Financial Innovation and Risk: Evidence from Operational Losses at U.S. Banking Organizations

W. Scott Frame, Ping McLemore and Atanas Mihov*

June 2024

Abstract

This study documents that financial innovation is associated with adverse operational risk externalities. Using supervisory data on operational losses from large U.S. bank holding companies (BHCs), we show that organizations with more financial patent innovation suffer higher operational losses per dollar of assets and more tail risk events. This result is more pronounced for BHCs with weaker risk management. Banking organizations engaging in more financial innovation prior to or during the global financial crisis have more severe operational losses during the crisis. Our findings have important implications for banking supervision and risk management in an environment of rapid technology adoption.

Keywords: Operational risk, operational losses, financial innovation, financial patents, financial technology, fintech, bank holding companies, banking sector

JEL Classifications: G20, G21

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* Frame is at the Structured Finance Association and can be reached at scott.frame@structuredfinance.org. McLemore is at the Federal Reserve Bank of Richmond and can be reached at ping.mclemore@rich.frb.org. Mihov is at the University of Kansas and can be reached at amihov@ku.edu. The authors thank Azamat Abdymomunov, David Cox, Jeff Coles, Filippo Curti, Serdar Dinc, Jeff Gerlach, Peter Haslag, Jie (Jack) He, Russell Jame, Nika Lazaryan, Justin Murfin, Philipp Schnabl, Kelly Shue and Charles Wallace for valuable comments and suggestions. The authors also thank Josh Lerner for providing financial patent data and Andrew Ellul for providing risk management data. The views expressed in this artide are solely those of the authors. They do not necessarily reflect the views of the Structured Finance Association or any of its member firms, the Federal Reserve Bank of Richmond, or the Federal Reserve System.

I. Introduction

Rapid advances in information technology continue to spur innovations that are transforming the financial system. Financial innovation was historically viewed favorably as a channel of improved economic efficiency and economic growth (Miller 1986, 1992; Merton 1992; Tufano 2003), but the global financial crisis (GFC) led to a reevaluation of its social value.[1] This has produced competing narratives of there being "bright" and "dark" sides to financial innovation. Much of the academic literature underlying these perspectives can be categorized as descriptive. Some theoretical analysis exists but is principally focused on novel security design. By contrast, empirical studies cover a wider range of specific adopted innovations (Frame and White, 2004; Frame, Wall, and White, 2019). However, there remains an important gap in our understanding about the firm-level benefits and risks of engaging in financial innovation.

This paper leverages new data on financial patents collected by Lerner, Seru, Short, and Sun (2023) to explore the link between financial innovation at U.S. banking organizations and operational risk between 2000 and 2018.[2] Patents are a viable and reasonable measure of financial innovation given the significant limitations of alternative measures for financial institutions such as research and development (R&D) expenditures (Lerner 2006; Lerner et al. 2023).[3] We focus on 29 large bank holding companies (BHCs) subject to Dodd-Frank Act Stress Testing (DFAST) because of the extensive regulatory reporting of their financial statements and risk exposures and large share of

[1] See *New York Times*: "Innovating Our Way to Financial Crisis" (P. Krugman, Dec. 3, 2007); *Wall Street Journal*: "Think More Boldly" (P. Volcker, Dec. 14, 2009).

[2] Financial innovation is defined as new financial technologies and business methods in financial services that could result in new business models, applications, processes, or products with sometimes material effects on financial markets, institutions, and the provision of financial services. Operational risk is defined as losses resulting from inadequate or failed internal processes, people, and systems or from external events (Basel Committee on Banking Supervision, 2006).

[3] Financial institutions have had extremely low levels of reported R&D, reflecting historical R&D tax credit ambiguities and associated decreased incentives to track this spending (National Research Council, 2005; Kung, 2020). See Section III.D for a discussion.

industry assets (74.5% as of year-end 2018). As we later document, banking and financial services companies account for 16% of financial patents, and much of this activity is conducted by the BHCs in our sample (54%).

The two most prominent types of patented innovations relate to payments (44%) and back-office technologies (25%). Because of this, operational risk is much more salient to financial innovation than traditional credit or market risks faced by banking organizations. While operational risk has received much less attention in the academic literature than other bank risks due to the scarcity of reliable operational loss data, operational risk is a significant source of concern for large BHCs in terms of its share of net income (Curti et al., 2022) and share of regulatory capital (Afonso et al., 2019). Furthermore, because operational risk is particularly heavy tailed, it poses unique challenges to BHC capital management and solvency and may even raise financial stability concerns (Berger et al., 2022b).

It is important to note that the effect of financial innovation on operational risk at banking organizations is *a priori* unclear. On the one hand, financial innovation may enhance a bank's processes, monitoring capabilities, or technical infrastructure. On the other hand, financial innovations may also exacerbate existing operational risks such as cybersecurity, regulatory, compliance, legal, transaction processing and execution. Our paper tests empirically the relation between operational losses and financial innovation at large banking organizations and thereby documents the "net effect" of these two sets of countervailing channels.

Our core result is a positive and statistically significant relation between operational losses (as a share of total assets) and financial patent applications by banking organizations. A one standard deviation increase in our patent-based measure of innovation is associated with a \$142,920 increase in quarterly operational losses per \$1 billion of BHC assets. This is equivalent to \$22.4 (= (142,920×157.0)/1,000,000) million per quarter for the median BHC in our sample (with \$157.0 billion in total assets and \$18.2 billion in book equity), a 45.5% increase in relative terms. Instrumental variables (IV) regressions using the proportion of "high science, engineering, and technology" (HSET) business establishments in neighboring states, among other robustness checks, confirm this core result.

We conduct several exercises aimed at better understanding the positive relationship between financial innovation and BHC operational losses. First, among patent types, operational losses are reliably related to those with subject matters of payments and (retail and commercial) banking. Second, operational loss types sensitive to financial innovation include failures in obligations to clients, faulty product design and business practices, as well as external fraud. Third, innovation activity is positively related to the frequency of severe "tail" operational risk events. Fourth, BHCs with poor risk management and internal controls suffer disproportionately more operational losses when engaging in innovation. Finally, we find that BHCs engaging in more financial innovation before the onset of the GFC incur more severe operational losses during the crisis.

The last part of our analysis explores how industry market share (in terms of assets and deposits), and franchise value are related to financial innovation intensity at banking organizations. While more innovative BHCs capture greater market share, this does not translate into higher BHC franchise values. Considering our previous set of findings, operational losses are one channel which may degrade the otherwise value-enhancing effect of financial innovation.

Our study contributes to the literature assessing the benefits and risks of financial innovation. An early descriptive literature identifies various economic conditions conducive to financial innovation and provides a framework for thinking about how such advances may improve efficiency and spur economic growth (e.g., Miller 1986, 1992; Merton 1992, 1995; Tufano 1995, 2003). Around the same time, theoretical models were developed to explore the welfare effects of innovations in security design (e.g., Allen and Gale, 1994; Duffie and Rahi, 1995). There are also related survey articles summarizing empirical research related to specific innovations, which were seen as lacking at that time (e.g., Berger

2003; Frame and White, 2004). Following the GFC, new theories related to security design were posited to explain the creation and collapse of mortgage securities and their derivatives (e.g., Gennaioli et al., 2012; Thakor, 2012; Fostel and Geanakoplos, 2012).

Our paper is most related to those exploring cross-sectional and time-series variation in financial innovation. Tufano (1989) examines competitive aspects among investment banks associated with the creation of a sample of innovative securities. Lerner (2006) identifies financial innovations from media and explores the characteristics of innovative firms. Beck et. al, (2016) use variation in survey responses relating to R&D expenses at banks in 32 countries and finds that innovation is positively related to bank growth and risk. Chen et al. (2019) identify fintech innovation in patent data and find that it provides substantial value to creators, especially those relating to blockchain. Lerner et. al, (2023) collect financial patent data and document increased financial innovation over time, as well as compositional shifts in the types of innovations and the firms producing them.

We focus on the firm-level net benefit/risk of engaging in financial innovation by exploring its relation to operational losses at large banking organizations. The type of financial innovation that we study does not pertain to security design but rather patentable technologies and business methods. We show that more innovative BHCs suffer higher operational losses. We interpret operational losses as one channel that counteracts innovation's value-enhancing effects. Crucially, however, the effects of innovation on operational risk may have implications that spread beyond BHC value. Specifically, financial innovation also appears to be related to the incidence of (massive) tail operational loss events, which are not only relevant for BHC failure risk but also have been shown to even degrade financial stability (e.g., Berger et al., 2022b).

Our study also contributes to the literature on operational risk at financial institutions. Cummins et al. (2006) and Gillet et al. (2010) analyze stock market reactions to operational loss announcements at financial institutions. Cope et al. (2012), Abdymomunov et al. (2020) and Frame et al. (2022) analyze financial industry operational losses over the GFC and explicitly link operational risk to the state of the macroeconomy. Chernobai et al. (2012), Wang and Hsu (2013), Abdymomunov and Mihov (2019) and Curti et al. (2023) show that better corporate governance, risk management and employee training at financial institutions decrease these organizations' operational losses. Chernobai et al. (2021) show that BHC expansions into non-banking activities result in more operational risk. Curti et al. (2022) and Frame et al. (2023) document that larger and faster growing banking organizations have higher operational losses per dollar of total assets. Berger et al. (2022a) show that banking organizations exposed to severe weather incur higher operational losses from damage to physical assets and business disruption.

Our study, on the other hand, focuses on financial innovation as a new source of operational risk. Higher losses from innovation can be traced to external fraud and failures in obligations to clients, and faulty product design. Innovation in payment technologies and retail and commercial banking seem to be particularly problematic in spawning operational losses. The staggering size of operational losses, as well as the challenges around measurement and monitoring of operational risk both within organizations and by outside investors, highlight the importance of understanding the organizational drivers of operational risk.

The results of our analysis are also relevant for supervisory policy as financial regulators continue to assess the risks and benefits created by the increasing use of innovative technologies by financial institutions (Board of Governors of the Federal Reserve System, 2022). Banking regulatory agencies have issued guidance on a wide range of topics to address associated risks (e.g., operational resilience, system authentication and access management). While banking regulators have voiced support for responsible technological innovation, they have also emphasized that such innovation should be paired with appropriate processes for identifying and managing risks. These regulators are also updating their supervisory programs to ensure examiners are equipped to assess the risks posed by financial innovations and other industry changes. Our findings confirm that financial innovation at banking organizations is indeed a relevant dimension for U.S. BHCs' risk outcomes and should be considered when assessing their operational risk profiles. Further, our findings on the amplification of innovation-induced operational risks at BHCs with weaker risk management implicitly support supervision approaches that subject such institutions to increased supervisory attention. Our results suggest the value of robust risk management frameworks in supporting financial innovation and associated activities.

