Catch the Thief!
Fraud in the U.S. Banking Industry[☆]

Filippo Curti[a], Atanas Mihov[a,*]

[a]*Federal Reserve Bank of Richmond, Quantitative Supervision & Research, 530 East Trade Street, Charlotte, NC 28202, USA*

October 29, 2019

Abstract

Little is known about fraud in the financial services sector. Using a rich supervisory dataset, this study dissects fraud at large U.S. banking organizations. We examine the different categories of fraud and their materiality, the recovery from fraud, the time from fraud occurrence to fraud discovery and accounting. We quantify exposure to fraud and study the determinants of fraud at the banking organization level. Lastly, we document a significant effect of fraud on bank credit intermediation. Overall, our analysis provides new, detailed evidence on fraud in the U.S. financial services industry, and its costs and consequences.

Keywords: Banking; Bank Holding Companies; Fraud; Operational Risk; Credit Intermediation

JEL Classification: G21, G28, G29

[☆]We thank Azamat Abdymomunov, Gara Afonso, Mehdi Beyhaghi, Bob DeYoung, Patrick de Fontnouvelle, Scott Frame, Jeff Gerlach, John Graham, Leming Lin, Elena Loutskina, João Santos, Phil Strahan, Kevin Tseng, Mihail Velikov, Andy Winton and seminar and conference participants at the University of Kansas, the 2019 American Bankers Association Risk Quantification Forum for helpful comments and suggestions. We thank David Cox and Cooper Killen for excellent research assistance. All remaining errors are those of the authors alone. The views expressed in this paper do not necessarily reflect the position of the Federal Reserve Bank of Richmond or the Federal Reserve System.

[*]Corresponding author. Tel.:+1(704)358-2464; fax:+1(704)358-2556.

Email addresses: `filippo.curti@rich.frb.org` (Filippo Curti), `atanas.mihov@rich.frb.org` (Atanas Mihov)

1. Introduction

A number of major fraud cases have rattled prominent banking institutions in the United States over recent years. For example, the investment arms of several large banks (e.g., HSBC, Santander, Royal Bank of Scotland, BNP Paribas and BBVA) lost billions of dollars to Bernard Madoff's Ponzi scheme discovered during the 2008 financial crisis.[1] In a different case, JPMorgan Chase lost more than $6 billion in 2012 amid a rogue trading scandal, in which a group of traders defrauded the bank by taking unauthorized positions in complex derivative securities that went wrong.[2]

Although fraud in the financial services industry is widely discussed and fundamentally important, it remains poorly understood. Much of the commentary on fraud, which financial companies are exposed to, is based on supposition or anecdotal evidence. The primary reason is the dearth of publicly available data. As a result, even the most basic questions remain unanswered: How big is fraud and what is the monetary cost to institutions in the financial services industry? What are the leading types of fraud and the company business lines that are most exposed to losses from fraud? How much is usually recovered? How quickly is fraud discovered? Which banks experience more fraud? Does fraud affect banks' credit intermediation functions? In this paper, we answer these questions using comprehensive supervisory data on fraud from 2000:Q1 to 2016:Q4 reported by large U.S. bank holding companies (BHCs) to the Federal Reserve System (FRS) for stress-testing purposes as mandated by the Dodd-Frank Wall Street Reform and Consumer Protection Act.

We find that exposure to fraud can be significant for banking organizations. Our estimates from a Value-at-Risk (VaR) model suggest that a BHC with assets of $500

---

[1] See *Wall Street Journal*: "Top Broker Accused of $50 Billion Fraud" (A. Efrati, T. Lauricella, D. Searcey, December 12, 2008).

[2] See *Wall Street Journal*: "J.P. Morgan Faces a Hard-Line SEC" (R. Sidel, S. Patterson, J. Eaglesham, September 19, 2013).

billion can expect to lose to fraud \$14.5 million in a "typical" calendar quarter and as much as \$334.6 million in a single calendar quarter once every 25 years. Around 90% of fraud losses are to external third parties and only 10% involve bank employees or other internal parties. The two largest business lines generating fraud losses are Retail Banking and Trading & Sales, which account for 51.2% and 15.4% of losses, respectively.[3] Little is recovered from fraud – only 4.9% on average. Additionally, when fraud occurs it is quickly discovered. It takes an average of 17 days from the occurrence to the discovery of a fraud event. Once the fraud event is discovered, it takes 46 days to be accounted and reflected on a bank's financial statements.

We document significant variation in fraud event severity, recovery, and time to discovery and accounting. Specifically, we find that internal fraud events are for larger amounts than external events. Fraud events in Asset Management are particularly severe. The longer it takes for fraud to be discovered, the higher the severity of fraud. Fraud events for lower amounts have lower recoveries. So do fraud events in Trading & Sales and Agency Services. Internal fraud takes longer to be discovered than external fraud. Fraud in Corporate Finance takes the longest to be discovered and accounted.

We next investigate the relation between fraud and various bank-level attributes. We find that larger banks, less efficient banks, banks that use deposits as a funding source and banks that operate in areas with high crime lose more to fraud. We also provide some evidence that fraud at financial institutions is related to the business cycle. Specifically, fraud tends to be pro-cyclical in nature, whereby banks lose more to fraud during economic booms compared to economic downturns.

[3]There are a total of nine BHC business lines as defined in Federal Reserve System (2017): Corporate Finance (CF), Trading & Sales (TS), Retail Banking (RB), Commercial Banking (CB), Payment & Settlement (PS), Agency Services (AS), Asset Management (AM), Retail Brokerage (RK), and Corporate Level Non-Business Line Specific (CO).

Lastly and most importantly, we also present evidence that fraud has consequences for credit intermediation at banking organizations. Specifically, deposit and loan growth decrease following quarters with abnormally high fraud. When fraud occurs in banking business lines, the magnitude of the associations is higher vis-à-vis when fraud occurs in other business lines. We additionally document that the relation between abnormal fraud and deposit growth is more pronounced when banks affected by fraud operate in more competitive markets, have less local branch representation, pay lower interest rates on their liabilities (e.g., deposits) as well as during banking sector distress (e.g., during the 2008 global financial crisis). The associations for loan growth are more pronounced when banks have less capital and hold less liquidity. Overall, these findings suggests that fraud not only imposes monetary costs to financial institutions, but also hinders their credit intermediation functions through deposit funding and lending channels.

Overall, our study presents some of the first empirical evidence on the costs, determinants, and consequences of fraud committed *against* companies in the financial services industry. We thus contribute to the large literature on financial fraud, which has so far almost exclusively focused on large-scale corporate fraud committed by insiders (e.g., Beasley (1996), Efendi et al. (2007), Dyck et al. (2010)) or on fraud committed by financial advisers and wealth managers (e.g., Dimmock and Gerken (2012), Egan et al. (2018)). In contrast, we dissect fraud incurred by banking organizations, providing rich, detailed evidence across a number of important dimensions. Our research is important for better understanding operational risk at financial institutions (e.g., Chernobai et al. (2012)), specifically the cost operational risk imposes and its effects on credit intermediation. Our findings suggest that fraud has important implications for firms in the financial services industry that can ultimately even affect the real economy in the extreme (e.g., through a combination of bank credit rationing and financial market frictions).

By quantifying fraud and documenting the determinants of fraud at the banking organization level, our findings could moreover inform regulatory policy and risk evaluation from a supervisory perspective. For example, the U.S. Office of the Comptroller of the Currency (OCC) recently formed a working group dedicated to understanding and tackling fraud in the banking industry, and is reviewing its guidance to bank examiners on assessing the adequacy of fraud detection and prevention frameworks.[4] This initiative comes amidst a broader inter-agency regulatory interest in financial fraud and a push for implementing better safeguards against fraud at financial institutions, including proposed rule making for new cyber-security and fraud regulations for large and interconnected financial institutions.[5]

The rest of this paper is organized as follows. Section 2 discusses prior research and this study's contribution to the literature. Sections 3, 4 and 5 describe our data and present our empirical results. Section 6 concludes.

2. Related Literature

Our study contributes to a large literature in accounting, banking and finance focusing on fraud, where most research has specifically focused on corporate fraud. Palmrose and Scholz (2004), Karpoff et al. (2008a) and Karpoff et al. (2008b) provide evidence on the costs borne by firms and managers for committing fraud. A number of papers examine factors in promoting or discouraging corporate fraud. Some link

[4] See *Risk*: "OCC Forms Working Group to Tackle Fraud" (T. Osborn, March 20, 2018).

[5] On October 19, 2016, the three federal banking regulators — the Federal Reserve System, the Office of the Comptroller of the Currency, and the Federal Deposit Insurance Corporation — issued an advance notice of proposed rule making for new cyber-security regulations for large financial institutions and critical financial infrastructure. The framework is intended to result in rules to address cyber incidents that could erode the safety and soundness of not just the directly impacted financial institution, but the soundness of the financial system and markets overall. For more information, see `https://www.federalreserve.gov/newsevents/pressreleases/bcreg20161019a.htm`.

fraud to equity compensation for executives (e.g., Burns and Kedia (2006), Goldman and Slezak (2006), Efendi et al. (2007), Peng and Röell (2008), Armstrong et al. (2010), Johnson et al. (2009)). Others link fraud to corporate boards lacking independence or financial and accounting expertise (e.g., Beasley (1996), Dechow et al. (1996), Agrawal and Chadha (2005)). A number of studies have also documented a commonality or "contagion" in misconduct among connected firms (Bizjak et al. (2009), Chiu et al. (2013), Kedia et al. (2015), Parsons et al. (2018)). Povel et al. (2007) and Wang et al. (2010) study how a firm's propensity to commit fraud varies with investor beliefs about industry prospects, monitoring intensity and the business cycle. Dyck et al. (2010) identify the most effective mechanisms for detecting corporate fraud. Li et al. (2018) study how bank monitoring affects corporate fraud. Giannetti and Wang (2016) suggest that corporate fraud can have far-reaching implications including a reduction in household stock market participation.

Our study is also closely related to a nascent literature on fraud in the financial services industry that focuses on fraud committed by financial advisers and investment managers. Dimmock and Gerken (2012) test the predictability of investment fraud and find that disclosures related to past regulatory and legal violations, conflicts of interest, and monitoring have significant power to predict fraud. Dimmock and Gerken (2016) use Securities and Exchange Commission rule changes to show that regulatory oversight reduces return misreporting by hedge funds. Li (2018) studies investor responses to disclosures of mutual fund fraud and documents significant heterogeneity in the responses across different mutual fund share classes. Dimmock et al. (2018) show that coworkers influence the propensity of an individual (financial advisor) to commit financial misconduct. Egan et al. (2018) provide the first large-scale evidence on the economy-wide extent of misconduct among financial advisers and the associated labor market consequences of misconduct. Gurun et al. (2018)

show that trust plays a critical role in the financial intermediation industry. For example, residents of communities that were exposed to fraud subsequently withdrew assets from investment advisers and increased deposits at banks. Apart from fraud committed by investment advisers and managers, Piskorski et al. (2015) and Griffin and Maturana (2016) document residential mortgage quality misrepresentation by financial intermediaries.

In contrast, our study has a different focus. We are the first to present comprehensive evidence on fraud committed *against* firms in the financial services industry. Specifically, using a rich supervisory dataset, we dissect fraud incurred by large U.S. BHCs. We examine the different categories of fraud and their materiality, the recovery from fraud, time from occurrence to fraud discovery and accounting. Further, we quantify exposure to fraud and study the organization-level determinants of fraud-related losses.

Losses from fraud are often characterized as an unavoidable cost of doing business and are classified as operational losses. Our work thus also contributes to the literature on operational risk of financial institutions. Jarrow (2008) describes operational risk from an economic and mathematical perspective with an emphasis on economic capital estimation. Chernobai et al. (2012) show that most operational losses can be traced to a breakdown of internal controls and focus on the role of corporate governance and managerial incentives in mitigating operational risk. Chernobai et al. (2018) and Curti et al. (2019) relate operational risk to bank size and complexity. Abdymomunov et al. (2019) argue that operational risk changes with the state of the macroeconomic environment. We contribute to this strand of literature by extensively and thoroughly analyzing losses from a particular type of operational risk – fraud. By linking fraud to credit intermediation at banks, we importantly argue that the consequences of fraud go beyond just direct monetary costs.

3. Fraud Data, Characteristics, Measurement and Determinants

3.1. Fraud Data Source

This study uses a supervisory dataset of fraud-related losses provided by U.S. bank holding companies and U.S. operations of foreign firms with total consolidated assets of $50 billion or more in accordance with the Dodd-Frank Wall Street Reform and Consumer Protection Act.[6] The reported data follows FR Y-14Q reporting requirements (current as of April 2017) and contains a complete history of fraud losses, captured by institutions as of the respective reporting quarter end, starting from the point-in-time at which the institutions began recording operational loss event data in a systematic manner.[7] The data is highly granular providing for every individual fraud event information such as gross amount, recovery amount, loss event type, and the business line associated with the event.

