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Highlights

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

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- The post-crisis regulations emphasize the business complexity of banks.
- Complexity weakens banks' risk management, as evidenced by operational risk events.
- These risk management weaknesses affect both banking and nonbanking activities.
- Complexity does not significantly improve performance.
- Managerial failure caused by complexity offsets the benefits of strategic risk taking.

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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 a financial institution's systemic importance

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to its complexity. However, little is known about how complexity affects banks' risk management. Using the 1996–1999 deregulations of U.S. banks' nonbanking activities as a natural experiment, we show that banks' business complexity increases their operational risk. This result is driven by banks that had been constrained by regulations, compared with other banks and also with nonbank financial institutions that were never subject to these regulations. We provide evidence that managerial failure underlying these events offsets benefits of strategic risk taking.

Keywords: operational risk, bank holding companies, financial deregulation, Glass-Steagall Act, business complexity
JEL Classification: G18, G20, G21, G32, L25.

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1. Introduction

The recent financial crisis has catapulted the regulation of complex financial institutions to the center of policy debate.[1] The business complexity of U.S. bank holding companies (BHCs) has increased significantly since late 1990s due to their aggressive expansion into nonbanking activities. This expansion has been driven primarily by the Gramm-Leach-Bliley Act (GLBA) of 1999, which removed the restrictions on business activities imposed under the Glass-Steagall Act (GSA) of 1933, including securities underwriting and trading. Using the passage of GLBA as a natural experiment, we find that banks' increased complexity due to expansion into nonbanking activities has caused a deterioration of banks' operational risk management. This effect is driven by BHCs that were particularly constrained by pre-GLBA regulations, i.e., those BHCs that dealt in bank-ineligible securities through their heavily regulated Section 20 investment banking subsidiaries.

The term *complexity* can be related to different concepts (Cetorelli and Goldberg, 2014), including business diversification, geographic diversification, and network interconnectedness.[2] We follow the guidelines provided by the Bank for International Settlements (BIS) and the Federal Reserve, which

[1] "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).

[2] See, for example, Gai, et al. (2011), Caballero and Simsek (2013), Neuhann and Saidi (2018), and Loutskina and Strahan (2011).

relate complexity to the activities of banks outside the traditional business of banking and strictly separate it from other measures, such as interconnectedness, geographic activity, and size (BCBS, 2014a; BGFRS, 2015).

There are five reasons why we focus on operational risk to study the effect of complexity on risk management. First, operational risk events generate sizable losses.[3] Second, unlike credit and market risks, where the source of uncertainty lies outside the firm, operational risk is created by sources internal to the firm and is a result of control failures (Jorion 2007). In particular, the operational risk events result from inadequate or failed internal processes, people, or systems and include fraud, flawed business and market practices, failed transaction processing and process management, improper employee and client relations, and system failures (BCBS 2001). Third, the unique feature of our data is that it allows us to use event origination dates, rather than realization dates. This feature prevents the identification problems associated with stale information, such as balance sheet losses from risks taken years earlier. Fourth, these events capture risk management failures without being influenced by confounding factors, such as implicit government guarantees, which can make a more complex bank appear less risky from the investors' perspective while being more risky from taxpayers' perspective (Atkeson, et al., 2018; Acharya, et al., 2016). Finally, failures in operational risk management indicate deficiencies in other risk management areas (Zeissler and Metrick, 2014).

We start with evidence that BHCs with greater non-interest income or nonbank asset ratios experience greater levels of operational risk. Moreover, whereas BHCs' mergers and acquisitions (M&A) activities involving nonbanks lead to an increase in operational risk, we do not observe the same pattern for BHCs' M&A activities involving other banks. While this evidence is suggestive, a major concern in the identification of the effect of complexity on risk management is reverse causality: A BHC may expand aggressively into previously evaded activities due to a weakening of its risk management.[4]

[3]In 2005, Bank of America and J.P. Morgan agreed to settle lawsuits for $460.5 million and $2 billion, respectively, because they failed to conduct proper due diligence while underwriting securities for WorldCom. The 2016 cross-selling scandal at Wells Fargo, which involved its credit cards, insurance, and brokerage businesses, led to an equity loss of about $30 billion and the departure of 5,300 employees and the CEO.

[4]An internal fraud example is the highly publicized debacle of Barings Bank, which had placed Nick Leeson, an arbitrage trader, in charge of both front and back offices.

We address this identification concern by using, as a natural experiment, the deregulation of nonbanking activities from the end of 1996 through the end of 1999, which culminated with the GLBA that enabled banks to diversify deeper into nonbanking activities. Under this identification, before 1996, the reason for BHCs to limit their nonbanking activities was not endogenous (strong internal controls), but instead exogenous (stringent regulatory restrictions). Under the GLBA, these restrictions were abolished for reasons unrelated to the operational risk of banks, which alleviates concerns over endogeneity stemming from reverse causality.[5] This natural experiment allows us to measure the causal effect of complexity on risk management.

We observe that the number of operational risk events of BHCs started to increase right after 1996 and more than tripled following the passage of the GLBA in 1999 (Figure 1, Panel A). However, because the deregulations and their impact were not immediate, this suggestive evidence still might be tainted by confounding effects during this time period that weakened the risk management mechanisms and simultaneously led to higher complexity through more aggressive diversification. To address this issue, we note that the BHCs that had already diversified into nonbanking activities before 1996 were more likely to be bound by regulations than the other, not pre-diversified BHCs. Accordingly, we find that after deregulation, pre-diversified BHCs expanded their nonbanking activities further than did other BHCs.

We use difference-in-differences analysis to study the differential effect of the deregulations on the operational risk of pre-diversified BHCs (treatment group) and other BHCs (control group). Because the pre-1996 diversification decisions were made before the deregulations, these decisions were not driven by confounding factors during the deregulation period. Moreover, we show that the difference in operational risk between the two groups exhibits no time trend before the deregulations, consistent with the parallel trend assumption. Hence, it is unlikely that a factor other than the deregulation-

Leeson speculated aggressively without supervision, ultimately accumulating losses in a secret account large enough to bring the bank to its collapse in 1995.

[5]Deregulation as a natural experiment has also been used in other studies (e.g., Neuhann and Saidi, 2016, 2018). Barth, et al. (2000) offer several economic reasons for exogeneity of the GLBA. Most importantly for our identification, after Section 20 investment banking subsidiaries were permitted by the Federal Reserve in the late 1980s, there was insufficient evidence that this increased diversification was responsible for the banking problems in subsequent years.

induced differential increase in complexity can explain our results. We also use nonbanks as an alternative control group, as in Neuhann and Saidi (2016, 2018). Since nonbanks' activities were not restricted by the GSA, nonbanks were not directly affected by the GLBA and remained active in businesses into which pre-diversified BHCs expanded.

Our key result is that the BHCs that experience a greater increase in complexity (the pre-diversified BHCs) suffer a greater increase in their operational risk compared with both other BHCs and nonbanks. This effect is almost entirely driven by those pre-diversified BHCs that dealt in securities through their Section 20 subsidiaries prior to the GLBA (Figure 1, Panel B). This result is consistent with the fact that the GLBA targeted nonbanking activities in which Section 20 subsidiaries engaged, such as underwriting and dealing in bank-ineligible securities.[6] Section 20 owners' annual operational risk losses increased eightfold after deregulation relative to losses of banks not previously engaged in regulated activities and nonbanks. The estimated economic impact is an additional $420 million drop in equity value per year for every Section 20 holder compared with a pre-diversified BHC without a Section 20 subsidiary, which is substantial when aggregated for the entire banking system.

Our results cannot be explained by a mechanical relationship between the increase in operational risk and the growth of the institutions. In particular, our results remain robust after controlling for change in size in various ways—by directly including it as a covariate in our econometric models, by normalizing the operational risk losses by size, and by creating growth-matched samples. They also are robust after controlling for other bank-specific attributes shown to be linked to operational risk in earlier literature and after using the synthetic control method. Moreover, the results still hold after accounting for the banking M&A activity and media attention. We also provide evidence that our results cannot be explained by the potentially riskier nature of nonbanking activities. Finally, the effect of complexity on operational risk persists for a long time after the deregulation.

We find that greater deregulation-induced complexity leads to greater operational risk for Section 20 holders, not only in the nonbanking business

[6]Figure C3 in the Internet Appendix C presents analogous graphical evidence for loss amounts. The Internet Appendix D.1 rules out pre-existing trends in operational risk during the 1991–1996 period.

lines but also in the banking (core) business line. This finding points to an overall weakening in risk management, rather than the BHCs using only the potentially riskier nonbanking activities to load on operational risk. At the same time, increased complexity does not improve performance significantly. Therefore, any possible attempt at strategic risk taking by a BHC is offset by an overarching risk-management failure. This interpretation is also consistent with "managerial action/inaction" and "lack of internal control" being cited as key contributing factors for a large portion of operational risk events in our dataset, whereas "strategic risk" or "business risk" are cited for very few events.[7]

Our study contributes to the recent debate about reinstating the GSA. At the heart of the debate lies the tradeoff between potential diversification benefits and potential risk management weaknesses arising from increased complexity that can result in losses for both the financial sector and taxpayers. Our approach, based on origination dates of operational risk events, highlights that any apparent benefit of diversification may come at the expense of increased risk that is not immediately evident. Our results also suggest that operational risk externalities, documented as intra-industry spillover effects in the earlier literature (e.g., Cummins, et al., 2011), are more likely to originate from more complex BHCs. Accordingly, these BHCs may warrant more stringent regulatory requirements for operational risk. Therefore, our results support the recent inclusion of operational risk events in the Comprehensive Capital Analysis and Review (CCAR) framework of the Federal Reserve for the stress-testing of systemically important financial institutions.

2. Background, Data, and Suggestive Evidence

In this section, we summarize institutional background on operational risk management, describe our operational risk data sample, and present stylized facts on the link between operational risk and business complexity.

[7]Examples of papers supporting the strategic risk-taking view include Demsetz and Strahan (1997), Neuhann and Saidi (2016), and Cornett, et al. (2002). Another strand of literature documents no performance gains (Acharya, et al., 2006), greater information asymmetries (Laeven and Levine, 2007; Song and Thakor, 2007), greater idiosyncratic risk (Stiroh, 2004), and greater contribution to systemic risk (Brunnermeier, et al., 2020; Laeven, et al., 2014) as adverse consequences of increased business diversification post-deregulation.

2.1. Background on Operational Risk Management

International banking regulatory standards define operational risk as "the risk of loss resulting from inadequate or failed internal processes, people and systems, or from external events" (BCBS, 2001, p. 2). There are seven distinct event types: internal fraud; external fraud; employment practices and workplace safety; clients, products and business practices; damage to physical assets; business disruption and system failures; and execution, delivery, and process management.[8] A distinctive feature of operational risk is its potential for devastating consequences ranging from large monetary losses and shattered reputations to threatening financial institutions' stability globally (BCBS, 2001; OCC, 2007).

Traditionally, the financial industry was believed to 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 an inability to meet short-term obligations). This belief has been shaken by a sharp increase in operational risk.[9] Accordingly, Jorion (2007) refers to operational risk as the most pernicious form of risk because of its contribution to numerous failures in financial institutions.[10]

Failures in operational risk may indicate broader control weaknesses. For example, Kieran Poynter, former U.K. chairman of PricewaterhouseCoopers, argued that "Organizations with weak data security are generally also weak in terms of wider risk management and governance."[11] Similarly, the \$6.2 billion

[8]The Internet Appendix A provides a detailed description of these event types.

[9]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. [...] [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`)

[10]The growing academic literature on operational risk ranges from operational risk capital charge estimation (e.g., de Fontnouvelle, et al., 2006; Chernobai, et al., 2007) and the correlation structure between operational, credit, and market risks (Rosenberg and Schuermann, 2006) to the internal root causes (Chernobai, et al., 2011; Basak and Buffa, 2019) and the consequences of such events to the firm (Brown, et al., 2008, 2012; Cummins, et al., 2006).

[11]"Good Data Security Is Not Just a Matter of Technology," *Financial Times*, July 16, 2008.

loss of J.P. Morgan in the 2012 "London Whale" case revealed significant deficiencies in the bank's overall risk management (Zeissler and Metrick, 2014).

