	(0.396)
After=1 × Non20HHI<1=1				-0.034	-0.018	-0.017
				(-0.905)	(-0.506)	(-1.169)
LnTA		-0.182	-0.079		-0.183	-0.082*
		(-1.416)	(-1.610)		(-1.414)	(-1.657)
Other Control Variables	No	No	Yes	No	No	Yes
Constant	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Num Observations	764	764	470	764	764	470
R-squared	0.128	0.141	0.915	0.128	0.141	0.916

Panel B: Market-to-Book Ratio

	(1) M/B	(2) M/B	(3) M/B	(4) M/B	(5) M/B	(6) M/B
After=1	0.331***	0.336***	0.294***	0.331***	0.336***	0.294***
	(11.237)	(9.595)	(5.965)	(11.226)	(9.550)	(5.931)
After=1 × Pre96HHI<1=1	-0.078*	-0.075*	-0.070*			
	(-1.849)	(-1.702)	(-1.675)			
After=1 × Section20=1				-0.088	-0.085	-0.073
				(-1.063)	(-0.991)	(-0.955)
After=1 × Non20HHI<1=1				-0.075*	-0.073	-0.069
				(-1.724)	(-1.616)	(-1.606)
LnTA		-0.019	0.066		-0.017	0.066
		(-0.204)	(0.597)		(-0.186)	(0.594)
Other Control Variables	No	No	Yes	No	No	Yes
Constant	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Num Observations	510	510	470	510	510	470
R-squared	0.428	0.428	0.557	0.428	0.428	0.557

Panel C: Standard Deviation of Return on Assets (%)

	(1) SD ROA%	(2) SD ROA%	(3) SD ROA%	(4) SD ROA%	(5) SD ROA%	(6) SD ROA%
After=1	0.033***	0.044	0.049	0.033***	0.045	0.051
	(2.592)	(1.495)	(1.310)	(2.590)	(1.519)	(1.391)
After=1 × Pre96HHI<1=1	0.006	0.009	0.006			
	(0.377)	(0.684)	(0.412)			
After=1 × Section20=1				0.029	0.035*	0.045*
				(1.296)	(1.687)	(1.861)
After=1 × Non20HHI<1=1				0.001	0.004	-0.003
				(0.035)	(0.265)	(-0.210)
LnTA		-0.041	-0.139*		-0.044	-0.145*
		(-0.564)	(-1.805)		(-0.604)	(-1.906)
Other Control Variables	No	No	Yes	No	No	Yes
Constant	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Num Observations	740	740	470	740	740	470
R-squared	0.052	0.055	0.364	0.054	0.058	0.375

Panel D: Z-Score

	(1) Z-Score	(2) Z-Score	(3) Z-Score	(4) Z-Score	(5) Z-Score	(6) Z-Score
After=1	-0.066	0.083	-0.151	-0.066	0.083	-0.153
	(-0.599)	(0.620)	(-1.401)	(-0.599)	(0.623)	(-1.414)
After=1 × Pre96HHI<1=1	0.072	0.119	0.010			
	(0.569)	(0.777)	(0.122)			
After=1 × Section20=1				0.064	0.147	-0.012
				(0.481)	(0.806)	(-0.136)
After=1 × Non20HHI<1=1				0.074	0.113	0.016
				(0.555)	(0.736)	(0.165)
LnTA		-0.544	0.114		-0.548	0.117
		(-1.007)	(0.511)		(-1.005)	(0.530)
Other Control Variables	No	No	Yes	No	No	Yes
Constant	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Num Observations	740	740	470	740	740	470
R-squared	0.001	0.011	0.431	0.001	0.011	0.431

Table 13: Difference-in-Differences Analysis of Annual Operational Risk Event Frequency: Second Placebo Test Using 2000–2002 vs. 2003–2005 Data

This table presents the results of the OLS models for the second placebo test of our difference-in-differences analysis. Instead of using the sample of 1994–1996 vs. 2000–2002 (Tables 4–6), we use the sample of 2000–2002 vs. 2003–2005 to construct the before and after periods. The dependent variable is annual operational risk event frequency (*Count*). All data are averaged over 2000–2002 and 2003–2005 sample periods. *t*-statistics reported in parentheses are based on robust standard errors clustered at the bank holding company level. Superscripts ***, **, and * indicate statistical significance at 1%, 5%, and 10% levels.

	(1) Count	(2) Count	(3) Count	(4) Count	(5) Count	(6) Count
After=1	0.008	-0.016	0.002	0.008	-0.016	-0.000
	(0.815)	(-0.715)	(0.068)	(0.814)	(-0.693)	(-0.003)
After=1 × Pre96HHI<1=1	-0.018	-0.015	-0.016			
	(-0.301)	(-0.240)	(-0.260)			
After=1 × Section20=1				0.051	0.055	0.042
				(0.143)	(0.155)	(0.113)
After=1 × Non20HHI<1=1				-0.031	-0.028	-0.026
				(-0.969)	(-0.855)	(-0.803)
LnTA		0.080	0.078		0.081	0.080
		(1.193)	(1.196)		(1.133)	(1.097)
MarketToBook			-0.061			-0.057
			(-1.123)			(-1.051)
CashToTA			-1.224			-1.242
			(-1.616)			(-1.649)
Tier1R			-1.841			-1.900
			(-1.214)			(-1.202)
ROE			0.007			0.007
			(1.010)			(1.017)
ExcessiveGrowth			-0.164*			-0.162*
			(-1.819)			(-1.795)
HighDividend			0.025			0.032
			(0.684)			(0.528)
Constant	0.192***	-0.419	0.068	0.192***	-0.428	0.050
	(15.678)	(-0.806)	(0.120)	(15.680)	(-0.772)	(0.079)
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Num Observations	562	562	500	562	562	500
R-squared	0.000	0.002	0.029	0.003	0.004	0.030

Table 14: Difference-in-Differences Analysis of Operational Risk Event Severity: Second Placebo Test Using 2000–2002 vs. 2003–2005 Data

This table presents the results of the OLS models for the second placebo test of our difference-in-differences analysis. Instead of using the sample of 1994–1996 vs. 2000–2002 (Tables 4–6), we use the sample of 2000–2002 vs. 2003–2005 to construct the before and after periods. The dependent variable is operational risk event severity: total annual loss (*LnLoss*) in Panel A and average annual loss (*LnAvgLoss*) in Panel B, in logarithmic form. All data are averaged over 2000–2002 and 2003–2005 sample periods. *t*-statistics reported in parentheses are based on robust standard errors clustered at the bank holding company level. Superscripts ***, **, and * indicate statistical significance at 1%, 5%, and 10% levels.