The final sample contains more than 17.5 million individual loss events from 38 large financial institutions over the period [2000:Q1-2016:Q4].[8] Our data is significantly richer than any known dataset offered by a private vendor. Publicly available data of fraud and other operational risks incurred by financial institutions are bound to omit the majority of loss events otherwise contained in the supervisory data we use (De Fontnouvelle et al. (2006)).

[6] Pursuant to the Federal Reserve's Dodd-Frank enhanced prudential standards final rule, foreign banking organizations with $50 billion or more in U.S. non-branch/agency assets are required to place their U.S. subsidiaries underneath top-tier U.S. intermediate holding companies (IHCs). In our study, we refer to both BHCs and IHCs as bank holding companies.

[7] Subsequent to the Economic Growth, Regulatory Relief, and Consumer Protection Act of 2018, financial institutions with under $100 billion in total assets are no longer required to file the FR Y-14Q reports, effective May 2018. More information about FR Y-14Q reporting requirements, instructions and forms can be found at: https://www.federalreserve.gov/apps/reportforms/.

[8] Although our fraud data comes from a small number of institutions, these institutions account for the majority of U.S. bank industry assets. The 38 institutions in our sample account for 85.2% of the total consolidated assets of all U.S. bank holding companies and U.S intermediate holding companies with assets of $1 billion or more as of 2016:Q4.

3.2. Fraud Classification

Consistent with Basel II definitions, fraud is categorized into two types: Internal Fraud and External Fraud. Table 1, Panel A presents definitions of both loss types. The key characteristic that differentiates internal from external fraud events is whether a bank's employees are involved in the fraudulent action. Events where the bank's employees are actively participating in the fraud are considered internal fraud, while events where the bank's employees are not actively participating are considered external fraud.

[Insert Table 1 about here]

Fraud losses are also classified by business line of origination (Federal Reserve System (2017)). There are nine categories: Corporate Finance, Trading & Sales, Retail Banking, Commercial Banking, Payment & Settlement, Agency Services, Asset Management, Retail Brokerage, and Corporate Level Non-Business Line Specific. Table 1, Panel B presents the definitions of all business lines.

Table 2, Panel A presents summary statistics on fraud amounts by event type and business line. The data contains more than $43 billion lost to fraud across the 38 data reporting BHCs. Figure 1, Panel A shows that internal and external fraud account for 10% and 90% of total losses, respectively. Figure 1, Panel B shows that Retail Banking is the business line originating the highest proportion of fraud losses. It accounts for 51.2% of the total fraud, followed by Trading & Sales, Corporate Level, and Corporate Finance, representing 15.4%, 14.8%, and 9.4%, respectively. The remaining five business lines represent less than 10% of total fraud losses in aggregate.

[Insert Table 2 and Figure 1 about here]

Available event descriptions in our data suggest that debit/credit card (e.g., counterfeit cards, "card-not-present" transactions, gas pump and ATM skimming) and check (e.g., counterfeit checks and return deposited items) fraud are some prevalent sources of losses in our data. Fraudulent online and other electronic transactions are also common. While frequent, most of these incidents are usually not severe. Some examples of severe fraud include investment fraud (where banks entrust clients' money into external fraudulent investment vehicles such as Ponzi schemes), cyber data breaches and fraudulent wire transfers. As previously discussed, the majority of these losses can be attributed to third parties (i.e. external fraud). Rogue trading, embezzlement, fraudulent deposits and loan issuances, on the other hand, are prominent examples of internal fraud.

3.3. Fraud Recoveries

After fraud is committed and discovered, a bank is sometimes able to recover some proportion of incurred losses.[9] Table 2, Panel B presents the average percentage of loss recovered by event type and business line, where we weight individual loss events either equally or by loss amount. The average recovery rates are 2.2% with equal weighting and 5.9% with loss amount weighting. In both weighting methodologies, internal fraud events exhibit a recovery rate that is roughly 3 percentage points higher than external fraud events. Losses from Asset Management and Commercial Banking generally have higher recovery rates. In contrast, losses from Trading & Sales and Agency Services generally have lower recovery rates.

Figure 2, Panel A shows the proportion of losses with zero vis-á-vis nonzero recoveries. The majority of fraud events, roughly 95% of events and 75% of loss

[9]Recovery is defined as an independent occurrence in which funds or economic benefits are recouped related to the original fraud event, excluding provisions, provision write-backs and funds received from insurance providers.

amounts, have zero recoveries. Figure 2, Panel B shows positive recoveries only. We group fraud events into five recovery buckets: (0,20%], (20,40%], (40,60%], (60,80%], (80,100%]. The majority of fraud by loss amount has a recovery rate below 20%. In contrast, in frequency terms, 40% of fraud events have a recovery between 80% and 100% while the other recovery buckets individually capture between 15% and 20% of loss events.

[Insert Figure 2 about here]

3.4. Fraud Discovery and Accounting

There are usually time lags between when fraud gets committed, discovered and accounted. Table 2, Panel C presents the average number of days between the occurrence, discovery and accounting of fraud by type and business line.[10] Similar to our previous section, we weight individual loss events either equally or by loss amount.

An "average" fraud event takes a bank 17 days to discover after it occurs and 46 days to account after it gets discovered. However, larger fraud events are associated with substantially longer lags: the loss amount weighted times from occurrence to discovery and discovery to accounting are 125 and 99 days, respectively. Notably, internal fraud takes longer to discover and shorter to account than external fraud. The equal (loss) weighted number of days between occurrence to discovery for internal fraud is 33 (172) days while it is 17 (119) days for external fraud. The equal (loss) weighted number of days between discovery to accounting for internal fraud is 32 (77) days while for external fraud it is 46 (101) days. One can also observe significant

[10] Formally, the *occurrence date* of a fraud event is defined as the date that fraud occurred or began. The *discovery date* reports the date that a fraud event was first discovered by the institution. The *accounting date* reports the date that the financial impact of the fraud event was recorded on the institution's financial statements.

variation in occurrence to discovery and discovery to accounting time lags across business lines. On an equal weighted basis, fraud events in Corporate Finance have the longest lags: the time between occurrence to discovery is 92 days, while the time between discovery to accounting is 107 days. On a loss amount weighted basis, Retail Brokerage has the longest discovery lag, 252 days, while Commercial Banking has the longest accounting lag, 377 days.

Figure 3, Panel A shows the proportion of fraud losses across buckets with different time to discovery. Specifically, we group fraud events into six buckets: [0,30 days), [30,60 days), [60,90 days), [90,120 days), [120,180 days), and more than 180 days. The vast majority of fraud events are discovered within 30 days of their occurrence. However, there are also some significant large losses discovered past 120 days of their occurrence. Figure 3, Panel B shows a similar bar chart, which visualizes the proportion of fraud losses across buckets with different time to accounting. Again, the majority of fraud events are accounted within 30 days of the discovery but this pattern is less pronounced than in Panel A. A significant portion of losses are accounted between 60 and 120 days of their discovery. Importantly, some larger losses take significantly longer (e.g., more than 180 days) to be accounted after discovery.

[Insert Figure 3 about here]

3.5. Fraud through Time

Table 2, Panel D presents the amount and the number of events per dollar of bank assets through time. Notably, assets-scaled fraud is highest in 2001, 2002 and 2008, driven by some massive high-severity fraud events (e.g., Enron and WorldCom scandals, and Bernard Madoff's Ponzi scheme). In contrast, assets-scaled frequency of losses seems to be higher towards the latter part of the sample, particularly post the global financial crisis.

Table 2, Panel E documents the occurrence of fraud across calendar quarters. The first quarter in a year is marked by the lowest occurrence of fraud. In contrast, the fourth quarter of the year is characterized by the highest occurrence of fraud. This pattern may be potentially explained by the higher intensity of fraud in retail banking around the winter holiday season, followed by a generally lower retail transaction volume (and incidence of fraud) during the first calendar quarter.

3.6. The Cost of Fraud: Evidence from Simulations

To gain more insight into the monetary effects of fraud, this section estimates loss scenarios that could occur in a probabilistic sense. We employ a simple Loss Distribution Approach (LDA) model to estimate the "Value-at-Risk" over a given quarter (for details of the model, see Appendix A).[11] Specifically, we use the model to produce estimates of the value that can be lost to fraud by the 38 bank holding companies in our sample at the 1^{st}, 25^{th}, 50^{th}, 75^{th}, 99^{th} percentiles of their loss distributions. We then present linear fits through the estimated losses as functions of bank asset size. Table 3 presents the results for selected bank sizes while Figure 4 show the results visually.

[Insert Table 3 and Figure 4 about here]

Our estimates show that quarterly fraud losses can be significant for banking institutions. The median quarterly fraud loss for bank holding companies with $500 billion in total assets is around $15 million, while for the largest institutions is above $70 million. Table 3 and Figure 4 also show that fraud losses can be substantial in

[11]The LDA is the most common methodology used by large financial institutions around the world to quantify fraud and other operational risks under the Advanced Measurement Approaches (AMA), one of the three methods allowed by Basel II regulation (Basel Committee on Banking Supervision, 2006). For a detailed discussion of LDA modeling, see Klugman et al. (1998) and Embrechts et al. (2004).

more extreme and less probable scenarios: the 99^{th} percentile is more than 23 times the median and more than 19 times the 75^{th} percentile. We estimate that quarterly fraud losses for the largest institutions in our sample can be higher than $1.5 billion.

It is important to note that our results only capture the direct monetary losses associated with fraud and do not reflect other channels through which fraud can impact institutions' financial performance. Fraud can also impose indirect costs associated with revamping internal information technology systems, the loss of key personnel and customers, and the impairment of future earnings due to reputational damage. In that sense, our VaR estimates omit non-monetary effects and thus provide a lower bound on the overall cost of fraud to financial institutions.

3.7. Fraud Determinants

To get some intuition about potential correlates of fraud, in this section we investigate the relation between quarterly fraud amounts and several characteristics at the bank and macro-economy levels in a multiple regression setting. Our measure of fraud is the log-transformed total dollar value of fraud losses incurred by a BHC during a given quarter. On the right-hand-side, we focus on six explanatory variables that capture key BHC characteristics and the environment they operate in.

First, we use banking organization size to capture banks' scale of operations, volume of transactions and number of business relationships (with customers, business partners and other counter-parties). We measure firm size by the logarithm of BHC total consolidated assets, $Ln(Size)$. Second, we include the ratio of deposits to total assets, $Deposits-to-TA$, the ratio of loans to total assets, $Loans-to-TA$, and the ratio of non-interest income to interest income, $NII-to-II$. These variables characterize banks' business strategies and activities, and specifically whether banks engage in traditional activities (i.e. deposit receiving and lending) versus non-traditional activities (e.g., non-core activities such as trading and investment banking). Third, we include a measure of cost efficiency (Berger and Mester (1997)). *Cost Efficiency* is the proximity of a bank's cost to that of a best-practice bank producing the same output under the same conditions. As argued by Berger and DeYoung (1997), it should capture the quality of bank management: sub-par managers do not sufficiently monitor and control their banks' operating expenses (e.g., due to inadequate loan underwriting, monitoring, and control), which is reflected in low measured cost efficiency. Fourth, we include a measure of bank locations' crime intensity (i.e. banks' physical exposures to crime). Specifically, *Crime* is calculated as the average property crime arrest rate weighted by the shares of a banks' branch deposits across different locations in a given quarter.[12] Lastly, in some of our specifications, we also include the unemployment rate, *Unemployment*, to capture the U.S. macroeconomic environment.[13] Table 4 presents descriptive statistics.

[Insert Table 4 about here]

We next estimate the following multiple linear regression via Ordinary Least Squares (OLS):

$$Ln(Fraud)_{b,t} = \alpha_b + \alpha_t + \beta \times Fraud\ Determinants_{b,t-1} + \epsilon_{b,t} \tag{1}$$

where b indexes BHCs, and t indexes quarters. $Ln(Fraud)$ is the log-transformed financial impact sum of fraud events that occur at a bank over a quarter. α_b represents BHC fixed effects and α_t represents quarter fixed effects. $Fraud\ Determinants$

[12] More specifically, *Crime* is constructed by multiplying banks' share of deposits in a Federal Information Processing Standard (FIPS) county by the number of property crime arrests in the same county per 1,000 inhabitants.

[13] To calculate the above variables we use data from several sources: FR Y-9C reports for bank financial data; St. Louis Federal Reserve Economic Data for unemployment data; FDIC Summary of Deposits for information on bank deposits at the county level; National Archive of Criminal Justice Data for information on property crimes at the county level.

represents our previously discussed set of explanatory variables, measured at the end of the quarter prior to fraud occurrence. We cluster standard errors at the bank and quarter levels. Table 5 presents the results.

