Do depositors monitor banks using accounting information? Evidence from the EDGAR log file*

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ABSTRACT

This paper investigates whether depositors monitor banks using accounting information. I develop a novel measure of depositor monitoring based on downloads of banks' SEC filings traced through the EDGAR log file. Descriptive evidence suggests that depositors are the primary users of banks' filings. Moreover, I find that higher depositor monitoring through accounting information (Form 10-K and 10-Q) is associated with a decline in future uninsured deposits, but only when the filings reveal negative information about bank performance. This finding is consistent with the theoretical prediction that depositors are primarily concerned with downside risks and that information about bank fundamentals influences their withdrawal decisions. In addition, I document how the role of depositor monitoring evolved during the Global Financial Crisis, shifting across different phases of the crisis in response to depositors' changing incentives before and after government interventions. Overall, this study provides direct, large-scale evidence on depositor monitoring via accounting disclosures and its implications for uninsured deposit flows and financial stability.

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1. *Introduction*

Depositors are the largest funding source for U.S. banks, providing approximately 75% of their total financial resources.[1] At the same time, they also pose a significant threat to financial stability due to their potential to trigger "bank runs", i.e. sudden and large-scale withdrawals of money (Diamond and Dybvig, 1983). Among the factors shaping depositors' withdrawal decisions, banks' accounting disclosures play a particularly important role (Bischof et al., 2021; Chen et al., 2022, 2024). Nevertheless, empirical evidence on how - and whether - depositors acquire and use this information remains very limited (Boyarchenko et al., 2025). The recent failure of Silicon Valley Bank (SVB) raises further questions about whether depositors effectively use accounting information to monitor banks: although SVB's losses were publicly disclosed in the fall of 2022 (SVB, 2022), depositors only ran on the bank in March 2023. Media reports suggest that depositors may have outright *disregarded* the available accounting information (Financial Times, 2023). This paper investigates depositor monitoring through banks' accounting disclosures and its implications for uninsured deposit flows.

Depositor monitoring theories suggest that (uninsured) depositors have incentives to monitor banks because they are concerned about downside risks, i.e. the risk of losing money in the event of a bank failure (Calomiris and Kahn, 1991). In fact, because of the so-called "sequential service constraint", by which banks make payments to demanders on a first-come, first-served basis, active depositors that monitor banks' performance incur the costs of vigilance, but receive the benefit of knowing that they will be "first in line" should it become necessary to withdraw their funds from the bank. Indeed, upon discovering negative news about the bank's performance, the depositors that "kept an eye on the bank" can protect their interests by withdrawing their deposits in a timely way. Based on this argument, I predict a *negative* association between depositor monitoring of banks' accounting disclosures and (uninsured) deposit flows when there is negative information about bank financial performance.

To test this prediction, the first step is to measure *depositor monitoring* and information acquisition, an aspect that the empirical literature has not yet systematically addressed. I contribute to filling this gap by drawing on the rich data made available by the Securities and Exchange Commission (SEC) through the EDGAR log file.[2] From 2003 to 2016, the EDGAR log file tracks the online activity performed by all the users that download SEC filings through the platform, and provide data about,

[1]Calculation based on Federal Reserve data seasonally adjusted as of July 2024, available at: https://www.federalreserve.gov/releases/h8/.

[2]EDGAR stands for Electronic Data Gathering, Analysis, and Retrieval, and is an online repository launched in 1992 to make corporate filings easily accessible by anyone online. EDGAR can be accessed at: https://www.sec.gov/search-filings.

among others, user location, user IP address and the filings requested. This data has already been used in the accounting (e.g., Drake et al., 2015; Dyer, 2021) and finance (e.g., Lee et al., 2015; Chen et al., 2020) literature but, to the best of my knowledge, not yet in the context of empirical banking.