Recent regulatory trends have put operational risk management in the spotlight. The Basel Capital Accords of 2004 and 2009 explicitly separate operational risk from credit risk and market risk and lay out a set of specific regulatory standards for banks globally. Regulatory filings (FR Y-9C) show that, in 2015, operational risk regulatory capital accounted for 12.8% of total regulatory capital and varied from 9% to 22% across banks.[12] In addition, the 2010 Dodd-Frank Act includes operational risk in stress testing through the CCAR framework. Operational risk has been a mandatory constituent of the European Banking Authority and the United Kingdom's Prudential Regulation Authority stress testing requirements since 2009 and 2013, respectively.[13] Also, ratings agencies have begun to incorporate operational risk in assigning corporate financial ratings (Moody's Investors Service, 2003; Morningstar, 2015; Fitch Ratings, 2004).[14]

Of the seven operational risk event types, this paper focuses on the four that are most likely to be associated with the risk management failures arising from increased complexity due to diversification into nonbanking activities. These four event types are internal fraud; external fraud; clients, products, and business practices; and execution, delivery, and process management. The Internet Appendix A provides relevant examples. These four event types have the highest percentage of event counts with "managerial action/inaction" and "lack of internal control" cited as the key contributing factors to operational failure in our operational risk database, and they account for 88.05% of events by frequency and 96.22% by severity.[15]

Of course, not every event occurs in deregulated nonbanking business lines. However, our goal is to capture the effect of increased complexity on any weakness in risk management that manifests as an operational failure.

[12]In 2015, operational risk capital amounts were $32 billion for J.P. Morgan, $26 billion for Citi, and $21 billion for Wells Fargo, to name a few.

[13]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`.

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

[15]Our results remain robust to the inclusion of the other three event types, as discussed in Section 5 and the Internet Appendix D.

Since these weaknesses can reveal themselves in any part of the business, we study the events in banking and nonbanking business lines together.[16]

2.2. Data on Operational Risk

Important business decisions, such as expanding into a nonbanking activity, are made at the parent level instead of the subsidiary level. Therefore, we are interested in the effects of complexity at the high holder (ultimate parent) level. Henceforth, we use the terms bank holding company (BHC) and high holder interchangeably. We construct operational risk variables for our sample of high holders using the Financial Institutions Risk Scenario Trends (IBM Algo FIRST) operational risk database marketed by IBM. In this section, we describe our process of cleaning and combining operational risk data with other relevant datasets.

The IBM Algo FIRST database contains several decades of data collected worldwide on more than 15,000 public operational risk events, with the bulk of the data from after 1980. The majority of data are from the United States, and about three-quarters comes from financial institutions. The database includes information on the date of the origination of each event, information about its public disclosure and settlement, the dollar amount of loss, event type, business line, contributory factors, and a narrative of event details. The format of the data conforms to BIS definitions of event types and business lines. The availability of an event's origination date is a key advantage of using the IBM Algo FIRST database for our analysis.

The database contains events that are made public and is a fair representation of the loss population. As explained in Chernobai, et al. (2011), this database includes a large variation in loss amounts, with some losses as small as \$1, and the loss distribution is similar to that typically observed for losses in banks' internal databases, thus reducing concerns about an upward bias of recorded losses. Figure 1 in Chernobai, et al. (2011, p. 1690) presents the histogram of losses in the IBM Algo FIRST database, and they argue that a formal examination of this distribution reveals that it is right-skewed and approximately lognormal, implying a moderately heavy right tail of the loss distribution. Moreover, in most cases, the source of the data is a third party (for example, a regulatory agency such as the SEC, FINRA, NASD,

[16] In a robustness test (Section 4.2), we distinguish between "banking" and "nonbanking" events, depending on the business line in which the events occurred, and find that increased complexity post-deregulation has impacted the operational risk of both types similarly.

NYSE, or FDIC; court decisions; affected customers; business partners; or shareholders) rather than the firms themselves, thus mitigating concerns over self-selection bias.

We manually match the firms in the IBM Algo FIRST database with the Compustat identifier (GVKEY). We use an event's origination date to capture the timing of an operational risk failure.[17] We link each GVKEY to the corresponding identifier PERMCO within the Center for Research in Security Prices (CRSP) U.S. Stock Database. We map each PERMCO to the corresponding Federal Reserve identifier, RSSD ID, through the PERMCO-RSSD ID links provided by the Federal Reserve Bank of New York. We then obtain each RSSD ID's high holder RSSD ID through Consolidated Financial Statements for Holding Companies (FR Y-9C) and Call Reports. For the GVKEYs with a missing high holder RSSD ID, we manually go through the IBM Algo FIRST database to match each event with its historical high holder at the event's origination date for our BHC sample. Our sample period begins in 1988, right after Section 20 subsidiaries were permitted, and includes all events that materialized by the end of 2012. This exercise yields a sample of 1,257 operational risk events.

We merge the operational risk data with our complete BHC sample from FR Y-9C filings, which are the source of our control variables. If a bank-quarter observation does not have an operational risk event recorded in IBM Algo FIRST, we treat this observation as having a zero event count and loss, following Chernobai, et al. (2011). In the cases with missing loss amounts, we use the median imputation method (Little and Rubin 2002) to fill in the missing values with the bank's annual median loss values. In a robustness check (Internet Appendix C, Table C7), we also replace all missing values with zeros, and our results still hold. Since our analysis of losses is in logarithmic form, our "zero" losses are set to \$0.01 million, which is below the minimum annual total loss amount in our sample of \$0.016 million.[18]

[17]We start with GVKEYs because the control variables for nonbanks, which we will use as an additional control group in our robustness tests, exist only in Compustat. IBM Algo FIRST defines the origination date as the date the actions causing the event first occurred, which is also the beginning date associated with an event's duration.

[18]Alternative transformations, such as inverse hyperbolic sine transformation, do not affect our results qualitatively. We also tried Tobit regressions, which led to similar results. However, we do not report these regressions because Tobit results are less robust than OLS to changes in the assumptions about the model such as non-spherical error terms.

Following Chernobai, et al. (2011), we truncate the last several years of data to account for 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, which minimizes concerns over downward bias in event counts during the last several years of our sample period. IBM Algo FIRST codes the origination date of an event as the first quarter of a year if 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.

Figure 1, Panel A, describes the evolution of the event count for all BHCs in our data. The pronounced increase in operational risk frequency overlaps with the deregulation period starting in 1996, with some leveling after 2001. This observation is consistent with our argument that operational risk increases due to the growing complexity enabled by the 1996–1999 deregulations. The number of BHCs has declined over the same period, confirming that this operational risk trend is not driven by a change in the number of BHCs in our sample.

2.3. Control Variables

For our control variables, 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, et al. (2011). These control variables include bank size (*Ln TA*), market-to-book ratio (*Market-To-Book*), cash-to-assets ratio (*Cash-To-TA*), Tier 1 ratio (*Tier 1 Ratio*), profitability (*ROE*), excessive growth dummy (*Excessive Growth*), and a dummy for a high dividend payout ratio (*High Dividend*).[19] Table 1 details the definitions of these variables.

Keeley (1990) finds that banks with larger market-to-book ratios have a lower default risk; hence, the inverse of the ratio serves as a proxy for distress. Acharya, et al. (2012) use the ratio of cash and short-term investments to assets as a proxy to identify "problem banks." Ellul and Yerramilli (2013) find that banks with weaker risk management functions tend to have higher Tier 1 capital ratios. Banks with high ROE are less financially con-

[19]An alternative measure for size can be the number of employees. However, in unreported regressions, we find that the coefficient of the number of employees loses economic and statistical significance after controlling for assets. When only the number of employees is included, all our results remain robust.

strained and are able to devote more resources to internal control, but at the same time they may increase operational risk (Chernobai, et al., 2011) or relax internal controls (Jin and Myers, 2006). Excessive growth is measured by excessive growth in liabilities; the Office of the Comptroller of the Currency (OCC 2001) and Moody's Investors Service (2002) 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 OCC for banks experiencing large losses and identified by regulators as problem banks (OCC, 2001; Collier, et al., 2003).

2.4. Complexity and Operational Risk: Suggestive Evidence

The central premise of our paper is based on the natural experiment in the next section. In this section, we present some suggestive evidence that establishes the positive link between operational risk and business complexity due to expansion into nonbanking activities. This evidence is based on our full sample, 1988 through 2005.[20]

For each BHC, we estimate the model:

$$Oprisk_{it} = \alpha + \beta \; Complexity_{i,t-1} + \textstyle\sum_{k=1}^{K} \delta_k \; Control_{k,i,t-1} + \epsilon_{i,t}, \qquad (1)$$

where, for each BHC i and year t, *Complexity* is one of the proxies for complexity described below, *Control* is a set of bank-level control variables described in Section 2.3, and ϵ is the residual term. The dependent variable *Oprisk* is a measure of operational risk originating in year t—either annual operational risk frequency (*Count*) or the severity amount, captured by either annual total loss (*Ln Total Loss*) or annual average loss per event (*Ln Avg Loss*) (both in logarithmic form). To reduce concerns over look-ahead bias, all explanatory variables have a one-year lag. In all models, standard errors are double-clustered by the BHC and by year. All monetary values are adjusted for inflation using the 2005 Consumer Price Index (CPI).

Our proxies for complexity come from earlier literature that studies nonbanking activities as a source of complexity. The first proxy is the non-interest income ratio (e.g., Brunnermeier, et al., 2020; Stiroh, 2004, 2006). Brunnermeier, et al., (2020) argue that banks with higher non-interest in-

[20]See Section 2.2 for the details behind the choice of our sample period.

come ratios make higher contributions to systemic risk. The second proxy is nonbank asset ratio (e.g., Avraham, et al., 2012; Cornett, et al., 2002). Avraham, et al. (2012) use this measure to capture increased complexity of BHCs since the early 1990s. Table 1 provides detailed definitions of these proxies to illustrate how they capture the nonbanking activities.[21]

Table 2, Panel A, summarizes the sample statistics of our data for the 1988–2005 period. On average, BHCs in our sample have a non-interest income ratio of 22.0% and a nonbank asset ratio of 2.5%. There is a large variability in these variables. For 98% of the data, the non-interest income ratio ranges from 4.3% to 73.5% and the nonbank asset ratio ranges from zero to 52.2%.

Table 3 presents evidence of a significant positive relation between a BHC's complexity and its operational risk over the 1988–2005 period.[22] Panel A of Table 3 shows that, for a one standard deviation increase in the non-interest income ratio (0.145), we observe an expected 0.04 increase in annual operational risk event frequency ($0.281 \times 0.145 = 0.04$), along with a 7% increase in annual total loss ($exp(0.469 \times 0.145) = 1.07$) and a 7% increase in average operational loss ($exp(0.445 \times 0.145) = 1.07$). Panel B of Table 3 shows that, for a one standard deviation increase in the nonbank asset ratio (0.087), the model predicts a 0.13 increase in the annual operational risk event count ($1.5 \times 0.087 = 0.13$), a 12% higher annual total operational loss ($exp(1.336 \times 0.087) = 1.12$), and a 9% higher annual average operational loss ($exp(1.032 \times 0.087) = 1.09$).

Nevertheless, these proxies may suffer from limitations. For example, non-interest income also includes certain fees that arise within the banking

[21]Due to limited information about individual subsidiary size and count, we do not use these as proxies. While some information is available about acquired subsidiaries (Cetorelli, et al., 2014; Cetorelli, 2017), information about organically established subsidiaries is limited to the post-2002 period and, still, some subsidiaries are not required to file reports with the banking supervisor. Moreover, subsidiary count is related more to organizational complexity than business complexity (Cetorelli and Goldberg, 2014), and many subsidiaries have been created for limiting regulatory and tax burden rather than operational expansion (Avraham, et al., 2012). Accordingly, Avraham, et al. (2012) do not find a significant correlation between subsidiary count and industry concentration.

[22]For brevity, these tables do not display the coefficients of the control variables. The full set of results is contained in the Internet Appendix C, Table C1. Similarly, for all tables in Sections 3 and 4 that omit the full set of control variables, complete results can be found in the Internet Appendix C.

business, such as transaction fees or service charges. The nonbank asset ratio addresses this problem by capturing the total assets of a high holder's nonbank subsidiaries. However, it comes with the caveat that if the subsidiary is absorbed by the parent BHC or by one of the parent's banking subsidiaries, the high holder's nonbank asset ratio will decline, although the BHC will not necessarily become less complex. One solution to these challenges comes from BHCs' M&A activities, because they allow us to focus on those M&As involving nonbanking business lines explicitly (Cetorelli, et al., 2014). Our results in the Internet Appendix B suggest that while M&A activities in the nonbanking business lines lead to an increase in operational risk, the banking M&A activities do not lead to higher operational risk, consistent with the notion that increased complexity through expansion of nonbanking activities weakens risk management. Although, unlike the first two proxies, M&A activity does not account for *organic* growth into nonbanking activities, it reassuringly gives results that are consistent with the two proxies.