[Insert Table 5 about here]

We present four specifications with different fixed effect schemes: Column (1) presents a pooled regression specification without fixed effects; Column (2) presents a regression specification with BHC fixed effects; Column (3) presents a regression specification with time fixed effects; and Column (4) presents a regression specification with both BHC and time fixed effects. Overall, the strongest predictors of losses to fraud at the bank level (significant in at least three out of the four specifications) are bank size, bank cost efficiency, bank deposits relative to total assets, and branch location crime. Specifically, we find that larger and less cost efficient banking organizations experience more fraud. Banks that tend to fund their assets with deposits and those that tend to operate branches in geographies with high crime also tend to experience more fraud. We also note some weak evidence that fraud is related to the U.S. macroeconomic conditions, whereby a strong macroeconomy is associated with higher fraud occurrence at financial institutions.

4. Effects on Credit Intermediation: Evidence from Deposits and Loans

4.1. Hypotheses

Fraud at banking organizations might affect deposit growth through several channels. First, it could affect deposit growth through negative customer experience. Direct victims of fraud at a financial institution might divert away deposits to other financial institutions as a result of the inconvenience and frustration of dealing with fraud as a customer. Second, fraud could affect deposit growth through reputation impairment, where prospective depositors (apart from direct victims) may also be less willing to transact with an institution that has been caught engaging in fraud or one that cannot protect its customers from external fraud. Third, in the case of large-scale fraud, bank customers might also withdraw their deposits in fear of bank solvency or bankruptcy issues. Even when customers' deposits are insured, recovery would require effort and entail delays in accessing funds. A fourth channel could be through loss of employee talent. For example, essential personnel with important field knowledge and customer relation functions may wish to leave their jobs at a banking organization with corroded reputation, resulting in the loss of customer know-how, service deterioration and the loss of business (e.g., deposits). These arguments lead to the following hypothesis:

H1a (Deposits & Fraud): *Fraud at banks leads to lower deposit growth.*

Fraud that directly affects depositors should have stronger effects on deposit growth than other fraud at bank holding companies. We thus expect more adverse effects on deposit growth when fraud occurs in banks' primary deposit taking business lines such as retail and commercial banking. In contrast, we expect that fraud that occurs in other business lines (e.g., corporate finance, trading and sales, payment and settlement, etc.) should have a less adverse effect on deposits.

H1b (Business Lines): *The effects of fraud on deposit growth are more pronounced when fraud occurs in banking business lines (e.g., retail and commercial banking) than in other business lines.*

The effects of fraud on bank deposit growth may also be amplified or attenuated by multiple factors related to banks' operating environment, business practices and strategies. For example, when a bank operates in a highly competitive market, customers have more opportunities to switch and bring their business to other depositary institutions (Martinez Peria and Schmukler (2001), Bliss (2014)). Consequently, market competition should enable depositors to "discipline" a fraud-belabored bank (by withdrawing deposits) through more banking services provider options to customers.

H1c (Market Competition): *The effects of fraud on deposit growth are more pronounced when banks operate in more competitive markets.*

Convenience and local representation are crucial factors in depositors' choice of financial services providers. In fact, Anenberg et al. (2018) note that the location of an institution's offices is the most important reason for a customer's choice of a financial institution. Branch availability and local representation should thus mitigate the negative effects of fraud on deposit growth by imposing higher switching costs on customers (e.g., loss of convenience).

H1d (Branch Intensity): *The effects of fraud on deposit growth are less pronounced when banks have more local branch representation.*

A significant proportion of consumers comparison-shop for terms on financial products, including deposit rates (Calem and Mester (1995)). This suggests that terms such as deposit rates could be a significant factor for customer retention and/or customer acquisition. In our context, a bank's higher deposit rates relative to other institutions' might help a bank mitigate the negative effect of fraud on deposit growth.

H1e (Deposit Rates): *The effects of fraud on deposit growth are more pronounced when banks pay lower interest on deposits.*

Finally, the negative effect of fraud on deposit growth might be particularly pronounced during periods of banking crises and market panics. In such periods, high fraud might incrementally tarnish the reputation of a financial institution, raising questions about its financial soundness and risk controls, and lead to more deposit withdrawals (i.e. "bank runs") (e.g., Diamond and Dybvig (1983), Traweek and Wardlaw (2018)).

H1f (Banking Crises): *The effects of fraud on deposit growth are more pronounced during banking crises.*

Since banks rely heavily on deposits for their funding, deposit outflows induce a contraction in credit provision (Drechsler et al. (2017), Lin (2019)). If *Hypothesis H1a* holds, then fraud at banking organizations should also spill over to bank lending.

H2a (Loans & Fraud): *Fraud at banks leads to lower loan growth.*

Additionally, if banks experience fraud in their banking business (e.g., fraud committed by borrowers), they might also tighten credit provision (e.g., Murfin (2012)). Specifically, after suffering payment defaults to their loan portfolios due to fraud, banks could tighten their lending standards, write stricter loan contracts and charge higher interest on loans. This should be reflected in slower loan growth.

H2b (Business Lines): *The effects of fraud on loan growth are more pronounced when fraud occurs in banking business lines (e.g., retail and commercial banking) than in other business lines.*

The effect of fraud on lending could be crucially amplified by bank-specific factors such as bank capital. Losses from fraud adversely affect bank capital positions ceteris paribus. More thinly capitalized banks might tighten lending standards more in response to fraud to protect their remaining capital and hedge against insolvency. Considerations related to regulatory capital minimums and recapitalization costs could additionally lead to tighter credit policies.

H2c (Bank Capital): *The effects of fraud on loan growth are more pronounced when banks are less capitalized.*

Similarly, bank (il)liquidity could be another amplifying factor. Liquid assets such as cash on hand can serve as buffers on a short term basis to absorb funding shocks, mitigating the shocks' transmission to banks' loan books. Lower levels of liquidity, on the other hand, suggest the lack of such a funding cushion and may thus magnify the effects of fraud on credit provision.

H2d (Bank Liquidity): *The effects of fraud on loan growth are more pronounced when banks hold less liquidity.*

4.2. Empirical Strategy

This section presents the two-step empirical methodology we use to examine the effect of fraud on bank credit intermediation. In the first step, we separate the *unanticipated* component of fraud losses relative to "normal levels" experienced by a financial institution by a calculating a measure of "abnormal" fraud. Specifically, we construct *Abnormal Fraud* to equal a bank's quarterly fraud loss at quarter t minus the trailing 20-quarter average quarterly fraud loss (measured over quarters $[t-20, t-1]$).[14] In the second step, we employ the following multiple regression model estimated via OLS:

$$\begin{aligned} &Deposit/Loan\ Growth_{b,t+k} = \\ &\alpha_b + \alpha_t + \beta \times Abnormal\ Fraud_{b,t} + \delta \times Ctrls_{b,t} + \epsilon_{b,t+k} \end{aligned} \tag{2}$$

where b indexes BHCs and t indexes quarters. *Deposit Growth* and *Loan Growth* measure bank deposit growth and bank loan growth, respectively, over the following year ($[t,\ t+4]$). *Abnormal Fraud* measures quarterly abnormal fraud calculated as previously defined. *Ctrls* is a vector of control variables further discussed in Section 3.7 including: BHC total assets growth, change in the non-interest income to interest

[14] Our results are also robust to using alternative trailing fraud measurement windows.

income ratio, change in cost efficiency, and change in branch location crime. All control variables are measured over $[t-1,\ t]$. Table 6 presents summary statistics. We also include BHC (α_b) and quarter (α_t) fixed effects, and use two-dimensional clustering of the error terms.

[Insert Table 6 about here]

Several features of our empirical setup attenuate potential endogeneity concerns and give a plausible causal interpretation of our results. Specifically, regressing changes in credit intermediation on abnormal fraud "differences out" the effect of latent time-invariant bank-level characteristics. Additional BHC fixed effects absorb potential persistence in BHC loan and deposit growth, while quarter fixed effects absorb potential period-specific shocks to loan and deposit growth across BHCs. More importantly, nearly 90% of fraud stems from parties external to the banking organizations (Figure 1, Panel A). Consequently, abnormal levels (or "shocks") of (mostly external) fraud should not systematically "coincide" with omitted BHC factors to drive changes in credit intermediation mitigating omitted variable issues. Finally, linking abnormal fraud at quarter t with deposit and loan growth over the following year also suggests that reverse causation should not be a concern.

4.3. Deposit Growth Results

Table 7, Panel A presents tests of *Hypothesis H1a*. Columns (1), (3) and (5) present specifications without controls, while Columns (2), (4) and (6) present specifications with controls. We focus on the relation of abnormal fraud to deposit growth over the following year after the occurrence of the fraud (Columns (1) and (2)), but also show results with alternative deposit growth horizons (e.g., 1 or 8 quarters in Columns (3)-(6)).

[Insert Table 7 about here]

Across all specifications, abnormal fraud is associated with significant reductions in deposit growth. Based on Column (2), a one-standard-deviation increase in *Abnormal Fraud* is associated with 1.53 percentage points reduction in deposit growth over the following year after fraud occurrence. The coefficient estimate of *Abnormal Fraud* is negative and statistically significant at the 5% level. Notably, the magnitude of the abnormal fraud coefficients is comparable across specifications with and without controls. This is consistent with the idea that the relation between abnormal fraud and deposit growth is largely exogenous to included bank-level controls. Columns (3)-(6) further confirm that the relation between abnormal fraud and deposit growth is robust to using deposit growth horizons shorter or longer than 1 year.

To test whether the effects of abnormal fraud are more pronounced when it occurs in banking business lines (i.e. retail and commercial banking) as in *Hypothesis H1b*, we calculate two separate variables of abnormal fraud. *Abnormal Fraud (Retail & Commercial Banking)* measures abnormal losses analogically to *Abnormal Fraud* in the business lines of retail and commercial banking. *Abnormal Fraud (Other Business Lines)* measures abnormal losses in business lines different from retail and commercial banking. We estimate models similar to Equation 2, including the two abnormal fraud measures separately along with control variables. Table 7, Panel B presents results. Consistent with *Hypothesis H1b*, we find that the effects of fraud on deposit growth in banking business lines is economically larger than in other business lines. The coefficient of *Abnormal Fraud (Retail & Commercial Banking)* is more than three times larger than the one of *Abnormal Fraud (Other Business Lines)*. The coefficients of both variables are significant at the 5% level.

We next proceed to test *Hypotheses H1c-H1f*. Table 8 presents the results. In order to test *Hypothesis H1c*, we construct an indicator variable, *Competition*, which equals 1 if a BHC operates in above-median competitive markets, and 0 otherwise.

We start by measuring competition at the county level with a Herfindahl-Hirschman Index (HHI) of deposits from all banking institutions operating in a given county during a given quarter. Competition measurements at the county level are then aggregated to the bank-quarter level by calculating a weighted average across counties where a bank operates during a given quarter (the weight assigned to a county is the share of the bank's deposits in that county during that quarter). Values of the resulting variable are assigned equal to 1 if above the sample median, and 0 otherwise.

We then estimate models similar to Equation 2, including an interaction term between *Abnormal Fraud* and *Competition*, as well as *Abnormal Fraud*, *Competition* and control variables separately. Table 8, Panel A presents results. Consistent with our hypothesis, we find that the effects of fraud on deposit growth are more pronounced when banks operate in more competitive markets. The coefficients on *Abnormal Fraud * Competition* are negative and significant at least at the 10% level.

[Insert Table 8 about here]

To test *Hypothesis H1d*, we construct an indicator variable, *Branch Intensity*, which equals 1 if a BHC has an above-median share of branches in the markets (counties) where it operates, and 0 otherwise. The county-level share of branches owned by a bank is measured as the ratio of the number of branches owned by a bank divided by the number of all branches owned by all banking organizations operating in a county. Measurements at the county level are then aggregated to the bank-quarter level by calculating a weighted average across counties where a bank operates during a given quarter (the weight assigned to a county is the share of the bank's deposits in that county during that quarter). Values of the resulting variable are assigned equal to 1 if above the sample median, and 0 otherwise.

Similar to the test of *Hypothesis H1c*, we estimate models in line with Equation 2, where we include an interaction term between *Abnormal Fraud* and *Branch Intensity*, as well as *Abnormal Fraud*, *Branch Intensity* and control variables separately. Table 8, Panel B presents results. Consistent with *Hypothesis H1d*, we find that the effects of fraud on deposit growth are less pronounced when banks have stronger local (branch) representation. The coefficients on *Abnormal Fraud * Branch Intensity* are positive and significant at the 10% level.

To test *Hypothesis H1e*, we construct an indicator variable, *Deposit Expense*, which equals 1 if a BHC pays a below-median interest rate on its deposits, and 0 otherwise. The interest rate on deposits is defined as the ratio of interest expense on deposits to deposits. We further subtract the 3-month Treasury bill rate to adjust for the nominal risk-free rate. We then test the interaction term between *Abnormal Fraud* and *Deposit Expense* in models similar to Equation 2, which also include *Abnormal Fraud*, *Deposit Expense* and control variables separately. Table 8, Panel C presents results. Consistent with our hypothesis, we find that the effects of fraud on deposit growth are more pronounced when banks pay less interest to their depositors.[15] The coefficients on *Abnormal Fraud * Deposit Expense* are negative and significant at the 5% level.