The rest of this paper is organized as follows. Section 2 discusses some potential channels through which financial innovation may result in higher operational losses. Section 3 describes our data, the construction of variables and descriptive statistics. Sections 4 and 5 present empirical results and check for robustness. Section 6 concludes.

II. Channels for Elevated Operational Losses

While financial innovation may enhance product value, broaden product menus, improve banking organizations' abilities to meet customer needs and expectations, it also creates operational risks. Risks stemming from innovative financial technologies are not unique but reflect and sometimes amplify "traditional" operational risks, particularly when banking organizations lack the appropriate internal controls to support innovation. Here we discuss some specific channels that link financial innovation to operational risks.

First, innovation at banking organizations may introduce cybersecurity risks, whereby new systems (e.g., payments transfer and processing) may give rise to vulnerabilities that hackers could exploit. For example, attackers may gain control over banks' telecommunication system credentials via such vulnerabilities, and then initiate fund transfers to hacker-controlled bank accounts. In another example, fraudsters could exploit seemingly non-sensitive marketing and financial data that banking organizations collect to fuel innovative systems. If security precautions are insufficient, it's possible to stitch these information threads together to create false identities and commit financial fraud. Newly deployed technologies that are insufficiently tested and quality-reviewed because of tight deadlines and pressure to meet consumer expectations provide yet another scenario exposing banks to malicious actions (and resulting financial losses) perpetrated by bad actors.

Second, financial innovation may increase regulatory, compliance and other legal risks.[4] [5] New products spurred by innovation may not meet regulatory or customer standards (e.g., products may not be well understood or properly marketed by bank employees or may lack proper disclosures), increasing the odds that banking organizations may be deemed to be engaged in unfair or deceptive practices. To the same effect, newly deployed systems (e.g., AI-based) may inadvertently discriminate against protected classes of customers and other groups due to biases baked into the historical data on which algorithms are trained. The rising complexity in data maintenance, traceability, and audit similarly result in data quality, privacy, and customer security challenges. For example, inadvertently using or revealing sensitive information hidden among anonymized data violates privacy rules such as the European Union's General Data Protection Regulation or the California Consumer Privacy Act.

Finally, financial innovation may increase risks from transaction execution errors. Advances in technology have led to the creation of new and highly sophisticated processes. Integrating innovations may create a "Frankenstein" of technology, where systems are patched together and lack cohesion. Creating data and process silos, in turn, erodes banking organizations' ability to execute transactions

[4] Some innovative operational technologies could, on the other hand, improve the bank's ability to comply with regulatory requirements by improving banks' monitoring capabilities. For example, technology that enhances fraud detection or provides more reliable customer authentication can strengthen a bank's ability to comply with the Bank Secrecy Act/Anti-Money Laundering (BSA/AML) requirements.

[5] Financial regulations are quickly evolving in this area. For example, there are artificial intelligence guidance and regulations proposed in the European Union (EU), Hong Kong, Japan, Saudi Arabia, Singapore, United Kingdom, and the United States. The EU AI Act proposes significant fines for inadequate AI governance. The proposed EU AI Liability Directive makes clear that developers, producers, and users are responsible not just for errors in AI but for any potential impact the AI can have, paving the way for EU-wide class action. With AI there is no longer a requirement for the injured person to prove a negligent or intentionally damaging act or omission (Townson, 2022).

and manage processes because information cannot seamlessly flow across systems in real time. For example, in one case, a major financial institution ran into trouble after its compliance software failed to spot trading issues because the data feeds no longer included all customer trades (Cheatham et al., 2019). Technology interconnections increase exposure to larger system-wide failures and may increase critical downtime if just one of them fails.

We acknowledge that the above discussed channels are not an exhaustive list and there could be other channels through which financial innovations affect operational risk in the banking sector.

III. Data Sample and Variable Definitions

III.A. Operational loss data

We employ supervisory data on operational losses reported by large banking organizations in accordance with the FR Y-14Q form requirements (current as of December 2021).[6] The Federal Reserve System gathers and employs these data in implementing the Dodd-Frank Act Stress Tests (DFAST) among other supervisory and regulatory uses. The data are provided by 35 BHCs with consolidated assets of $100 billion or more. We supplement these data with that for five additional institutions (Comerica, CIT Group, Zions Bancorporation, BBVA USA Bancshares, and SunTrust Banks), which used to participate in DFAST, but no longer do so pursuant to the Economic Growth, Regulatory Relief, and Consumer Protection Act of 2018 or due to merger activity. While the original data contains losses from 40 institutions, the availability of market value of equity reduces the number of institutions in our sample from 40 to 29.

Per FR Y-14Q reporting instructions, BHCs must report a complete history of operational losses "starting from the point-in-time at which the institution began capturing operational loss event data

[6] More information about FR Y-14Q reporting requirements, instructions and forms can be found at: https://www.federalreserve.gov/apps/reportingforms/Report/Index/FR_Y-14Q.

in a systematic manner." The majority of BHCs in our sample report losses for periods prior to the Dodd-Frank Act. BHCs collected such loss data under the umbrella of supervisory frameworks such as Basel and for internal use. These data are subject to significant data quality checks, including regular data exams conducted by Federal Reserve staff and BHC internal audit functions. The data are at the individual loss event level and provide information such as loss amounts, loss dates, and loss classifications.

Consistent with Basel II Accord definitions, operational losses are categorized into seven event types: Internal Fraud (IF), External Fraud (EF), Employment Practices and Workplace Safety (EPWS), Clients, Products and Business Practices (CPBP), Damage to Physical Assets (DPA), Business Disruption and System Failures (BDSF), and Execution, Delivery and Process Management (EDPM). Table 1, Panel A presents definitions of each loss type.

[Insert Table 1 and Figure 1]

Figure 1 presents the allocation of losses across the seven event type categories. The event type with the largest proportion of total losses is CPBP, which accounts for 76.3% of losses or $298.4 billion over the sample period. This suggests that the majority of BHC operational losses are the result of poor services to customers or flawed products. A review of the data further indicates that CPBP contains many of the largest and most severe losses incurred by BHCs over our sample period. The second largest event type by share of total losses is EDPM, accounting for 13.8% of losses or $53.8 billion. The remaining five event types combined comprise 10% of total losses, or $39 billion.

The banking organizations in our sample have different thresholds for collecting individual operational losses. To mitigate the impact of firm heterogeneity in collection thresholds on our results, we follow Abdymomunov et al. (2020) and discard operational losses below $20,000, which is the highest threshold across reporting institutions. We next aggregate loss data at the BHC-quarter level, where we use the quarter of the date when an operational loss event occurred (or began) for aggregation purposes.

Finally, we merge loss data with financial data from FR Y-9C, stock market data from CRSP, and the patent data from Lerner et al. (2023). Our final sample has 1,374 observations from 29 publicly traded large BHCs over the period 2000:Q1-2018:Q4. While our combined data contain losses from only 29 BHCs, this small number of institutions, however, accounts for the majority of U.S. banking industry assets (74.5% as of 2018:Q4).

It is important to note that, for the covered institutions, our data is substantially more comprehensive than operational loss data offered by private vendors that rely on publicly available information. For example, Hess (2011) uses loss data from SAS OpRisk Global Data, which consists of around 7,300 loss events. Chernobai et al. (2012) analyze loss data from Algo FIRST, which consists of 2,426 events. In contrast, we have 434,714 individual loss events in our sample. As discussed in De Fontnouvelle et al. (2006), public sources of data compiled from press accounts omit substantial operational losses otherwise contained in the supervisory data used in this study.

III.B. Operational loss measures

Table 1, Panel B presents variable definitions. Our main measure of operational risk is the total dollar value of operational losses that occur at a BHC in a quarter. We follow previous operational risk literature (e.g., Curti et al., 2022; Curti et al., 2023), and other studies on bank risk and performance (e.g., James, 1991; Ahmed et al., 1999; Ellul and Yerramilli, 2013), and scale losses by total assets. To avoid a potential mechanical relation between operational losses and institution size (e.g., an asset impairment channel of operational risk), we use lagged total assets. Our results are also robust if we use alternative variables for scaling operational losses such as liabilities or equity.[7] For presentation

[7] Results of using liabilities and equity to scale operational losses are not reported for brevity and are available upon request.

purposes, we multiply the loss-to-assets ratio by 10,000 and label it *LtA*. In some of our regression specifications, we also use log-transformed total dollar losses in a quarter, *Ln(Loss)*, log-transformed frequency of loss events, *Ln(N Evts)*, and log-transformed average severity of loss events, *Ln(Avg Sev)*.

[Insert Table 2 about here]

Table 2, Panel A presents descriptive statistics. On average, the BHCs in our sample lose $235.22 million or the equivalent of 0.05% (=235.22/(483.45×1,000) ×100) of their assets per quarter to operational risk. Further, the standard deviations of both dollar losses ($1.38 billion) and assets-scaled operational losses (LtA) (9.55) are high relative to the means, indicating substantial time-series and cross-sectional variation of operational losses. The average BHC in our sample experiences 295 operational loss events (with an average severity of $0.77 million) over a given quarter.

A well-known property of operational losses is the extremely heavy tails of the empirical loss distributions (Chernobai and Rachev, 2006; Jobst, 2007). Indeed, only a few "catastrophic" events account for a large proportion of the total dollar losses in our sample. Thus, we also analyze tail operational risk. We use three frequency-based measures of tail losses. We start with the 434,714 individual loss events in our sample and scale dollar loss amounts by BHC total assets. We calculate the 90^{th} ,95^{th}, and 99^{th} percentiles of the resulting empirical distribution and classify all loss events with severities above the respective percentiles as "tail losses." We then count the number of tail losses that occur at an institution in a quarter for each tail threshold definition and label the variables *N Evts Tail 90*, *N Evts Tail 95*, and *N Evts Tail 99*, respectively. Finally, we take natural log transformations of these count-based measures. For robustness, and to better capture the severity of tail operational losses, we calculate three additional measures of tail risk. Using the same three definitions of tail loss events, we calculate *LtA Tail 90*, *LtA Tail 95* and *LtA Tail 99* defined as tail operational dollar losses that occur at a BHC in a quarter as a proportion of BHC total assets (multiplied by 10,000).

III.C. Financial patent data

Our study uses financial patent data from Lerner et al. (2023), who leverage machine learning techniques to identify the financial patents and extensively audit the results to ensure their reasonableness. We refer interested readers to that study for details about the large-scale process of constructing the data and extensive quality checks. The dataset contains over 24,000 U.S. financial patents applied for between 2000 and 2018. The data includes the patent ID, patent application and grant dates, first assignee name, and patent subject matter (patent type).