Still, this empirical evidence may be tainted by endogeneity concerns. A bank may expand into previously evaded nonbanking activities due to weakening of its risk management. Using lags of complexity measures would not fully resolve this concern if weakened risk management takes time to manifest as operational risk events. Thus, the findings in this section are only suggestive evidence in support of our study. Section 3 presents our formal identification strategy to establish the causal link between complexity and operational risk.

3. The Repeal of the GSA as a Natural Experiment

We begin our analysis by presenting the institutional background to the gradual repeal of the Glass-Steagall Act of 1933 that led to the enactment of the Gramm-Leach-Bliley Act in 1999. Our identification strategy exploits the financial deregulation period of the late 1990s as a natural experiment that triggered an *exogenous* change in complexity. Our econometric framework employs the difference-in-differences estimator to examine the effects of changes in business complexity on changes in operational risk.

3.1. Regulatory Background

The Glass-Steagall Act (GSA) of 1933 prohibited commercial banks from having securities affiliates, thus separating commercial and securities activities. The GSA made it unlawful for commercial banks to be affiliated with any company that was "engaged principally" in underwriting or dealing in securities. The GSA also prohibited BHCs from creating interlocks of officers, directors, or employees between a commercial bank and any company "primarily engaged" in securities underwriting or dealing (Lown, et al., 2000).

Later, these restrictions were gradually relaxed due to the ambiguity of the terms "engaged principally" and "primarily engaged." In April 1987, the Federal Reserve allowed U.S. bank holding companies to establish investment banking subsidiaries that could underwrite certain "bank-ineligible securities" on a case-by-case basis under Section 20 of the GSA, the so-called "Section 20 subsidiaries." Initially, the revenues from bank-ineligible securities were capped at 5% of a Section 20 subsidiary's gross revenue. This cap was raised to 10% in September 1989 and then to 25% in December 1996. 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% to 27% and their share in the underwriting business from about 5% to about 15% between 1996 and 1998. Overall, Section 20 subsidiaries made significant inroads in underwriting following the loosening of the "ineligible" underwriting revenue restriction at the end of 1996.

On November 12, 1999, the Gramm-Leach-Bliley Act (GLBA) was passed, repealing the GSA and eliminating the cap. The GLBA also repealed the parts of the Bank Holding Company Act of 1956 that separated commercial banking from the insurance business. As a result, banks' share of fixed annuity sales increased from about 30% in 1999 to 38% in 2001 (Kehrer, 2006). In sum, since the GLBA, BHCs have been able to engage in a wide range of activities, including securities underwriting and dealing and insurance underwriting.

3.2. Identification Strategy

The main identification challenge is finding an exogenous variation of bank complexity arising from diversification into nonbanking businesses. Using deregulations as a natural experiment is a common identification approach in the literature to resolve similar endogeneity concerns (Beck, et al., 2010; Rice and Strahan, 2010; Krishnan, et al., 2015). We use the gradual repeal of the GSA over the 1996–1999 period, which presented new opportunities for banks to expand into the previously restricted nonbanking business lines, leading to their increased complexity.

This approach is similar to that of Neuhann and Saidi (2016, 2018), who examine the effects of the gradual repeal of the GSA on banks' idiosyncratic stock-return volatilities and participation in the market for syndicated loans.

They argue that banks' repeated requests to eliminate the firewalls in the early 1990s were rejected by the U.S. government, and so banks were unlikely to anticipate the deregulatory policy before 1996.[23] Moreover, Figure 1, Panel A, shows that the operational risk in the banking sector was stable before the deregulations started at the end of 1996, indicating that the timing of the deregulations is exogenous to operational risk. While Neuhann and Saidi (2018) compare pre-1996 and post-1996 using the start of the deregulation period as the cutoff, we compare pre-1996 and post-1999 to measure the full effect of the gradual deregulation on operational risk. Our robustness tests also use the full sample of 1988 through 1996 versus 1997 through 2005 to construct the before (pre-deregulation) and after (post-deregulation) periods for completeness.

We identify those BHCs that are more likely to be affected by the deregulations. The pre-1996 regulations were more likely to bind those BHCs that were already diversified into nonbanking activities before the 1996–1999 deregulations. Based on the investments they had already made following the early deregulations in the late 1980s, these BHCs had, on average, a stronger motivation to expand further into nonbanking business lines than did other BHCs, but they were 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 BHCs that had nonbank subsidiaries before the end of 1996 (from Cetorelli, et al., 2014), which we call pre-diversified BHCs.[24] The control group contains BHCs that did not have nonbank subsidiaries before the end of 1996.

Figure 2 supports this identification approach. The left figures in each

[23] The Citicorp-Travelers merger in 1998 might have forced the hand of the regulators seeking to avoid a large divestiture by the newly formed Citigroup. However, this event occurred after 1996 and therefore could not be the trigger of the gradual deregulations that started in 1996. Nevertheless, to alleviate any remaining concerns, we drop Citibank from our sample, which does not change our results.

[24] These nonbank subsidiaries are in one of nine industries: asset manager, broker-dealer, financial technology, insurance broker, insurance underwriter, investment company, real estate, savings bank/thrift/mutual, and specialty lender. We use the full organizational tree developed by Cetorelli, et al. (2014), which contains not only the cases of BHCs' acquisitions of nonbank subsidiaries but also the cases in which the acquired entity is another BHC that has a nonbank subsidiary. We thank Nicola Cetorelli for generously providing us with a summary version of this dataset.

panel show that the non-interest income ratios and nonbank asset ratios of the treatment and control groups move in tandem until 1996, when the deregulation period begins. After 1996, the ratios for the treatment group increase at a higher speed than those for the control group. In particular, the pre-diversified BHCs' median non-interest income ratio increased from 19.9% in 1996 to 25.5% in 2000, whereas for other BHCs this ratio increased from 15% to 18.1%. Similarly, the pre-diversified BHCs' median nonbank asset ratio increased from 0.16% in 1996 to 0.66% in 2000, whereas for other BHCs this ratio increased from zero to 0.07%. In a formal test, this widening of the gap between pre-diversified BHCs and other BHCs is statistically significant at the 1% level.[25]

We first study whether pre-diversified BHCs experienced a greater increase in their operational risk than did BHCs that were not pre-diversified. One potential problem with this specification is that a BHC can be assigned to the treatment group only by having subsidiaries that are not among the business lines affected by the 1996–1999 deregulations. Therefore, some of the BHCs in our current treatment group may not have been strictly bound by the regulations before the end of 1996. Moreover, some nonbanking activities may not be as different from banking activities as the securities and underwriting activities that were deregulated. As a result, our empirical results may underestimate the full effect of deregulation.

To address this issue, we augment our treatment group by dividing it into two subgroups: BHCs that had a Section 20 subsidiary before the repeal of the Glass-Steagall Act and the remaining pre-diversified BHCs. Because the deregulations significantly relaxed the restrictions on Section 20 subsidiaries' activities, those BHCs that owned a Section 20 subsidiary should have experienced a much greater increase in their deregulation-driven complexity due to their binding position before the 1996–1999 deregulations. Indeed, according to the testimony by Federal Reserve Governor Susan M. Phillips on March 20, 1997, due to the deregulations, "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." This statement aligns with the significant increase in the market share of the Section 20 subsidiaries in the securities and underwriting business, as discussed in Section 3.1.

[25]Table E1 in the Internet Appendix E provides the results of a formal test.

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

The right-hand-side figures in each panel of Figure 2 compare the evolution of non-interest income ratios and nonbank asset ratios of the pre-diversified BHCs that owned a Section 20 subsidiary with those that did not own such a subsidiary before the repeal of the Glass-Steagall Act.[26] The Section 20 group's median non-interest income ratio increased from 35% in 1996 to 48% in 2000, while for the non-Section 20 group this ratio increased from 17% to a mere 19%. Similarly, the Section 20 group's median nonbank asset ratio increased from 2.2% in 1996 to 7.1% in 2000, while for the non-Section 20 group this ratio increased from zero to only 0.16%. In a formal test, the widening of the gap between Section 20 and non-Section 20 groups is statistically significant at the 1% level.[27] While these measures are noisy proxies for complexity, as discussed in Section 2.4, it is nevertheless reassuring that they move in the direction we expected.

Based on this discussion, we study whether the increase in operational risk after deregulation is more pronounced for pre-diversified BHCs that owned Section 20 subsidiaries before the repeal of the Glass-Steagall Act than it is for other BHCs, including pre-diversified BHCs with other types of subsidiaries and BHCs that were not pre-diversified.

3.3. Econometric Framework: Difference-in-Differences Estimator

Our identification strategy exploits the 1996–1999 deregulations as an *exogenous* shock to banks' propensity to diversify into nonbanking activities and thereby grow in complexity. This approach allows us to compare BHCs that are more likely to benefit from these deregulations with not only other BHCs but also nonbank financial institutions, the latter of which were not the target of the deregulations (Neuhann and Saidi, 2016, 2018). We describe

[26]The Glass-Steagall Act was gradually eliminated during the 1996–1999 period. Restricting Section 20 ownership to before 1996 instead of 1999 for the treatment group does not change our results.

[27]Table E1 in the Internet Appendix E provides the results of a formal test.

the econometric framework for our analysis within the BHC sample; the econometric framework that uses nonbanks as the control group is analogous.

We rely on a difference-in-differences estimator that uses the 1996–1999 deregulations as a natural experiment. For each BHC, we specify our baseline model as follows:

$$\begin{aligned} Oprisk_{it} &= \alpha_i + \beta\ After_t + \gamma\ After_t \times Pre\text{-}Diversified_i \\ &+ \textstyle\sum_{k=1}^{K} \delta_k\ Control_{k,it} + \epsilon_{it}, \end{aligned} \tag{2}$$

where $After$ is a dummy variable taking a value of 1 after deregulation, $Pre\text{-}Diversified$ is a dummy variable equal to 1 for pre-diversified banks, $Control$ is a set of bank-level control variables, and subscripts i and t refer to bank and time indices, respectively. The model does not include the stand-alone $Pre\text{-}Diversified$ dummy variable, because it is subsumed by the BHC-specific fixed effect α. The dependent variable $Oprisk$ is a measure of operational risk—either annual operational risk frequency ($Count$) or the severity amount, captured by either annual total loss ($Ln\ Total\ Loss$) or annual average loss per event ($Ln\ Avg\ Loss$) (both in logarithmic form).

Our main difference-in-differences analysis uses the 1994–1996 and 2000–2002 sample periods for pre- and post-deregulation periods to capture the impact of the deregulations that became effective between the end of 1996 and the end of 1999.[28] To address the bias in standard errors when performing difference-in-differences estimation with time series data of serially correlated outcomes, we follow Bertrand, et al. (2004) and take the averages of the observations in our sample in the before period (1994 through 1996) and in the after period (2000 through 2002).[29] We also conduct various robustness checks and falsification tests, including the use of different time periods, to verify the validity of our results and rule out alternative explanations. One of these robustness checks uses the interim period (1997 through 1999) as the "after" period to present the gradual nature of the increase in operational risk, consistent with Figure 1.

Table 2, Panel A, summarizes the sample descriptive statistics of our key

[28] Our choice of three-year periods is motivated by Cornett, et al. (2002), who also use a three-year period in their study that focuses on how balance-sheet performance is affected by the establishment of a Section 20 subsidiary.

[29] Bertrand, et al. (2004) present this approach as the most robust of the alternatives, including bootstrapping and asymptotic approximation of the variance-covariance matrix.

variables for the 1994–1996 and 2000–2002 periods. An average BHC in our natural experiment sample has $9.98 billion in total assets with a market-to-book ratio of about 1.7. There is a big variation in the cash-to-assets ratio and Tier 1 ratio, ranging from about 0.02 to 0.28 and from 0.04 to 0.29 for 98% of the BHCs. In addition, 39% of the banks have excessive growth in liabilities, and 56% have an above-the-industry-median dividend payout ratio within the previous year.[30] The frequency and severity of operational risk events also differ significantly across BHCs, with an average total annual operational loss of $300 million per institution, which is an economically significant figure. Table 2, Panel B, compares sample descriptive statistics for Section 20 BHCs and non-Section 20 BHCs in the 1994–1996 pre-deregulation period. The statistics for the control variables used in our DID regressions are similar, except for size.[31] We control for size in a variety of ways.[32]

4. Evidence from the Natural Experiment

This section presents our empirical findings about the effects of complexity on operational risk. We also explore the managerial failure and strategic risk-taking channels through which complexity can lead to greater operational risk.