Using this data, I employ a novel approach to measure *depositor monitoring* based on the ownership information of IP addresses requesting filings on EDGAR. The measure captures depositor monitoring by counting downloads made by telecommunication companies (representing *retail* depositors) and non-financial companies (representing *corporate* depositors). Descriptive evidence suggests that depositors constitute the largest user group of banks' disclosures by number of downloads, accounting for nearly 30% of total downloads, in line with the importance of depositors for the banking system. Then, I analyze the relation between *depositor monitoring* and uninsured deposit flows drawing on the theoretical model developed by Egan et al. (2017). With this design, the relation is identified from between banks differences in EDGAR downloads in a given quarter, after considering variables that theory predicts to affect uninsured deposits, and abstracting from bank-specific time-invariant differences in downloads and any time trends in the data.

The results show a negative and significant association between *depositor monitoring* using banks' accounting disclosure (more specifically annual reports, 10-K and quarterly reports, 10-Q) and future *uninsured* deposit flows, as predicted. This association is stronger in quarters when depositors discover negative ROE news about the bank, and is absent in positive-ROE news quarters, in line with the theoretical idea that depositors are primarily concerned with downside risks and that gaining more information about bank fundamentals affects their withdrawal decisions. Given that the sample period includes the crisis of 2007-2008, I investigate how the effect of depositor monitoring on uninsured deposit flows varies during the different phases of the crisis. The results indicate that, in the most severe phase prior to the government interventions in the fall of 2008, greater monitoring was associated with a decrease in future uninsured deposits, consistent with the fact that learning about bank fundamentals led to even further depositor withdrawals. However, after the government interventions, the results show a positive and significant association between depositor monitoring and uninsured deposit flows. Finally, robustness tests indicate that the effect of depositor monitoring on uninsured deposit flows varies by bank size, and is concentrated among larger banks.

This paper contributes to the literature in three main ways. First, it adds to the literature on the relation between accounting disclosure and depositor decisions. Recent studies find that depositors are sensitive to the transparency of banks financial statements (Chen et al., 2022) and to the fair value information disclosed in the footnotes (Chen et al., 2024); however, these studies derive their conclusions from indirect evidence about the statistical association between banks' financial reporting characteristics and deposit flows. This paper complements their work by providing large-scale quantification of depositor information acquisition and monitoring using banks' accounting information, providing a credible mechanism in support of their results. Second, this paper is related to research on the the role of information and transparency for financial stability, both empirical (e.g., Granja, 2018; Bischof et al., 2021) and theoretical (e.g., Dai et al., 2023; Dang et al., 2017; Zhang and Zheng, 2024; Boyarchenko et al., 2025), which is discussed in various literature reviews (e.g., Acharya and Ryan, 2016; Beatty et al., 2023). This literature is not conclusive about the desirability of transparency versus opacity: while more transparency can lead to better monitoring, it could also lead to higher instability and inefficient bank runs. This paper informs the debate by providing additional empirical evidence that transparency matters because depositors do use financial information in making their decisions. Future research could study more in depth the determinants of depositor monitoring. Finally, the paper speaks to the broader research information acquisition via EDGAR (e.g., Drake et al., 2015; Loughran and McDonald, 2017; Dyer, 2021; Li et al., 2023). By focusing on a specific industry (banking) and a specific class of users (depositors), this paper provides novel empirical evidence from a setting which is often overlooked, despite being a setting in which information plays a crucial role.

2. *Background*

2.1 *Institutional Setting*

2.1.1 *Banks' Disclosure Regimes in the U.S.*

In the U.S., banks can operate either as standalone entities or, more commonly, as part of larger groups known as a Bank Holding Companies (BHCs).[3] In both cases, banks have the option to remain private or become publicly-listed, and their disclosure requirements vary based on their status. In particular, if a bank is *publicly listed*, it has to file annual (10-K), quarterly (10-Q), and other types of reports to the SEC via the EDGAR platform. Instead, *all* the banks, regardless of their public or private status, also have to file regulatory reports required by bank regulators. Regulatory reports contain banks' financial information and the two main regulatory reports are Consolidated Reports of Condition and Income (or Call Reports) and form Y-9Cs. Both are filed at the calendar-quarter level,

[3]Throughout this paper, I use the term "bank" to refer interchangeably to both individual banks and BHCs, unless otherwise specified.

but Call Reports are filed at the individual bank level, while form Y-9Cs at the BHC level.