Panel A: Total Annual Operational Loss

	(1) LnLoss	(2) LnLoss	(3) LnLoss	(4) LnLoss	(5) LnLoss	(6) LnLoss
After=1	-0.021	-0.116*	-0.129	-0.021	-0.114*	-0.111
	(-0.491)	(-1.696)	(-1.414)	(-0.490)	(-1.685)	(-1.204)
After=1 × Pre96HHI<1=1	-0.173	-0.160	-0.141			
	(-1.193)	(-1.101)	(-0.942)			
After=1 × Section20=1				-0.601	-0.584	-0.587
				(-0.875)	(-0.852)	(-0.841)
After=1 × Non20HHI<1=1				-0.096	-0.083	-0.067
				(-0.843)	(-0.731)	(-0.551)
LnTA		0.326*	0.373*		0.318*	0.357*
		(1.829)	(1.833)		(1.827)	(1.762)
MarketToBook			-0.056			-0.087
			(-0.558)			(-0.947)
CashToTA			-2.110			-1.978
			(-1.340)			(-1.187)
Tier1R			-4.556*			-4.104
			(-1.667)			(-1.479)
ROE			0.004			0.006
			(0.211)			(0.289)
ExcessiveGrowth			-0.364			-0.380*
			(-1.594)			(-1.720)
HighDividend			0.062			0.003
			(0.384)			(0.015)
Constant	-4.173***	-6.657***	-6.030***	-4.173***	-6.598***	-5.893***
	(-137.543)	(-4.903)	(-3.873)	(-138.303)	(-4.964)	(-3.848)
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Num Observations	562	562	500	562	562	500
R-squared	0.015	0.020	0.038	0.027	0.032	0.050

Panel B: Average Annual Operational Loss

	(1) LnAvgLoss	(2) LnAvgLoss	(3) LnAvgLoss	(4) LnAvgLoss	(5) LnAvgLoss	(6) LnAvgLoss
After=1	-0.023	-0.112*	-0.140	-0.023	-0.110*	-0.120
	(-0.555)	(-1.666)	(-1.599)	(-0.554)	(-1.653)	(-1.365)
After=1 × Pre96HHI<1=1	-0.187	-0.174	-0.153			
	(-1.350)	(-1.261)	(-1.065)			
After=1 × Section20=1				-0.674	-0.658	-0.649
				(-1.065)	(-1.044)	(-1.009)
After=1 × Non20HHI<1=1				-0.099	-0.087	-0.070
				(-0.884)	(-0.777)	(-0.586)
LnTA		0.304*	0.358*		0.296*	0.341*
		(1.729)	(1.811)		(1.726)	(1.738)
MarketToBook			-0.023			-0.057
			(-0.237)			(-0.637)
CashToTA			-2.028			-1.881
			(-1.387)			(-1.225)
Tier1R			-3.959			-3.455
			(-1.488)			(-1.304)
ROE			0.003			0.005
			(0.150)			(0.244)
ExcessiveGrowth			-0.332			-0.350*
			(-1.541)			(-1.681)
HighDividend			0.061			-0.005
			(0.382)			(-0.029)
Constant	-4.205***	-6.525***	-6.108***	-4.205***	-6.458***	-5.956***
	(-145.223)	(-4.867)	(-3.995)	(-146.425)	(-4.941)	(-3.969)
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Num Observations	562	562	500	562	562	500
R-squared	0.019	0.023	0.040	0.036	0.041	0.057

Table 15: Difference-in-Differences Analysis of Performance Measures: Second Placebo Test Using 2000–2002 vs. 2003–2005 Data

This table presents the results of the OLS models for the second placebo test of our difference-in-differences analysis. Instead of using the sample of 1994–1996 vs. 2000–2002 (Tables 4–6), we use the sample of 2000–2002 vs. 2003–2005 to construct the before and after periods. The dependent variable is a metric of performance. All data are averaged over 2000–2002 and 2003–2005 sample periods. *t*-statistics reported in parentheses are based on robust standard errors clustered at the bank holding company level. Superscripts ***, **, and * indicate statistical significance at 1%, 5%, and 10% levels.

Panel A: Return on Assets (%)

	(1) ROA%	(2) ROA%	(3) ROA%	(4) ROA%	(5) ROA%	(6) ROA%
After=1	-0.023	-0.033	0.078	-0.023	-0.033	0.079
	(-1.031)	(-0.679)	(1.402)	(-1.030)	(-0.680)	(1.403)
After=1 × Pre96HHI<1=1	0.034	0.035	-0.022			
	(1.118)	(1.120)	(-0.787)			
After=1 × Section20=1				0.054	0.056	-0.057
				(1.277)	(1.274)	(-0.877)
After=1 × Non20HHI<1=1				0.030	0.031	-0.016
				(0.931)	(0.945)	(-0.712)
LnTA		0.035	-0.056		0.036	-0.057
		(0.307)	(-0.993)		(0.309)	(-1.005)
Other Control Variables	No	No	Yes	No	No	Yes
Constant	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Num Observations	562	562	500	562	562	500
R-squared	0.005	0.006	0.752	0.006	0.007	0.753

Panel B: Market-to-Book Ratio

	(1) M/B	(2) M/B	(3) M/B	(4) M/B	(5) M/B	(6) M/B
After=1	0.362***	0.429***	0.544***	0.362***	0.432***	0.545***
	(6.244)	(5.632)	(6.144)	(6.238)	(5.775)	(6.144)
After=1 × Pre96HHI<1=1	-0.242***	-0.251***	-0.198**			
	(-2.766)	(-2.930)	(-2.317)			
After=1 × Section20=1				-0.693***	-0.705***	-0.564***
				(-3.984)	(-4.133)	(-3.727)
After=1 × Non20HHI<1=1				-0.155*	-0.163*	-0.132
				(-1.738)	(-1.868)	(-1.531)
LnTA		-0.231	-0.420*		-0.241	-0.422*
		(-0.906)	(-1.814)		(-0.964)	(-1.844)
Other Control Variables	No	No	Yes	No	No	Yes
Constant	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Num Observations	506	506	500	506	506	500
R-squared	0.148	0.153	0.283	0.177	0.183	0.301

Panel C: Standard Deviation of Return on Assets (%)

	(1) SD ROA%	(2) SD ROA%	(3) SD ROA%	(4) SD ROA%	(5) SD ROA%	(6) SD ROA%
After=1	-0.001	-0.003	0.020	-0.001	-0.003	0.019
	(-0.057)	(-0.144)	(0.648)	(-0.057)	(-0.159)	(0.609)
After=1 × Pre96HHI<1=1	-0.010	-0.010	-0.019			
	(-0.785)	(-0.750)	(-1.140)			
After=1 × Section20=1				0.034	0.035	-0.001
				(1.272)	(1.284)	(-0.030)
After=1 × Non20HHI<1=1				-0.019	-0.018	-0.022
				(-1.357)	(-1.310)	(-1.457)
LnTA		0.007	-0.027		0.008	-0.026
		(0.166)	(-0.659)		(0.188)	(-0.642)
Other Control Variables	No	No	Yes	No	No	Yes
Constant	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Num Observations	560	560	498	560	560	498
R-squared	0.004	0.004	0.208	0.015	0.015	0.210

Panel D: Z-Score

	(1) Z-Score	(2) Z-Score	(3) Z-Score	(4) Z-Score	(5) Z-Score	(6) Z-Score
After=1	-0.025	-0.122	0.063	-0.025	-0.120	0.077
	(-0.445)	(-0.750)	(0.582)	(-0.444)	(-0.739)	(0.692)
After=1 × Pre96HHI<1=1	0.106	0.120	0.054			
	(1.057)	(1.160)	(0.556)			
After=1 × Section20=1				-0.200	-0.182	-0.286
				(-0.994)	(-0.903)	(-1.415)
After=1 × Non20HHI<1=1				0.162	0.175	0.112
				(1.515)	(1.596)	(1.072)
LnTA		0.333	0.130		0.327	0.117
		(0.788)	(0.513)		(0.774)	(0.467)
Other Control Variables	No	No	Yes	No	No	Yes
Constant	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Num Observations	560	560	498	560	560	498
R-squared	0.005	0.014	0.274	0.016	0.024	0.287

Table 16: Difference-in-Differences Analysis of Annual Operational Risk Event Frequency: Robustness Test for Banks vs. Nonbanks

This table presents the results of the OLS models for the robustness test of our difference-in-differences analysis that focuses on banks vs. nonbanks. The dependent variable is annual operational risk event frequency (*Count*). All data are averaged over 1994–1996 (pre-deregulation) and 2000–2002 (post-deregulation) sample periods. *t*-statistics reported in parentheses are based on robust standard errors clustered at the firm level. Superscripts ***, **, and * indicate statistical significance at 1%, 5%, and 10% levels.