4.1. Complexity and Operational Risk

We begin by showing that, following the deregulations, pre-diversified BHCs experienced a greater increase in their operational risk relative to BHCs that were not pre-diversified. Furthermore, our main result is confirmed by an additional robustness test in which we use U.S. nonbank financial firms as the control group.

The results of the frequency and severity models for BHCs are presented in Table 4. Our first frequency model is an unconditional difference-in-

[30]Section 4.2 uses several performance measures to study the mechanism underlying our results. These measures range widely from –0.3% to 1.6% for ROA, 0.08% to 0.97% for volatility of ROA, and –0.5 to 5.1 for the Z-score.

[31]Table E2 in the Internet Appendix compares sample descriptive statistics during the 1994–1996 and 2000–2002 subperiods.

[32]Following Chernobai, et al. (2007), Cope, et al. (2012), and Dahen and Dionne (2010), we control for size by adding it as a covariate in the loss severity models. In our robustness checks, we normalize our losses by total assets, by book equity, and by net income, and exclude bank size from the list of controls (Internet Appendix C, Table C2) or match treatment and control groups by asset growth (Section 4.2) and obtain similar results.

differences regression in which the treatment group consists of BHCs that were pre-diversified (*Pre-Diversified*) before the end of 1996 (Table 4, Panel A, Model (1)). The coefficient for the treatment effect (*After* $\times$ *Pre-Diversified*) is positive and statistically significant at the 1% level. Pre-diversified BHCs experienced, on average, a 0.243 greater increase in their event count per year compared with other BHCs, which experienced a modest increase of only 0.01 in their event count. This effect is robust to the inclusion of the bank size (*Ln TA*) variable in Model (2) and other bank-specific controls in Model (3). This result is economically significant. Cummins, et al. (2006) estimate a 1.5% drop in the market value around an operational risk event announcement, which means a $450 million equity value decline for an average bank with a $30 billion market capitalization in their sample; this value drop is in addition to their reported average operational loss of about $84 million. In our sample, a single pre-diversified BHC with an average market capitalization of $4.3 billion is expected to lose about $64 million of its equity value, which is a substantial impact for the overall banking system when aggregated across all BHCs.

Next, we distinguish between pre-diversified BHCs that own a Section 20 subsidiary from other pre-diversified BHCs. As discussed in Section 3.2, we expect the deregulation-induced complexity to increase the operational risk of Section 20 owners in particular, because the GLBA directly targeted the securities activities. As shown in Models (4) through (6) of Table 4, Panel A, the impact of the deregulation is indeed much greater for Section 20 owners. In particular, the coefficients of the *After* $\times$ *Pre-Diversified Sec20* variable have a greater magnitude and statistical significance compared with those of the *After* $\times$ *Pre-Diversified NonSec20* variable. Specifically, the deregulation-induced increase in operational risk frequency for Section 20 owners is, on average, 1.5 events per year greater than the increase for the control group of non-pre-diversified BHCs. The estimated economic impact of this is an additional drop of nearly half a billion dollars in equity value per year for each Section 20 holder.[33] Not surprisingly, this result also implies that the treatment effect for the remaining pre-diversified banks is less pro-

[33]The average market capitalization of Section 20 holders in our sample is $18.5 billion. Then, the added market value drop is estimated as $18.5 billion $\times$ 0.015 $\times$ 1.5 = $0.42 billion, where 0.015 is the estimated average percentage drop in equity market value experienced by banks around an operational risk announcement, as per Cummins, et al. (2006).

nounced than what we observe in Models (1) through (3) for the whole sample of pre-diversified banks (about 0.24 versus 0.05). However, the effect is still statistically significant. When we add the full set of bank-specific controls (Model (6)), the relative effect on pre-diversified non-Section 20 BHCs becomes slightly higher (0.06 versus 0.05) albeit statistically insignificant. The relative effect on Section 20 owners retains both its magnitude and statistical significance.

For our severity models, we estimate difference-in-differences regressions in which the dependent variables are the annual total loss (Table 4, Panel B) and the average loss per event (Table 4, Panel C). These results echo those from our frequency models. In particular, Panel B, Model (3) shows that the pre-diversified banks experience an approximately 65% ($exp(0.5) = 1.65$) greater increase in their annual total loss compared with non-pre-diversified banks. Moreover, Models (4) through (6) show that, as in the frequency models, this result is predominantly driven by Section 20 owners, whose increase in annual total loss is more than eight times ($exp(2.102) = 8.18$) that of non-pre-diversified BHCs. This result agrees with the fact that Section 20 owners' binding position before the deregulations has led to a greater increase in their complexity due to more aggressive expansion into the deregulated nonbanking activities, as described in Section 3.2 and Figure 2. Table 4, Panel C, confirms these results for the annual average loss per event.

Our results show that the impact of complexity on operational risk cannot be captured by bank size or other bank-specific confounding variables. The coefficient of size is positive and significant at 10% or less in all models, consistent with previous findings (Chernobai, et al., 2011; Wang and Hsu, 2013). As alternative methods of controlling for bank size, we normalize losses by total assets, by book equity, and by net income, and exclude bank size from the list of controls (Internet Appendix C, Table C2); or we match treatment and control groups by asset growth (Section 4.2). The results are qualitatively the same in all specifications.

In the previous regressions, our control group consists of BHCs that were not diversified before 1996. In the following, we re-estimate our key equations with U.S. nonbank financial firms as the control group, because they were never subject to banking regulations and hence the deregulations should not have affected their complexity. To address the concern that different nonbanking business lines of BHCs can have different risk levels by nature and that not all their business lines were affected equally by the deregulations, we use the securities firms (SIC codes 62xx) as our nonbank control group and add a dummy variable for each of the remaining nonbanking financial sectors interacted with the *After* dummy.[34] Since nonbanks do not file FR Y-9C reports, we construct equivalent firm-specific controls for both BHCs and nonbank financial firms using Compustat. Our treatment group is Section 20 holders, because their nonbanking activities are more directly comparable to the control group, the securities firms, and also because we do not have detailed information about the extent to which other BHCs were engaged in other individual nonbanking activities. Nevertheless, we include BHCs that do not have a Section 20 subsidiary in our regressions as a separate group for completeness.

Table 5 summarizes the findings. The main result is that BHCs that are Section 20 subsidiary owners (*BHC Sec20*) experience a substantially greater increase in operational risk compared with their nonbank counterparts ($SIC62$, the control group), as evidenced by the coefficient of *After* $\times$ *BHC Sec20* in Models (4) through (6). Moreover, the coefficients of the nonbanks with SIC codes 63xx and higher are not significantly different from those of the SIC 62xx control group in Table 5. Overall, the Section 20 holders' higher complexity due to business diversification increased their operational risk significantly relative to all other nonbank institutions. This result lends additional support to our hypothesis that Section 20 owners experienced a greater increase in operational risk due to deregulation-driven complexity.

A complementary approach to create a more balanced control group is to apply the synthetic control method, following Cetorelli and Traina (2018).[35] The synthetic control method provides a systematic way to address the possibility that the treated and the control BHCs had pre-existing differences before the deregulation period. In a nutshell, the BHCs in the control group are reweighted so that the averages of important bank characteristics for the synthetic group resemble those of the treated group before the deregulation period, thereby ensuring a more balanced comparison.

Figure 3 illustrates the results of the synthetic control analysis for an-

[34]These sectors include 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). Uninteracted industry dummy variables are absorbed by the fixed effects.

[35]The synthetic control method is detailed in Abadie, et al. (2010, 2015) and Cavallo, et al. (2013).

nual operational risk frequency (Panel A), annual total loss (Panel B), and average loss per event (Panel C), applied to Section 20 BHCs and nonbanks. The figures in the left column show closely matched operational risk trends between Section 20 BHCs and the reweighted nonbanks sample in the three years leading to the pre-deregulation period. The gap widens dramatically immediately after 1996 and remains robust until the end of 2005. Specifically, while there is no noticeable increase in operational risk for the synthetic Section 20 BHCs group, there is a noticeable upward shift in operational risk for the Section 20 BHCs. The discrepancy between the two time series suggests a large positive effect of deregulation-induced complexity on operational risk, which is supported by the small p-values in the bottom panel of each figure. The tables in the right column of Figure 3 show the pre-deregulation covariate averages for the Section 20 BHCs and the reweighted nonbank sample. If a particular covariate is important in predicting the pre-deregulation variation in the mean of the operational risk response variable, then it will receive a high weight in the synthetic control method. Accordingly, the covariates with the smallest mean differences are the ones with the highest statistical significance in Table 4.

For the sake of completeness, we also apply the same synthetic control approach to compare Section 20 BHCs with non-prediversified BHCs and to compare non-Section 20 pre-diversified BHCs with non-prediversified BHCs. This analysis, presented in Figure C1 and Figure C2 of the Internet Appendix, respectively, supports our previous results. In particular, while there is a noticeable upward shift in operational risk for the Section 20 BHCs, there is no noticeable increase in operational risk for the synthetic Section 20 BHCs group generated with non-prediversified BHCs.[36] Moreover, when we compare non-Section 20 pre-diversified BHCs with the synthetic non-Section 20 pre-diversified BHCs generated using non-prediversified BHCs, the increase in the difference between these groups is much more subdued. These results are consistent with Table 4.

[36]The minor difference in the response of the Section 20 BHCs in Figure 3 and Figure C1 comes from the data source. Figure 3 uses only those bank-year observations for which the control variables are nonmissing in Compustat, to be consistent with Table 5. Figure C1 uses only those bank-year observations for which the control variables are nonmissing in FR Y-9C, to be consistent with Table 4.

4.2. Underlying Mechanism

In this section, we study the channels through which complexity can lead to greater operational risk. We first study whether greater complexity increases risk management simply because the BHCs load on operational risk in the potentially riskier nonbanking activities or because complexity leads to an overall weakening in risk management.

For this purpose, we separate the operational risk events into banking and nonbanking events.[37] To study the change in operational risk stemming from banking events, we compare Section 20 owners with other banks; and to study the change in operational risk stemming from nonbanking events, we compare Section 20 owners with nonbanks engaged in similar activities, i.e., securities firms. We also simultaneously address the possibility that the true cause of heightened operational risk post-deregulation is the rapid growth in the size of Section 20 owners for reasons unrelated to complexity. While we have addressed this issue by adding size as an additional control (Table 4) and also by normalizing the loss amounts by bank size (total assets, book equity, or net income) in a separate robustness test (Internet Appendix C, Table C2), we tackle any remaining concerns by matching the treatment and control groups according to their annual asset growth.

To fully utilize these advantages, we compare banking events of Section 20 owners with those of other BHCs, and nonbanking events of Section 20 owners with those of securities firms. We separate a BHC's assets into the banking and nonbanking parts. We compute the asset growth rate for each part, measured from the pre-deregulation period (1994 through 1996) to the post-deregulation period (2000 through 2002). To study banking events, we match Section 20 owners with the non-Section 20 BHCs by the growth of their average banking assets. Similarly, to study nonbanking events, we match Section 20 owners with securities firms (SIC code 62xx) by their nonbanking asset growth.[38] To improve the matching quality, we perform the growth

[37]Following the BIS business line classification, we define an operational risk event as a banking event if it originated from one of the following business lines: retail banking, commercial banking, payment and settlement, or agency services; we define an event as a nonbanking event if it originated from one of the asset management, corporate finance, retail brokerage, trading and sales, or insurance business lines. About 40% of the operational risk events in our sample are nonbanking events.

[38]We compute the banking assets of a Section 20 holder as its total assets minus the assets of its nonbank subsidiaries (item BHCP4778 from the FR Y-9L filings), and the

matching with replacement; i.e., we require that the selections of non-Section 20 firms for different Section 20 owners are independent of each other. To ensure a sufficiently large sample size for our matched sample, we match each Section 20 owner with the top three non-Section 20 firms based on the shortest Mahalanobis distance. The mean and median banking assets' growth rates are 69.77% and 86.3%, respectively, with a standard deviation of 61.35% for Section 20 owners, and they are 81.15% and 95.56%, respectively, with a standard deviation of 54.93% for non-Section 20 BHCs. The mean and median nonbanking assets' growth rates are 168.20% and 158.29% with a standard deviation of 80.48% for Section 20 owners, and they are 149.41% and 131.06% with a standard deviation of 91.15% for the securities firms.