The information disclosed in SEC filings and regulatory reports overlaps only partially. First, the SEC mandates listed entities to disclose a wide range of information, extending beyond financial data to include forms such as statements of ownership changes (Form 4) and proxy statements (Form DEF14A). Second, the SEC financial reports (From 10-K and Form 10-Q) include disclosures absent in regulatory filings, such as the statement of cash flows and footnotes to financial statements, which contain both qualitative and quantitative disclosures that are crucial for understanding a bank's financial position. (Badertscher et al., 2018).

2.1.2 *The Role of Depositors in the Banking Industry*

Depositors are a primary source of funding for U.S. banks: approximately 75% of total banks' funds are represented by deposits.[4] Deposits are also a very cheap source of funding for banks, which, due to to their market power, pay deposit rates that are low and almost insensitive to market interest rates (Drechsler et al., 2021).

However, funding through deposits comes with the drawback of being very short-term and, in many cases, withdrawable on-demand, depending on the terms of the specific deposit contract. For this reason, and differently from all other industries where debt holders typically bear the risk of a company failing, depositors are granted an *insurance* on the money they provide to the bank. Should the bank go bankrupt, the depositor is entitled to have her money back, dollar-for-dollar, including principal and any accrued interest, up to the applicable insurance limit.

The underpinning behind the existence of deposit insurance is that it acts as an "equilibrium selection device" to prevent "panic-based" bank runs (Diamond and Dybvig, 1983), i.e. runs driven by coordination failures among depositors rather than poor bank fundamentals. In the U.S., deposit insurance is provided by the Federal Deposit Insurance Corporation (FDIC), which was established in 1933 in response to the Great Depression. Currently, the FDIC insures deposits up to $250,000, though this limit varied over time.[5] Considering the existence of deposit insurance, only *uninsured* depositors have incentives to monitor bank behavior given that they face the risk of losing their money in the event of bank failure (Calomiris and Kahn, 1991; Diamond and Rajan, 2001); for this reason,

[4] See Footnote 1.

[5] During the sample period, there was one change in the deposit insurance limit: before 2008, the limit was $100,000; then, in the aftermath of the global financial crisis, it was raised to $250,000 and remained at that level ever since. The measures of deposits used in the empirical analysis take this change into account since they are based on Call Reports, which incorporated the change in their reporting structure.

in the empirical analysis I focus on changes in *uninsured* deposits.

2.2 *Theoretical Framework*

In theory, depositors are often characterized as the main claim holders of banks whose actions influence the functioning of the whole banking sector, a characterization which is deeply rooted in the data. Prominent banking models suggest that depositors are crucial for the existence of banks, but at the same time, they are also the very main cause of banks' financial fragility. Indeed, depositors typically have the right to withdraw their cash on demand, which gives them the ability to initiate a run on the bank - suddenly withdrawing all their funds, forcing the bank to liquidate its assets immediately.

Why do bank runs occur and are they desirable? On the one hand, uninsured depositors may decide to run on the bank because of *panic*, in which case bank runs lead to inefficient and undesirable outcomes (Diamond and Dybvig, 1983). On the other hand, bank runs can also occur due to information about poor bank fundamentals (Chari and Jagannathan, 1988; Jacklin and Bhattacharya, 1988; Goldstein and Pauzner, 2005), in which case bank runs could be efficient if they prevent the inefficient continuation of "bad banks". Furthermore, fundamental-driven runs can provide incentives for bank managers to behave prudently, helping to mitigate the bank's moral hazard problem (Calomiris and Kahn, 1991). Indeed, by incurring the cost of "vigilance", depositors can acquire information about banks' activities and, if they find that the bank prospects are poor enough, they can "vote with their feet" by pulling out their deposits.

Empirical literature aligns with theoretical predictions, finding that (uninsured) deposit flows are indeed responsive to bank fundamentals and that depositors move their funds when there are negative news about banks' prospects (e.g., Beck et al., 2022; Chen et al., 2023; Das et al., 2023; Goldberg and Hudgins, 2002; Iyer and Puri, 2012; Kleymenova and Tomy, 2022; Correia et al., 2024).