	(1) Count	(2) Count	(3) Count	(4) Count	(5) Count	(6) Count
After=1	0.223*	0.185	0.298	0.223*	0.184	0.296
	(1.830)	(1.516)	(1.531)	(1.830)	(1.512)	(1.520)
After=1 × BHC=1	-0.049	-0.062	-0.216			
	(-0.368)	(-0.473)	(-1.064)			
After=1 × Section20=1				1.634**	1.622**	1.072*
				(2.390)	(2.396)	(1.934)
After=1 × Non20BHC=1				-0.160	-0.174	-0.316
				(-1.293)	(-1.404)	(-1.593)
After=1 × SIC61=1	-0.157	-0.157	-0.230	-0.157	-0.157	-0.230
	(-1.216)	(-1.221)	(-1.092)	(-1.216)	(-1.221)	(-1.091)
After=1 × SIC63=1	-0.153	-0.155	-0.318	-0.153	-0.156	-0.317
	(-1.224)	(-1.247)	(-1.595)	(-1.224)	(-1.247)	(-1.588)
After=1 × SIC64=1	-0.131	-0.143	-0.267	-0.131	-0.144	-0.271
	(-0.919)	(-1.008)	(-1.237)	(-0.918)	(-1.010)	(-1.251)
After=1 × SIC65=1	-0.223*	-0.215*	-0.323*	-0.223*	-0.214*	-0.329*
	(-1.830)	(-1.765)	(-1.737)	(-1.830)	(-1.763)	(-1.770)
After=1 × SIC67=1	-0.223*	-0.241**	-0.334*	-0.223*	-0.241**	-0.339*
	(-1.830)	(-1.967)	(-1.774)	(-1.830)	(-1.971)	(-1.797)
LnTA		0.063**	0.087***		0.065**	0.092***
		(2.135)	(2.598)		(2.439)	(2.914)
MarketToBook			0.000			0.000
			(0.590)			(0.707)
CashToTA			-0.053			-0.072
			(-0.435)			(-0.582)
Tier1R			-0.003			-0.004
			(-0.290)			(-0.355)
ROE			-0.004			-0.003
			(-1.297)			(-1.059)
ExcessiveGrowth			-0.019			-0.020
			(-0.322)			(-0.360)
HighDividend			-0.020			-0.015
			(-0.409)			(-0.334)
Constant	0.030***	-0.342*	-0.439**	0.030***	-0.351**	-0.477**
	(4.080)	(-1.797)	(-2.000)	(4.488)	(-2.067)	(-2.357)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Num Observations	2576	1680	986	2576	1680	986
R-squared	0.036	0.042	0.064	0.204	0.210	0.233

Table 17: Difference-in-Differences Analysis of Operational Risk Event Severity: Robustness Test for Banks vs. Nonbanks

This table presents the results of the OLS models for the robustness test of our difference-in-differences analysis that focuses on banks vs. nonbanks. The dependent variable is operational risk event severity: total annual loss (*LnLoss*) in Panel A and average annual loss (*LnAvgLoss*) in Panel B, in logarithmic form. All data are averaged over 1994–1996 (pre-deregulation) and 2000–2002 (post-deregulation) sample periods. *t*-statistics reported in parentheses are based on robust standard errors clustered at the bank holding company level. Superscripts ***, **, and * indicate statistical significance at 1%, 5%, and 10% levels.

Panel A: Total Annual Operational Loss

	(1)	(2)	(3)	(4)	(5)	(6)
	LnLoss	LnLoss	LnLoss	LnLoss	LnLoss	LnLoss
After=1	0.148	0.073	0.106	0.148	0.072	0.104
	(0.738)	(0.384)	(0.380)	(0.737)	(0.379)	(0.372)
After=1 × BHC=1	0.111	0.086	0.037			
	(0.531)	(0.414)	(0.128)			
After=1 × Section20=1				1.738***	1.715***	1.647***
				(3.286)	(3.252)	(2.767)
After=1 × Non20BHC=1				0.004	-0.022	-0.088
				(0.018)	(-0.107)	(-0.306)
After=1 × SIC61=1	-0.073	-0.075	-0.107	-0.073	-0.075	-0.107
	(-0.348)	(-0.364)	(-0.363)	(-0.348)	(-0.364)	(-0.364)
After=1 × SIC63=1	0.010	0.006	-0.166	0.010	0.006	-0.165
	(0.046)	(0.025)	(-0.522)	(0.046)	(0.024)	(-0.519)
After=1 × SIC64=1	0.466	0.441	0.524	0.466	0.441	0.519
	(0.916)	(0.873)	(0.796)	(0.916)	(0.873)	(0.789)
After=1 × SIC65=1	-0.148	-0.132	-0.217	-0.148	-0.131	-0.225
	(-0.738)	(-0.671)	(-0.793)	(-0.737)	(-0.670)	(-0.824)
After=1 × SIC67=1	-0.152	-0.185	-0.245	-0.152	-0.186	-0.251
	(-0.757)	(-0.922)	(-0.901)	(-0.757)	(-0.924)	(-0.924)
LnTA		0.123***	0.199***		0.124***	0.205***
		(3.131)	(2.764)		(3.240)	(2.987)
MarketToBook			0.000*			0.000*
			(1.831)			(1.947)
CashToTA			0.282			0.258
			(0.896)			(0.818)
Tier1R			-0.028			-0.029
			(-1.313)			(-1.388)
ROE			-0.002			-0.001
			(-0.623)			(-0.272)
ExcessiveGrowth			-0.118			-0.119
			(-1.165)			(-1.256)
HighDividend			-0.030			-0.023
			(-0.348)			(-0.282)
Constant	-4.492***	-5.188***	-5.604***	-4.492***	-5.197***	-5.652***
	(-405.793)	(-21.087)	(-11.617)	(-421.410)	(-21.605)	(-12.366)
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Num Observations	2576	1680	986	2576	1680	986
R-squared	0.041	0.051	0.063	0.111	0.122	0.142