Finally, we test *Hypothesis H1f*. We construct an indicator variable, *Financial Crisis*, which equals 1 if a given quarter falls within the 2008 global financial crisis, which we broadly define as the period [2007:Q3-2009:Q2], and 0 otherwise. Similar to before, we proceed to test the interaction term between *Abnormal Fraud* and *Financial Crisis* in models similar to Equation 2. Because we also include quarter fixed effects per Equation 2, we are not able to identify the coefficients on the financial crisis variables individually. Table 8, Panel D presents results. Consistent with

[15] In unreported analysis, we also test whether abnormal fraud is associated with increases in the interest rates that banks pay on their deposits. We do not find significant effects, consistent with prior research documenting deposit rate rigidity or "stickiness" (e.g., Hannan and Berger (1991), Neumark and Sharpe (1992), Drechsler et al. (2017)).

our hypothesis, we find that the effects of fraud on deposit growth are particularly pronounced during the 2008 global financial crisis. The coefficients on *Abnormal Fraud * Financial Crisis* are negative and significant at the 1% level.

4.4. Loan Growth Results

Table 9, Panel A presents tests of *Hypothesis H2a*. Columns (1), (3) and (5) present specifications without controls, while Columns (2), (4) and (6) present specifications with controls. As in our analysis of fraud effects on deposit growth, we focus on the relation between abnormal fraud at quarter t and loan growth over the following year after fraud occurs (Columns (1) and (2)). However, we also show results with alternative loan growth horizons (e.g., 1 or 8 quarters in Columns (3)-(6)).

[Insert Table 9 about here]

Across all specifications, abnormal fraud is associated with significant reductions in loan growth. Based on Column (2), a one-standard-deviation increase in *Abnormal Fraud* is associated with 0.91% percentage points reduction in loan growth over the following year after fraud occurrence. The coefficient estimate of *Abnormal Fraud* is negative and statistically significant at the 5% level. Similar to our deposit growth specifications, the magnitude of the abnormal fraud coefficients is comparable across specifications with and without controls, which is consistent with the interpretation that the relation between abnormal fraud and deposit growth is largely exogenous to included bank-level controls. The results in Columns (3)-(6) additionally suggest that the effects of fraud on loan growth are robust to using loan growth horizons shorter or longer than 1 year.

We next test whether the loan growth effects of fraud are stronger when fraud occurs in (retail and commercial) banking business lines as opposed to other business lines (*Hypothesis H2b*). To do so we estimate regressions of loan growth on our previously introduced measures of abnormal fraud *Abnormal Fraud (Retail & Commercial Banking)* and *Abnormal Fraud (Other Business Lines)*. Table 9, Panel B presents the results, which are consistent with our hypothesis. The coefficients of *Abnormal Fraud (Retail & Commercial Banking)* are (more than three times) larger than those of *Abnormal Fraud (Other Business Lines)*. Coefficients are significant at the 5% level.

Table 10 presents tests of *Hypothesis H2c* and *Hypothesis H2d*. To test *Hypothesis H2c*, we construct an indicator variable, *Capital*, which equals 1 if a BHC has below-median capitalization (Tier 1 capital ratio), and 0 otherwise. We then estimate models similar to Equation 2, including an interaction term between *Abnormal Fraud* and *Capital*, as well as *Abnormal Fraud*, *Capital* and control variables separately. Table 10, Panel A presents results. Consistent with our hypothesis, we find that the effects of fraud on loan growth are more pronounced when banks are less capitalized. The coefficients on *Abnornal Fraud * Capital* are negative and significant at the 1% level.

[Insert Table 10 about here]

To test *Hypothesis H2d*, we construct an indicator variable, *Liquidity*, which equals 1 if a BHC has below-median liquidity (cash-to-assets ratio), and 0 otherwise. Consequently, we test the interaction term between *Abnormal Fraud* and *Liquidity* in models in line with Equation 2 (including *Abnormal Fraud*, *Liquidity* and control variables separately). Table 10, Panel B presents results. Consistent with our hypothesis, we find that the effects of fraud on loan growth are more pronounced when banks hold less liquidity. The coefficients on *Abnormal Fraud * Liquidity* are negative and significant at the 1% level.

5. Additional Analysis

5.1. Bank Profitability

The results from Section 4 suggest that abnormal fraud at banking organizations has negative implications for their credit intermediation functions (e.g., through lower deposit and loan growths). In this section, we examine whether abnormal fraud ultimately affects banks' bottom lines (i.e. their profitability). We estimate the following model via OLS:

$$\Delta Profit_{b,t+k} = \alpha_b + \alpha_t + \beta \times Abnormal\ Fraud_{b,t} + \delta \times Ctrls_{b,t} + \epsilon_{b,t+k} \qquad (3)$$

where b indexes BHCs, and t indexes quarters. $\Delta Profit$ is one of two profitability measures: ΔROE or ΔROA. ΔROE is the year-over-year change in return on equity. ΔROA is the year-over-year change in return on assets. *Abnormal Fraud* measures quarterly abnormal fraud calculated as previously defined in Section 4.2. *Ctrls* is a vector of control variables. Similar to Equation 2, we include BHC fixed effects (α_b) and quarter fixed effects (α_t), and use two-dimensional clustering of the error terms. Table 11 presents the results.

[Insert Table 11 about here]

Columns (1) and (3) present specifications without controls, while Columns (2) and (4) present specifications with controls. In all cases, the coefficients of *Abnormal Fraud* are negative and significant at the 1% level. Overall, these results suggest that abnormal fraud not only disrupts credit intermediation at banks, but ultimately also spills over to a reduction in bank profitability.

5.2. Fraud Attributes at the Event Level

This section focuses on individual fraud events, where we examine the associations among different fraud attributes (e.g., severity, recovery, discovery and accounting time lags, loss types, and business lines) in multiple regressions. We start with fraud severity and estimate the following OLS model:

$$Ln(Fraud)_{i,b,t} = \alpha_{b\times t} + \alpha_{et} + \alpha_{bl} + \beta \times Event\ Characteristics_{i,b,t} + \epsilon_{i,b,t} \quad (4)$$

where i indexes fraud events, b indexes BHCs, and t indexes quarters. $Ln(Fraud)$ is a natural log transformation of the fraud event severity (i.e. fraud amount). $\alpha_{b\times t}$ are BHC×quarter fixed effects (which absorb time-invariant and time-varying BHC characteristics). α_{et} is an indicator differentiating internal from external fraud. α_{bl} are indicators for the bank business lines generating the fraud, where Retail Banking is the relative group for comparison. *Event Characteristics* represents two variables: the log-transformed number of days between fraud occurrence and discovery (*Ln(Occurrence to Discovery)*) and the log-transformed number of days between fraud discovery and accounting (*Ln(Discovery to Accounting)*). We cluster regression error terms at the BHC level. Table 12, Panel A presents the results:

[Insert Table 12 about here]

Columns (1) and (2) present specifications with different subsets of regressors, while Column (3) presents the full specification. Fraud that remains undiscovered for longer is associated with higher loss amounts. This suggests shorter detection time (e.g., through stronger internal controls and information technology infrastructure) might improve loss outcomes through a reduction in fraud event severity. There are also significant effects across loss types and business lines. Fraud committed by insiders is more severe relative to fraud committed by outsiders. This suggests that insiders are better able to defraud BHCs of larger amounts when they engage in fraud relative to external parties. Additionally, fraud in Asset Management is the most severe among all business lines, potentially reflecting the nature of the business. Other business lines with relative higher loss severity of individual events include Commercial Banking, Retail Brokerage and Agency Services. In contrast, fraud events in Trading & Sales and Payments & Settlement are for the lowest amounts.

We next focus on fraud recovery. We estimate the following OLS model:

$$Recovery\ Rate_{i,b,t} = \alpha_{b\times t} + \alpha_{et} + \alpha_{bl} + \beta \times Event\ Characteristics_{i,t,b} + \epsilon_{i,b,t} \quad (5)$$

where i indexes the fraud event, b indexes BHCs, and t indexes quarters. *Recovery Rate* is defined as the total amount recovered as a percentage of the amount lost. Similar to before: $\alpha_{b\times t}$ are BHC×quarter fixed effects; α_{et} is an indicator differentiating internal from external fraud; α_{bl} are indicators for the business lines generating the fraud (Retail Banking is the relative group for comparison). *Event Characteristics* include: log-transformed fraud severity (*Ln(Fraud)*), the log-transformed number of days between fraud occurrence and discovery (*Ln(Occurrence to Discovery)*), and the log-transformed number of days between fraud discovery and accounting (*Ln(Discovery to Accounting)*). We cluster regression error terms at the BHC level. Table 12, Panel B presents the results.

Columns (1) and (2) present specifications with different subsets of regressors, while Column (3) presents the full specification. Fraud that remains undiscovered for longer is associated with higher loss amounts. Both Columns (1) and (3) suggest that there is no significant difference in recovery rates between internal and external fraud. Similarly both columns suggest that fraud in Corporate Finance and Commercial Banking have the highest recoveries among all business lines, while Corporate Level and Agency Services have the lowest recovery rates. Similarly, Columns (2) and

(3) consistently show that more severe fraud has higher recovery. One potential explanation is that banking organizations exert more effort in recovering funds when fraud is material. This is also likely reflected in the positive and significant coefficient of *Ln(Discovery to Accounting)*, which suggests that longer periods between the discovery and accounting of fraud are associated with more recovery.

Lastly, we investigate the correlates of fraud time lags. We estimate the following OLS model:

$$Time\ Lag_{i,b,t} = \alpha_{b\times t} + \alpha_{et} + \alpha_{bl} + \beta \times Event\ Characteristics_{i,b,t} + \epsilon_{i,b,t} \qquad (6)$$

where i indexes the fraud event, b indexes BHCs, and t indexes quarters. $Time\ Lag$ is one of two variables: the log-transformed number of days between fraud occurrence and discovery (*Ln(Occurrence to Discovery)*) and the log-transformed number of days between fraud discovery and accounting (*Ln(Discovery to Accounting)*). Similar to before: $\alpha_{b\times t}$ are BHC×quarter fixed effects; α_{et} is an indicator differentiating internal from external fraud; and α_{bl} are indicators for the business lines generating the fraud (Retail Banking is the relative group for comparison). $Event\ Characteristics$ includes the total amount recovered as a percentage of the amount lost (*Recovery Rate*), the log-transformed severity of fraud (*Ln(Fraud)*), and the log-transformed number of days between fraud occurrence and discovery (*Ln(Discovery to Accounting)*). We cluster regression error terms at the BHC level. Table 12, Panel C presents the results.

Column (1) shows the results of regressing *Ln(Occurrence to Discovery)* on loss type and business line indicators. Fraud takes significantly longer to be discovered when committed by bank insiders. Further, fraud in Corporate Level and Corporate Finance takes longer to be discovered, while fraud in Payments & Settlement takes significantly shorter to be discovered. Columns (2)-(4) show specifications where the dependent variable is *Ln(Discovery to Accounting)*. Both Columns (2) and (4) suggest that there are no significant difference between internal and external fraud with respect to the time it takes a banking organization to account for a loss after discovery. Fraud in Corporate Finance takes the longest to be accounted, while fraud in Trading & Sales takes significantly shorter to be accounted. Interestingly, Columns (3) and (4) suggest that events that take longer to be discovered also take longer to be accounted. One possible explanation is that fraud taking longer to be discovered is more complex thus also taking longer to be ultimately accounted on BHCs' financial statements.

6. Conclusion

This study provides an important first characterization of fraud in the financial services sector. We focus on large financial institutions for which a regulatory framework, the Dodd-Frank Wall Street Reform and Consumer Protection Act, provides us with rich and detailed data on monetary losses related to fraud. Using a sample of more than 17 million individual fraud events from the 38 largest banking organizations in the U.S. over the period [2000:Q1-2016:Q4], we examine the different categories of fraud and their materiality, the recovery from fraud, and the timing of fraud. We quantify bank exposure to fraud and study determinants of fraud losses at the organizational level. Importantly, we also investigate and find a significant effect of fraud on bank credit intermediation. Our findings are consistent with anecdotal evidence that fraud imposes significant costs to the firms in the financial industry. Our evidence and analysis provides a rich perspective of fraud at banking organizations, and can inform bank risk managers, policy makers and bank supervisors alike.

References

Abdymomunov, A., Curti, F., and Mihov, A. (2019). U.S. banking sector operational losses and the macroeconomic environment. *Journal of Money, Credit and Banking, Forthcoming*.

Agrawal, A. and Chadha, S. (2005). Corporate governance and accounting scandals. *The Journal of Law and Economics*, 48(2):371–406.