Table 3, Panel A presents the number of patents across different industries for three subperiods and in total. Software and IT Services companies are responsible for the largest number of financial patents (6,872), accounting for 28.3% of all patents in the sample. Banking and Financial Services companies follow with 3,944 patents or 16.3% of the sample. The panel also splits out the patents assigned to the BHCs in our sample, which are otherwise included in the Banking & Financial Services industry category. These large BHCs are assigned 2,142 patents or 54% of the patents assigned to the entire Banking and Financial Services industry group. Patent applications are relatively evenly distributed across the three subperiods (i.e., 2000-2006, 2007-2011, and 2012-2018).

[Insert Table 3 about here]

Lerner et al. (2023) classify financial patents according to their specific functions in financial services. They use natural language processing and a set of key words (listed in Appendix A) to perform textual analysis of the abstract and text of the patent awards to identify patent subject matters.[8] More than ten separate patent types are identified: accounting, commercial and retail banking, communications, cryptocurrency, currency, insurance, investment banking, payments, real estate, and wealth management. Table 3, Panel B presents the composition of financial patents

[8] The keywords are determined by Lerner et al. (2023) from a review of the patent abstracts, finance glossaries, and industry knowledge.

according to subject matter (i.e., patent types) for the entire financial patent sample, for patents assigned to companies in the Banking and Financial Services industry group as well as for the BHCs in our sample. Focusing on the BHCs in our sample, the panel shows the bulk of patents are in payments – 44%, back-office technologies (e.g., security, communications) – 25%, and banking (retail, commercial, and investment) – 21%. The distribution of patents across types is roughly similar in the broader samples of patents granted to all banking and financial services firms and the entire sample of financial patents.

III.D. Financial innovation measure

We use the log-transformed number of (ultimately successful) quarterly average financial patent applications over four quarters (from quarter *t*-3 to current quarter *t*), *Ln(N Patents)*, as our financial innovation measure for large banking organizations. To deal with quarters of zero patent applications, we add 1 to *N Patents* before the log transformation. In later sections, we differentiate between different patent types and examine several innovation measurement horizons.

Lerner et al. (2023) emphasize that patents are a reasonable measure of financial innovation for several reasons. First, an important court ruling in 1998 (*State Street Bank and Trust v. Signature Financial Group*) established the patentability of business methods as statutory subject matter on an equal footing with more traditional technologies.[9] Second, patterns seen in financial patenting closely reflect patterns in innovative investment measures and do not appear to be driven by shifts in the reliance on trade

[9] Before *State Street Bank and Trust v. Signature Financial Group*, there had long been ambiguity about the patentability of financial discoveries in the United States. Many judges and lawyers had presumed that business methods were not patentable subject matter. While the U.S. Patent and Trademark Office (USPTO) issued patents on financial and other business methods during the twentieth century, many observers questioned their enforceability. The July 1998 appellate decision in *State Street Bank and Trust v. Signature Financial Group* changed the attitudes toward business method patents. This case originated with a software program used to determine the value of mutual funds, on which Signature had obtained a patent in 1993. State Street Bank sued to have the patent invalidated on grounds that it covered a business method. While State Street's argument prevailed in the district court, the Court of Appeals for the Federal Circuit (the central appellate court for patent cases, also known as the CAFC) reversed the finding. The court affirmed the patentability of the software since it produced a "useful, concrete, and tangible result." Numerous trade press articles interpreted the case as unambiguously establishing the patentability of business methods.

secrets. Third, financial patents are associated with significantly higher value (stock market reactions) than other types of patents. Fourth, major finance innovations are patented.[10]

In contrast, most non-patent metrics of innovative activity in financial services are problematic. For instance, finance has had extremely low levels of reported R&D. In 2016, the U.S. finance and insurance industry spent 0.17% of total revenue on R&D, as opposed to 13.5% for pharmaceuticals, 10.7% for computers and electronic products, and 3.4% for manufacturing (Kung, 2020). This low number likely reflects the historical ambiguities about whether R&D tax credit covered such expenditures, which reduced the incentives for financial firms to track this spending (National Research Council, 2005).

III.E. Control variables

Our multivariate regression analysis includes several control variables that capture time varying BHC characteristics. We follow Curti et al. (2022) and use the logarithm of BHC total assets to control for organizational size. Larger BHCs may have higher exposure to operational risk due to factors such as organizational complexity or moral hazard associated with too-big-too-fail. We include the non-interest to interest income ratio (*NII-to-II*) to account for exposure to traditional vs. non-traditional business activities of banking organizations. Brunnermeier et al. (2020) document that more traditional banks focused on deposit receiving and lending have different risk profiles from others with higher non-interest income from non-core activities such as trading and investment banking. For similar reasons, we also explicitly control for the proportion of assets funded through deposits (*Deposits-to-Assets*) and the proportion of lending relative to total assets (*Loans-to-Assets*). We control for BHC profitability as measured by return on equity (*ROE*), which we define as the ratio of net income to

[10] For example, popular media (e.g., *MIT Technology Review*) identifies online banking as one of the most significant financial innovations since the GFC. This has been an area of extensive patenting. The listed patent, by industry leader Bank of America, covers advanced fraud detection techniques fundamental to online banking. The patent is the most important financial patent in terms of Kogan et al. (2017) value and is among the most cited.

book value of equity. Higher profitability may allow the allocation of more resources to risk management, or alternatively, senior management can turn a blind eye to internal control failures when firms are less financially constrained (Jin and Myers, 2006). Because operational risk is closely related to credit risk (e.g., Chernobai et al., 2012), we also control for BHCs' loan charge-off rates (*Loan Losses*). To further control for BHC risk, we include the ratio of BHC total assets to book value of equity (*Leverage*) and the log absolute difference between assets and liabilities that reprice or mature within a year (*Maturity Gap*).

III.F. Variable correlations

Table 2, Panel B presents pairwise variable correlations as a first step in quantifying the relation between financial innovation intensity and operational losses at BHCs. The correlation between *Ln(N Patents)* and *Ln(Loss)* is 0.604, suggesting that the more innovative BHCs in our sample have more operational losses in dollar terms. Additionally, the correlation between *Ln(N Patents)* and *LtA* is 0.199, further indicating that more innovative BHCs not only have more operational losses in dollar terms, but also incur more operational losses per dollar of assets. In both cases, the correlation coefficients are significant at the 1% level.

We also highlight this last point visually in Figure 2. We start by sorting BHCs into innovation intensity terciles based on the average quarterly number of patent applications they file ("*Low*," "*Medium*," and "*High*"). The figure then presents a bar chart of the average quarterly *LtA* for the three terciles of BHCs, clearly showcasing that the less innovative BHCs in our sample incur less operational losses per dollar of assets than the more innovative BHCs.

[Insert Figure 2 about here]

Table 2, Panel B additionally reveals strong positive correlations between *Ln(N Patents)* and our tail loss measures (*N Evts Tail 90-99* and *LtA Tail 90-99*). In all cases, the correlation coefficients are again significant at the 1% level. Innovative BHCs tend to suffer a larger number of tail operational loss events.

IV. Regression Analysis

IV.A. Operational losses

To examine whether more innovative BHCs incur more operational losses, we estimate the following multiple regression specification using Ordinary Least Squares (OLS):

$$Operational\ Loss_{i,t} = \beta_t + \beta_1 Ln(N\ Patents)_{i,t-1} + \beta_2 Controls_{i,t-1} + \varepsilon_{i,t} \quad (1)$$

where i indexes BHCs and t indexes time periods (quarters). *Operational Loss* is one of four operational loss measures: (i) operational losses as a proportion of total assets that occur at BHC i during quarter t; (ii) log-transformed operational dollar losses that occur at BHC i during quarter t; (iii) log-transformed frequency of operational losses that occur at BHC i during quarter t; or (iv) log-transformed average severity of operational losses that occur at BHC i during quarter t. *Controls* represents our previously discussed vector of control variables. All explanatory variables are lagged one period.

We include quarter fixed effects (β_t) to absorb period-specific shocks common across all BHCs (e.g., industry-level operational risks). We do not include BHC fixed effects because the average innovation intensity of BHCs is informative about the average level of operational losses incurred by the BHCs. (Section V.B additionally shows our results are robust to the inclusion of BHC fixed effects.) We deal with potential endogeneity issues introduced by omitted variables including time-invariant factors relevant to operational losses that would be absorbed by BHC fixed effects in the next section. We cluster standard errors at the BHC and quarter levels (i.e., two-dimensional clustering) to account for within-bank and within-quarter correlation of the error terms. Table 4 presents the results.

[Insert Table 4 about here]

The results in Column (1) suggest that more innovative banking organizations experience more operational losses per dollar of assets. The coefficient estimate of *Ln(N Patents)* is positive and statistically significant at the 1% level. A one standard deviation increase in *Ln(N Patents)* is associated with a $142,920 increase in quarterly operational losses per $1 billion of BHC assets, which is a 45.5% (=(1.985×0.72)/3.14) increase in *LtA* relative to its mean value. Column (2) provides consistent evidence, which suggests that a 1% increase in *N Patents* is associated with a 7.4% increase in operational losses. In Columns (3) and (4), we decompose operational losses into loss frequency and severity components, respectively. Column (3) shows that operational loss frequency is significantly positively related to *Ln(N Patents)*. While average loss severity is also positively related to *Ln(N Patents)* in Column (4), the relation is statistically insignificant at conventional levels. Even though the incidence of severe losses significantly increases at more innovative BHCs (see Section IV.E), the overall increase in the frequency of operational loss events moderates their average severity.

Apart from innovation, we find that only BHC size is consistently related to operational losses across all specifications. Larger institutions incur more operational losses.

IV.B. Endogeneity and reverse causality

One may naturally be concerned about the possibility that endogeneity or reverse causality is driving the empirical associations in the previous section. A particular identification concern is that omitted variables related to both operational losses and financial innovation at banking organizations might be driving the results. For example, more innovative BHCs may deemphasize risk management and relax internal controls to boost innovation output. (We come back to the topic of BHC risk management and internal controls in Section IV.F.) Alternatively, it could be that BHCs with high operational losses may turn to innovation to curtail future operational risk. In this section, we pursue an IV approach to mitigate such identification concerns.