Panel B: Average Annual Operational Loss

	(1) LnAvgLoss	(2) LnAvgLoss	(3) LnAvgLoss	(4) LnAvgLoss	(5) LnAvgLoss	(6) LnAvgLoss
After=1	0.104	0.035	0.049	0.104	0.035	0.047
	(0.554)	(0.200)	(0.195)	(0.554)	(0.196)	(0.188)
After=1 × BHC=1	0.127	0.104	0.084			
	(0.653)	(0.539)	(0.320)			
After=1 × Section20=1				1.451***	1.430***	1.462***
				(2.993)	(2.946)	(2.657)
After=1 × Non20BHC=1				0.040	0.016	-0.023
				(0.206)	(0.086)	(-0.089)
After=1 × SIC61=1	-0.040	-0.042	-0.061	-0.040	-0.042	-0.061
	(-0.205)	(-0.219)	(-0.231)	(-0.205)	(-0.219)	(-0.232)
After=1 × SIC63=1	0.041	0.037	-0.108	0.041	0.036	-0.107
	(0.191)	(0.172)	(-0.371)	(0.190)	(0.172)	(-0.369)
After=1 × SIC64=1	0.498	0.475	0.585	0.498	0.475	0.580
	(1.011)	(0.972)	(0.924)	(1.011)	(0.971)	(0.917)
After=1 × SIC65=1	-0.104	-0.088	-0.156	-0.104	-0.088	-0.163
	(-0.554)	(-0.485)	(-0.631)	(-0.554)	(-0.484)	(-0.660)
After=1 × SIC67=1	-0.108	-0.137	-0.182	-0.108	-0.138	-0.187
	(-0.574)	(-0.732)	(-0.742)	(-0.574)	(-0.734)	(-0.764)
LnTA		0.112***	0.180***		0.113***	0.186***
		(2.966)	(2.681)		(3.025)	(2.871)
MarketToBook			0.000*			0.000**
			(1.934)			(2.037)
CashToTA			0.313			0.293
			(1.005)			(0.937)
Tier1R			-0.028			-0.028
			(-1.371)			(-1.434)
ROE			-0.001			0.000
			(-0.334)			(0.033)
ExcessiveGrowth			-0.120			-0.121
			(-1.289)			(-1.373)
HighDividend			-0.023			-0.017
			(-0.282)			(-0.218)
Constant	-4.498***	-5.130***	-5.512***	-4.498***	-5.137***	-5.552***
	(-431.376)	(-21.751)	(-12.189)	(-443.554)	(-21.965)	(-12.839)
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Num Observations	2576	1680	986	2576	1680	986
R-squared	0.038	0.047	0.060	0.090	0.100	0.124

APPENDIX

Table A1: Difference-in-Differences Analysis of Annual Operational Risk Event Frequency: Analysis Using All Event Types

This table presents the results of the OLS models for our difference-in-differences analysis with all event types available. The dependent variable is annual operational risk event frequency (*Count*). All data are averaged over 1994–1996 (pre-deregulation) and 2000–2002 (post-deregulation) sample periods. *t*-statistics reported in parentheses are based on robust standard errors clustered at the bank holding company level. Superscripts ***, **, and * indicate statistical significance at 1%, 5%, and 10% levels.

	(1) Count	(2) Count	(3) Count	(4) Count	(5) Count	(6) Count
After=1	0.015**	-0.148*	-0.248*	0.015**	-0.163**	-0.328**
	(2.244)	(-1.869)	(-1.699)	(2.242)	(-2.176)	(-2.224)
After=1 × Pre96HHI<1=1	0.324***	0.324***	0.384**			
	(2.873)	(2.893)	(2.553)			
After=1 × Section20=1				2.114***	2.123***	2.165***
				(2.969)	(3.010)	(2.915)
After=1 × Non20HHI<1=1				0.056**	0.055*	0.079
				(1.971)	(1.947)	(1.649)
LnTA		0.207**	0.382**		0.225**	0.410**
		(2.052)	(2.132)		(2.366)	(2.504)
MarketToBook			0.023			-0.073
			(0.302)			(-0.807)
CashToTA			0.364			-1.437
			(0.283)			(-0.939)
Tier1R			3.723**			3.154**
			(2.018)			(2.285)
ROE			-0.012			0.016
			(-0.742)			(1.012)
ExcessiveGrowth			-0.017			0.077
			(-0.170)			(0.896)
HighDividend			-0.254			-0.189
			(-1.281)			(-1.087)
Constant	0.061***	-1.334*	-3.039**	0.061***	-1.457**	-3.135**
	(2.712)	(-1.911)	(-2.052)	(3.181)	(-2.224)	(-2.350)
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Num Observations	694	694	412	694	694	412
R-squared	0.062	0.073	0.117	0.319	0.332	0.355

Table A2: Difference-in-Differences Analysis of Operational Risk Event Severity: Analysis Using All Event Types

This table presents the results of the OLS models for our difference-in-differences analysis with all event types available. The dependent variable is operational risk event severity: total annual loss (*LnLoss*) in Panel A and average annual loss (*LnAvgLoss*) in Panel B. All data are averaged over 1994–1996 (pre-deregulation) and 2000–2002 (post-deregulation) sample periods. *t*-statistics reported in parentheses are based on robust standard errors clustered at the bank holding company level. Superscripts ***, **, and * indicate statistical significance at 1%, 5%, and 10% levels.

Panel A: Total Annual Operational Loss

	(1) LnLoss	(2) LnLoss	(3) LnLoss	(4) LnLoss	(5) LnLoss	(6) LnLoss
After=1	0.048	-0.070	-0.181	0.048	-0.087	-0.274
	(1.156)	(-0.575)	(-0.828)	(1.155)	(-0.817)	(-1.480)
After=1 × Pre96HHI<1=1	0.456***	0.457***	0.576***			
	(3.426)	(3.433)	(3.879)			
After=1 × Section20=1				2.535***	2.541***	2.638***
				(5.083)	(5.076)	(5.410)
After=1 × Non20HHI<1=1				0.145	0.144	0.223*
				(1.371)	(1.379)	(1.764)
LnTA		0.150	0.262		0.171	0.294
		(1.051)	(1.173)		(1.416)	(1.508)
MarketToBook			0.102			-0.009
			(0.476)			(-0.046)
CashToTA			-2.107			-4.193*
			(-0.734)			(-1.745)
Tier1R			3.984			3.325
			(1.302)			(1.352)
ROE			0.007			0.040
			(0.177)			(1.195)
ExcessiveGrowth			-0.233			-0.124
			(-1.253)			(-0.730)
HighDividend			-0.307			-0.232
			(-1.431)			(-1.051)
Constant	-4.413***	-5.427***	-6.513***	-4.413***	-5.570***	-6.624***
	(-156.879)	(-5.636)	(-3.535)	(-179.339)	(-6.806)	(-3.932)
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Num Observations	694	694	412	694	694	412
R-squared	0.086	0.090	0.149	0.302	0.307	0.362

Panel B: Average Annual Operational Loss

	(1) LnAvgLoss	(2) LnAvgLoss	(3) LnAvgLoss	(4) LnAvgLoss	(5) LnAvgLoss	(6) LnAvgLoss
After=1	0.048	-0.047	-0.146	0.048	-0.061	-0.225
	(1.156)	(-0.405)	(-0.699)	(1.155)	(-0.593)	(-1.237)
After=1 × Pre96HHI<1=1	0.400***	0.400***	0.513***			
	(3.214)	(3.219)	(3.672)			
After=1 × Section20=1				2.161***	2.165***	2.267***
				(4.578)	(4.561)	(4.869)
After=1 × Non20HHI<1=1				0.136	0.135	0.212*
				(1.327)	(1.333)	(1.713)
LnTA		0.121	0.207		0.139	0.234
		(0.899)	(0.992)		(1.194)	(1.255)
MarketToBook			0.084			-0.010
			(0.411)			(-0.054)
CashToTA			-2.367			-4.142*
			(-0.843)			(-1.730)
Tier1R			3.517			2.956
			(1.225)			(1.244)
ROE			0.013			0.041
			(0.355)			(1.255)
ExcessiveGrowth			-0.233			-0.140
			(-1.372)			(-0.866)
HighDividend			-0.271			-0.207
			(-1.344)			(-0.999)
Constant	-4.426***	-5.241***	-6.081***	-4.426***	-5.362***	-6.176***
	(-167.091)	(-5.801)	(-3.549)	(-185.631)	(-6.832)	(-3.859)
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Num Observations	694	694	412	694	694	412
R-squared	0.077	0.080	0.137	0.254	0.257	0.314

Table A3: Difference-in-Differences Analysis of Performance Measures: Analysis Using All Event Types

This table presents the results of the OLS models for our difference-in-differences analysis with all event types available. The dependent variable is a metric of performance. All data are averaged over 1994–1996 (pre-deregulation) and 2000–2002 (post-deregulation) sample periods. *t*-statistics reported in parentheses are based on robust standard errors clustered at the bank holding company level. Superscripts ***, **, and * indicate statistical significance at 1%, 5%, and 10% levels.