Anenberg, E., Chang, A. C., Grundl, S., Moore, K. B., and Windle, R. (2018). The branch puzzle: Why are there still bank branches? *FEDS Notes. Washington: Board of Governors of the Federal Reserve System, August 20, 2018*.

Armstrong, C., Jagolinzer, A. D., and Larcker, D. F. (2010). Chief executive officer equity incentives and accounting irregularities. *Journal of Accounting Research*, 48(2):225–271.

Basel Committee on Banking Supervision (2006). International convergence of capital measurement and capital standards. Bank of International Settlements.

Beasley, M. S. (1996). An empirical analysis of the relation between the board of director composition and financial statement fraud. *The Accounting Review*, 71(4):443–465.

Berger, A. N. and DeYoung, R. (1997). Problem loans and cost efficiency in commercial banks. *Journal of Banking & Finance*, 21(6):849 – 870.

Berger, A. N. and Mester, L. J. (1997). Inside the black box: What explains differences in the efficiencies of financial institutions? *Journal of Banking & Finance*, 21(7):895–947.

Bizjak, J., Lemmon, M., and Whitby, R. (2009). Option backdating and board interlocks. *The Review of Financial Studies*, 22(11):4821–4847.

Bliss, R. (2014). Market discipline in financial markets: Theory, evidence, and obstacles. *Oxford Handbook of Banking, 2nd Edition edited by Allen Berger, Philip Molyneux, and John Wilson*.

Burns, N. and Kedia, S. (2006). The impact of performance-based compensation on misreporting. *Journal of Financial Economics*, 79(1):35 – 67.

Calem, P. S. and Mester, L. J. (1995). Consumer behavior and the stickiness of credit-card interest rates. *The American Economic Review*, 85(5):1327–1336.

Chernobai, A., Jorion, P., and Yu, F. (2012). The determinants of operational risk in U.S. financial institutions. *Journal of Financial and Quantitative Analysis*, 46:1683–1725.

Chernobai, A., Ozdagli, A., and Wang, J. (2018). Business complexity and risk management: Evidence from operational risk events in U.S. bank holding companies. *Working Paper*.

Chiu, P.-C., Teoh, S. H., and Tian, F. (2013). Board interlocks and earnings management contagion. *The Accounting Review*, 88(3):915–944.

Curti, F., Frame, W. S., and Mihov, A. (2019). Are the largest banking organizations operationally more risky? *Working Paper*.

de Fontnouvelle, P., Dejesus-Rueff, V., Jordan, J. S., and Rosengren, E. S. (2006). Capital and risk: New evidence on implications of large operational losses. *Journal of Money, Credit and Banking*, 38(7):pp. 1819–1846.

Dechow, P. M., Sloan, R. G., and Sweeney, A. P. (1996). Causes and consequences of earnings manipulation: An analysis of firms subject to enforcement actions by the SEC. *Contemporary Accounting Research*, 13(1):1–36.

Diamond, D. W. and Dybvig, P. H. (1983). Bank runs, deposit insurance, and liquidity. *Journal of Political Economy*, 91(3):401–419.

Dimmock, S. G. and Gerken, W. C. (2012). Predicting fraud by investment managers. *Journal of Financial Economics*, 105(1):153 – 173.

Dimmock, S. G. and Gerken, W. C. (2016). Regulatory oversight and return misreporting by hedge funds. *Review of Finance*, 20(2):795–821.

Dimmock, S. G., Gerken, W. C., and Graham, N. P. (2018). Is fraud contagious? Coworker influence on misconduct by financial advisors. *The Journal of Finance*, 73(3):1417–1450.

Drechsler, I., Savov, A., and Schnabl, P. (2017). The Deposits Channel of Monetary Policy. *The Quarterly Journal of Economics*, 132(4):1819–1876.

Dyck, A., Morse, A., and Zingales, L. (2010). Who blows the whistle on corporate fraud? *The Journal of Finance*, 65(6):2213–2253.

Efendi, J., Srivastava, A., and Swanson, E. P. (2007). Why do corporate managers misstate financial statements? The role of option compensation and other factors. *Journal of Financial Economics*, 85(3):667 – 708.

Egan, M., Matvos, G., and Seru, A. (2018). The market for financial adviser misconduct. *Journal of Political Economy, Forthcoming.*

Embrechts, P., Kaufmann, R., and Samorodnitsky, G. (2004). Ruin theory revisited: stochastic models for operational risk. *Risk Management for Central Bank Foreign Reserves, European Central Bank*, pages 243–261.

Federal Reserve System (2017). Instructions for the Capital Assessments and Stress Testing information collection.

Giannetti, M. and Wang, T. Y. (2016). Corporate scandals and household stock market participation. *The Journal of Finance*, 71(6):2591–2636.

Goldman, E. and Slezak, S. L. (2006). An equilibrium model of incentive contracts in the presence of information manipulation. *Journal of Financial Economics*, 80(3):603 – 626.

Griffin, J. M. and Maturana, G. (2016). Who facilitated misreporting in securitized loans? *The Review of Financial Studies*, 29(2):384–419.

Gurun, U. G., Stoffman, N., and Yonker, S. E. (2018). Trust busting: The effect of fraud on investor behavior. *The Review of Financial Studies*, 31(4):1341–1376.

Hannan, T. H. and Berger, A. N. (1991). The rigidity of prices: Evidence from the banking industry. *The American Economic Review*, 81(4):938–945.

Jarrow, R. A. (2008). Operational risk. *Journal of Banking & Finance*, 32(5):870 – 879.

Johnson, S. A., Ryan, Jr., H. E., and Tian, Y. S. (2009). Managerial incentives and corporate fraud: The sources of incentives matter. *Review of Finance*, 13(1):115–145.

Karpoff, J. M., Lee, D. S., and Martin, G. S. (2008a). The consequences to managers for financial misrepresentation. *Journal of Financial Economics*, 88(2):193 – 215.

Karpoff, J. M., Lee, D. S., and Martin, G. S. (2008b). The cost to firms of cooking the books. *The Journal of Financial and Quantitative Analysis*, 43(3):pp. 581–611.

Kedia, S., Koh, K., and Rajgopal, S. (2015). Evidence on contagion in earnings management. *The Accounting Review*, 90(6):2337–2373.

Klugman, S. A., Panjer, H. H., and Willmot, G. E. (1998). *Loss Models: From Data to Decision*. Wiley.

Li, M., Makaew, T., and Winton, A. (2018). Bank monitoring and corporate fraud: Evidence from a natural experiment. *Working Paper*.

Li, R. (2018). Missing in action: Investor reaction to mutual fund misconduct. *Working Paper*.

Lin, L. (2019). Bank deposits and the stock market. *Review of Financial Studies, Forthcoming*.

Martinez Peria, M. S. and Schmukler, S. L. (2001). Do depositors punish banks for bad behavior? Market discipline, deposit insurance, and banking crises. *The Journal of Finance*, 56(3):1029–1051.

Murfin, J. (2012). The supply-side determinants of loan contract strictness. *The Journal of Finance*, 67(5):1565–1601.

Neumark, D. and Sharpe, S. A. (1992). Market structure and the nature of price rigidity: Evidence from the market for consumer deposits. *The Quarterly Journal of Economics*, 107(2):657–680.

Palmrose, Z. and Scholz, S. (2004). The circumstances and legal consequences of non-GAAP reporting: Evidence from restatements. *Contemporary Accounting Research*, 21(1):139–180.

Parsons, C. A., Sulaeman, J., and Titman, S. (2018). The geography of financial misconduct. *The Journal of Finance*, 73(5):2087–2137.

Peng, L. and Röell, A. (2008). Executive pay and shareholder litigation. *Review of Finance*, 12(1):141–184.

Piskorski, T., Seru, A., and Witkin, J. (2015). Asset quality misrepresentation by financial intermediaries: Evidence from the RMBS market. *The Journal of Finance*, 70(6):2635–2678.

Povel, P., Singh, R., and Winton, A. (2007). Booms, busts, and fraud. *The Review of Financial Studies*, 20(4):1219–1254.

Traweek, V. and Wardlaw, M. (2018). Depositor behavior and institutional trust: Evidence from the freedman's savings bank. *Working Paper*.

Wang, T. Y., Winton, A., and Yu, X. (2010). Corporate fraud and business conditions: Evidence from IPOs. *The Journal of Finance*, 65(6):2255–2292.

Appendix A: Value-at-Risk Model

For every bank in our sample, we first estimate a frequency distribution $\rho(N_t)$ that describes the number of fraud events N_t in a given quarter t. We follow a common banking industry practice and assume that the frequency follows a Poisson distribution with a parameter λ equal to the average number of fraud events per quarter. Subsequently, we estimate a severity distribution $f(X_{i,t})$ that describes the loss amount of a single loss event $X_{i,t}$ that occurs in period t. To estimate the severity distribution, there are two popular alternatives: use the empirical distribution of dollar losses, or alternatively, fit the dollar losses into a parametric distribution and use the estimated parameters to generate individual losses. In this analysis, we follow the former approach, where we further adjust the dollar losses for inflation, using 2016:Q4 as a reference point (t). Finally, the convolution of the frequency and severity distributions gives rise to the quarterly loss distribution. The steps of the convolution are as follows: 1) draw a number of quarterly events N_t from the frequency distribution; 2) draw N_t losses from the severity distribution $f(X_{i,t})$ (for simplicity, we assume that the frequency and severity distributions are independent); 3) sum the N_t losses drawn from step 2 and obtain one quarterly loss $L_t = \Sigma_{i=1}^{N_t} X_{i,t}$; 4) repeat 1 million times steps 1 through 3 to obtain a series of quarterly simulated losses; 5) rank all the simulated quarterly losses L_t and determine the quarterly loss corresponding to a given quantile.

Appendix B: Variable Definitions

Abnormal Fraud – the difference between *Fraud* (the financial impact sum of fraud events that occur at a BHC over a calendar quarter) at quarter t and the 20 quarter average of *Fraud* measured over $[t-20, t-1]$ in millions of U.S. dollars. *Abnormal Fraud* aggregates fraud from all BHC business lines. *Abnormal Fraud (Retail & Commercial Banking)* aggregates fraud from BHCs' retail and commercial banking business lines. *Abnormal Fraud (Other Business Lines)* aggregates fraud from BHCs' business lines other than retail and commercial banking.

Branch Intensity – an indicator variable, which equals 1 if a BHC has a greater than median share of branches in the FIPS counties where it operates, 0 otherwise. The county-level share of branches owned by a bank is measured as the ratio of the number of branches owned by a bank to the number of all banks' branches in a county. Measurements at the county level are then aggregated to the bank-quarter level by calculating a weighted average across counties where a bank operates during a given quarter (the weight assigned to a county is the share of the bank's deposits in that county during that quarter). *Branch Intensity* equals 1 for values greater than the median, 0 otherwise

Capital – an indicator variable, which equals 1 if a BHC has below-median capitalization (Tier 1 capital ratio), 0 otherwise

Competition – an indicator variable, which equals 1 if a BHC operates in FIPS counties with above median competition, 0 otherwise. Competition at the country level is measured by the Herfindahl-Hirschman Index of deposits from all banking institutions operating in that county. Competition measurements at the county level are then aggregated to the bank-quarter level by calculating a weighted average across counties where a bank operates during a given quarter (the weight assigned to a county is the share of the bank's deposits in that county during that quarter). *Competition* equals 1 for values greater than the median, 0 otherwise

Cost Efficiency – BHC cost efficiency (Berger and Mester (1997))

Crime – average (weighted by BHC share of deposits) property crime arrests per 1,000 inhabitants of FIPS counties where a BHC operates branches

Deposits-to-TA – the ratio of BHC deposits to total assets

Deposit Expense – an indicator variable, which equals 1 if a BHC pays a below-median interest rate on its deposits, 0 otherwise. The interest rate on deposits is defined as the ratio of interest expense on deposits to deposits, from which we further subtract 3-month Treasury bill rate to adjust for the nominal risk-free rate

Deposit Growth – BHC deposit growth, defined as $[(Deposits_{t+n} - Deposits_t)/Deposits_t] - 1$, where n is either 1, 4, or 8 quarters

Discovery to Accounting – the number of days between the discovery and the accounting of a fraud event

Financial Crisis – an indicator variable, which equals 1 if a given calendar quarter is during the period [2007:Q3-2009:Q2], 0 otherwise

Fraud – the financial impact sum of fraud events that occur at a BHC over a calendar quarter (Section 3.7) or the financial impact of a fraud event (Section 5.2) in millions of U.S. dollars

Liquidity – an indicator variable, which equals 1 if a BHC has below-median liquidity (cash-to-assets ratio), 0 otherwise

Ln(Fraud) – a natural log transformation of *Fraud*

Ln(Discovery to Accounting) – a natural log transformation of *Discovery to Accounting*

Ln(Occurrence to Discovery) – a natural log transformation of *Occurrence to Discovery*