To identify the impact of interest, we need a source of exogenous variation in banking organization innovation. Our IV approach draws on the agglomeration economies literature, which provides support for the notion that innovation emerges in large part from the regional mixing of ideas (Glaeser et al., 1992; Agrawal et al., 2008) and that use of innovation is disproportionately local (Jaffe et al., 1993; Kerr, 2010). In our approach, we specifically argue that a business establishment mix that favors innovative behaviors in a region should spill over to BHC financial innovation. To that purpose, we use a Science & Engineering State Indicator published by the National Science Foundation that measures the proportion of "high science, engineering, and technology" or HSET business establishments among all business establishments, available at the state level from 2003 to 2016.[11]

Our instrument, *Neighbor State HSET Businesses*, is measured as the average proportion (in percentage points) of HSET business establishments across the neighboring states of the BHC headquarters state. The proportion of HSET business establishments in each state is a quarterly average from quarter t-3 to quarter t. We account for the diminishing returns to scale in innovation activities (Jones 1995a, 1995b) and geographic boundaries to information flows and knowledge spillovers across states (Krugman 1991, Audretsch and Feldman 1996) by applying a log-transformation to *Neighbor State HSET Businesses.*

The validity of the instrument hinges on two requirements. First, neighboring states' HSET business establishment mix should be related to BHCs' innovation activities through technological

[11] HSET employment industries are defined as those in which the proportion of employees in technology-oriented occupations is at least twice the average proportion for all industries. Scientific, engineering, and technician occupations employ workers who generally possess in-depth knowledge of the theories and principles of science, engineering, and mathematics at a postsecondary level.

spillovers (relevance condition). We argue that BHC innovation activities should be influenced by neighboring states' business mix because of technological ties derived from geographic proximity. Second, the instrument should not directly affect BHC operational losses other than through the effect on BHC innovation (exclusion restriction). To that point, we do not directly consider the HSET business establishment mix of the BHC headquarters states to eliminate the possibility that our instrument is contaminated by headquarters state factors that may impact BHC operational losses.

[Insert Table 5 about here]

Table 5, Column (1) reports the first-stage estimation results. The estimated coefficient of the instrumental variable is positive and highly significant. The HSET business establishment mix of neighboring states is related to the financial innovation intensity of a banking organization. The adjusted R^2 is high, and the *F*-statistic is above the threshold of 10 prescribed by Stock et al. (2002), suggesting that our estimation does not suffer from a weak-instrument problem. Column (2) presents second-stage results and shows that the estimated coefficient on *Ln(N Patents)* retains its positive sign and is significant at the 5% level. These findings suggest that the results in the previous section are robust to accounting for endogeneity and reverse causality concerns, confirming the positive relation between BHC financial innovation and operational losses.

IV.C. Patent types

In this section, we examine the types of innovation that may be driving the documented positive relation between BHC operational losses and financial innovation. For this purpose, we center our attention on the most significant patent types representing payments technologies, back-office technologies (security and communications), and banking (commercial, retail, and investment). As mentioned earlier, each of these innovation types represents over 5% of the patents in the sample, collectively accounting for more than 90%. Innovation types that represent less than 5% of patents are grouped into a separate category labeled "Other," which comprises approximately 9% of the patents in the sample. We next re-estimate Equation (1) for different patent types according to their classifications. Table 6 presents the results.

[Insert Table 6 about here]

The coefficient estimates are positive across all columns, suggesting that all patent types are positively related to operational losses. In four cases – patents with subject matters of payments, security, commercial and retail banking, and "other" – the coefficient estimates are statistically significant at conventional levels suggesting a reliable positive effect of innovation in these areas on BHC operational losses. In the remaining two cases, while positive, the coefficient estimates are statistically insignificant at conventional levels.[12]

IV.D. Operational loss types

Operational risk is an amalgamation of various types of subcomponent risks. There are seven major loss categories in our sample: Internal Fraud (IF), External Fraud (EF), Employment Practices and Workplace Safety (EPWS), Clients, Products and Business Practices (CPBP), Damage to Physical Assets (DPA), Business Disruption and System Failures (BDSF), and Execution, Delivery and Process Management (EDPM). While Section IV.A documented a robust relation between aggregate operational losses at the BHC level and financial innovation, there may be heterogeneous relationships across loss categories. We next re-estimate Equation (1) for the seven event type categories separately and report the results in Table 7.

[12] In unreported results, we disaggregate the "Other" patent category into separate patent types (accounting, crypto, currency, insurance, real estate, and wealth management) and individually estimate their relations with LtA. We find that most patent types within this group are individually insignificantly related to operational losses. The only exceptions are currency and insurance patents, which are significantly positively related to LtA. This finding suggests that while currency and insurance innovations account for a relatively small proportion of total innovations, they are associated with higher operational losses.

[Insert Table 7 about here]

Columns (2) and (4) indicate that losses in both EF and CPBP are positively and significantly (at the 10% and 1% level, respectively) related to *Ln(N Patents)*. More innovation at banking organizations increases the institutions' losses from external fraud (e.g., cyber losses) and failures to meet obligations to clients, faulty products, and improper business practices (e.g., regulatory, compliance and other legal losses). In contrast, the coefficient of *Ln(N Patents)* is indistinguishable from zero in Columns (1), (3), (5), (6) and (7) suggesting that innovation does not significantly impact other operational loss categories (e.g., internal fraud, employment practices and workplace safety, damage to physical assets, business disruption, and failed execution, delivery, and transaction processing).

IV.E. Tail operational losses

Our analysis in the previous sections investigated the association between financial innovation and operational losses by modeling the conditional average (asset-scaled) operational losses. This section, on the other hand, focuses on tail operational losses. The distinction between experiencing a higher level of operational losses versus experiencing tail operational loss events is important. A higher-than-average level of operational losses due to innovation activities may have adverse implications for a BHC's performance. However, it does not necessarily pose fundamental concerns for the institution's solvency. In contrast, a higher incidence of tail operational loss events is more concerning as tail losses may pose difficulties for loss reserving practices and capital management.

Section III.B described our tail risk measures, *Ln(N Evts Tail),* the log-transformed frequency of tail operational loss events at a BHC over a given quarter. We use three different tail threshold definitions for robustness – the 90^{th}, 95^{th} and 99^{th} percentiles. The pairwise correlations in Table 2, Panel B already provided some initial evidence that innovation is associated with higher incidence of tail events. We next show in Table 8 that these associations also persist in multiple regression specifications similar to Equation (1).

[Insert Table 8 about here]

Table 8, Columns (1)-(3) show that more innovative BHCs suffer more frequent tail operational loss events. Depending on the tail threshold used, a 1% increase in the number of patents filed is associated with a 10.94-26.62% increase in the frequency of tail operational losses. The coefficients of *Ln(N Patents)* are all significant at the 1% level. Columns (4)-(6) further indicate the robustness of our results to using tail loss measures *LtA Tail* that better capture loss size rather than tail event frequencies. In each case, *Ln(N Patents)* retains its positive sign and statistical significance. Overall, we conclude that financial innovation is relevant not only for banking organizations' average level of operational losses, but also for the occurrence of severe tail operational risk events.

IV.F. Risk management

Risk-management functions at banking organizations assess, manage, and monitor assumed risks to ensure they are within the limits set by the banking organizations' management and boards of directors. Prior studies have shown that weak BHC risk controls and a lack of independence of risk-management functions are associated with increased risk exposures at large BHCs (e.g., Ellul and Yerramilli, 2013; Abdymomunov and Mihov, 2019; Frame et al., 2020). Here we examine whether strong risk management at banking organizations helps these institutions mitigate the risk-increasing effects of innovation.

To study this issue, we use the risk-management index (RMI) developed by Ellul and Yerramilli (2013). The *RMI* is a continuous measure of the organizational strength and independence of the risk-management functions at large banking organizations. The *RMI* is constructed as the first principal component of seven measures of BHC risk-management quality, including variables that capture whether a BHC has a designated risk officer to manage enterprise-wide risk and variables that capture how well quantitative and qualitative risk information is shared between BHC business segments and senior management. Higher values of the index indicate better risk management.

The *RMI* is available to us at an annual frequency from the beginning of our sample period to 2013 and covers 20 of the 29 BHCs in our baseline sample. Since the RMI is available annually, to match the frequency of our other data, we assign a BHC's RMI value for a given year to all quarters in that year. We next estimate a model similar to Equation (1), which also includes an interaction between *Ln(N Patents)* and *RMI* along with a standalone *RMI* term. Table 9 presents the results.

[Insert Table 9 about here]

The coefficient estimate on *Ln(N Patents)* × *RMI* in Column (1) is negative and significant at the 5% level. Innovative BHCs with strong risk-management functions tend to incur less operational losses. Increasing *Ln(N Patents)* by one standard deviation and contemporaneously increasing *RMI* by one standard deviation (i.e., increasing the quality of BHC risk management) decreases *LtA* by 76.1% relative to its unconditional mean. Column (2) indicates the robustness of our results to discretizing *RMI* into a binary variable, *RMI (0/1)*, which is equal to 1 if *RMI* is greater than the sample median, 0 otherwise. The interaction *Ln(N Patents)* × *RMI (0/1)* retains a negative sign and is statistically significant at the 1% level. Overall, these findings suggest that strong risk management functions help BHC to reign in operational risks brought about by financial innovation.

IV.G. Global financial crisis

Financial innovation at banking organizations could be related to the build-up of significant operational risks (e.g., due to poorly understood and untested new innovation-driven products, processes, and technologies) that are later realized during periods of economic and financial stress

(Biais et al., 2015). Multiple banking organizations experienced large operational losses during the GFC, and notable differences existed across institutions (Abdymomunov and Mihov, 2019).

In this section, we investigate how innovation at banking organizations relates to these institutions' operational losses during the GFC period. We start by examining whether BHCs which innovated more prior to the crisis had larger operational losses during the crisis. To test this, we calculate *Ln(N Patents 2005-06)* as the log-transformed average number of patents that BHCs applied for over the period [2005:Q1-2006:Q4]. We then interact *Ln(N Patents 2005-06)* with *Financial Crisis 2007-09* (an indicator variable equal to 1 during the period [2007:Q4-2009:Q2], and 0 otherwise) and test the term's significance in a regression framework similar to Equation (1). While our specifications separately include *Ln(N Patents 2005-06)* and *Financial Crisis 2007-09*, the stand-alone coefficient of *Financial Crisis 2007-09* cannot be identified due to the inclusion of quarter fixed effects and is thus not reported. Table 10, Column (1) presents results.

[Insert Table 10 about here]

The coefficient of *Ln(N Patents 2005-06)* × *Financial Crisis 2007-09* is positive and significant at the 5% level. This finding suggests that higher innovation at banking organizations in the pre-crisis period subsequently contributed to larger operational losses during the GFC. Column (2) shows that our findings are also robust to a broader definition of the crisis period that spans [2007:Q4-2011:Q4]. Finally, Columns (3) and (4) show the more immediate impact of financial innovation during the crisis. Specifically, innovation during the crisis period served to amplify losses during the crisis period. Overall, these results suggest both a lagged and a contemporaneous adverse effect of financial innovation on operational losses during periods of financial turmoil.