Panel A: Return on Assets (%)

	(1) ROA%	(2) ROA%	(3) ROA%	(4) ROA%	(5) ROA%	(6) ROA%
After=1	-0.097***	-0.084*	-0.007	-0.097***	-0.084*	-0.008
	(-4.117)	(-1.838)	(-0.393)	(-4.114)	(-1.829)	(-0.472)
After=1 × Pre96HHI<1=1	0.083**	0.083**	0.028**			
	(2.427)	(2.426)	(1.985)			
After=1 × Section20=1				0.052	0.051	0.057**
				(0.902)	(0.893)	(2.041)
After=1 × Non20HHI<1=1				0.087**	0.087**	0.023
				(2.427)	(2.419)	(1.651)
LnTA		-0.016	-0.001		-0.016	-0.001
		(-0.295)	(-0.071)		(-0.301)	(-0.049)
Other Control Variables	No	No	Yes	No	No	Yes
Constant	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Num Observations	694	694	412	694	694	412
R-squared	0.053	0.053	0.855	0.053	0.054	0.856

Panel B: Market-to-Book Ratio

	(1) M/B	(2) M/B	(3) M/B	(4) M/B	(5) M/B	(6) M/B
After=1	0.146**	0.042	0.192*	0.146**	0.042	0.182*
	(2.061)	(0.401)	(1.958)	(2.059)	(0.394)	(1.879)
After=1 × Pre96HHI<1=1	0.253**	0.252**	0.251***			
	(2.357)	(2.342)	(3.219)			
After=1 × Section20=1				0.286	0.292	0.430***
				(1.568)	(1.642)	(2.763)
After=1 × Non20HHI<1=1				0.246**	0.244**	0.217***
				(2.152)	(2.114)	(2.622)
LnTA		0.130	0.037		0.131	0.040
		(0.896)	(0.396)		(0.898)	(0.424)
Other Control Variables	No	No	Yes	No	No	Yes
Constant	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Num Observations	482	482	412	482	482	412
R-squared	0.115	0.120	0.328	0.115	0.120	0.334

Panel C: Standard Deviation of Return on Assets (%)

	(1) SD ROA%	(2) SD ROA%	(3) SD ROA%	(4) SD ROA%	(5) SD ROA%	(6) SD ROA%
After=1	-0.029**	-0.018	-0.004	-0.029**	-0.018	-0.003
	(-2.089)	(-0.712)	(-0.270)	(-2.088)	(-0.701)	(-0.183)
After=1 × Pre96HHI<1=1	0.047***	0.047***	0.015			
	(2.610)	(2.617)	(1.171)			
After=1 × Section20=1				0.013	0.013	-0.014
				(0.385)	(0.373)	(-0.519)
After=1 × Non20HHI<1=1				0.052***	0.052***	0.020
				(2.816)	(2.823)	(1.487)
LnTA		-0.014	-0.017		-0.014	-0.018
		(-0.503)	(-0.991)		(-0.518)	(-1.025)
Other Control Variables	No	No	Yes	No	No	Yes
Constant	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Num Observations	660	660	408	660	660	408
R-squared	0.021	0.022	0.420	0.023	0.025	0.426

Panel D: Z-Score

	(1) Z-Score	(2) Z-Score	(3) Z-Score	(4) Z-Score	(5) Z-Score	(6) Z-Score
After=1	-0.325*	-0.391	0.044	-0.325*	-0.393	0.031
	(-1.880)	(-1.575)	(0.480)	(-1.878)	(-1.582)	(0.326)
After=1 × Pre96HHI<1=1	0.375*	0.375*	0.009			
	(1.926)	(1.925)	(0.087)			
After=1 × Section20=1				0.589**	0.593**	0.298
				(2.298)	(2.297)	(1.268)
After=1 × Non20HHI<1=1				0.342*	0.342*	-0.039
				(1.715)	(1.715)	(-0.385)
LnTA		0.083	0.037		0.086	0.042
		(0.536)	(0.461)		(0.550)	(0.532)
Other Control Variables	No	No	Yes	No	No	Yes
Constant	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Num Observations	660	660	408	660	660	408
R-squared	0.016	0.016	0.082	0.017	0.017	0.101

Table A4: Difference-in-Differences Analysis of Annual Operational Risk Event Frequency: Matched Sample Analysis with Additional M&A and Media Attention Controls

This table presents the results of the OLS models for our matched sample difference-in-differences analysis with additional M&A and media attention controls. Column (7) reports the alternative M&A analysis after excluding affiliate mergers in the banking sector. Column (8) reports the alternative M&A analysis with the accumulated M&As during the previous three years. Column (9) reports the additional analysis with the media attention control. The dependent variable is annual operational risk event frequency (*Count*). All data are averaged over 1994–1996 (pre-deregulation) and 2000–2002 (post-deregulation) sample periods. *t*-statistics reported in parentheses are based on robust standard errors clustered at the bank holding company level. Superscripts ***, **, and * indicate statistical significance at 1%, 5%, and 10% levels.

	(1) Count	(2) Count	(3) Count	(4) Count	(5) Count	(6) Count	(7) Count	(8) Count	(9) Count
After=1	0.000	-0.494**	-0.689**	0.099**	-0.483**	-0.449**	-0.432**	-0.430*	-0.531**
	(0.000)	(-2.021)	(-2.457)	(2.321)	(-2.133)	(-2.076)	(-2.023)	(-1.803)	(-2.253)
After=1 × Pre96HHI<1=1	0.479***	0.388**	0.578**						
	(2.856)	(2.429)	(2.190)						
After=1 × Section20=1				1.438**	1.430***	1.243***	1.259***	1.399***	0.990**
				(2.613)	(2.751)	(2.867)	(2.779)	(2.750)	(2.299)
LnTA		0.767**	0.681**		0.781**	0.681**	0.584***	0.765**	0.794***
		(2.175)	(2.226)		(2.559)	(2.602)	(2.703)	(2.030)	(2.673)
MarketToBook			-0.041			-0.083	-0.035	-0.161	-0.064
			(-0.300)			(-0.578)	(-0.242)	(-0.826)	(-0.456)
CashToTA			0.093			-2.195	-2.225	-2.564	0.964
			(0.044)			(-0.879)	(-0.716)	(-0.850)	(0.563)
Tier1R			3.494			2.409	3.111	3.227	1.801
			(0.910)			(0.749)	(0.979)	(0.983)	(0.462)
ROE			0.003			0.024	0.022	0.033	0.052
			(0.097)			(0.820)	(0.708)	(0.976)	(1.210)
ExcessiveGrowth			-0.452			-0.166	-0.043	0.190	-0.108
			(-1.348)			(-0.622)	(-0.180)	(0.905)	(-0.472)
HighDividend			-0.338			-0.307	-0.260	-0.324	-0.137
			(-1.075)			(-1.117)	(-0.960)	(-1.306)	(-0.750)
BankingM&A			-0.050*			-0.041	-0.186**	-0.028	-0.054**
			(-1.694)			(-1.295)	(-2.138)	(-1.178)	(-2.262)
BankingTarRatio			-1.376			-0.697	1.337	0.617	-0.649
			(-1.410)			(-0.839)	(1.101)	(0.673)	(-1.135)
NonbankM&A			0.533			0.390	0.444*	0.068	0.424**
			(1.664)			(1.481)	(1.683)	(0.887)	(2.337)
News									0.001*
									(1.891)
Constant	0.203***	-6.739**	-5.948**	0.203***	-6.872**	-5.843**	-5.314**	-6.681**	-7.811***
	(2.896)	(-2.076)	(-2.008)	(3.254)	(-2.444)	(-2.264)	(-2.415)	(-2.188)	(-2.660)
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Num Observations	164	164	158	164	164	158	158	158	154
R-squared	0.112	0.174	0.343	0.296	0.362	0.446	0.467	0.421	0.610