The results are presented in Table 6. For banking events (Models (1) through (3)), the treatment effect is consistent with our main findings (Table 4). In particular, in Table 4, Models (6), the coefficients for the Section 20 treatment effect for all events were 1.569 for operational risk frequency, 2.102 for total annual operational loss, and 1.822 for annual average operational loss. Comparable coefficients for only banking events (Table 6, Models (3)) are 0.871, 2.325, and 2.131. For nonbanking events (Models (4) through (6)), our results parallel those from the banks versus nonbanks robustness check (Table 5), and the treatment effect remains highly consistent despite a much smaller sample size. In particular, in Table 5, Models (6), the coefficients for the Section 20 treatment effect were 1.072, 1.647, and 1.462 in the frequency model and the two severity models, respectively. These are close to the numbers obtained for only nonbanking events, 1.159, 1.759, and 1.393 (Table 6, Models (6)). The weaker statistical significance stems from the limited size of our matched sample.[39] In sum, we find that Section 20 owners experienced a greater increase in operational risk compared with other BHCs, not only in the new, nonbanking business lines, but also in their core (banking) business line.

These results suggest that complexity leads to an overall weakening of risk management in BHCs. A natural question is whether this weakening

nonbanking assets as the assets of its nonbank subsidiaries. We treat total assets of securities firms as their nonbanking assets.

[39]To increase sample size, and thereby precision, Internet Appendix C, Table C5 uses the full sample instead of the matched samples. The treatment effect due to nonbanking events has a similar magnitude and is statistically more significant, and the results for banking events remain large and statistically significant.

is accompanied by greater performance, which may imply that BHCs take these risks strategically to reward shareholders. To test this implication, we use the same DID framework and replace the dependent variable with several balance-sheet and market-based measures of performance drawn from earlier literature (e.g., Cornett, et al., 2002; Laeven and Levine, 2009). These measures include return on assets (ROA), volatility of the ROA, the Z-score, and market-to-book ratio. The control variables are the same as in the operational risk models, but we exclude market-to-book ratio, as it is now a dependent variable, and ROE, because it is highly correlated with ROA.

The findings are presented in Table 7, Panel A. Models (1) and (2) of ROA show that pre-diversified BHCs do not experience a significant increase in their ROA after the deregulation relative to other BHCs. In fact, according to Model (2), Section 20 owners experience a small and insignificant decline in their ROA relative to not pre-diversified BHCs. Moreover, the results with the standard deviation of ROA and the Z-score suggest that complexity does not bring the benefit of reduced balance-sheet riskiness either. If the strategic risk-taking hypothesis were the primary reason for the increase in operational risk, then we would observe performance improvement during the after period (2000 through 2002), because this three-year period would allow sufficient time for the potential benefits of complexity to appear on the balance sheet.[40] We find no evidence that for more complex BHCs, loading on additional risk was compensated with better performance.[41]

The market-to-book models in Table 7, Panel A, reveal that pre-diversified BHCs' market-to-book ratios increase following the deregulations (Model (1)), and the increase is especially greater for Section 20 owners (Model (2)). In particular, Section 20 owners experience a 32-basis-point increase in their market-to-book values relative to the non-pre-diversified BHCs, all else held equal. Although this suggests that investors value the expansion of BHCs into nonbanking business lines as positive news, this result is not

[40] See, for example, Cornett, et al. (2001), who also use a three-year period in their study that focuses on how balance-sheet performance is affected by the establishment of a Section 20 subsidiary.

[41] There may be other benefits from diversification, such as higher market share and greater political power. However, if these benefits do not manifest as performance improvement, it will suggest that the managers are given the wrong incentives to expand their business. Such an agency problem would imply managerial failure rather than strategic risk taking.

accompanied by a simultaneous increase in ROA. This pattern may be due to an increase in implicit government guarantees (Atkeson, et al., 2018; Carow and Heron, 2002). Alternatively, investors may have been expecting higher balance-sheet performance following the deregulations, which would not be immediately observed but would be immediately priced in market values because stock prices are forward-looking. In this case, market valuations would be soon corrected downward because the expected improvement in balance-sheet performance did not materialize. As a result, the positive treatment effect in the market-to-book ratios would be temporary.

To examine whether this treatment effect persists, in Panel B of Table 7 we summarize the results of the DID estimation using 2000–2002 and 2003–2005 sample periods. We observe a negative and statistically significant treatment effect for the market-to-book ratio of the Section 20 subsidiary holders. The magnitude of this negative effect is larger than the positive effect we find in Panel A.[42] Therefore, we conclude that the increase in market-to-book values of the Section 20 owners relative to other BHCs following the deregulations was, at best, temporary.[43] At the same time, we continue to observe no significant treatment effect for the balance-sheet measures in Panel B of Table 7.[44]

Altogether, these findings suggest that any attempt at strategic risk taking by a BHC will be offset by an overarching risk-management failure. This conclusion is consistent with "managerial action/inaction" and "lack of internal control" being cited as key contributing factors for a large portion of operational risk events in our dataset, whereas "strategic risk" and "business

[42]The drop in market-to-book ratios of Section 20 owners after 2002 is probably not surprising given the increase in operational risk events originating until 2002, reaching a pinnacle with WorldCom in 2002, when the BHCs underwriting its securities were blamed for not doing their due diligence.

[43]To further verify the lack of persistence of the treatment effect, we compare the 1994–1996 and 2003–2005 periods as summarized in the Internet Appendix C, Table C6. As the table demonstrates, the treatment effect for the market-to-book value is small and statistically insignificant.

[44]An alternative explanation for why the market-to-book ratio goes up whereas ROA does not could be that balance sheet variables are an imperfect measure of performance due to delays in payoffs and losses. However, we observe a lack of positive effect on ROA even six years after deregulation. Moreover, the implicit government guarantees are potentially a greater source of imperfection that affects market-to-book values more substantially than it does ROA.

risk" are cited for very few events.

5. Other Robustness Checks

We summarize the results of our further robustness checks in this section and provide the details in the Internet Appendix D. These robustness checks address any remaining concerns regarding whether our results are truly driven by changes in complexity or whether there are alternative explanations. First, we conduct several placebo (falsification) tests with the same treatment and control groups but different "before" and "after" periods (Internet Appendix D, Section D.1). Second, we try different before and after periods to address other questions (Internet Appendix D, Section D.2). In one test, we confirm the persistence of the treatment effect using 1994 through 1996 versus 2003 through 2005 to construct the before and after periods. In another test, we use 1997 through 1999 (our interim period) as the after period; our results confirm the gradual increase in operational risk in the interim period, consistent with the gradual nature of the deregulations. Moreover, we use the full sample of 1988 through 1996 versus 1997 through 2005 to construct the before and after periods to give an overall view, confirming our main results.

Third, to test whether the Riegle-Neal Act affected our results because it may have increased consolidation through affiliate and non-affiliate mergers, we control for the merger activity (Internet Appendix D, Section D.3). Fourth, as we explain in Section 2.1, our focus has been on four of the seven Basel-defined event types that are more likely to be affected by changes in business complexity; we omitted the following event types: employment practices and workplace safety, damage to physical assets, and business disruption and system failures. After including these events, our results remain robust (Internet Appendix D, Section D.4). Fifth, we examine whether our results for Section 20 owners can be attributed to the insurance deregulations during the same time frame. In particular, we limit our sample to only those BHCs that derive less than 1% of their income from insurance activities and confirm that the Section 20 owners in this sample also have experienced a significantly greater increase in operational risk (Internet Appendix D, Section D.5).[45] Finally, we use the number of news articles from the Factiva business news database as a proxy for media attention to the BHCs in our

[45] Our choice of the 1% threshold is guided by the general disclosure threshold of FR Y-9C filings.

sample and find that potentially greater media attention for the BHCs in our treatment group cannot explain our results (Internet Appendix D, Section D.6).

6. Conclusion

Using the repeal of the Glass-Steagall Act during the 1996–1999 period as a natural experiment, we show that the frequency and magnitude of operational risk events increased significantly with bank complexity. This trend is particularly strong for BHCs that were constrained by the regulations restricting their nonbanking activities. In particular, the trend is driven by those with existing Section 20 subsidiaries, when we compare these BHCs with those BHCs that did not engage in extensive securities underwriting and dealing activities and with nonbank financial institutions that were not subject to the same regulations. Our findings are robust to an extensive array of tests. We show that higher complexity generates greater operational risk not only in BHCs' nonbanking business lines but also in their core (banking) business line. This evidence, coupled with the finding that complexity does not appear to reward shareholders with a large or permanent improvement in BHCs' performance, suggests that managerial failure offsets the potential benefits from any strategic risk taking.

Some recent studies document negative externalities of operational risk events affecting other financial firms (e.g., Cummins, et al., 2011; Chernobai, et al., 2007). These externalities imply that the higher levels of operational risk we observe after the deregulations are not socially optimal. Our results suggest that these spillovers are more likely to originate from more complex BHCs. Moreover, these externalities may remain hidden until far too late due to the long gap between origination and realization of operational risk events. While our paper focuses on business complexity, we hope our study jump-starts new scholarly research on the interaction between other sources of complexity and risk management in the financial sector.

Supplementary Materials

Supplementary material associated with this article can be found, in the online version, at ....

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All three authors share equal credit in every contribution aspect of the preparation of the manuscript.

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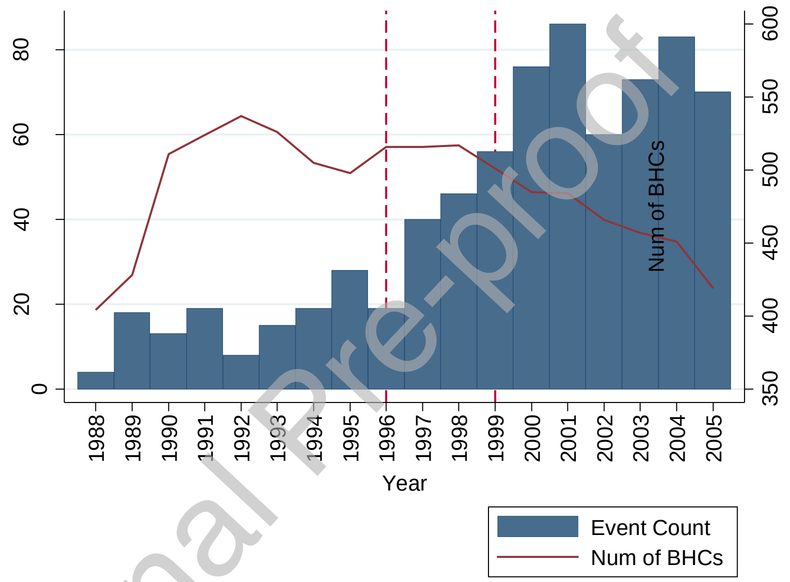
Figure 1: Frequency of Operational Risk Events

Panel A illustrates the annual count of operational risk events by origination year, along with the number of bank holding companies, in our sample period. The dashed lines at 1996 and 1999 indicate the timing of deregulations. Our operational risk data end in 2012 by event realization date; following Chernobai, Jorion, and Yu (2011), we truncate the last several years according to event origination date to ensure that our sample is not underpopulated due to omitted events that originated before the end of our sample but that had not yet materialized. This truncation accounts for the delays between the time a risk is taken and the time it materializes (in our sample, 4 years on average). To be on the conservative side, we include only events that originated before the end of 2005, which include our natural experiment period and minimizes concerns over downward bias in event counts during the last several years of our sample period. Panel B illustrates the evolution of operational risk event frequency from 1991 to 2005 for the reduced sample of BHCs used in our DID models. The numbers represent BHC averages at the group level for the groups indicated in the legend: Section 20 owners (*Section 20*), the pre-diversified BHCs that do not own a Section 20 subsidiary (*NS20 Prediv*), and other (non-pre-diversified) BHCs (*NS20 Non-Prediv*, our control group).