Ln(Size) – a natural log transformation of *Size*

Loans-to-TA – the ratio of BHC loans to total assets

Loan Growth – BHC loan growth, defined as $[(Loans_{t+n} - Loans_t)/Loans_t] - 1$, where n is either 1, 4, or 8 quarters

NII-to-II – the ratio of BHC non-interest income to interest income

Occurrence to Discovery – the number of days between the occurrence and the discovery of a fraud event

Recovery Rate – amount recovered in a fraud event (as % of gross amount lost)

Size – BHC total assets in millions of U.S. dollars

Size Growth – BHC total asset growth (quarter-over-quarter)

Unemployment – the unemployment rate at quarter t

ΔCost Efficiency – change in *Cost Efficiency* (quarter-over-quarter)

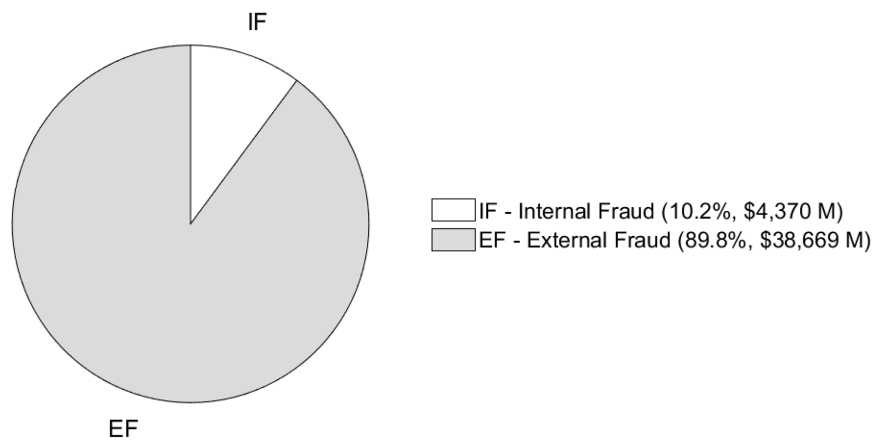
ΔCrime – change in *Crime* (quarter-over-quarter)

Δ**NII-to-II** – change in *NII-to-II* (quarter-over-quarter)

Δ**ROA** – (4-quarter) change in BHC return on assets ($\times$100)

Δ**ROE** – (4-quarter) change in BHC return on equity ($\times$100)

Panel A: By Event Type



Panel B: By Business Line

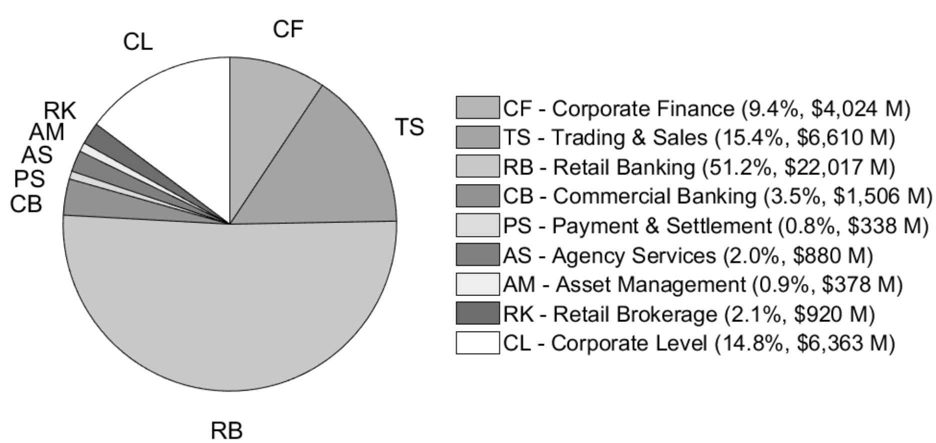
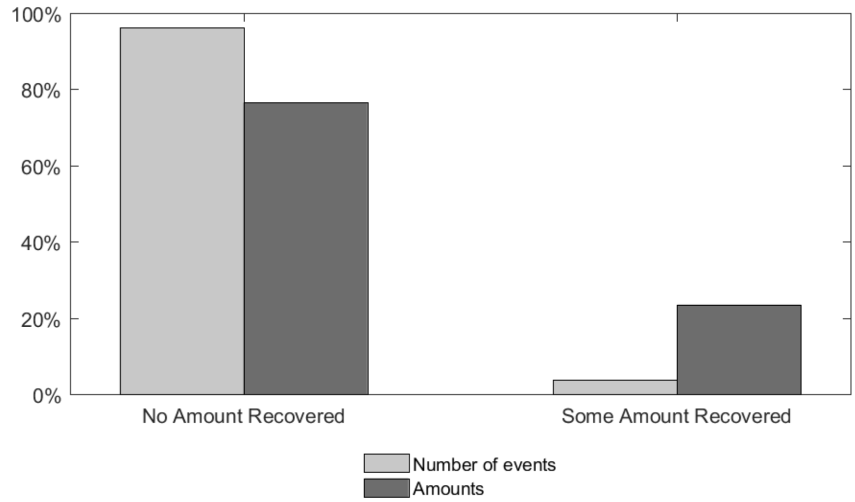


Figure 1: **Fraud by Event Types and Business Lines**
The sample includes 17,512,671 fraud losses incurred by 38 large U.S. bank holding companies over the period [2000:Q1-2016:Q4]. This figure presents the allocation of losses, the percentage of total losses and U.S. dollar loss amounts, among two different fraud loss classifications. Panel A presents fraud by fraud event types. Panel B presents fraud by business lines generating fraud losses.

Panel A: Zero and Non-zero Recoveries



Panel B: Non-zero Recoveries

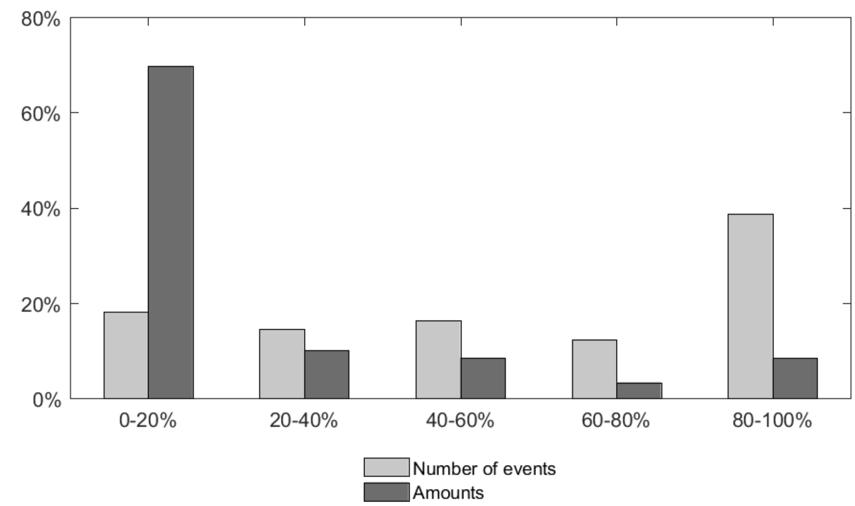
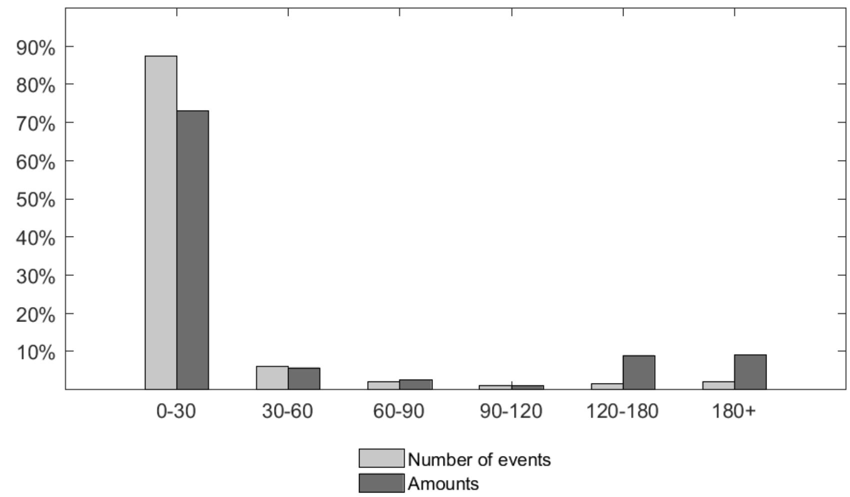


Figure 2: **Fraud Recovery**
The sample includes 17,512,671 fraud losses incurred by 38 large U.S. bank holding companies over the period [2000:Q1-2016:Q4]. The figure presents fraud recoveries by number of events (as a proportion of total number of events) and loss amount (as a proportion of total loss amount). Panel A presents zero vis-á-vis non-zero recoveries. Panel B presents non-zero recoveries grouping events into 5 recovery categories: 0^{+}-20%, 20-40%, 40-60%, 60-80%, 80-100%.

Panel A: Number of Days b/w Occurrence and Discovery



Panel B: Number of Days b/w Discovery and Accounting

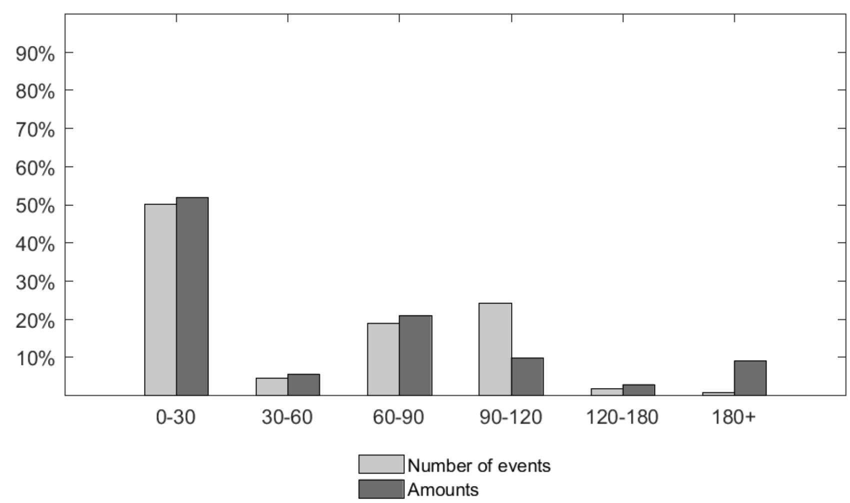


Figure 3: **Fraud Timing**
The sample includes 17,512,671 fraud losses incurred by 38 large U.S. bank holding companies over the period [2000:Q1-2016:Q4]. The figure presents fraud timing by number of events (as a proportion of total number of events) and loss amount (as a proportion of total loss amount). Panel A presents the number of days between fraud occurrence and fraud discovery. Panel B presents the number of days between fraud discovery and fraud accounting. The fraud events are grouped into 5 categories: 0-30 days, 30-60 days, 60-90 days, 90-120 days, 120-180 days, and more than 180 days.

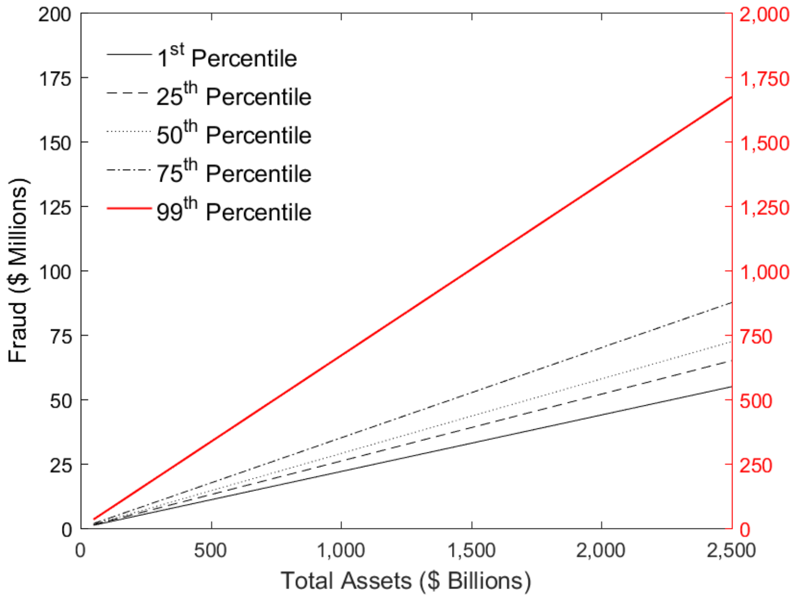


Figure 4: **Fraud Value-at-Risk Estimates**
This figure presents linear fits of Value-at-Risk model estimates (in millions of 2016:Q4 constant dollars) at the 1^{st}, 25^{th}, 50^{th}, 75^{th}, 99^{th} percentiles of the fraud loss distributions of 38 large U.S. bank holding companies as a function of bank total assets. The 1^{st}, 25^{th}, 50^{th}, 75^{th} percentile lines are plotted against the left vertical axis, while the 99^{th} percentile line is plotted against the right vertical axis. Note that the linear fits are based on information from all BHCs in the sample and thus cannot be used to identify loss quantiles for individual BHCs. See Section 3.6 for more details on the Value-at-Risk model.