Table A5: Difference-in-Differences Analysis of Operational Risk Event Severity: Matched Sample Analysis with Additional M&A and Media Attention Controls

This table presents the results of the OLS models for our matched sample difference-in-differences analysis with additional M&A and media attention controls. Column (7) reports the alternative M&A analysis after excluding affiliate mergers in the banking sector. Column (8) reports the alternative M&A analysis with the accumulated M&As during the previous three years. Column (9) reports the additional analysis with the media attention control. The dependent variable is operational risk event severity: total annual loss (*LnLoss*) in Panel A and average annual loss (*LnAvgLoss*) in Panel B. All data are averaged over 1994–1996 (pre-deregulation) and 2000–2002 (post-deregulation) sample periods. *t*-statistics reported in parentheses are based on robust standard errors clustered at the bank holding company level. Superscripts ***, **, and * indicate statistical significance at 1%, 5%, and 10% levels.

Panel A: Total Annual Operational Loss

	(1) LnLoss	(2) LnLoss	(3) LnLoss	(4) LnLoss	(5) LnLoss	(6) LnLoss	(7) LnLoss	(8) LnLoss	(9) LnLoss
After=1	-0.274	-0.812	-1.185**	0.298*	-0.365	-0.484	-0.534	-0.404	-0.481
	(-0.770)	(-1.568)	(-2.192)	(1.681)	(-1.007)	(-1.172)	(-1.292)	(-1.056)	(-1.133)
After=1 × Pre96HHI<1=1	1.085**	0.985**	1.280**						
	(2.590)	(2.214)	(2.485)						
After=1 × Section20=1				1.671***	1.661***	1.790***	1.757***	1.745***	1.757***
				(2.837)	(2.821)	(3.142)	(3.056)	(2.936)	(2.856)
LnTA		0.835	1.068**		0.891*	1.107**	1.058**	0.846*	1.113**
		(1.578)	(2.063)		(1.854)	(2.416)	(2.296)	(1.862)	(2.389)
MarketToBook			-0.247			-0.300	-0.245	-0.204	-0.326
			(-0.627)			(-0.755)	(-0.611)	(-0.515)	(-0.794)
CashToTA			-1.103			-4.310	-5.062	-6.588	-4.114
			(-0.339)			(-1.289)	(-1.484)	(-1.584)	(-1.247)
Tier1R			12.317			9.817	10.515	8.986	10.330
			(1.469)			(1.330)	(1.425)	(1.315)	(1.388)
ROE			0.075			0.102	0.095	0.114	0.129
			(1.178)			(1.431)	(1.323)	(1.554)	(1.543)
ExcessiveGrowth			-0.633			-0.182	-0.198	-0.237	-0.105
			(-1.180)			(-0.310)	(-0.350)	(-0.557)	(-0.168)
HighDividend			-0.668			-0.605	-0.588	-0.654	-0.633
			(-1.391)			(-1.381)	(-1.329)	(-1.578)	(-1.434)
BankingM&A			0.010			0.020	0.012	-0.033	0.016
			(0.229)			(0.490)	(0.117)	(-1.229)	(0.387)
BankingTarRatio			-2.094**			-1.105	-1.935	1.790	-1.047
			(-2.073)			(-1.077)	(-1.570)	(1.120)	(-0.987)
NonbankM&A			-0.072			-0.295	-0.255	-0.052	-0.297
			(-0.213)			(-0.898)	(-0.827)	(-0.465)	(-0.888)
News									0.000
									(0.016)
Constant	-3.971***	-11.530**	14.408***	-3.971***	12.037***	14.482***	14.064***	12.060***	14.814***
	(-40.411)	(-2.413)	(-3.014)	(-42.848)	(-2.769)	(-3.279)	(-3.158)	(-2.781)	(-3.294)
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Num Observations	164	164	158	164	164	158	158	158	154
R-squared	0.158	0.194	0.305	0.251	0.292	0.382	0.386	0.391	0.363

Panel B: Average Annual Operational Loss

	(1) LnAvgLoss	(2) LnAvgLoss	(3) LnAvgLoss	(4) LnAvgLoss	(5) LnAvgLoss	(6) LnAvgLoss	(7) LnAvgLoss	(8) LnAvgLoss	(9) LnAvgLoss
After=1	-0.253	-0.697	-1.021**	0.291*	-0.261	-0.354	-0.409	-0.310	-0.341
	(-0.729)	(-1.412)	(-2.008)	(1.692)	(-0.752)	(-0.911)	(-1.041)	(-0.861)	(-0.849)
After=1 × Pre96HHI<1=1	0.984**	0.902**	1.189**						
	(2.437)	(2.135)	(2.454)						
After=1 × Section20=1				1.404**	1.396**	1.568***	1.534***	1.493**	1.557***
				(2.543)	(2.504)	(2.966)	(2.893)	(2.600)	(2.764)
LnTA		0.688	0.928*		0.741	0.967**	0.933**	0.727*	0.957**
		(1.413)	(1.962)		(1.637)	(2.267)	(2.154)	(1.685)	(2.203)
MarketToBook			-0.257			-0.302	-0.256	-0.188	-0.327
			(-0.670)			(-0.782)	(-0.658)	(-0.488)	(-0.823)
CashToTA			-1.016			-3.814	-4.701	-6.126	-3.994
			(-0.328)			(-1.229)	(-1.473)	(-1.588)	(-1.295)
Tier1R			11.894			9.564	10.095	8.649	10.141
			(1.567)			(1.418)	(1.500)	(1.372)	(1.495)
ROE			0.080			0.103	0.099	0.115	0.127
			(1.324)			(1.494)	(1.432)	(1.626)	(1.551)
ExcessiveGrowth			-0.581			-0.180	-0.228	-0.291	-0.111
			(-1.133)			(-0.322)	(-0.424)	(-0.732)	(-0.189)
HighDividend			-0.616			-0.559	-0.557	-0.612	-0.606
			(-1.405)			(-1.372)	(-1.344)	(-1.549)	(-1.463)
BankingM&A			0.029			0.037	0.059	-0.027	0.035
			(0.758)			(1.043)	(0.613)	(-0.992)	(0.957)
BankingTarRatio			-1.928**			-1.060	-2.271*	1.527	-1.013
			(-1.996)			(-1.075)	(-1.862)	(0.947)	(-1.012)
NonbankM&A			-0.159			-0.356	-0.324	-0.070	-0.362
			(-0.526)			(-1.197)	(-1.162)	(-0.630)	(-1.200)
News									-0.000
									(-0.557)
Constant	-4.016***	-10.251**	13.265***	-4.016***	-10.726**	13.363***	12.995***	11.083***	13.443***
	(-43.507)	(-2.330)	(-3.025)	(-45.422)	(-2.619)	(-3.242)	(-3.113)	(-2.704)	(-3.189)
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Num Observations	164	164	158	164	164	158	158	158	154
R-squared	0.147	0.175	0.295	0.218	0.250	0.358	0.362	0.353	0.339