Panel A: Operational Risk Events Total Annual Count, by Origination Year, for All BHCs



Panel B: Average Frequency of Operational Risk Events for BHCs in Different Groups, by Origination Year, for Reduced Sample of BHCs Used in DID Models

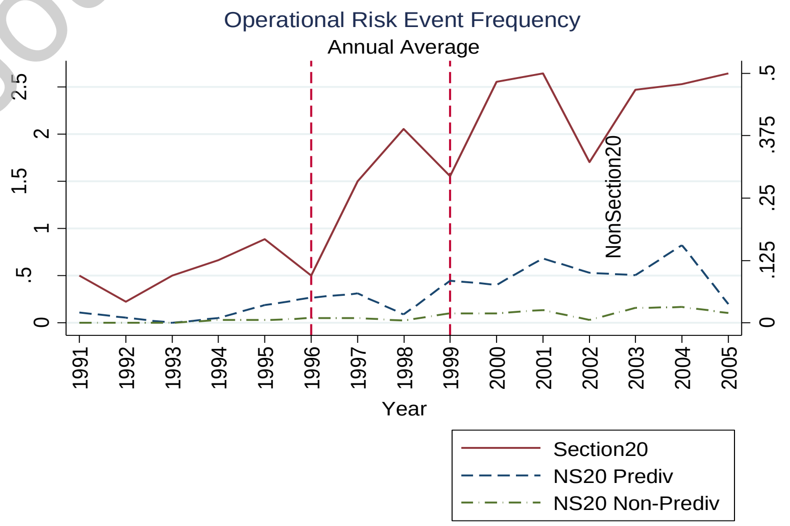
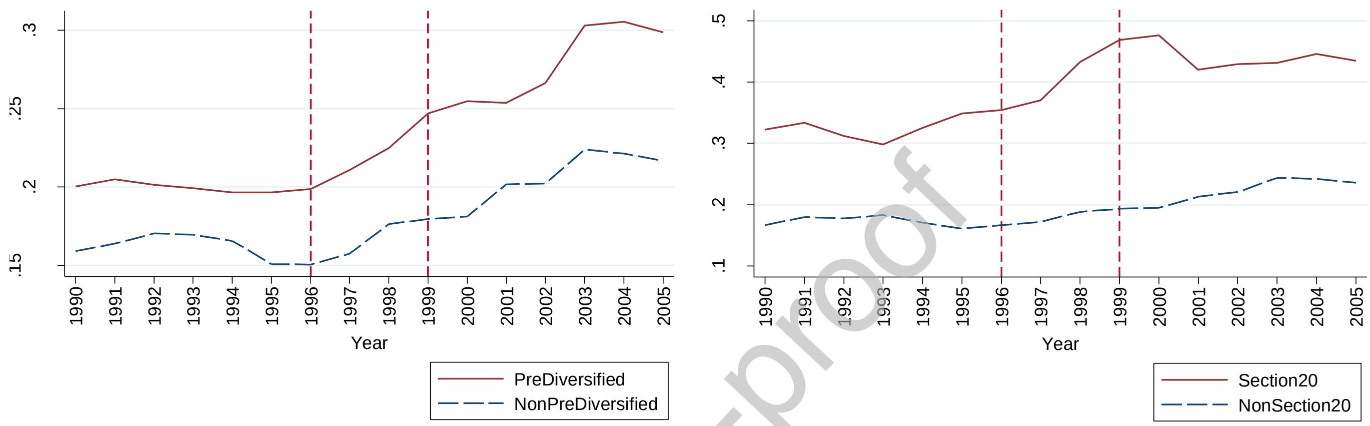


Figure 2: Non-Interest Income Ratios and Nonbank Asset Ratios

This figure illustrates non-interest income ratios (Panel A) and nonbank asset ratios (Panel B) for the bank holding companies in our sample. The “pre-diversified” group refers to bank holding companies that diversified into nonbanking businesses before 1996, and the “Section 20” group refers to bank holding companies with a Section 20 subsidiary. The dashed lines at 1996 and 1999 indicate the timing of deregulations.

Panel A: Non-Interest Income Ratio



Panel B: Nonbank Asset Ratio

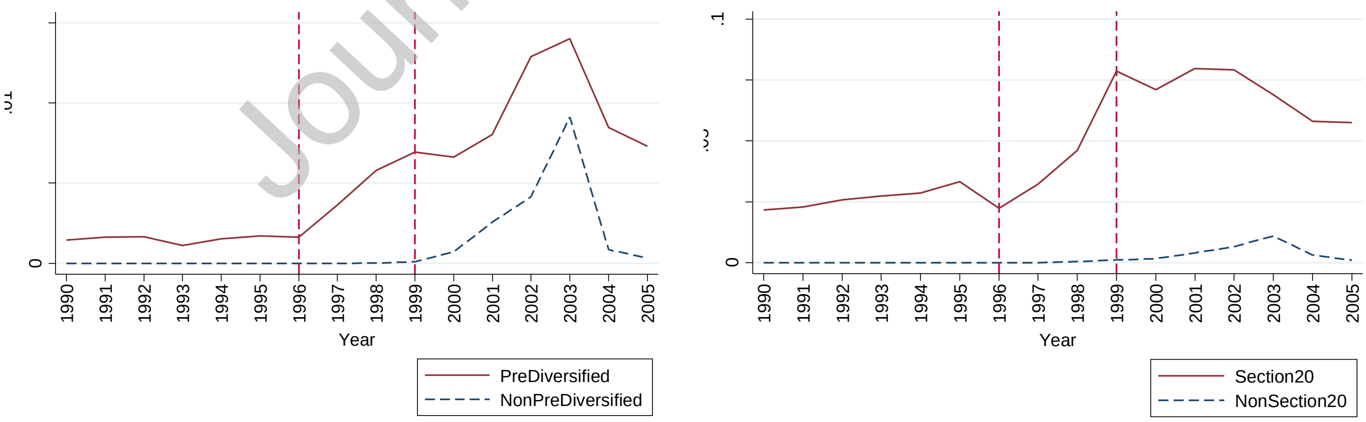
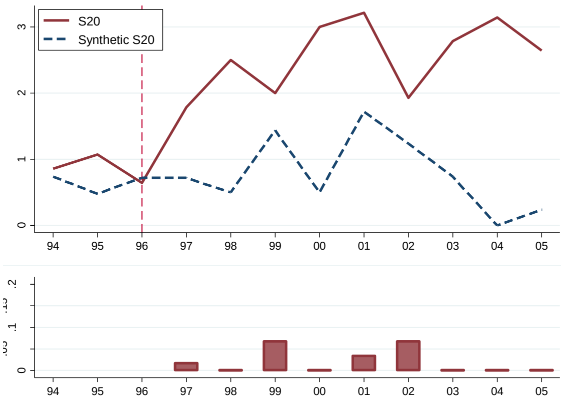


Figure 3. Synthetic Matching of Section 20 Holders Using Nonbanks

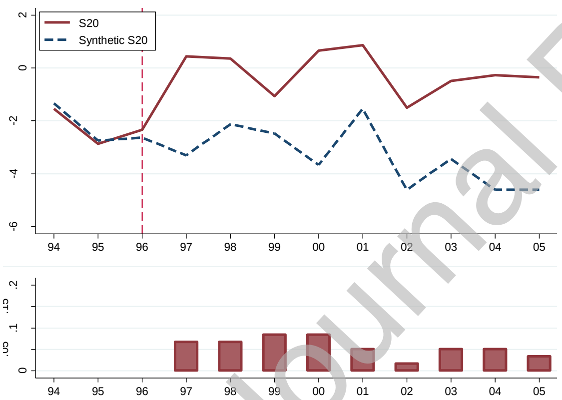
This figure illustrates the results of the application of the synthetic control method. The treatment group consists of Section 20 BHCs. The synthetic control group consists of a rebalanced sample of nonbank financial institutions. The left column shows the evolution of the dependent variables for the average Section 20 holders and the synthetic Section 20 holders. The dashed line at 1996 indicates the beginning of our deregulation period. The right column shows covariates' averages for the Section 20 BHCs and the reweighted nonbank sample during the pre-1996 period. In these figures, we use only those bank-year observations for which the control variables are non-missing in Compustat.

Panel A: Annual Operational Risk Event Frequency



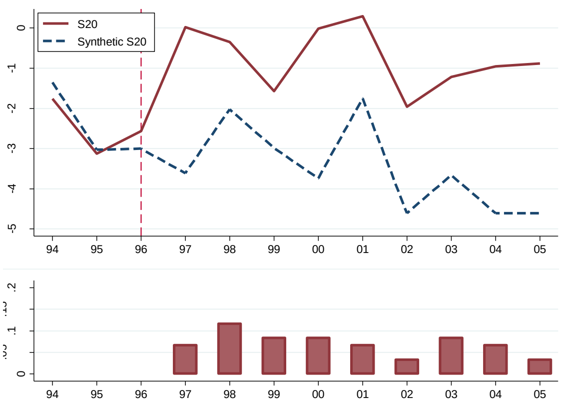
	Section 20 BHCs	Reweighted Nonbanks
Ln TA	10.684	10.686
Market-To-Book	1.943	1.956
Cash-To-TA	0.082	0.134
Tier 1 Ratio	0.126	0.126
ROE	11.235	22.040
Excessive Growth	0.452	0.492
High Dividend	0.881	0.474

Panel B: Annual Total Operational Loss



	Section 20 BHCs	Reweighted Nonbanks
Ln TA	10.684	10.624
Market-To-Book	1.943	1.458
Cash-To-TA	0.082	0.095
Tier 1 Ratio	0.126	0.259
ROE	11.235	18.229
Excessive Growth	0.452	0.453
High Dividend	0.881	0.620

Panel C: Annual Average Operational Loss per Event



	Section 20 BHCs	Reweighted Nonbanks
Ln TA	10.684	10.526
Market-To-Book	1.943	1.767
Cash-To-TA	0.082	0.107
Tier 1 Ratio	0.126	0.188
ROE	11.235	18.530
Excessive Growth	0.452	0.464
High Dividend	0.881	0.587

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
<u>Treatment Group Indicators (1988–2005)</u>	
Pre-Diversified	An indicator variable equal to 1 if the BHC is pre-diversified into nonbanking activities before the end of 1996.
Pre-Diversified Sec20	An indicator variable equal to 1 if a BHC owned a Section 20 subsidiary before the repeal of the Glass-Steagall Act.
Pre-Diversified NonSec20	An indicator variable equal to 1 if a BHC did not own a Section 20 subsidiary before the repeal of the Glass-Steagall Act but was pre-diversified before the end of 1996.
After	An indicator variable equal to 1 for the post-deregulation period (after 1999).
<u>Operational Risk Variables (1988–2005)</u>	
Count	Annual number of operational risk events, from the IBM Algo FIRST database.
Ln Total Loss	Annual total operational loss amount, from the IBM Algo FIRST database. Units: *ln*(USD millions).
Ln Avg Loss	Annual average operational loss amount per event, from the IBM Algo FIRST database. Units: *ln*(USD millions).
<u>Bank Level Characteristics (1988–2005)</u>	
Ln TA	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. Units: *ln*(USD millions).
Market-To-Book	Market-to-book ratio is a proxy for bank growth opportunities and is inversely related to default risk. 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.
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.
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.
Cash-To-TA	Ratio of cash and short-term investments to assets is a proxy for "problem banks." 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.
Tier 1 Ratio	Ratio of regulatory Tier 1 capital to risk-weighted assets. The Basel 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 and then by quarterly ATQ – LTQ from CCM.
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.
Excessive Growth	Excessive growth in liabilities is a proxy for bank aggressive growth. It is 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.
High Dividend	High dividend payout ratio is used to capture "troubled banks." It is an indicator equal to 1 if a bank's dividend payout ratio during the previous year exceeded the annual median across all sample BHCs. It 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.

Other Variables

Non-Interest Income Ratio	Non-interest income divided by the sum of net interest income and non-interest income, BHCK4079/(BHCK4079 +BHCK4074) from FR Y-9C. Non-interest income (BHCK4079) includes fiduciary income, fees and service charges, trading revenue, and other income from non-interest activities, such as brokerage, advisory services, and underwriting.
Nonbank Asset Ratio	Nonbank assets divided by total assets, BHCP4778/BHCK2170 from FR Y-9LP. Nonbank assets (BHCP4778) refer to the assets derived from nonbank subsidiaries. Nonbank subsidiaries exclude all banks (including commercial, savings and industrial banks that file the commercial bank Reports of Condition and Income) and their subsidiaries, and Edge and Agreement corporations and their subsidiaries that are held through a bank subsidiary.
Banking M&A	The number of banking sector M&As for each BHC in the previous three years, from the Federal Reserve Bank of Chicago's M&A database. The database contains the complete banking sector M&A records of our sample BHCs since 1976 for all the acquirers existing in the FR Y-9C data or Call Reports. For each M&A deal, it provides information on the top holding company of the acquirer, along with the total assets of the acquiring bank and the target bank.
Banking M&A Target Assets Ratio	Annual target assets ratio for banking sector M&As for each BHC in a given year is 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. Banking M&A Target Assets Ratio is the average of annual target assets ratio over the last three years. The data are obtained from the Federal Reserve Bank of Chicago's M&A database. For several cases in which the total assets of the target were 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 estimate the total assets by using the change from the previous quarter in the total assets of the acquirer. To measure the size of a high holder's banking sector M&A activities, we calculate an annual target assets ratio, 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.
BHC	An indicator variable equal to 1 if the financial institution is a BHC.
BHC Sec20	An indicator variable equal to 1 if a BHC owned a Section 20 subsidiary before the repeal of the Glass-Steagall Act. This variable is the same as *Pre-Diversified Sec20*.
BHC NonSec20	An indicator variable equal to 1 if a BHC did not own a Section 20 subsidiary before the repeal of the Glass-Steagall Act.
SIC61 – SIC65, SIC67	Nonbank indicator variables for each financial sub-industry, according to the SIC two-digit code: non-depository credit institutions (*SIC61*), securities firms (*SIC62*), insurance carriers (*SIC63*), insurance agents, brokers, and services (*SIC64*), real estate firms (*SIC65*), and other investment offices excluding SIC codes 671x (*SIC67*).
Media	Annual count of news articles for each BHC from the Factiva business news database.