V. Additional Analyses

This section presents additional analysis. Section V.A studies the lag structure of the financial innovation effect on operational losses. Section V.B checks the robustness of our baseline results to the inclusion of BHC fixed effects. Section V.C examines the effect of innovation on BHC market share and charter value.

V.A. Lag structure of effect

We use the quarterly averaged financial patent applications from quarter *t*-4 to *t*-1 as our main measure of BHC financial innovation. However, it is important to understand the relation between operational losses and innovation over longer time horizons. An important reason is that while there might be an initial positive impact of innovative activities on operational losses, there could be a reversal in that relationship as institutions get more experience with adopting new technologies and such technologies help them lower operational risks.

To that end, we first check whether our baseline results continue to hold if we measure financial innovation over longer periods. Table 11, Columns (1) and (2) show the operational loss impact of innovation measured over two-year and three-year horizons (instead of one-year) using regression specifications similar to Equation (1). In both cases, the innovation measures remain positively and significantly related to banking organization operational losses. There is a marginal decrease in the magnitude as the calculation horizon extends from one to three years.

[Insert Table 11 about here]

To get at the longer-term effect of financial innovation on operational losses more directly, we also zero in on the lagged effect of financial patent applications beyond the one-year period preceding an operational loss. Specifically, Table 11, Columns (3) and (4) test the effect of financial patent applications averaged over quarters [*t*-8, *t*-5] and [*t*-12, *t*-9], respectively, on operational losses incurred in quarter *t*. In both cases, the lagged innovation measures are positively related to future operational losses, although they are statistically weaker (e.g., insignificant at conventional levels in Column (3)). Finally, we perform a horse race among innovation measures of non-overlapping lags in Column (5). The effect of financial patent applications closest to the operational loss date dominates. Importantly, once we factor in the effect of the most recent patent applications (i.e., over quarters [*t*-4, *t*-1]), neither of the more distant measures (i.e., over quarters [*t*-8, *t*-5] and [*t*-12, *t*-9]) have significant predictive power over operational losses.

V.B. Group and BHC fixed effects

Our baseline specifications omit BHC fixed effects as we contend that average innovation intensity is informative about BHC operational risk profiles. In this section, we test whether our baseline results are robust to the inclusion of BHC fixed effects as well as broader BHC group fixed effects. We start with the latter first. Table 12 presents the results.

[Insert Table 12 about here]

In Column (1), we apply fixed effects for the five groups of stress tested BHCs outlined in Kazinnik et al. (2023).[13] In Column (2), we apply fixed effects for the four BHC categories used in the Federal Reserve's implementation of DFAST (e.g., Board of Governors of the Federal Reserve System, 2023).[14] Finally, in Column (3), we apply granular BHC fixed effects. Our baseline results are robust

[13] Kazinnik et al. (2023) classify BHCs in the following five groups. "Big 6" includes the four largest U.S. BHCs (Bank of America, Wells Fargo, Citigroup, and JPMorgan Chase) and two largest trading banks (Goldman Sachs and Morgan Stanley). "Trusts" includes custodian BHCs, which are principally involved in the trust business (Bank of New York Mellon, Northern Trust, and State Street). "Credit Cards" includes banks with credit cards as their primary line of business (American Express, Capital One, and Discover). "Regionals" includes large regional bank holding companies. "IHCs" includes intermediate holding companies for foreign banks with over $50 billion in U.S. non-branch / agency assets.
[14] The Federal Reserve classifies stress-tested banks in the following four categories. Category I includes U.S. global systemically important BHCs. Category II includes domestic and foreign BHCs with $700 billion or more in total assets or $75 billion or more in cross-jurisdictional activity. Category III includes domestic and foreign bank holding companies with $250 billion or more in total assets or $75 billion or more in weighted short-term wholesale funding, nonbank assets, or off-balance-sheet exposure. Category IV includes domestic and foreign bank holding companies with $100 billion or more in total assets that do not meet the requirements for every-year stress testing.

to the inclusion the BHC group and BHC fixed effects. *Ln(N Patents)* retains its positive coefficient and remains statistically significant at the 1% level across the three specifications.

V.C. BHC value and innovation

A unifying prediction of Schumpeterian models of growth is that firms grow through successful innovation – e.g., through acquiring new products and services or improving existing varieties. By contrast, innovation by competitors has a negative effect through, for example, "business stealing." Based on this premise, in this section, we examine the effect of financial innovation at banking organizations on market share and franchise value.

To study market share effects, we construct two variables. *Asset Share* is the ratio of a BHC's total assets to aggregate banking industry assets and *Deposit Share* is the ratio of a BHC's deposits to aggregate banking industry deposits. We test the relation of these two variables to *Ln(N Patents)* and report results in Table 13, Columns (1) and (2).

[Insert Table 13 about here]

Both *Asset Share* and *Deposit Share* are strongly positive related to *Ln(N Patents)* with coefficient estimates significant at least at the 5% level. Banking organizations with higher intensity of innovation tend to have higher market shares both in terms of assets and deposits.

Given such a positive impact on market shares, we next turn to explore if financial innovation increases BHCs' franchise values. *Market-to-Book* is the ratio of the market value of equity to the book value of equity and *Tobin's Q* is the ratio of market value of assets to book value of assets.[15] We proceed to test these two variables' relation to *Ln(N Patents)*.

[15] The market value of assets is estimated by the book value of assets minus the book value of equity and preferred stock plus the market value of equity and preferred stock.

Table 13, Columns (3) and (4) present the results. Across both specifications, while positive, the coefficient estimates of *Ln(N Patents)* are indistinguishable from zero. Financial innovation is not reliably related to BHC valuation metrics. In other words, the market share gains resulting from financial innovation do not translate into higher values for those BHCs engaging in innovative activities. Minding our findings in the previous sections, operational losses are one channel, which degrades the otherwise value-enhancing effect of financial innovation. This is consistent with prior research showing that operational losses translate into lower BHC equity market values as such losses can be large and may also convey negative information about a BHC's prospects (e.g., Cummins et al., 2006; Gillet et al., 2010; Curti et al., 2022).

These results also speak to the puzzle regarding the failure of banking organizations to maintain pace in financial innovation. Lerner et al. (2023) hint at factors such as the seeming decrease in relevant contemporaneous academic discoveries (e.g., Eaton and Kortum, 2002; Bloom et al., 2020), or the ability to identify and absorb them, and regulatory pressures after the GFC (Prieger, 2002; Buchak et al., 2018; Aghion et al., 2021). Our results suggest that increased operational risk externalities associated with financial innovation may be another reason for the slower pace of such activity at banking organizations.

VI. Conclusion

Despite the recent intense interest in financial innovation and its consequences, we know remarkably little about how such activity relates to banking organization risk. We particularly study the effects of new (patentable) financial technologies and business methods on a major but understudied source of financial losses in the banking industry – operational risk.

We identify operational risk as an important risk externality of financial innovation. We find that organizations that engage in more financial innovation suffer higher operational losses per dollar of assets and experience more tail risk events. Among different patent types, operational losses are reliably related to those with subject matters of payments, and commercial and retail banking. Among different operational loss types, "external fraud" and "failures in obligations to clients, faulty product design, and business practices" are particularly sensitive to financial innovation at banking organizations. The innovation-risk nexus is more pronounced for institutions that have weaker risk management and internal controls. We demonstrate that more innovation activity predicts worse operational losses during the global financial crisis.

We are careful in the interpretation of our findings. While our results may provide context for the risks that banking organizations face when innovating, they do not represent the only path in adopting innovative financial technologies. In fact, we do not find any evidence that financial innovation is value-destroying for banking organizations, but we do find evidence that innovative BHCs expand their market share. One way to interpret our findings is that with appropriate risk management and compliance guardrails that help curtail operational and other risks, responsible financial innovation presents an opportunity for banks to strengthen existing operations and bolster competitiveness.

We conclude by pointing out two limitations of our study. First, financial innovation within banking organizations can be a resource-intensive endeavor that may not bear short-term returns. In fact, it is possible that it may take several years for banks to realize gains from significant commitments to innovation. Our results should thus be interpreted mostly as short-term effects of financial innovation on operational losses at banking organizations. Second, our study focuses on the operational risk effects of in-house innovation at banking organizations. As such, we are unable to directly speak to innovation risks associated with third-party service providers, which banks increasingly depend on for their operational and technological infrastructures. The interconnectedness of the financial system, service provider concentrations, and the lack of substitutes for these services make these third parties critical. We leave answering these important questions to future research.

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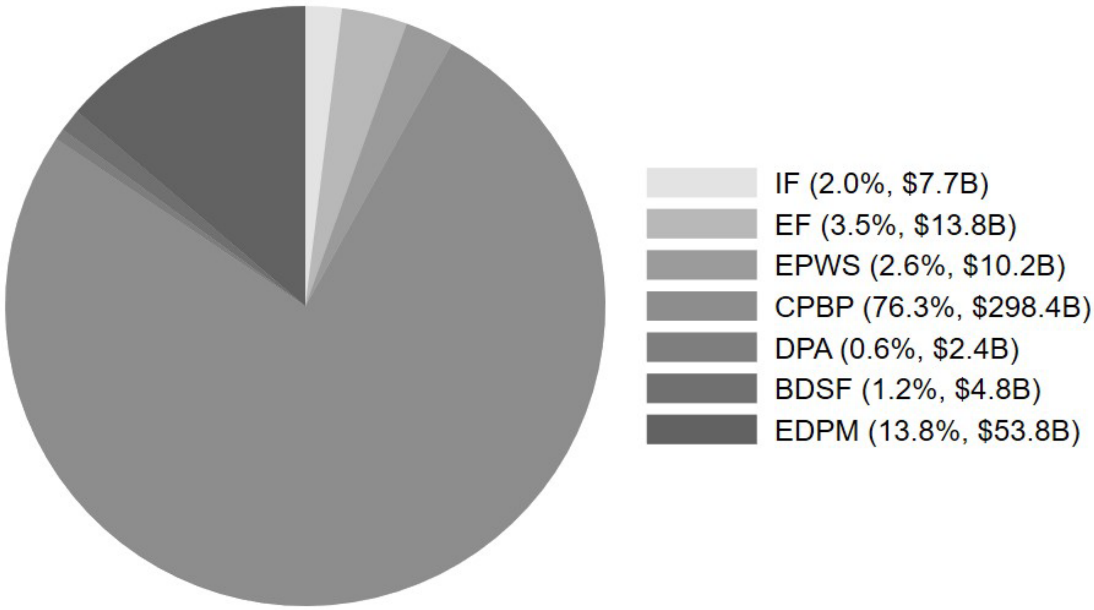

Figure 1. Operational Loss Types

This figure presents the percentage allocation of losses among the 7 operational risk event type categories. The nomenclature for event types is as follows: Internal Fraud (IF), External Fraud (EF), Employment Practices and Workplace Safety (EPWS), Clients, Products and Business Practices (CPBP), Damage to Physical Assets (DPA), Business Disruption and System Failures (BDSF), and Execution, Delivery and Process Management (EDPM). The sample comprises an unbalanced panel of 1,374 quarterly observations of 29 large U.S. bank holding companies over the period [2000:Q1-2018:Q4].