Table A6: Difference-in-Differences Analysis of Performance Measures: Matched Sample Analysis with Additional M&A and Media Attention Controls

This table presents the results of the OLS models for our matched sample difference-in-differences analysis with additional M&A and media attention controls. Column (7) reports the alternative M&A analysis after excluding affiliate mergers in the banking sector. Column (8) reports the alternative M&A analysis with the accumulated M&As during the previous three years. Column (9) reports the additional analysis with the media attention control. The dependent variable is a metric of performance. All data are averaged over 1994–1996 (pre-deregulation) and 2000–2002 (post-deregulation) sample periods. *t*-statistics reported in parentheses are based on robust standard errors clustered at the bank holding company level. Superscripts ***, **, and * indicate statistical significance at 1%, 5%, and 10% levels.

Panel A: Return on Assets (%)

	(1) ROA%	(2) ROA%	(3) ROA%	(4) ROA%	(5) ROA%	(6) ROA%	(7) ROA%	(8) ROA%	(9) ROA%
After=1	0.043	0.030	0.021	0.010	-0.002	0.021	0.021	0.037	0.020
	(0.464)	(0.274)	(0.523)	(0.308)	(-0.035)	(1.027)	(0.991)	(1.463)	(0.927)
After=1 × Pre96HHI<1=1	-0.052	-0.054	-0.001						
	(-0.532)	(-0.560)	(-0.025)						
After=1 × Section20=1				-0.055	-0.056	-0.008	-0.007	0.011	-0.023
				(-0.885)	(-0.886)	(-0.260)	(-0.210)	(0.391)	(-0.701)
LnTA		0.021	0.020		0.017	0.020	0.017	0.005	0.016
		(0.305)	(0.684)		(0.255)	(0.697)	(0.585)	(0.133)	(0.558)
Other Control Variables	No	No	Yes	No	No	Yes	Yes	Yes	Yes
Constant	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Num Observations	164	164	158	164	164	158	158	158	154
R-squared	0.005	0.006	0.862	0.008	0.009	0.862	0.862	0.861	0.839

Panel B: Market-to-Book Ratio

	(1) M/B	(2) M/B	(3) M/B	(4) M/B	(5) M/B	(6) M/B	(7) M/B	(8) M/B	(9) M/B
After=1	0.341	0.339	0.592**	0.546***	0.531**	0.618***	0.630***	0.634***	0.589***
	(1.199)	(1.077)	(2.528)	(4.017)	(2.144)	(3.764)	(3.781)	(3.778)	(3.762)
After=1 × Pre96HHI<1=1	0.208	0.207	0.056						
	(0.671)	(0.653)	(0.280)						
After=1 × Section20=1				-0.114	-0.114	0.093	0.154	0.042	0.204
				(-0.523)	(-0.525)	(0.472)	(0.874)	(0.253)	(0.957)
LnTA		0.003	0.101		0.020	0.101	0.117	0.120	0.120
		(0.015)	(0.618)		(0.085)	(0.626)	(0.702)	(0.669)	(0.766)
Other Control Variables	No	No	Yes	No	No	Yes	Yes	Yes	Yes
Constant	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Num Observations	162	162	158	162	162	158	158	158	154
R-squared	0.218	0.218	0.525	0.216	0.216	0.526	0.548	0.548	0.555

Panel C: Standard Deviation of Return on Assets (%)

	(1) SD ROA%	(2) SD ROA%	(3) SD ROA%	(4) SD ROA%	(5) SD ROA%	(6) SD ROA%	(7) SD ROA%	(8) SD ROA%	(9) SD ROA%
After=1	0.021	0.034	-0.003	0.024	0.040	0.024	0.024	0.046*	0.027
	(0.375)	(0.536)	(-0.093)	(1.433)	(1.115)	(1.001)	(1.007)	(1.818)	(1.161)
After=1 × Pre96HHI<1=1	-0.006	-0.003	0.023						
	(-0.103)	(-0.056)	(0.699)						
After=1 × Section20=1				-0.040	-0.040	-0.051	-0.050	-0.034	-0.019
				(-1.123)	(-1.125)	(-1.429)	(-1.495)	(-1.074)	(-0.686)
LnTA		-0.021	-0.031		-0.021	-0.027	-0.030	-0.059	-0.017
		(-0.566)	(-0.931)		(-0.564)	(-0.874)	(-0.961)	(-1.589)	(-0.548)
Other Control Variables	No	No	Yes	No	No	Yes	Yes	Yes	Yes
Constant	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Num Observations	162	162	158	162	162	158	158	158	154
R-squared	0.013	0.018	0.483	0.028	0.033	0.501	0.496	0.508	0.637

Panel D: Z-Score

	(1) Z-Score	(2) Z-Score	(3) Z-Score	(4) Z-Score	(5) Z-Score	(6) Z-Score	(7) Z-Score	(8) Z-Score	(9) Z-Score
After=1	0.107	0.059	0.099	-0.001	-0.053	0.036	0.052	-0.114	0.002
	(1.435)	(0.499)	(0.588)	(-0.019)	(-0.369)	(0.298)	(0.439)	(-0.873)	(0.016)
After=1 × Pre96HHI<1=1	-0.057	-0.066	-0.002						
	(-0.509)	(-0.581)	(-0.013)						
After=1 × Section20=1				0.266	0.266	0.350*	0.376*	0.332*	0.128
				(1.297)	(1.299)	(1.836)	(1.959)	(1.823)	(0.973)
LnTA		0.075	-0.002		0.069	-0.016	-0.032	0.285	-0.033
		(0.541)	(-0.017)		(0.514)	(-0.135)	(-0.277)	(1.530)	(-0.243)
Other Control Variables	No	No	Yes	No	No	Yes	Yes	Yes	Yes
Constant	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Num Observations	162	162	158	162	162	158	158	158	154
R-squared	0.009	0.011	0.298	0.037	0.039	0.340	0.335	0.347	0.449

Table A7: Comparisons of Difference-in-Differences Analysis of Annual Operational Risk Event Frequency and Severity

This table presents the main results of the OLS models for our difference-in-differences analysis. The dependent variables are annual operational risk event frequency (*Count*) in Columns (1)–(3), total annual loss (*LnLoss*) in Columns (4)–(6), and average annual loss (*LnAvgLoss*) in Columns (7)–(9). Columns (1), (4), and (7) present the results from our original analysis. Columns (2), (5), and (8) present the results from our analysis after controlling for the securities underwriting and dealing activities in the non-Section 20 group. Columns (3), (6), and (9) present the results from our analysis after controlling for the insurance activities of the bank holding companies. All data are averaged over 1994–1996 (pre-deregulation) and 2000–2002 (post-deregulation) sample periods. *t*-statistics reported in parentheses are based on robust standard errors clustered at the bank holding company level. Superscripts ***, **, and * indicate statistical significance at 1%, 5%, and 10% levels.