Table 2: Summary Statistics of Key Bank-Level Characteristics

This table summarizes the sample statistics of key bank-level characteristics used in our study, measured at event origination and at the bank-year level. Panel A uses the full sample of BHCs during the 1988–2005 period (left) and reduced sample for DID models over the 1994–1996 (pre-deregulation) and 2000–2002 (post-deregulation) periods (right). Panel B compares the summary statistics for Section 20 holders (left) and non-Section 20 BHCs (right) during the 1994–1996 (pre-deregulation) period. For the first three operational risk variables (*Count*, *Ln Total Loss*, and *Ln Avg Loss*), the reported statistics are conditional on having at least one operational risk event in a given bank-year observation; such instances are marked "conditional" in parentheses. Our full sample consists of 968 unique BHCs, of which 262 are pre-diversified and 41 are Section 20 holders. Our reduced sample consists of 482 unique BHCs, of which 192 are pre-diversified and 29 are Section 20 holders.

Panel A: Full Sample (1988–2005) and Reduced Sample (1994–1996 and 2000–2002)

	Full Sample, 1988–2005						Reduced Sample, 1994–1996 and 2000–2002					
	Mean	Median	SD	1%	99%	Num Obs	Mean	Median	SD	1%	99%	Num Obs
Count (conditional)	2.55	1.00	3.31	1.00	17.00	288	2.15	1.00	2.88	1.00	13.00	105
Ln Total Loss (conditional)	1.44	1.96	3.69	-4.61	9.08	288	1.01	1.60	3.46	-4.61	8.18	105
Ln Avg Loss (conditional)	0.94	1.83	3.27	-4.61	6.84	288	0.63	1.26	3.09	-4.61	5.73	105
Count	0.09	0.00	0.79	0.00	2.00	7,751	0.10	0.00	0.77	0.00	2.00	2,257
Total Loss (Millions USD)	10.50	0.00	290.90	0.00	48.15	7,751	9.24	0.00	289.44	0.00	55.26	2,257
Ln TA	7.09	6.68	1.59	4.82	12.16	7,751	7.18	6.73	1.61	5.06	12.31	2,257
Market-To-Book	1.77	1.59	5.27	0.26	4.84	6,222	1.70	1.56	0.87	0.54	4.69	1,816
Cash-To-TA	0.09	0.08	0.06	0.02	0.31	7,751	0.09	0.08	0.05	0.02	0.28	2,257
Tier 1 Ratio	0.13	0.12	0.07	-0.00	0.26	7,751	0.14	0.13	0.06	0.04	0.29	2,257
ROE (%)	6.52	7.60	19.49	-20.46	16.11	7,751	7.65	7.93	4.87	-4.32	16.06	2,257
Excessive Growth	0.42	0.00	0.49	0.00	1.00	6,800	0.38	0.00	0.49	0.00	1.00	2,075
High Dividend	0.51	1.00	0.50	0.00	1.00	7,743	0.56	1.00	0.50	0.00	1.00	2,254
ROA (%)	0.60	0.64	0.51	-1.11	1.43	7,751	0.69	0.69	0.41	-0.29	1.58	2,257
SD ROA (%)	0.36	0.33	0.29	0.06	1.28	7,624	0.37	0.36	0.22	0.08	0.97	2,217
Z-Score	2.17	2.21	1.20	-1.43	4.49	7,624	2.29	2.20	1.82	-0.53	5.09	2,217
Non-Interest Income Ratio	0.22	0.19	0.14	0.04	0.73	7,751	0.22	0.19	0.18	0.04	0.74	2,257
Nonbank Asset Ratio	0.02	0.00	0.09	0.00	0.52	7,751	0.02	0.00	0.08	0.00	0.48	2,257

Panel B: Section 20 vs. Non-Section 20 BHCs during the Pre-Deregulation Period (1994–1996)

	Section 20 BHCs						Non-Section 20 BHCs					
	Mean	Median	SD	1%	99%	Num Obs	Mean	Median	SD	1%	99%	Num Obs
Count (conditional)	2.39	1.50	2.09	1.00	9.00	18	1.11	1.00	0.32	1.00	2.00	18
Ln Total Loss (conditional)	2.59	3.47	2.59	-4.61	5.73	18	0.16	0.70	2.95	-4.61	4.03	18
Ln Avg Loss (conditional)	1.99	2.47	2.33	-4.61	5.73	18	0.08	0.70	2.87	-4.61	4.03	18
Count	0.49	0.00	1.35	0.00	9.00	87	0.02	0.00	0.14	0.00	1.00	1,211
Total Loss (Millions USD)	11.08	0.00	39.59	0.00	306.75	87	0.15	0.00	2.33	0.00	0.60	1,211
Ln TA	10.63	10.80	1.30	7.49	12.73	87	6.64	6.32	1.22	5.05	9.90	1,211
Market-To-Book	1.74	1.63	0.53	0.79	3.35	87	1.59	1.50	0.65	0.60	3.62	872
Cash-To-TA	0.09	0.09	0.03	0.02	0.18	87	0.10	0.09	0.05	0.02	0.28	1,211
Tier 1 Ratio	0.12	0.12	0.02	0.06	0.18	87	0.14	0.13	0.05	0.03	0.28	1,211
ROE (%)	9.84	10.04	2.17	0.41	14.86	87	7.64	7.86	5.55	-6.15	17.18	1,211
Excessive Growth	0.43	0.00	0.50	0.00	1.00	87	0.30	0.00	0.46	0.00	1.00	1,036
High Dividend	0.83	1.00	0.38	0.00	1.00	87	0.50	1.00	0.50	0.00	1.00	1,211
ROA (%)	0.71	0.74	0.18	0.02	1.19	87	0.70	0.70	0.38	-0.33	1.60	1,211
SD ROA (%)	0.37	0.38	0.09	0.16	0.59	87	0.37	0.36	0.18	0.09	0.90	1,183
Z-Score	2.13	2.16	0.34	0.40	2.83	87	2.33	2.19	2.35	-0.52	6.08	1,183
Non-Interest Income Ratio	0.36	0.33	0.13	0.17	0.76	87	0.19	0.17	0.10	0.04	0.67	1,211
Nonbank Asset Ratio	0.06	0.03	0.08	0.00	0.31	87	0.02	0.00	0.09	0.00	0.57	1,211

Table 3: Business Complexity and Operational Risk: Preliminary Evidence

This table presents the results from the models for our preliminary analysis used in Section 2.4. The dependent variables are annual operational risk event frequency (*Count*), annual total loss (*Ln Total Loss*), and annual average loss per event (*Ln Avg Loss*). The second and third variables are in logarithms. The key explanatory variables are proxies for business complexity: non-interest income ratio (Panel A) and nonbank asset ratio (Panel B). For each operational risk measure, Model (1) contains only size as a control and Model (2) contains the full set of controls. All models use annual data for 1988–2005. *t*-statistics reported in parentheses are based on robust standard errors double-clustered by the BHC and by year. Superscripts ***, **, and * indicate statistical significance at 1%, 5%, and 10% levels. The coefficients of control variables are omitted due to space limitations; complete results can be found in the Internet Appendix C, Table C1.

Panel A: Measure of Complexity: Non-Interest Income Ratio

	Count		*Ln Total Loss*		*Ln Avg Loss*	
	(1)	(2)	(1)	(2)	(1)	(2)
Non-Interest Income Ratio	0.351*	0.281	0.520**	0.469*	0.469**	0.445**
	(1.930)	(1.185)	(2.324)	(1.722)	(2.466)	(1.964)
Ln TA	0.163***	0.225***	0.309***	0.397***	0.273***	0.346***
	(2.887)	(2.931)	(4.491)	(4.488)	(4.794)	(4.797)
Other Control Variables	No	Yes	No	Yes	No	Yes
Num Observations	7,751	4,735	7,751	4,735	7,751	4,735
R-squared	0.130	0.154	0.162	0.184	0.154	0.174

Panel B: Measure of Complexity: Nonbank Asset Ratio

	Count		*Ln Total Loss*		*Ln Avg Loss*	
	(1)	(2)	(1)	(2)	(1)	(2)
Nonbank Asset Ratio	1.168*	1.511*	1.137**	1.336**	0.882**	1.032**
	(1.868)	(1.956)	(2.339)	(2.195)	(2.286)	(2.100)
Ln TA	0.165***	0.221***	0.319***	0.403***	0.283***	0.355***
	(3.050)	(3.100)	(4.757)	(4.866)	(5.084)	(5.231)
Other Control Variables	No	Yes	No	Yes	No	Yes
Num Observations	7,751	4,735	7,751	4,735	7,751	4,735
R-squared	0.146	0.172	0.167	0.188	0.157	0.176

Table 4: Difference-in-Differences Analysis: Evidence from the Natural Experiment

This table presents the results from our difference-in-differences analysis for operational risk. The dependent variables are annual operational risk event frequency (*Count*) in Panel A, annual total loss (*Ln Total Loss*) in Panel B, and annual average loss per event (*Ln Avg Loss*) in Panel C. The second and third variables are in logarithms. All data are averaged over the 1994–1996 (pre-deregulation) and 2000–2002 (post-deregulation) sample periods. All models include bank-level fixed effects, which subsume the effect of the stand-alone treatment and control group dummies. *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: Annual Operational Risk Event Frequency

	(1)	(2)	(3)	(4)	(5)	(6)
After	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 × Pre-Diversified	0.243***	0.243***	0.282**			
	(2.856)	(2.882)	(2.525)			
After × Pre-Diversified Sec20				1.527***	1.533***	1.569***
				(2.807)	(2.853)	(2.787)
After × Pre-Diversified NonSec20				0.051**	0.050**	0.061
				(2.151)	(2.140)	(1.555)
Ln TA		0.171**	0.316**		0.184**	0.337***
		(2.143)	(2.190)		(2.490)	(2.614)
Market-To-Book			0.012			-0.057
			(0.234)			(-0.875)
Cash-To-TA			-0.082			-1.383
			(-0.086)			(-1.191)
Tier 1 Ratio			3.105**			2.694**
			(2.096)			(2.434)
ROE			-0.010			0.011
			(-0.775)			(0.861)
Excessive Growth			0.011			0.080
			(0.119)			(1.002)
High Dividend			-0.188			-0.141
			(-1.244)			(-1.071)
Num Observations	694	694	412	694	694	412
R-squared	0.061	0.075	0.118	0.293	0.309	0.336

Panel B: Annual Total Operational Loss

	(1)	(2)	(3)	(4)	(5)	(6)
After	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 × *Pre-Diversified*	0.383***	0.383***	0.501***			
	(3.080)	(3.105)	(3.458)			
After × *Pre-Diversified Sec20*				1.918***	1.927***	2.102***
				(3.436)	(3.474)	(4.091)
After × *Pre-Diversified NonSec20*				0.152	0.151	0.227*
				(1.559)	(1.576)	(1.831)
Ln TA		0.237*	0.401*		0.252**	0.426**
		(1.776)	(1.796)		(2.139)	(2.144)
Market-To-Book			-0.124			-0.210
			(-0.688)			(-1.163)
Cash-To-TA			-3.298			-4.916**
			(-1.518)			(-2.478)
Tier 1 Ratio			4.628			4.116
			(1.506)			(1.542)
ROE			0.026			0.052
			(0.734)			(1.579)
Excessive Growth			-0.153			-0.068
			(-0.836)			(-0.419)
High Dividend			-0.304			-0.246
			(-1.490)			(-1.215)
Num Observations	694	694	412	694	694	412
R-squared	0.074	0.085	0.145	0.211	0.223	0.294

Panel C: Annual Average Operational Loss per Event

	(1)	(2)	(3)	(4)	(5)	(6)
After	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 × *Pre-Diversified*	0.341***	0.341***	0.452***			
	(2.914)	(2.935)	(3.304)			
After × *Pre-Diversified Sec20*				1.643***	1.651***	1.822***
				(3.150)	(3.172)	(3.746)
After × *Pre-Diversified NonSec20*				0.146	0.145	0.217*
				(1.528)	(1.543)	(1.805)
Ln TA		0.206*	0.344*		0.219**	0.365*
		(1.667)	(1.673)		(1.970)	(1.955)
Market-To-Book			-0.131			-0.204
			(-0.738)			(-1.156)
Cash-To-TA			-3.350			-4.735**
			(-1.581)			(-2.430)
Tier 1 Ratio			4.133			3.695
			(1.470)			(1.492)
ROE			0.031			0.053
			(0.903)			(1.645)
Excessive Growth			-0.163			-0.091
			(-0.993)			(-0.600)
High Dividend			-0.276			-0.226
			(-1.430)			(-1.176)
Num Observations	694	694	412	694	694	412
R-squared	0.068	0.078	0.137	0.179	0.189	0.261

Table 5: Robustness Test with Nonbanks as the Control Group

This table presents the results from a robustness test for operational risk with nonbanks as the control group. The dependent variables are annual operational risk event frequency (*Count*) in Panel A, annual total loss (*Ln Total Loss*) in Panel B, and annual average loss per event (*Ln Avg Loss*) in Panel C. The second and third variables are in logarithms. All data are averaged over the 1994–1996 (pre-deregulation) and 2000–2002 (post-deregulation) sample periods. All models include bank/firm-level fixed effects, which subsume the effect of the stand-alone treatment and control group dummies. *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. The coefficients of control variables are omitted due to space limitations; complete results can be found in the Internet Appendix C, Table C3.