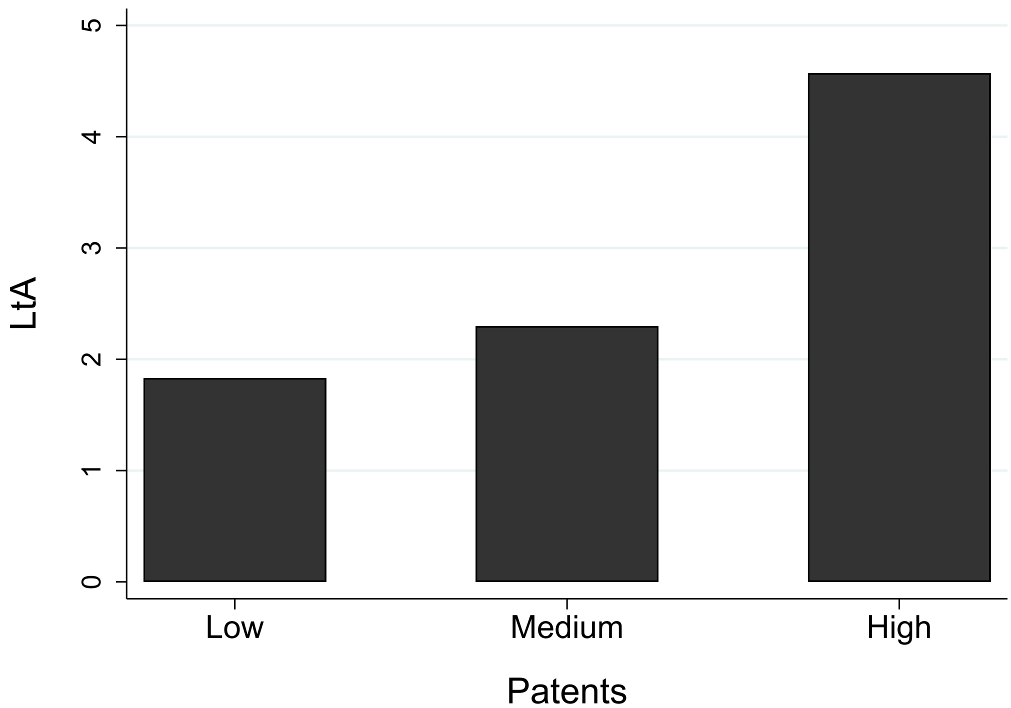

Figure 2. Operational Losses by Innovation Groups
This figure presents a bar chart of the average ratio of operational losses to total assets (multiplied by 10,000), *LtA*, for BHCs sorted in terciles based on the average quarterly number of patent applications they file ("Low," "Medium," and "High"). The chart presents the average *LtA* for each of the innovation groups. The sample comprises an unbalanced panel of 1,374 quarterly observations of 29 large U.S. bank holding companies over the period [2000:Q1-2018:Q4].

Table 1. Definitions

Panel A presents operational loss event type definitions. Panel B presents variable definitions.

Panel A: Event Type Definitions

Event type category	Short	Description
Internal Fraud	IF	Acts of a type intended to defraud, misappropriate property, or circumvent regulations, which involves at least one internal party
External Fraud	EF	Acts of a type intended to defraud, misappropriate property, or circumvent the law, by a third party
Employment Practices and Workplace Safety	EPWS	Acts inconsistent with employment, health or safety laws or agreements, from payment of personal injury claims, or from diversity / discrimination events
Clients, Products and Business Practices	CPBP	An unintentional or negligent failure to meet a professional obligation to specific clients, or from the nature or design of a product
Damage to Physical Assets	DPA	Damage to physical assets from natural disasters or other events
Business Disruption and System Failures	BDSF	Disruption of business or system failures
Execution, Delivery and Process Management	EDPM	Failed transaction processing or process management, from relations with trade counterparties and vendors

Table 1 (continued)

Panel B: Variable Definitions	
Variable	Definition
Operational Risk Variables	
Avg Sev	The average severity of operational losses that occur at a BHC over a given calendar quarter in millions of U.S. Dollars
Loss	Operational losses that occur at a BHC over a given calendar quarter in millions of U.S. Dollars
LtA	Operational losses that occur at a BHC over a given calendar quarter as a proportion of the BHC's lagged total assets, multiplied by 10,000
LtA Tail (90, 95, 99)	Tail operational losses at the 99th, 95th or 99th percentile, respectively, that occur at a BHC over a given calendar quarter as a proportion of the BHC's lagged total assets, multiplied by 10,000
N Evts	The frequency of total assets-scaled tail operational losses that occur at a BHC over a given calendar quarter
N Evts Tail (90, 95, 99)	The frequency of total assets-scaled tail operational losses at the 90th, 95th or 99th percentile, respectively, that occur at a BHC over a given calendar quarter
Innovation Variables	
N C&R Banking Patents	The number of successful patent applications by a BHC in commercial and retail banking, quarterly aggregated and averaged from quarter *t*-3 to *t*.
N Communications Patents	The number of successful patent applications by a BHC in communications, quarterly aggregated and averaged from quarter *t*-3 to *t*.
N Other Patents	The number of successful communications patent applications by a BHC in accounting, crypto, currency, insurance, real estate, and wealth management, quarterly aggregated and averaged from quarter *t*-3 to *t*.
N Patents	The number of successful patent applications by a BHC, quarterly aggregated and averaged from quarter *t*-3 to *t*.
N Patents 2005-06	The number of successful patent applications by a BHC over the period [2005:Q1-2006:Q4]
N Payments Patents	The number of successful patent applications by a BHC in payments, quarterly aggregated and averaged from quarter *t*-3 to *t*.
N Security Patents	The number of successful patent applications by a BHC in security, quarterly aggregated and averaged from quarter *t*-3 to *t*.

Table 1 Panel B (continued)

Other Variables	
Asset Share	The ratio of a BHC's total assets to aggregated banking industry total assets
Deposit Share	The ratio of a BHC's deposits to aggregated banking industry deposits
Deposits-to-Assets	The ratio of BHC deposits to total assets
Financial Crisis (2007-09, 2007-11)	*Financial Crisis 2007-09* is an indicator variable that equals 1 during the period [2007:Q4-2009:Q2], and 0 otherwise. *Financial Crisis 2007-11* is an indicator variable that equals 1 during the period [2007:Q4-2011:Q4], and 0 otherwise
Leverage	The ratio of BHC total assets to book value of equity
Loan Losses	BHC loan charge-off rate
Loans-to-Assets	The ratio of BHC loans to total assets
Market-to-Book	The ratio of the market value of equity to the book value of equity
Maturity Gap	A natural log transformation of the absolute difference between all assets that either reprice or mature within a year and all the liabilities that reprice or mature within a year
MVE	BHC market value of equity in billions of U.S. Dollars
Neighbor States HSET Businesses	The percentage of "high science, engineering, and technology" business establishments in neighboring states of the BHC headquarters state
NII-to-II	The ratio of BHC interest income to non-interest income
ROE	BHC return on equity, define as the ratio of net income to book value of equity
RMI (0/1)	RMI is the risk-management index developed by Ellul and Yerramilli (2013). RMI (0/1) is an indicator variable equal to 1 if RMI is greater than the sample median, and 0 otherwise
Total Assets (TA)	BHC total assets in billions of U.S. Dollars
Tobin's Q	The market value of assets divided by the book value of assets, where the market value is estimated by the book value of assets minus the book value of equity and preferred stock plus the market value of equity and preferred stock
Variable Transformation	
Ln(.)	A natural log transformation operator applied to a variable. For example, *Ln(TA)* is a natural log transformation of *Total Assets*

Table 2. Variable Descriptive Statistics and Correlation

This table presents variable descriptive statistics in Panel A and variable correlations in Panel B. The definitions of all variables are reported in Table 1 Panel B. The sample comprises an unbalanced panel of 1,374 quarterly observations of 29 large U.S. bank holding companies over the period [2000:Q1-2018:Q4].

Panel A: Descriptive Statistics

	Mean	SD	P10	P50	P90	N
Operational Risk Variables						
Loss ($M)	235.22	1375.31	2.14	18.61	372.56	1,374
LtA (×10,000)	3.14	9.55	0.26	1.01	5.71	1,374
Ln(Loss)	3.33	2.06	0.86	3.07	6.06	1,374
N Evts	294.64	450.39	21.00	87.00	950.00	1,374
Avg Sev ($M)	0.77	3.23	0.08	0.20	1.19	1,374
N Evts Tail 90	25.05	21.47	9.00	20.00	46.00	1,374
N Evts Tail 95	12.67	10.73	4.00	10.00	23.00	1,374
N Evts Tail 99	2.55	2.73	0.00	2.00	6.00	1,374
LtA Tail 90	2.92	9.51	0.18	0.81	5.19	1,374
LtA Tail 95	2.83	9.50	0.13	0.71	5.08	1,374
LtA Tail 99	2.57	9.47	0.00	0.45	4.75	1,374
Measures of Innovation and Other Variables						
N Patents	1.24	3.18	0.00	0.00	3.75	1,374
Ln(N Patents)	0.42	0.72	0.00	0.00	1.56	1,374
Total Assets (TA) ($B)	483.45	667.85	54.98	156.97	1,822.07	1,374
Ln(TA)	5.38	1.22	4.01	5.06	7.51	1,374
NII-to-II	1.04	1.04	0.27	0.62	2.85	1,374
Deposits-to-Assets	0.60	0.18	0.35	0.66	0.78	1,374
Loans-to-Assets	0.52	0.22	0.13	0.62	0.74	1,374
ROE	0.02	0.03	0.01	0.02	0.04	1,374
Leverage	0.88	0.05	0.84	0.88	0.93	1,374
Maturity Gap	17.84	1.36	16.30	17.68	19.93	1,374
Loan Losses	0.29	0.35	0.01	0.15	0.73	1,374
RMI	0.97	0.25	0.62	1.00	1.29	1,107
Neighbor States HSET Businesses	8.16	0.96	6.81	8.26	9.39	1,309