Taken together, these theoretical and empirical studies suggest that (uninsured) depositors have both the incentives and the sophistication to monitor banks' financial information. However, perhaps surprisingly, there is no direct empirical evidence about depositors' information acquisition and monitoring efforts (Boyarchenko et al., 2025). To fill this gap, this paper introduces a novel approach to measuring depositor monitoring and examines the relation between depositor monitoring and uninsured deposit flows. Based on the arguments above, I predict a *negative* relation between depositor monitoring and uninsured deposit flows when depositors find out negative news about bank performance.

3. *Data and Measure*

3.1 *Data*

I measure depositor monitoring with a novel approach based on the EDGAR log file, which records individual "clicks" for SEC filings downloads. Each log entry contains the following information: (i) the requesting user's IP address with the final octet replaced by a unique three-letter mask for privacy reasons; (ii) the exact time stamp of the request; (iii) the Central Index Key (CIK) identifying the company associated with the requested filing; (iv) a unique identifier for the specific filing downloaded. The sample used in this study ranges from the first quarter of 2003 to the last quarter of 2016, as the SEC ceased providing IP address data thereafter due to privacy concerns.

To identify EDGAR downloads of *bank* filings, I apply the following three steps (also summarized in Table 1a). First, I consider all the daily log files from 2003 to 2016, which account for approximately 21 billion downloads. Second, I clean the log files following prior literature to retain only downloads originating from human users.[6] More specifically, I exclude: (i) unsuccessfully delivered requests, i.e. requests with server codes greater than 200 (e.g., URL not found); (ii) index observations; (iii) self-identified web crawlers; (iv) IP addresses with more than 25 downloads per minute, or more than 500 downloads during a day, or more than 3 different companies searched in a minute (Drake et al., 2015; Loughran and McDonald, 2017; Ryans, 2017). The cleaning procedure reduces the number of downloads to 4.3% of the initial total. Third, I restrict the sample to the downloads that are addressed solely to banks' filings.[7] This results in 2,610 unique bank CIKs and 69.6 million of EDGAR downloads (7.7% of the total EDGAR human downloads). In the regressions, I exclude observations before March 2003 and from the last quarter of 2005 to the first quarter of 2006 (included), because these observations are labeled by the SEC as damaged or incomplete (Loughran and McDonald, 2017).

Deposit data and other bank financial data are obtained from U.S. Call Reports. As discussed, Call Reports present information at the individual-bank level. I aggregate data at the BHC level, because typically the BHC is the listed entity that files with the SEC; when there is no BHC, I retain the data at the individual bank level.[8] As standard in this literature (e.g., Chen et al., 2022), I use data

[6] I follow the approach of Ryans (2017), as it prioritizes retaining downloads from more sophisticated users. Given the complexity of banks, this method appears particularly suitable for my analysis. However, as Ryans (2017) notes, other standard methods commonly used in the literature (e.g., Drake et al., 2015; Loughran and McDonald, 2017) yield very similar results.

[7] Since EDGAR log file does not contain industry information, I first link EDGAR CIKs to Compustat through WRDS SEC Analytics linking table, and then get industry information from Compustat. I use Fama-French 48 classification to keep only CIKs belonging to the banking sector (industry code 44).

[8] To perform the BHC-level aggregation, I use the data from Drechsler et al. (2017) available on the authors' website.

from Call Reports and not from form Y9-C reports, which are filed by BHCs, because forms Y9-C do not distinguish between insured and uninsured deposits. Then, I match Call Reports data to EDGAR bank downloads using bank identifiers (Table 1b). I remove bank-quarter observations with quarterly asset growth greater than 10% to avoid the impact of business combinations (e.g., Chen et al., 2022, 2024). I also winsorize all continuous variables at 1% and 99% level.