Panel A: Annual Operational Risk Event Frequency

	(1)	(2)	(3)	(4)	(5)	(6)
After	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 × BHC	-0.049	-0.062	-0.216			
	(-0.368)	(-0.473)	(-1.064)			
After × BHC Sec20				1.634**	1.622**	1.072*
				(2.390)	(2.396)	(1.934)
After × BHC NonSec20				-0.160	-0.174	-0.316
				(-1.293)	(-1.404)	(-1.593)
After × SIC61	-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 × SIC63	-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 × SIC64	-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 × SIC65	-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 × SIC67	-0.223*	-0.241**	-0.334*	-0.223*	-0.241**	-0.339*
	(-1.830)	(-1.967)	(-1.774)	(-1.830)	(-1.971)	(-1.797)
Ln TA		0.063**	0.087***		0.065**	0.092***
		(2.135)	(2.598)		(2.439)	(2.914)
Other Control Variables	No	No	Yes	No	No	Yes
Num Observations	2,576	1,680	986	2,576	1,680	986
R-squared	0.036	0.042	0.064	0.204	0.210	0.233

Panel B: Annual Total Operational Loss

	(1)	(2)	(3)	(4)	(5)	(6)
After	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 × BHC	0.111	0.086	0.037			
	(0.531)	(0.414)	(0.128)			
After × BHC Sec20				1.738***	1.715***	1.647***
				(3.286)	(3.252)	(2.767)
After × BHC NonSec20				0.004	-0.022	-0.088
				(0.018)	(-0.107)	(-0.306)
After × SIC61	-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 × SIC63	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 × SIC64	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 × SIC65	-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 × SIC67	-0.152	-0.185	-0.245	-0.152	-0.186	-0.251
	(-0.757)	(-0.922)	(-0.901)	(-0.757)	(-0.924)	(-0.924)
Ln TA		0.123***	0.199***		0.124***	0.205***
		(3.131)	(2.764)		(3.240)	(2.987)
Other Control Variables	No	No	Yes	No	No	Yes
Num Observations	2,576	1,680	986	2,576	1,680	986
R-squared	0.041	0.051	0.063	0.111	0.122	0.142

Panel C: Annual Average Operational Loss per Event

	(1)	(2)	(3)	(4)	(5)	(6)
After	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 × BHC	0.127	0.104	0.084			
	(0.653)	(0.539)	(0.320)			
After × BHC Sec20				1.451***	1.430***	1.462***
				(2.993)	(2.946)	(2.657)
After × BHC NonSec20				0.040	0.016	-0.023
				(0.206)	(0.086)	(-0.089)
After × SIC61	-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 × SIC63	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 × SIC64	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 × SIC65	-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 × SIC67	-0.108	-0.137	-0.182	-0.108	-0.138	-0.187
	(-0.574)	(-0.732)	(-0.742)	(-0.574)	(-0.734)	(-0.764)
Ln TA		0.112***	0.180***		0.113***	0.186***
		(2.966)	(2.681)		(3.025)	(2.871)
Other Control Variables	No	No	Yes	No	No	Yes
Num Observations	2,576	1,680	986	2,576	1,680	986
R-squared	0.038	0.047	0.060	0.090	0.100	0.124

Table 6: Difference-in-Differences Analysis with Banking and Nonbanking Events for Growth-Matched BHCs

This table presents the results for banking and nonbanking operational risk events separately. The dependent variables are annual operational risk event frequency (*Count*) in Panel A, annual total loss (*Ln Total Loss*) in Panel B, and annual average loss per event (*Ln Avg Loss*) in Panel C. The second and third variables are in logarithms. We use matched samples in which Section 20 subsidiary holders are matched by asset growth with other BHCs for banking events and with nonbanks for nonbanking events. For each operational risk measure, Models (1), (2), and (3) present the results for banking events and Models (4), (5), and (6) present the results for nonbanking events. All data are averaged over the 1994–1996 (pre-deregulation) and 2000–2002 (post-deregulation) sample periods. All models include bank/firm-level fixed effects, which subsume the effect of the stand-alone treatment and control group dummies. *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. The coefficients of control variables are omitted due to space limitations; complete results can be found in the Internet Appendix C, Table C4.

Panel A: Annual Operational Risk Event Frequency

	Banking Events			Nonbanking Events		
	(1)	(2)	(3)	(4)	(5)	(6)
After	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 × *BHC Sec20*	0.724***	0.736***	0.871***	0.630*	0.846**	1.159*
	(3.154)	(3.221)	(2.994)	(1.996)	(2.090)	(1.815)
Ln TA		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
Num Observations	130	130	90	72	72	62
R-squared	0.376	0.398	0.482	0.239	0.271	0.332

Panel B: Annual Total Operational Loss

	Banking Events			Nonbanking Events		
	(1)	(2)	(3)	(4)	(5)	(6)
After	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 × *BHC Sec20*	1.894***	1.915***	2.325***	1.065*	1.416*	1.759
	(4.123)	(4.207)	(5.064)	(1.798)	(1.982)	(1.683)
Ln TA		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
Num Observations	130	130	90	72	72	62
R-squared	0.402	0.413	0.527	0.274	0.297	0.348

Panel C: Annual Average Operational Loss per Event

	Banking Events			Nonbanking Events		
	(1)	(2)	(3)	(4)	(5)	(6)
After	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 × *BHC Sec20*	1.757***	1.774***	2.131***	0.888	1.165*	1.393
	(4.044)	(4.094)	(4.784)	(1.683)	(1.889)	(1.524)
Ln TA		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
Num Observations	130	130	90	72	72	62
R-squared	0.387	0.395	0.503	0.273	0.291	0.335

Table 7: Difference-in-Differences Analysis: Performance Measures

This table presents our results for performance measures. The dependent variables are metrics of performance: return on assets, standard deviation of return on assets, *Z*-score, and market-to-book ratio. Panel A contains the results from our main regressions that use the 1994–1996 (pre-deregulation) and 2000–2002 (post-deregulation) sample periods; all data are averaged over the 1994–1996 (pre-deregulation) and 2000–2002 (post-deregulation) sample periods. Panel B presents the estimation results that use the samples from 2000–2002 vs. 2003–2005 to construct the *Before* and *After* periods; all data are averaged over the 2000–2002 and 2003–2005 sample periods. All models include bank-level fixed effects, which subsume the effect of the stand-alone treatment and control group dummies. *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: Main Regressions with the 1994–1996 (Pre-Deregulation) and 2000–2002 (Post-Deregulation) Periods

	Return on Assets		Standard Deviation of Return on Assets		*Z*-Score		Market-to-Book Ratio	
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
After	-0.050	-0.048	-0.005	-0.003	0.017	0.001	0.133	0.127
	(-1.194)	(-1.161)	(-0.258)	(-0.154)	(0.158)	(0.011)	(1.169)	(1.125)
After × Pre-Diversified	0.012		0.020		-0.016		0.228***	
	(0.404)		(1.353)		(-0.176)		(2.700)	
After × Pre-Diversified Sec20		-0.018		-0.015		0.223		0.324*
		(-0.324)		(-0.488)		(1.066)		(1.747)
After × Pre-Diversified NonSec20		0.018		0.027*		-0.062		0.210**
		(0.574)		(1.761)		(-0.666)		(2.366)
Ln TA	-0.027	-0.027	-0.022	-0.022	0.021	0.024	0.002	0.003
	(-0.645)	(-0.660)	(-1.145)	(-1.186)	(0.270)	(0.301)	(0.017)	(0.025)
Cash-To-TA	-0.383	-0.348	-0.138	-0.098	-0.720	-1.000	0.579	0.466
	(-1.038)	(-0.961)	(-0.562)	(-0.405)	(-0.574)	(-0.757)	(0.501)	(0.401)
Tier 1 Ratio	2.257***	2.270***	0.859***	0.874***	1.990*	1.891*	-1.756	-1.796
	(3.821)	(3.830)	(2.966)	(3.033)	(1.950)	(1.905)	(-1.074)	(-1.089)
Excessive Growth	0.018	0.016	-0.068***	-0.071***	0.298**	0.314**	-0.006	-0.000
	(0.426)	(0.373)	(-2.935)	(-3.005)	(2.393)	(2.505)	(-0.057)	(-0.001)
High Dividend	0.190***	0.189***	0.073***	0.071***	-0.051	-0.036	0.237*	0.243*
	(3.756)	(3.667)	(3.330)	(3.220)	(-0.416)	(-0.303)	(1.944)	(1.954)
Num Observations	412	412	408	408	408	408	412	412
R-squared	0.245	0.247	0.252	0.260	0.060	0.074	0.186	0.188

Panel B: DID Estimation with the 2000–2002 and 2003–2005 Periods

	Return on Assets		Standard Deviation of Return on Assets		*Z*-Score		Market-to-Book Ratio	
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
After	-0.064	-0.063	-0.005	-0.005	-0.152	-0.151	0.444***	0.445***
	(-1.529)	(-1.526)	(-0.278)	(-0.282)	(-0.892)	(-0.885)	(5.190)	(5.219)
After × Pre-Diversified	0.005		-0.013		0.091		-0.186**	
	(0.170)		(-0.995)		(0.858)		(-2.099)	
After × Pre-Diversified Sec20		-0.006		0.009		-0.239		-0.558***
		(-0.111)		(0.279)		(-1.186)		(-3.339)
After × Pre-Diversified NonSec20		0.007		-0.017		0.152		-0.118
		(0.245)		(-1.320)		(1.365)		(-1.314)
Ln TA	0.136	0.136	0.005	0.005	0.456	0.452	-0.259	-0.261
	(1.550)	(1.547)	(0.125)	(0.131)	(1.115)	(1.108)	(-1.042)	(-1.065)
Cash-To-TA	0.622	0.625	-0.191	-0.198	1.215	1.315	0.118	0.222
	(0.655)	(0.656)	(-0.478)	(-0.491)	(0.572)	(0.617)	(0.031)	(0.058)
Tier 1 Ratio	5.762***	5.783***	1.804***	1.764***	7.195*	7.797**	-9.933***	-9.258***
	(3.658)	(3.601)	(2.918)	(2.828)	(1.948)	(2.101)	(-3.150)	(-2.925)
Excessive Growth	-0.001	-0.001	-0.014	-0.014	0.193	0.186	-0.215**	-0.223**
	(-0.014)	(-0.019)	(-0.667)	(-0.636)	(1.282)	(1.230)	(-1.974)	(-2.062)
High Dividend	0.112*	0.110*	0.001	0.004	0.421*	0.376*	0.170	0.118
	(1.743)	(1.698)	(0.038)	(0.138)	(1.895)	(1.749)	(1.443)	(0.992)
Num Observations	500	500	498	498	498	498	500	500
R-squared	0.258	0.258	0.133	0.136	0.082	0.094	0.221	0.241