Table 1: **Fraud Categories**

This table presents fraud event type definitions according to Basel Committee on Banking Supervision (2006) in Panel A, and business line definitions according to Federal Reserve System (2017) in Panel B.

Panel A: Event Types

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

Panel B: Business Lines

Business Line Category	Short	Activity Groups
Corporate Finance	CF	Mergers and acquisitions, underwriting, privatizations, securitization, research, debt (government, high yield), equity, syndications, IPO, secondary private placements.
Trading and Sales	TS	Fixed income, equity, foreign exchanges, commodities, credit, funding, own position securities, lending and repos, brokerage, debt, prime brokerage.
Retail Banking	RB	Retail and private lending and deposits, banking services, trust and estates, investment advice, Merchant/commercial/corporate cards, private labels and retail.
Commercial Banking	CB	Project finance, real estate, export finance, trade finance, factoring, leasing, lending, guarantees, bills of exchange.
Payment and Settlement	PS	Payments and collections, funds transfer, clearing and settlement.
Agency Services	AS	Escrow, depository receipts, securities lending (customers) corporate actions, issuer and paying agents.
Asset Management	AM	Pooled, segregated, retail, institutional, closed, open, private equity.
Retail Brokerage	RK	Execution and full service.
Corporate Level (Other)	CO	Losses originating from a corporate/firm-wide function that cannot be linked to a specific business line.

Table 2: **Summary of Fraud**

The sample includes 17,512,671 fraud losses incurred by 38 large U.S. bank holding companies over the period [2000:Q1-2016:Q4]. Panel A presents the allocation of fraud (loss amounts in millions of U.S. dollars and percentage of total losses) by fraud category. Panel B presents average recovery (%) by fraud category. There are two types of averages: equally weighting each loss event (*Loss Event Weighted*) and weighting proportional to loss amounts (*Loss Amount Weighted*). Panel C presents average number of days between fraud *Occurrence to Discovery* and fraud *Discovery to Accounting* by fraud category. There are two types of averages: equally weighting each loss event (*Loss Event Weighted* and weighting proportional to loss amounts (*Loss Amount Weighted*). Panel D presents fraud amounts and numbers of fraud events over time. Panel E presents average fraud amounts and numbers of fraud events over calendar quarters. In both Panels D and E, the fraud amounts and numbers of fraud events are scaled by the total assets of all banks with data in a given year and multiplied by 1,000.

Panel A: Fraud Amounts

	Internal Fraud	External Fraud	Total
Corporate Finance	45	3,979	4,024
	(0.10%)	(9.24%)	(9.35%)
Trading & Sales	2,142	4,468	6,610
	(4.97%)	(10.38%)	(15.35%)
Retail Banking	1,370	20,647	22,017
	(3.18%)	(47.97%)	(51.15%)
Commercial Banking	54	1,452	1,506
	(0.12%)	(3.37%)	(3.49%)
Payment & Settlement	39	298	338
	(0.09%)	(0.69%)	(0.78%)
Agency Services	21	859	880
	(0.04%)	(1.99%)	(2.04%)
Asset Management	75	303	378
	(0.17%)	(0.70%)	(0.88%)
Retail Brokerage	467	453	920
	(1.08%)	(1.05%)	(2.13%)
Other	155	6,207	6,363
	(0.36%)	(14.42%)	(14.78%)
Total	4,370	38,669	43,040
	(10.15%)	(89.84%)	(100.00%)

Panel B: Fraud Recovery

	Loss Event Weighted			Loss Amount Weighted		
	Internal Fraud	External Fraud	Total	Internal Fraud	External Fraud	Total
Corporate Finance	3.91	18.13	18.04	15.17	0.08	0.25
Trading & Sales	6.90	0.26	0.27	0.72	3.75	2.77
Retail Banking	4.69	2.26	2.26	16.04	5.79	6.42
Commercial Banking	6.07	7.20	7.20	6.43	7.93	7.87
Payment & Settlement	12.40	0.03	0.03	14.41	3.76	5.01
Agency Services	17.86	1.86	1.89	12.72	1.61	1.88
Asset Management	8.22	4.11	4.48	0.23	21.92	17.62
Retail Brokerage	1.47	2.35	2.34	2.85	2.73	2.79
Other	5.44	0.41	0.47	45.07	2.96	3.99
Total	4.69	2.24	2.24	7.72	4.57	4.89

Panel C: Time between Fraud Occurrence, Discovery and Accounting

	Loss Event Weighted			Loss Amount Weighted		
	Internal Fraud	External Fraud	Total	Internal Fraud	External Fraud	Total
Occurrence to Discovery						
Corporate Finance	98	91	91	741	17	25
Trading & Sales	113	5	5	40	72	61
Retail Banking	24	17	17	235	166	170
Commercial Banking	116	24	24	387	27	40
Payment & Settlement	235	0	0	731	16	100
Agency Services	134	29	29	646	33	48
Asset Management	160	29	41	371	51	114
Retail Brokerage	247	15	17	303	198	252
Other	29	27	27	111	100	101
Total	33	17	17	172	119	125
Discovery to Accounting						
Corporate Finance	94	107	107	58	134	134
Trading & Sales	132	10	10	15	112	81
Retail Banking	27	46	46	96	80	81
Commercial Banking	100	65	65	382	376	376
Payment & Settlement	57	0	0	36	47	46
Agency Services	63	70	70	66	64	64
Asset Management	117	58	63	117	225	204
Retail Brokerage	90	96	96	102	475	286
Other	52	17	18	580	51	64
Total	32	46	46	77	101	99

Panel D: Fraud over Time		
Year	Amount	Frequency
2000	0.399	27.915
2001	1.192	50.031
2002	1.119	36.895
2003	0.190	93.429
2004	0.259	103.582
2005	0.204	86.321
2006	0.218	77.733
2007	0.228	86.608
2008	0.580	72.913
2009	0.145	86.610
2010	0.281	102.708
2011	0.154	109.575
2012	0.119	119.527
2013	0.177	118.542
2014	0.160	142.191
2015	0.119	151.027
2016	0.088	106.027

Panel E: Seasonality of Fraud		
Quarter	Amount	Frequency
First Quarter	0.033	24.173
Second Quarter	0.065	25.505
Third Quarter	0.069	25.948
Fourth Quarter	0.071	26.993

Table 3: **Fraud Value-at-Risk Estimates**

This table presents linear fits of fraud Value-at-Risk model estimates (in millions of 2016:Q4 constant dollars) at the 1^{st}, 25^{th}, 50^{th}, 75^{th}, 99^{th} percentiles of the fraud loss distributions of 38 large U.S. bank holding companies as a function of bank total assets. Note that the linear fits are based on information from all BHCs in the sample and thus cannot be used to identify loss quantiles for individual BHCs. See Section 3.6 for more details on the Value-at-Risk model.

	Fraud Percentile ($ Mil)				
Total Assets ($ Bil)	1^{st}	25^{th}	50^{th}	75^{th}	99^{th}
50	1.097	1.299	1.447	1.750	33.463
100	2.194	2.599	2.895	3.501	66.926
250	5.487	6.498	7.237	8.753	167.315
500	10.974	12.997	14.475	17.506	334.631
1,000	21.949	25.994	28.951	35.013	669.262
1,500	32.924	38.991	43.426	52.519	1,003.893
2,000	43.899	51.988	57.902	70.026	1,338.524
2,500	54.874	64.985	72.377	87.533	1,673.155

Table 4: **Summary Statistics**

This table presents summary statistics for the main variables used in Section 3.7. The sample includes 991 quarterly observations of fraud losses incurred by 38 large U.S. bank holding companies over the period [2000:Q1-2016:Q4] for which requisite data is available. The definitions of all variables are presented in Appendix B.

	Mean	Std	P25	P50	P75
Fraud	29.360	157.482	0.451	2.268	14.701
Ln(Fraud)	1.692	1.578	0.372	1.184	2.754
Ln(Size)	12.324	1.256	11.393	12.013	13.358
Deposits-to-TA	0.600	0.172	0.535	0.651	0.706
Loans-to-TA	0.557	0.209	0.417	0.649	0.707
NII-to-II	0.905	0.918	0.418	0.581	0.896
Cost Efficiency	0.613	0.226	0.458	0.647	0.762
Crime	1.376	0.487	1.058	1.301	1.588
Unemployment	6.807	1.796	5.333	6.167	8.267

Table 5: **Fraud and BHC Attributes**

This table reports coefficients from panel regression of fraud losses on BHC attributes. The sample includes 991 quarterly observations of fraud losses incurred by 38 large U.S. bank holding companies over the period [2000:Q1-2016:Q4] for which requisite data is available. In Column (1), we do not include BHC or time fixed effects. In Column (2), we include BHC fixed effects. In Column (3), we include quarter fixed effects. In Column (4), we include BHC and quarter fixed effects. The regression error terms in all specifications are clustered at the BHC and quarter levels. The definitions of all variables are presented in Appendix B. P-values are presented in parentheses.

	Ln(Fraud)			
	(1)	(2)	(3)	(4)
Ln(Size)	0.944***	1.069***	0.968***	0.822**
	(0.000)	(0.000)	(0.000)	(0.017)
Deposits-to-TA	2.192***	0.706	2.532***	1.421**
	(0.001)	(0.248)	(0.004)	(0.029)
Loans-to-TA	−1.180	−3.670*	−0.846	−2.345
	(0.337)	(0.100)	(0.526)	(0.201)
NII-to-II	−0.228	−0.206	−0.161	−0.089
	(0.292)	(0.123)	(0.507)	(0.480)
Cost Efficiency	−1.365***	−1.219*	−1.469**	−1.103*
	(0.007)	(0.080)	(0.012)	(0.099)
Crime	0.652*	0.393*	0.707*	0.277
	(0.073)	(0.060)	(0.066)	(0.172)
Unemployment	−0.070**	−0.035		
	(0.028)	(0.333)		
BHC FE	No	Yes	No	Yes
Quarter FE	No	No	Yes	Yes
N	991	991	991	991
Adj R^2	0.558	0.783	0.562	0.798

*$p < 0.10$, **$p < 0.05$, ***$p < 0.01$

Table 6: **Summary Statistics**

This table presents summary statistics for the main variables used in Section 4. The sample includes 991 quarterly observations of fraud losses incurred by 38 large U.S. bank holding companies over the period [2001:Q1-2016:Q4] for which requisite data is available. The definitions of all variables are presented in Appendix B.

	Mean	Std	P25	P50	P75
Abnormal Fraud	-4.085	113.154	-3.766	-0.401	1.230
Deposit Growth	12.514	23.585	2.664	6.891	14.552
Loan Growth	8.411	18.921	0.460	4.811	10.907
ΔROE	-36.838	1,607.387	-281.424	-16.625	209.731
ΔROA	-1.807	169.097	-24.436	-0.859	21.129
Size Growth	5.753	22.577	-2.397	4.518	11.617
ΔNII-to-II	0.030	1.268	-0.201	0.004	0.230
ΔCost Efficiency	-0.000	0.129	-0.047	-0.001	0.041
ΔCrime	-0.019	0.422	-0.002	0.000	0.000
Competition	0.500	0.500	0.000	0.000	1.000
Branch Intensity	0.528	0.499	0.000	1.000	1.000
Interest Expense	0.476	0.500	0.000	0.000	1.000
2007-09 Financial Crisis	0.156	0.363	0.000	0.000	0.000
Capital	0.483	0.500	0.000	0.000	1.000
Liquidity	0.551	0.498	0.000	1.000	1.000

Table 7: **Deposit Growth**

This table reports coefficients from panel regressions of BHC deposit growth on abnormal fraud incurred by BHCs. The sample includes 871 quarterly observations from 38 large U.S. bank holding companies over the period [2000:Q1-2016:Q4] for which requisite data is available. In Panel A, our abnormal fraud measure aggregates fraud from all business lines. In Panel B, our abnormal fraud measures split fraud into retail and commercial banking business lines vis-á-vis other business lines. All specifications include BHC and quarter fixed effects and cluster regression error terms at the BHC and quarter levels. The definitions of all variables are presented in Appendix B. P-values are presented in parentheses.