3.2 *Developing a New Measure of Depositor Monitoring*

Based on the data described above, I develop a new measure of *depositor monitoring* through banks' accounting disclosure. Ideally, constructing such a measure would require at least three inputs: (i) data on the EDGAR traffic directed to banks' accounting information; (ii) data on the ownership of the IP addresses that generate this traffic; and (iii) data on the identity of banks' depositors. In practice, data availability imposes significant constraints. While the first input is readily accessible from the EDGAR log files described above, the other two are more challenging to obtain due to their sensitive nature. Specifically, the third input - the identity of banks' depositors - is proprietary information owned by banks and is inaccessible to researchers. However, the second input - the ownership of IP addresses requesting SEC filings - can be inferred from the EDGAR log files data as follows.

Identifying the ownership of such IP addresses is challenging because the SEC masks the final octet of each IP address in the log files, replacing it with letters to preserve privacy. Nonetheless, it is possible to identify user groups (e.g., companies) based on their ownership of an entire range of IP addresses, as this information is publicly available.[9] I employ a *WhoIs* query through the Python library *ipwhois* for all the IP addresses ranges that belong to the same user.[10] Then, I manually classify the top 5,000 IP addresses by number of downloads (accounting for 60.8% of EDGAR bank downloads) based on their company names, as displayed in Table 2b.

At this point, in order to build the new proxy for *depositor monitoring*, I classify downloads coming from *depositors* as the sum of "telecommunication" and "non-financial companies" downloads. The validity of this proxy depends on the following assumptions: (i) if a non-financial company downloads SEC filings for a bank, that company is likely to be a *corporate* depositor of that bank; and (ii)

The authors use RSSD9348 to identify bank holding companies and RSSD9001 to identify individual entities.

[9]A IPv4 range of addresses starts with .000 and ends with .255 as the last octect.

[10]*WhoIs* queries are commonly used in the literature (e.g., Bozanic et al., 2017). The *ipwhois* Python library retrieves information from administrative publicly available data, such as the American Registry of Internet Numbers (ARIN; see: https://www.arin.net/) for the U.S., and similar registries for other countries. These registries provide current ownership information for IP addresses, as well as the IP registration date. However, since IP addresses can be reassigned, I treat as "n.a." all the IP addresses that are registered after the end of my sample period (2016). An alternative, more time-consuming method would be to use manual IP *WhoWas* requests as in Dyer (2021).

downloads originated by telecommunication companies are likely to be downloads coming from *retail* depositors.

Regarding assumption (i), the literature recognizes that downloads originating from non-financial companies are typically "*for purposes other than financial investment*" (Drake et al., 2020). In the context of this study, it is therefore reasonable to attribute such downloads to *corporate* depositors. As for assumption (ii), downloads originating from telecommunication companies are classified as "retail" downloads in the literature, meaning they are generated by users who do not own an entire IP range, such as individuals accessing the internet through their home Internet Service Provider (ISP) (Drake et al., 2020). Within this framework, it seems sensible to assume that retail downloads primarily come from *retail* depositors, as depositors constitute the main class of banks' claim holders.

Finally, since this novel measurement approach hinges on the richness of the EDGAR log file data, it is important to mention that EDGAR is not the only source of publicly disclosed financial information of banks. In fact, depositors could obtain this information from alternative sources such as company websites, bank regulatory reports, Bloomberg, Refinitiv etc. In spite of this, EDGAR remains arguably one of the most important sources of information, for several reasons (Loughran and McDonald, 2017). First, EDGAR is a freely accessible repository that provides centralized access to information of all SEC-filing companies in a single location. Second, alternative sources often reclassify most accounting data such as income statement and balance sheet items or, as in the case of Call Reports, lack the qualitative disclosure contained in the SEC filings (e.g., the footnotes to the financial statements). Importantly, recent evidence suggests that depositors react to information disclosed exclusively in footnotes (Chen et al., 2024). This underscores the critical role of EDGAR as a primary source of financial information for depositors, lending further credibility to the measure introduced in this study.

3.3 *Aggregate Evidence on Bank Downloads*

Bank downloads represent 7.7% of the total human downloads to all SEC-filing companies (Table 1a).