Panel B: Correlations

	Ln(N Patents)	LtA	Ln(Loss)	N Evts	Ln(Avg Sev)	N Evts Tail 90	N Evts Tail 95	N Evts Tail 99	LtA Tail 90	LtA Tail 95	LtA Tail 99
Ln(N Patents)	1										
LtA	0.199***	1									
Ln(Loss)	0.604***	0.453***	1								
N Evts	0.698***	0.208***	0.688***	1							
Ln(Avg Sev)	0.249***	0.579***	0.730***	0.201***	1						
N Evts Tail 90	0.242***	0.152***	0.367***	0.323***	0.113***	1					
N Evts Tail 95	0.302***	0.186***	0.410***	0.316***	0.210***	0.920***	1				
N Evts Tail 99	0.383***	0.271***	0.506***	0.282***	0.454***	0.555***	0.709***	1			
LtA Tail 90	0.237***	0.867***	0.446***	0.222***	0.562***	0.107***	0.148***	0.249***	1		
LtA Tail 95	0.235***	0.868***	0.443***	0.220***	0.562***	0.0997***	0.143***	0.247***	1.000***	1	
LtA Tail 99	0.228***	0.870***	0.436***	0.213***	0.560***	0.0850**	0.126***	0.239***	0.999***	1.000***	1

Table 3. Financial Patenting

The table presents financial patenting information across industries and subperiods. The sample is based on Lerner et al. (2023) and includes 24,255 financial patents that were applied for over the period [2000-2018]. The industry classification uses the Global Industry Classification Standard as applied to the industry of the patent assignee. Slight modifications are made to the industry classifications to ensure comparability of the patent data. The table also splits out the patents assigned to the BHCs in our sample, which are otherwise included in the Banking & Financial Services industry category. Panel A shows the number of patents across different industries for three subperiods (2000-2006, 2007-2011, and 2012-2018) and in total. Panel B presents the distribution of patents across types according to their functions in financial services (accounting, investment banking, commercial banking, communications, payments, crypto, currency, insurance, real estate, retail banking, security, and wealth management).

Panel A: Financial Patents Across Industries and Subperiods

Industry	(1) 2000-2006	(2) 2007-2011	(3) 2012-2018	(4) Total (N)	(5) Total (%)
Banking & Financial Services	1,276	1,596	1,072	3,944	16.3%
In-sample BHCs	560	813	769	2,142	8.8%
Insurance	150	469	506	1,125	4.6%
Software & IT Services	2,083	2,257	2,532	6,872	28.3%
Tech Hardware & Semicond.	1,198	843	809	2,850	11.8%
Other	1,141	982	1,121	3,244	13.4%
Missing Classification	2,224	2,183	1,813	6,220	25.6%
All Industries	8,072	8,330	7,853	24,255	100%

Panel B: Financial Patent Types

Patent Types	All Industries	Banking & Financial Services	In-sample BHCs
Accounting	4.2%	3.6%	3.2%
Commercial and retail banking	11.1%	12.5%	15.0%
Communications	13.9%	8.3%	8.2%
Payments	37.3%	36.8%	44.5%
Cryptocurrency	1.2%	0.8%	1.3%
Currency	0.6%	1.4%	0.8%
Insurance	1.3%	0.3%	0.3%
Investment banking	7.9%	15.9%	6.2%
Real estate	1.3%	2.9%	1.8%
Security	19.8%	14.5%	17.0%
Wealth management	1.4%	3.1%	1.7%
All Types	100%	100%	100%

Table 4. Operational Losses and Financial Innovation

This table reports coefficients from panel regressions of operational losses on a patents-based measure of innovation and control variables. Columns (1), (2), and (4) are estimated via Ordinary Least Squares regression with quarter fixed effects. The error terms are clustered at the BHC and quarter levels. Column (3) is estimated via Negative Binomial regression with quarter fixed effects. The definitions of all variables are reported in Table 1 Panel B. All specifications include quarter fixed effects. The error terms are clustered at the BHC and quarter levels. *p*-values are presented in parentheses. ***, **, and * indicate *p*<0.01, *p*<0.05, and *p*<0.1, respectively.

	(1)	(2)	(3)	(4)
	LtA	Ln(Loss)	N Evts	Ln(Avg Sev)
Ln(N Patents)	1.985***	0.323**	0.268***	0.089
	(0.001)	(0.012)	(0.000)	(0.145)
Ln(TA)	0.610*	1.345***	1.115***	0.228***
	(0.054)	(0.000)	(0.000)	(0.001)
NII-to-II	0.200	0.262**	0.263***	0.000
	(0.513)	(0.018)	(0.000)	(0.999)
Deposits-to-Assets	-0.838	0.231	1.210***	-1.005***
	(0.284)	(0.444)	(0.000)	(0.001)
Loans-to-Assets	-0.231	0.441	1.044***	-0.677**
	(0.916)	(0.418)	(0.000)	(0.017)
ROE	4.018	3.674***	3.352***	-0.394
	(0.436)	(0.003)	(0.002)	(0.578)
Leverage	-8.269	-1.603*	-2.067***	0.390
	(0.326)	(0.086)	(0.000)	(0.446)
Maturity Gap	-0.099	-0.039	-0.040	-0.046
	(0.795)	(0.762)	(0.197)	(0.310)
Loan Losses	-1.369**	0.156	0.598***	-0.384***
	(0.017)	(0.396)	(0.000)	(0.001)
Observations	1,374	1,374	1,374	1,374
Adjusted R^2	0.146	0.712		0.282

Table 5. Instrumental Variables

This table reports results of an instrumental variable regression of operational losses on a patents-based measure of innovation and control variables. Coefficients in Column (1) are estimated from a panel regression of BHC innovation on the instrumental variable, *Neighbor State HSET Businesses*, and controls. Coefficients in Column (2) are estimated from a panel regression of operational losses on instrumented BHC innovation and control variables. Control variables (*Ln(TA)*, *NII-to-II*, *Deposits-to-Assets*, *Loans-to-Assets*, *ROE*, *Leverage*, *Maturity Gap*, and *Loan Losses*) are included, but their coefficient estimates are omitted for brevity. The definitions of all variables are reported in Table 1 Panel B. All specifications include quarter fixed effects. The error terms are clustered at the BHC and quarter levels. *p*-values are presented in parentheses. ***, **, and * indicate $p<0.01$, $p<0.05$, and $p<0.1$, respectively.

	(1)	(2)
	Ln(N Patents)	LtA
Neighbor States HSET Business	1.236***	
	(0.006)	
Ln(N Patents)		2.746**
		(0.034)
Controls	Yes	Yes
Observations	1,080	1,080
Adjusted R^2	0.593	0.044

Table 6. Financial Patent Types

This table reports coefficients from panel regressions of operational losses on a patents-based measure of innovation and control variables. Commercial banking and retail banking are grouped together as C&R banking. Accounting, crypto, currency, insurance, real estate, and wealth management are grouped together as "Other." Appendix A presents the key words for patent type determination. Control variables (*Ln(TA)*, *NII-to-II*, *Deposits-to-Assets*, *Loans-to-Assets*, *ROE*, *Leverage*, *Maturity Gap*, and *Loan Losses*) are included, but their coefficient estimates are omitted for brevity. The definitions of all variables are reported in Table 1 Panel B. All specifications include quarter fixed effects. The error terms are clustered at the BHC and quarter levels. *p*-values are presented in parentheses. ***, **, and * indicate $p<0.01$, $p<0.05$, and $p<0.1$, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	LtA	LtA	LtA	LtA	LtA	LtA
Ln(N Payments Patents)	2.780***					
	(0.000)					
Ln(N Security Patents)		3.764**				
		(0.011)				
Ln(N Communications Patents)			1.629			
			(0.375)			
Ln(N C&R Banking Patents)				4.159***		
				(0.005)		
Ln(N Investment Banking Patents)					2.944	
					(0.297)	
Ln(N Other Patents)						5.015**
						(0.011)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,374	1,374	1,374	1,374	1,374	1,374
Adjusted R^2	0.147	0.144	0.136	0.144	0.137	0.143

Table 7. Operational Loss Types

This table reports coefficients from panel regressions of operational losses on a patents-based measure of innovation and control variables. Operational losses are categorized into seven categories: Internal Fraud (IF), External Fraud (EF), Employment Practices and Workplace Safety (EPWS), Clients, Products and Business Practices (CPBP), Damage to Physical Assets (DPA), Business Disruption and System Failures (BDSF), and Execution, Delivery and Process Management (EDPM). Control variables (*Ln(TA)*, *NII-to-II*, *Deposits-to-Assets*, *Loans-to-Assets*, *ROE*, *Leverage*, *Maturity Gap*, and *Loan Losses*) are included, but their coefficient estimates are omitted for brevity. The definitions of operational loss event types are presented in Table 1 Panel A. The definitions of all variables are reported in Table 1 Panel B. All specifications include quarter fixed effects. The error terms are clustered at the BHC and quarter levels. *p*-values are presented in parentheses. ***, **, and * indicate $p<0.01$, $p<0.05$, and $p<0.1$, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	IF	EF	EPWS	CPBP	DPA	BDSF	EDPM
Ln(N Patents)	-0.086	0.186*	0.016	1.649***	-0.005	0.012	0.213
	(0.159)	(0.058)	(0.255)	(0.010)	(0.795)	(0.787)	(0.127)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,374	1,374	1,374	1,374	1,374	1,374	1,374
Adjusted R^2	0.048	0.203	0.163	0.142	0.196	0.059	0.088

Table 8. Tail Operational Losses

This table reports coefficients from panel regressions of tail operational losses on a patents-based measure of innovation and control variables. Columns (1)-(3) are estimated via Negative Binomial regression and Columns (4)-(6) are estimated via Ordinary Least Square regression. Control variables (*Ln(TA)*, *NII-to-II*, *Deposits-to-Assets*, *Loans-to-Assets*, *ROE*, *Leverage*, *Maturity Gap*, and *Loan Losses*) are included, but their coefficient estimates are omitted for brevity. The definitions of all variables are reported in Table 1 Panel B. All specifications include quarter fixed effects. The error terms are clustered at the BHC and quarter levels. *p*-values are presented in parentheses. ***, **, and * indicate $p<0.01$, $p<0.05$, and $p<0.1$, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	N Evts Tail 90	N Evts Tail 95	N Evts Tail 99	LtA Tail 90	LtA Tail 95	LtA Tail 99
Ln(N Patents)	0.144***	0.206***	0.328***	1.922***	1.914***	1.825***
	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.002)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,374	1,374	1,374	1,374	1,374	1,374
Adjusted R^2				0.141	0.140	0.137

Table 9. Risk Management Quality

This table reports coefficients from panel regressions of operational losses on patents-based measures of innovation, measures of risk management quality, their interactions and control variables. Control variables (*Ln(TA)*, *NII-to-II*, *Deposits-to-Assets*, *Loans-to-Assets*, *ROE*, *Leverage*, *Maturity Gap*, and *Loan Losses*) are included, but their coefficient estimates are omitted for brevity. The definitions of all variables are reported in Table 1 Panel B. All specifications include quarter fixed effects. The error terms are clustered at the BHC and quarter levels. *p*-values are presented in parentheses. ***, **, and * indicate p<0.01, p<0.05, and p<0.1, respectively.