Panel A: All Business Lines

	Deposit Growth		Deposit Growth 1Q		Deposit Growth 8Q	
	(1)	(2)	(3)	(4)	(5)	(6)
Abnormal Fraud	-0.013^{***}	-0.013^{**}	-0.017^{**}	-0.016^{*}	-0.006^{*}	-0.005^{*}
	(0.009)	(0.011)	(0.018)	(0.061)	(0.080)	(0.091)
Size Growth		-0.040		-0.048		-0.043
		(0.483)		(0.710)		(0.248)
ΔNII-to-II		0.024		0.966		-0.275
		(0.961)		(0.456)		(0.551)
ΔCost Efficiency		5.169		42.425		5.240
		(0.525)		(0.280)		(0.418)
ΔCrime		-0.042		-1.392		2.036^{**}
		(0.966)		(0.853)		(0.048)
BHC FE	Yes	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
N	871	871	871	871	871	871
Adj R^2	0.186	0.183	0.050	0.056	0.265	0.266

Panel B: Retail and Commercial Banking		
	Deposit Growth	
	(1)	(2)
Abnormal Fraud (Retail & Commercial Banking)	-0.042^{**}	-0.040^{**}
	(0.028)	(0.031)
Abnormal Fraud (Other Business Lines)	-0.012^{**}	-0.012^{**}
	(0.019)	(0.027)
Controls	*No*	*Yes*
BHC FE	Yes	Yes
Quarter FE	Yes	Yes
N	871	871
Adj R^2	0.186	0.183

Table 8: **Deposit Growth: Interaction Effects**

This table reports coefficients from panel regressions of BHC deposit growth on abnormal fraud incurred by BHCs. The sample includes 871 quarterly observations from 38 large U.S. bank holding companies over the period [2000:Q1-2016:Q4] for which requisite data is available. Panel A presents results of interactions between abnormal fraud and local market competition. Panel B presents results of interactions between abnormal fraud and bank branch intensity. Panel C presents results of interactions between abnormal fraud and bank interest expense. Panel D presents results of interactions between abnormal fraud and the 2007-2009 Financial Crisis. All specifications include BHC and quarter fixed effects and cluster regression error terms at the BHC and quarter levels. The definitions of all variables are presented in Appendix B. P-values are presented in parentheses.

Panel A: Competition		
	Deposit Growth	
	(1)	(2)
Abnormal Fraud	-0.008^{*}	-0.010
	(0.056)	(0.578)
Competition	-1.795	-1.851
	(0.572)	(0.580)
Abnormal Fraud * Competition	-0.005^{***}	-0.004^{*}
	(0.004)	(0.099)
Controls	*No*	*Yes*
BHC FE	Yes	Yes
Quarter FE	Yes	Yes
N	871	871
Adj R^2	0.184	0.182

Panel B: Branch Intensity		
	Deposit Growth	
	(1)	(2)
Abnormal Fraud	−0.026***	−0.025***
	(0.000)	(0.000)
Branch Intesity	5.387	4.588
	(0.370)	(0.410)
Abnormal Fraud * Branch Intensity	0.013*	0.013*
	(0.067)	(0.068)
Controls	*No*	*Yes*
BHC FE	Yes	Yes
Quarter FE	Yes	Yes
N	871	871
Adj R^2	0.189	0.188

Panel C: Deposit Expense		
	Deposit Growth	
	(1)	(2)
Abnormal Fraud	−0.003*	−0.003*
	(0.082)	(0.070)
Deposit Expense	−0.843	−0.898
	(0.891)	(0.880)
Abnormal Fraud * Deposit Expense	−0.043**	−0.044**
	(0.018)	(0.013)
Controls	*No*	*Yes*
BHC FE	Yes	Yes
Quarter FE	Yes	Yes
N	871	871
Adj R^2	0.190	0.188

Panel D: 2007-2009 Financial Crisis

	Deposit Growth	
	(1)	(2)
Abnormal Fraud	-0.009^{**}	-0.009^{***}
	(0.011)	(0.009)
Abnormal Fraud * Financial Crisis	-0.013^{**}	-0.014^{***}
	(0.044)	(0.000)
Controls	*No*	*Yes*
BHC FE	Yes	Yes
Quarter FE	Yes	Yes
N	871	871
Adj R^2	0.187	0.186

Table 9: **Loan Growth**

This table reports coefficients from panel regressions of BHC loan growth on abnormal fraud incurred by BHCs. The sample includes 871 quarterly observations from 38 large U.S. bank holding companies over the period [2000:Q1-2016:Q4] for which requisite data is available. In Panel A, our abnormal fraud measure aggregates fraud from all business lines. In Panel B, our abnormal fraud measures split fraud into retail and commercial banking business lines vis-á-vis other business lines. All specifications include BHC and quarter fixed effects and cluster regression error terms at the BHC and quarter levels. The definitions of all variables are presented in Appendix B. P-values are presented in parentheses.

Panel A: All Business Lines

	Loan Growth		Loan Growth 1Q		Loan Growth 8Q	
	(1)	(2)	(3)	(4)	(5)	(6)
Abnormal Fraud	−0.009***	−0.008**	−0.015***	−0.014***	−0.005**	−0.004**
	(0.009)	(0.012)	(0.001)	(0.001)	(0.030)	(0.025)
Size Growth		0.015		−0.124		0.016
		(0.494)		(0.150)		(0.407)
ΔNII-to-II		0.053		−2.666		0.212
		(0.945)		(0.246)		(0.652)
ΔCost Efficiency		14.400**		22.114		1.779
		(0.034)		(0.207)		(0.617)
ΔCrime		0.955		6.479		2.136*
		(0.601)		(0.214)		(0.086)
BHC FE	Yes	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
N	871	871	871	871	871	871
Adj R^2	0.192	0.197	0.045	0.058	0.310	0.312

Panel B: Retail and Commercial Banking		
	Loan Growth	
	(1)	(2)
Abnormal Fraud (Retail & Commercial Banking)	-0.025^{**}	-0.022^{**}
	(0.029)	(0.048)
Abnormal Fraud (Other Business Lines)	-0.008^{**}	-0.007^{**}
	(0.012)	(0.014)
Controls	*No*	*Yes*
BHC FE	Yes	Yes
Quarter FE	Yes	Yes
N	871	871
Adj R^2	0.191	0.197

Table 10: **Loan Growth: Interaction Effects**

This table reports coefficients from panel regressions of BHC loan growth on abnormal fraud incurred by BHCs. The sample includes 871 quarterly observations from 38 large U.S. bank holding companies over the period [2000:Q1-2016:Q4] for which requisite data is available. Panel A presents results of interactions between abnormal fraud and bank capitalization. Panel B presents results of interactions between abnormal fraud and bank liquidity. All specifications include BHC and quarter fixed effects and cluster regression error terms at the BHC and quarter levels. The definitions of all variables are presented in Appendix B. P-values are presented in parentheses.

Panel A: Capital		
	Loan Growth	
	(1)	(2)
Abnormal Fraud	0.000	0.001
	(0.816)	(0.374)
Capital	−3.103	−2.995
	(0.136)	(0.152)
Abnormal Fraud * Capital	−0.035***	−0.036***
	(0.001)	(0.001)
Controls	*No*	*Yes*
BHC FE	Yes	Yes
Quarter FE	Yes	Yes
N	871	871
Adj R^2	0.200	0.205

Panel B: Liquidity		
	Loan Growth	
	(1)	(2)
Abnormal Fraud	-0.006^{***}	-0.006^{***}
	(0.004)	(0.001)
Liquidity	0.419	0.388
	(0.889)	(0.901)
Abnormal Fraud * Liquidity	-0.035^{***}	-0.036^{***}
	(0.002)	(0.000)
Controls	*No*	*Yes*
BHC FE	Yes	Yes
Quarter FE	Yes	Yes
N	871	871
Adj R^2	0.188	0.186

Table 11: **Profitability**

This table reports coefficients from panel regressions of changes in BHC profitability on abnormal fraud incurred by BHCs. The sample includes 871 quarterly observations from 38 large U.S. bank holding companies over the period [2000:Q1-2016:Q4] for which requisite data is available. All specifications include BHC and quarter fixed effects and cluster regression error terms at the BHC and quarter levels. The definitions of all variables are presented in Appendix B. P-values are presented in parentheses.

	ΔROE		ΔROA	
	(1)	(2)	(3)	(4)
Abnormal Fraud	−0.501***	−0.533***	−0.059***	−0.061***
	(0.000)	(0.000)	(0.005)	(0.003)
Size Growth		0.249		0.180
		(0.940)		(0.580)
ΔNII-to-II		−9.956		−1.856
		(0.758)		(0.613)
ΔCost Efficiency		−339.001		−21.385
		(0.582)		(0.789)
ΔCrime		−162.836		−18.780
		(0.176)		(0.174)
BHC FE	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes
N	871	871	871	871
Adj R^2	0.073	0.071	0.070	0.069

Table 12: **Fraud Event Severity, Recovery and Timing**

This table reports coefficients from regressions of fraud event severity, recovery or timing on fraud event characteristics. The sample includes 17,512,671 fraud losses incurred by 38 large U.S. bank holding companies over the period [2000:Q1-2016:Q4]. Panel A presents results on fraud severity. Panel B presents results on fraud recovery. Panel C presents results on fraud timing. All specifications include BHC×Quarter fixed effects and cluster regression error terms at the BHC level. The definitions of all variables are presented in Appendix B. P-values are presented in parentheses.

Panel A: Fraud Severity			
	Ln(Fraud)		
	(1)	(2)	(3)
Ln(Occurrence to Discovery)		0.077^{**}	0.071^{*}
		(0.021)	(0.054)
Ln(Discovery to Accounting)		0.005^{***}	0.001
		(0.000)	(0.535)
Internal Fraud	1.586^{***}		1.572^{***}
	(0.000)		(0.000)
Corporate Finance	0.266^{***}		0.211^{***}
	(0.000)		(0.000)
Trading & Sales	-0.415^{***}		-0.352^{***}
	(0.000)		(0.000)
Commercial Banking	0.607^{***}		0.623^{***}
	(0.000)		(0.000)
Payments & Settlement	-0.460^{***}		-0.270^{***}
	(0.000)		(0.006)
Agency Services	0.528^{***}		0.562^{***}
	(0.000)		(0.000)
Asset Management	1.174^{***}		1.180^{***}
	(0.000)		(0.000)
Retail Brokerage	0.586^{***}		0.614^{***}
	(0.000)		(0.000)
Other	0.481^{***}		0.385^{***}
	(0.000)		(0.000)
BHC×Quarter FE	Yes	Yes	Yes
N	17,512,671	17,512,671	17,512,671
Adj R^2	0.005	0.003	0.007

$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

Panel B: Fraud Recovery

	Recovery Rate		
	(1)	(2)	(3)
Ln(Fraud)		0.004***	0.004***
		(0.000)	(0.000)
Ln(Occurrence to Discovery)		0.001	0.001
		(0.601)	(0.520)
Ln(Discovery to Accounting)		0.003***	0.003***
		(0.000)	(0.000)
Internal Fraud	0.009		0.003
	(0.158)		(0.674)
Corporate Finance	0.169***		0.160***
	(0.000)		(0.000)
Trading & Sales	−0.017***		−0.007***
	(0.000)		(0.000)
Commercial Banking	0.047***		0.044***
	(0.000)		(0.000)
Payments & Settlement	0.000		0.004
	(0.665)		(0.294)
Agency Services	−0.007***		−0.009***
	(0.000)		(0.000)
Asset Management	−0.005		−0.010
	(0.791)		(0.613)
Retail Brokerage	−0.001*		−0.004***
	(0.080)		(0.000)
Other	−0.018***		−0.020***
	(0.000)		(0.000)
BHC×Quarter FE	Yes	Yes	Yes
N	17,512,671	17,512,671	17,512,671
Adj R^2	0.001	0.003	0.004

$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

Panel C: Fraud Timing

	(1) Ln(Occurrence to Discovery)	(2) Ln(Discovery to Accounting)	(3) Ln(Discovery to Accounting)	(4) Ln(Discovery to Accounting)
Recovery Rate			0.233	0.200
			(0.108)	(0.105)
Ln(Fraud)			0.002***	−0.000
			(0.007)	(0.877)
Ln(Occurrence to Discovery)			0.018***	0.015***
			(0.000)	(0.000)
Internal Fraud	0.200***	−0.018		−0.022
	(0.000)	(0.838)		(0.799)
Corporate Finance	0.738***	2.965***		2.920***
	(0.000)	(0.000)		(0.000)
Trading & Sales	−0.836***	−3.171***		−3.155***
	(0.000)	(0.000)		(0.000)
Commercial Banking	−0.220***	0.402**		0.396**
	(0.000)	(0.045)		(0.044)
Payments & Settlement	−2.693***	0.000		0.041***
	(0.000)	(0.966)		(0.000)
Agency Services	−0.470***	−0.048***		−0.039***
	(0.000)	(0.000)		(0.000)
Asset Management	−0.084	0.072		0.075
	(0.447)	(0.441)		(0.415)
Retail Brokerage	−0.395***	0.353***		0.359***
	(0.000)	(0.000)		(0.000)
Other	1.361***	−0.635***		−0.652***
	(0.000)	(0.000)		(0.000)
BHC×Quarter FE	Yes	Yes	Yes	Yes
N	17,512,671	17,512,671	17,512,671	17,512,671
Adj R^2	0.058	0.034	0.001	0.035

$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$