Table 2a shows that the number of human downloads directed to banks' filings increased significantly over time, going from less than 1 million in 2003 to more than 10 million in 2016.[11] The mean (median) number of downloads per bank-year went up from 120 (41) in 2003 to 1,072 (74) in 2016. From the comparison between the mean and the median, it can also be noted that the distribution of EDGAR downloads is highly skewed. For this reason, in the regression analyses I use the natural logarithm of

[11] Bank downloads increase in all years except 2006; this is likely due to the damages in log file that the SEC reported in that period, which is in fact excluded from the regression analyses as explained above.

the EDGAR downloads, in line with prior literature (e.g., Drake et al., 2020).

Table 2b displays the distribution of EDGAR downloads by user type. Importantly, depositors are the first largest category of users, accounting for 29.9% of the total bank downloads. Most depositor downloads come from retail depositors. Among other user types, banks represent the second-largest category, suggesting that banks request SEC filings related to other banks, potentially for competition-related reasons.

Table 2c provides information about the types of filings downloaded by depositors. Periodic accounting reports account for 26.4% of the total depositors' downloads, with quarterly reports (Form 10-Q) and annual reports (Form 10-K) representing 13.6% and 12.8%, respectively. The rest of the downloads is represented by current filings (Form 8-K) for 14.8%, and by other types of filings, e.g. proxy statements (Form DEF14A), which are not the focus of this study.

Finally, Figure 1 shows that while most of the EGDAR bank downloads originate from the U.S. (approximately 66%), there are also significant downloads from other parts of the world. Within the U.S., most of the downloads come from the STate with the highest economic activity and income levels (Figure 2).

4. *Depositor Monitoring and Uninsured Deposit Flows*

4.1 *Research Design*

To study the relation between *depositor monitoring* and uninsured deposit flows, I rely on a specification used in prior research to investigate the behavior of uninsured depositors (e.g., Chen et al., 2022, 2024). This specification is based on a model developed by Egan et al. (2017), in which *uninsured* deposit flows are a function of four factors: (i) the perceived default risk, (ii) the deposit rate, (iii) the bank's service quality, and (iv) changes in aggregate demand for deposits.

In this framework, upon observing measures of bank performance, depositors periodically update their views about a bank's default risk and move their funds accordingly. I augment this framework with my measure of *depositor monitoring* based on EDGAR downloads, to shed light on the relation (if any) between deposit flows and monitoring of banks' accounting disclosure:

$$\begin{aligned} \Delta Dep^{U}_{i,t+1} = \alpha_0 + \beta_1 Ln(EDGAR\ downloads_{i,t}) + \Gamma Controls_{i,t} + \\ + Bank\ FE_i + Time\ FE_t + \varepsilon_{i,t+1}. \end{aligned} \tag{1}$$

The unit of observation is a bank-quarter, where i indexes the bank and t the quarter. Uninsured deposit change ($\Delta Dep^U_{i,t+1}$) is measured as the difference in bank i uninsured deposit balance over the two quarters following the end of quarter t (scaled by assets at the end of quarter t), to allow six months for deposit flows to respond to quarter t information, in accordance with prior literature (e.g., Chen et al., 2024). The coefficient of interest is β_1.

Control variables are included to account for factors other than *depositor monitoring* that theory and previous literature have shown to affect uninsured deposit flows. To control for (i) *perceived bank default risk*, I include ROE and other time-varying bank characteristics used in previous studies (e.g., Chen et al., 2022, 2023, 2024). An alternative to using ROE would be to use CDS spreads which, however, are quoted only for a few large banks. To control for (ii) *deposit rate*, I include the deposit rate calculated from Call Reports. I include bank fixed effects to capture banks time-invariant characteristics, including *service quality* (iii). To control for (iv) *aggregate deposit demand*, I add time fixed effects. Time fixed effects flexibly absorb the variation in monitoring and performance that results from common macroeconomic changes, so that the estimates are derived purely from bank-specific idiosyncratic changes. Standard errors are clustered at the bank level.

Descriptive statistics related to the variables used in the empirical analysis are reported in Table 3.