	(1)	(2)
	LtA	LtA
Ln(N Patents)	15.191***	4.464***
	(0.006)	(0.004)
Ln(N Patents) × RMI	-13.277**	
	(0.011)	
RMI	1.255	
	(0.496)	
Ln(N Patents) × RMI (0/1)		-4.174***
		(0.007)
RMI (0/1)		-0.387
		(0.530)
Controls	Yes	Yes
Observations	797	797
Adjusted R^2	0.194	0.189

Table 10. Global Financial Crisis

This table reports coefficients from panel regressions of operational losses on patents-based measures of innovation, their interactions with global financial crisis indicators and control variables. Control variables (*Ln(TA)*, *NII-to-II*, *Deposits-to-Assets*, *Loans-to-Assets*, *ROE*, *Leverage*, *Maturity Gap*, and *Loan Losses*) are included, but their coefficient estimates are omitted for brevity. Columns (1) and (2) also control for *N Patents 2005-06*. The definitions of all variables are reported in Table 1 Panel B. All specifications include quarter fixed effects. The error terms are clustered at the BHC and quarter levels. *p*-values are presented in parentheses. ***, **, and * indicate $p<0.01$, $p<0.05$, and $p<0.1$, respectively.

	(1) LtA	(2) LtA	(3) LtA	(4) LtA
Ln(N Patents)	1.399***	1.484***	0.997**	1.019**
	(0.004)	(0.003)	(0.028)	(0.028)
Ln(N Patents 2005-06) × Financial Crisis 2007-09	9.588**			
	(0.040)			
Ln(N Patents 2005-06) × Financial Crisis 2007-11		5.589*		
		(0.078)		
Ln(N Patents) × Financial Crisis 2007-09			10.128**	
			(0.012)	
Ln(N Patents) × Financial Crisis 2007-11				6.365**
				(0.018)
Controls	Yes	Yes	Yes	Yes
Observations	1,374	1,374	1,374	1,374
Adjusted R^2	0.177	0.161	0.199	0.176

Table 11. Lag Structure

This table reports coefficients from panel regressions of operational losses on patents-based measures of innovation and control variables. Control variables (*Ln(TA)*, *NII-to-II*, *Deposits-to-Assets*, *Loans-to-Assets*, *ROE*, *Leverage*, *Maturity Gap*, and *Loan Losses*) are included, but their coefficient estimates are omitted for brevity. The definitions of all variables are reported in Table 1 Panel B. All specifications include quarter fixed effects. The error terms are clustered at the BHC and quarter levels. *p*-values are presented in parentheses. ***, **, and * indicate $p<0.01$, $p<0.05$, and $p<0.1$, respectively.

	(1) LtA	(2) LtA	(3) LtA	(4) LtA	(5) LtA
Ln(N Patents [t-4, t-1])					4.646**
					(0.047)
Ln(N Patents [t-8, t-1])	1.606***				
	(0.001)				
Ln(N Patents [t-12, t-1])		1.507***			
		(0.003)			
Ln(N Patents [t-8, t-5])			0.597		-3.320
			(0.364)		(0.176)
Ln(N Patents [t-12, t-9])				0.926*	0.202
				(0.082)	(0.711)
Controls	Yes	Yes	Yes	Yes	Yes
Observations	1,355	1,333	1,355	1,333	1,333
Adj R^2	0.141	0.122	0.136	0.118	0.139

Table 12. Group and BHC Fixed Effects

This table reports coefficients from panel regressions of operational losses on a patents-based measure of innovation and control variables. Control variables (*Ln(TA)*, *NII-to-II*, *Deposits-to-Assets*, *Loans-to-Assets*, *ROE*, *Leverage*, *Maturity Gap*, and *Loan Losses*) are included, but their coefficient estimates are omitted for brevity. All specifications include quarter fixed effects. Column (1) includes fixed effects for the five groups of stress tested BHCs outlined in Kazinnik et al. (2023). Column (2) includes fixed effects for the four BHC categories used in the Federal Reserve's implementation of DFAST (e.g., Board of Governors of the Federal Reserve System, 2023). Column (3) includes bank fixed effects. The error terms are clustered at the BHC and quarter levels. *p*-values are presented in parentheses. ***, **, and * indicate $p<0.01$, $p<0.05$, and $p<0.1$, respectively.

	(1)	(2)	(3)
	LtA	LtA	LtA
Ln(N Patents)	1.802***	1.974***	1.836***
	(0.001)	(0.001)	(0.000)
Controls	Yes	Yes	Yes
Quarter Fixed Effects	Yes	Yes	Yes
5-Group Fixed Effects	Yes	No	No
4-Group Fixed Effects	No	Yes	No
Bank Fixed Effects	No	No	Yes
Observations	1,374	1,374	1,374
Adjusted R^2	0.147	0.147	0.162

Table 13. Charter Value and Financial Innovation

This table reports coefficients from panel regressions of market share and charter value measures on a patents-based measure of innovation and control variables. Control variables include *Ln(TA)*, *NII-to-II*, *Deposits-to-Assets*, *Loans-to-Assets*, *ROE*, *Leverage*, *Maturity Gap*, and *Loan Losses*. The definitions of all variables are reported in Table 1 Panel B. All specifications include quarter fixed effects. The error terms are clustered at the BHC and quarter levels. *p*-values are presented in parentheses. ***, **, and * indicate p<0.01, p<0.05, and p<0.1, respectively.

	(1)	(2)	(3)	(4)
	Asset Share	Deposit Share	Market-to-Book	Tobin's Q
Ln(N Patents)	0.009**	0.012***	0.721	0.019
	(0.017)	(0.002)	(0.130)	(0.249)
Ln(TA)	0.024***	0.026***	-1.787**	-0.017
	(0.000)	(0.000)	(0.034)	(0.197)
NII-to-II	-0.010***	-0.008***	-0.802	0.033
	(0.000)	(0.003)	(0.327)	(0.120)
Deposits-to-Assets	-0.016	0.038	-0.838	-0.040
	(0.213)	(0.102)	(0.734)	(0.444)
Loans-to-Assets	-0.023*	-0.009	-7.204	0.078
	(0.093)	(0.505)	(0.146)	(0.431)
ROE	-0.024	0.005	6.386	0.908***
	(0.468)	(0.896)	(0.326)	(0.005)
Leverage	0.019	-0.027	19.639*	0.157*
	(0.274)	(0.145)	(0.099)	(0.096)
Maturity Gap	0.001	-0.001	0.460	-0.005
	(0.710)	(0.727)	(0.144)	(0.501)
Loan Losses	-0.001	-0.001	0.986	0.037*
	(0.934)	(0.949)	(0.272)	(0.088)
Observations	1,374	1,374	1,374	1,373
Adjusted R^2	0.880	0.852	0.087	0.523

Appendix A: List of Key Words in Patent Type Determination

Accounting: accounting, accounts payable, accounts receivable, audit, auditor, bookkeeper, budget, budgeting, cash flow, controller, FIFO, financial controls, first in first out, forecasting, free cash flows, GAAP, Generally Accepted Accounting Principles, gross margin, information system, interest coverage, inventory, last in first out, LIFO, net present value, net working capital, payable, payback, payroll taxes, quick ratio, working capital

Consumer banking: bridge finance, commercial loan, covenant, debtor finance, debtor in possession, default, event, indicator lending rate, interest coverage, letter of credit, line of credit, material adverse change, sweep account, term loan, zero balance account

Communications: broadcast, broadcasts, communication, communications, message, news feed, news feeds

Cryptocurrencies: altcoin, Bitcoin, blockchain, cryptocurrency, distributed ledger, initial coin offering, token

Currency: currency conversion, exchange rate, foreign exchange, forex, swap

Funds: ETF, exchange traded fund, hedge fund, mutual fund, private equity, venture capital

Investment banking: asset analysis, asset characterization, bid ask, bond, call option, Chinese wall, derivative, dummy order, gilt, haircut, hidden liquidity, initial public offering, liquidity pool, liquidity provider, margin, moving average, option, order book, price level, put option, short selling, trading protocol, valuation

Insurance: actuarial, auto insurance, beneficiary, catastrophe bond, catastrophe loss, claims adjustment, coinsurance, crash, disability, driving behavior, driving environment, earned premium, home insurance, homeowners insurance, indemnity, insurance risk, life insurance, life settlement, long-term care, malpractice, reinsurance, structured settlement, term insurance, umbrella liability, vehicle damage

Passive funds: index fund, passive fund

Payments: authorized, card reader, cash register, contactless, credit transaction, customer, debit transaction, interbank fee, keypad, kiosk, merchant, NFC, payment, point of sale, POS

Real estate: appraisal, cap rate, closing costs, closing fee, conforming loan, cumulative loan to value, deed, delinquency, dual agency, easement, eminent domain, escrow, eviction, foreclosure, home equity, home warranty, jumbo loan, loan to value, mortgage, non-conforming loan, prepayment, real estate investment trust, realtor, refinancing, REIT, tax lien, title search, zoning

Retail banking: ATM, automatic teller machine, availability policy, balance transfer, certificate of deposit, check, checking, credit score, direct deposit, direct payroll deposit, interbank fee, money market, NOW account, online banking, overdraft, passbook, savings, student loan, time deposit, withdrawal fee

Security: authentic, authenticate, authenticating, biometric, cipher, ciphers, credential, cryptographic, decipher, decrypt, decryption, detection, encrypt, encryption, fraud, fraudulent, identifier, identity, public key, secure key, security, spoofing, symmetric key, theft, token, verify

Wealth management: active management, asset allocation, asset class, back-end load, benchmark, capital appreciation, capital preservation, custodian, financial industry regulatory authority, FINRA, front-end load, individual retirement account, prospecti, prospectus, target date fund, tax avoidance, tax benefit, tax cost, tax deduction, wrap fee