	(1) Count	(2) Count	(3) Count	(4) LnLoss	(5) LnLoss	(6) LnLoss	(7) LnAvgLoss	(8) LnAvgLoss	(9) LnAvgLoss
After=1	-0.282**	-0.340**	-0.325*	-0.356**	-0.341	-0.325*	-0.298*	-0.272	-0.273
	(-2.388)	(-2.197)	(-1.931)	(-2.011)	(-1.648)	(-1.934)	(-1.756)	(-1.386)	(-1.647)
After=1 × Section20=1	1.569***	1.599***	1.812**	2.102***	2.160***	1.468**	1.822***	1.873***	1.256**
	(2.787)	(2.805)	(2.156)	(4.091)	(4.242)	(2.474)	(3.746)	(3.893)	(2.140)
After=1 × Non20HHI<1=1	0.061	0.032	-0.019	0.227*	0.121	-0.068	0.217*	0.116	-0.068
	(1.555)	(0.724)	(-0.445)	(1.831)	(0.993)	(-0.594)	(1.805)	(0.994)	(-0.617)
LnTA	0.337***	0.385**	0.456**	0.426**	0.271	0.578***	0.365*	0.202	0.505***
	(2.614)	(2.196)	(2.242)	(2.144)	(1.103)	(3.076)	(1.955)	(0.879)	(2.771)
MarketToBook	-0.057	-0.078	-0.071	-0.210	-0.227	-0.404**	-0.204	-0.221	-0.393**
	(-0.875)	(-0.894)	(-1.330)	(-1.163)	(-1.337)	(-2.320)	(-1.156)	(-1.365)	(-2.289)
CashToTA	-1.383	-2.090	-1.175	-4.916**	-6.664***	-3.869*	-4.735**	-6.337***	-3.786*
	(-1.191)	(-1.494)	(-0.915)	(-2.478)	(-2.984)	(-1.742)	(-2.430)	(-2.871)	(-1.721)
Tier1R	2.694**	2.836**	2.316*	4.116	3.011	4.271	3.695	2.564	3.802
	(2.434)	(2.143)	(1.680)	(1.542)	(1.021)	(1.655)	(1.492)	(0.945)	(1.525)
ROE	0.011	0.015	0.012	0.052	0.028	0.051	0.053	0.028	0.049
	(0.861)	(0.828)	(0.899)	(1.579)	(0.964)	(1.392)	(1.645)	(1.028)	(1.375)
ExcessiveGrowth	0.080	0.115	0.070	-0.068	0.008	0.012	-0.091	-0.025	0.002
	(1.002)	(1.320)	(0.741)	(-0.419)	(0.055)	(0.073)	(-0.600)	(-0.199)	(0.012)
HighDividend	-0.141	-0.113	-0.103	-0.246	-0.071	-0.097	-0.226	-0.057	-0.083
	(-1.071)	(-0.697)	(-0.647)	(-1.215)	(-0.293)	(-0.502)	(-1.176)	(-0.249)	(-0.450)
Constant	-2.561**	-2.865**	-3.348**	-7.455***	-5.864***	-8.391***	-7.004***	-5.362***	-7.842***
	(2.712)	(-2.042)	(-2.123)	(-4.404)	(-2.941)	(-5.581)	(-4.404)	(-2.889)	(-5.408)
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Num Observations	412	316	300	412	316	300	412	316	300
R-squared	0.336	0.346	0.332	0.294	0.364	0.270	0.261	0.326	0.238

Table A8: Difference-in-Differences Subgroup Analysis with Banking and Nonbanking Operational Risk Events

This table presents the results of the OLS models for our difference-in-differences subgroup analysis with the banking and nonbanking operational risk events. The dependent variable is a metric of operational risk. Columns (1), (2), and (3) present the results from the matched sample analysis between the Section 20 and non-Section 20 group using only their banking events. Columns (4), (5), and (6) present the results from the matched sample analysis between the Section 20 owners and the nonbank underwriting firms using only their nonbanking events. All data are averaged over 1994–1996 (pre-deregulation) and 2000–2002 (post-deregulation) sample periods. *t*-statistics reported in parentheses are based on robust standard errors clustered at the bank holding company or firm level. Superscripts ***, **, and * indicate statistical significance at 1%, 5%, and 10% levels.

Panel A: Annual Operational Risk Event Frequency

	Banking Event Analysis			Nonbanking Event Analysis		
	(1) Count	(2) Count	(3) Count	(4) Count	(5) Count	(6) Count
After=1	0.035*	-0.107	-0.341*	0.093**	-0.332	-0.719
	(1.692)	(-1.211)	(-1.853)	(2.052)	(-1.229)	(-1.499)
After=1 × Section20=1	0.724***	0.736***	0.871***	0.630*	0.846**	1.159*
	(3.154)	(3.221)	(2.994)	(1.996)	(2.090)	(1.815)
LnTA		0.173*	0.256**		0.290	0.627*
		(1.700)	(2.078)		(1.454)	(1.724)
Other Control Variables	No	No	Yes	No	No	Yes
Constant	Yes	Yes	Yes	Yes	Yes	Yes
Bank/Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Num Observations	130	130	90	72	72	62
R-squared	0.376	0.398	0.482	0.239	0.271	0.332

Panel B: Total Annual Operational Loss

	Banking Event Analysis			Nonbanking Event Analysis		
	(1) LnLoss	(2) LnLoss	(3) LnLoss	(4) LnLoss	(5) LnLoss	(6) LnLoss
After=1	0.070	-0.176	-0.624	0.387*	-0.303	-0.855
	(0.489)	(-0.717)	(-1.524)	(1.766)	(-0.486)	(-0.860)
After=1 × Section20=1	1.894***	1.915***	2.325***	1.065*	1.416*	1.759
	(4.123)	(4.207)	(5.064)	(1.798)	(1.982)	(1.683)
LnTA		0.299	0.401		0.472	0.979
		(1.364)	(1.291)		(1.073)	(1.366)
Other Control Variables	No	No	Yes	No	No	Yes
Constant	Yes	Yes	Yes	Yes	Yes	Yes
Bank/Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Num Observations	130	130	90	72	72	62
R-squared	0.402	0.413	0.527	0.274	0.297	0.348

Panel C: Average Annual Operational Loss

	Banking Event Analysis			Nonbanking Event Analysis		
	(1) LnAvgLoss	(2) LnAvgLoss	(3) LnAvgLoss	(4) LnAvgLoss	(5) LnAvgLoss	(6) LnAvgLoss
After=1	0.075	-0.128	-0.502	0.387*	-0.159	-0.563
	(0.529)	(-0.534)	(-1.244)	(1.804)	(-0.280)	(-0.633)
After=1 × Section20=1	1.757***	1.774***	2.131***	0.888	1.165*	1.393
	(4.044)	(4.094)	(4.784)	(1.683)	(1.889)	(1.524)
LnTA		0.246	0.327		0.373	0.763
		(1.183)	(1.126)		(0.952)	(1.222)
Other Control Variables	No	No	Yes	No	No	Yes
Constant	Yes	Yes	Yes	Yes	Yes	Yes
Bank/Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Num Observations	130	130	90	72	72	62
R-squared	0.387	0.395	0.503	0.273	0.291	0.335