4.2 *Main Results*

Table 4 presents the results related to the new measure of *depositor monitoring*. To ease interpretation, I use the demeaned versions of EDGAR downloads and the other bank characteristics included in the regressions (i.e., I subtract from the variables their sample mean). In this way, the coefficient on EDGAR downloads measures the sensitivity of uninsured deposit flows growth with respect to EDGAR downloads for the bank with the average values of EDGAR downloads and the other control variables. To capture depositor monitoring through accounting disclosure, I focus on downloads of periodic and mandatory *accounting* reports (annual, Form 10-K, and quarterly, Form 10-Q), with the idea that these downloads should more closely capture the information acquisition efforts related to bank fundamentals performed by *attentive* depositors, as discussed in Section 2.

Table 4 Column 1 shows that, when depositor monitor banks' accounting reports (Form 10-K and Form 10-Q), future uninsured deposits *decrease* (coef = -0.257, p-value = 0.057). This negative relation is unique to annual and quarterly reports and is aligned with the theoretical prediction. Then, to determine whether monitoring is associated with deposit withdrawals when there are negative news about bank performance, Columns 2 and 3 distinguish quarters with positive and negative changes in ROE with respect to the previous quarter, respectively. Depositors are primarily concerned about downside risks: they lose money if the bank fails, but they do not gain if the bank performs particularly well. Consequently, I expect monitoring to lead to lower deposits in the quarters where depositors receive negative news about the bank's performance. The results confirm this expectation. No significant association is observed in Column 2, whereas a negative and significant association is observed in Column 3 (coef. = -0.529, p-value < 0.01).

4.3 *Depositor Monitoring during the Global Financial Crisis (2007-2008)*

The sample period of this study includes the 2007–2008 Global Financial Crisis, an unprecedented event with profound consequences for the banking sector. It is therefore crucial to first analyze whether the crisis is driving the results and, second, to understand how the effect of depositor monitoring behaves during this period.

I investigate the first point by excluding the crisis quarters (2007 Q3 - 2009Q2) from the sample. Column 1 of Table 5 shows that the negative association observed in Table 4 continues to hold, as the association between U.S. depositor monitoring and future uninsured deposits remains negative and significant (coef = -0.316, p-value = 0.025). Then, I examine the second point, i.e., how the relation between depositor monitoring and uninsured deposits evolved during the crisis. Specifically, I analyze each crisis quarter separately to account for the progression of the crisis and the various events that influenced depositors' decisions differently (Acharya and Mora, 2015). To do so, in Column 2 of Table 5, I interact the measure of U.S. depositor monitoring of bank fundamentals (natural logarithm of 1 + of U.S. depositor downloads of 10-K and 10-Q filings) with indicator variables for each quarter of the crisis. Interestingly, the interaction term shows a negative sign for the second quarter of 2008, arguably the most severe period of the crisis [12], and then it turns positive and significant starting from the first quarter of 2009, soon after the American government began its public interventions to rescue banks.[13] While prior research documents that depositors started to put their money back into bank deposit accounts during this period (Acharya and Mora, 2015), the positive coefficient (coef = 1.580; p-value = 0.004) observed in Column 2 might suggest that depositor monitoring amplified this trend, perhaps because depositors wanted to understand more about banks' books to decide whether

[12] This quarter marked one of the most critical phases of the crisis, with the bankruptcy of Bear Stearns in March 2008 and Lehman Brothers reporting the massive losses that ultimately led to its bankruptcy a few months later.

[13] For example, the famous Troubled Asset Relief Program (TARP) was passed by the U.S. Congress on October 3, 2008. Among others, the TARP increased the deposit insurance limit from $100,000 to $250,000 per depositor.

to deposit their money back.

4.4 *Robustness analyses*

In Table 6, I analyze how the effects of U.S. depositor monitoring on uninsured deposit flows vary by bank size, dividing the banks into quintiles based on their total assets. I find that the association is negative and significant for banks in the third quintile (coef = -0.498, p-value = 0.039), which represent medium-sized banks similar to SVB. These results may reflect differences in the behaviors of depositors and the compositions of the depositor base across banks of different sizes, as already documented in prior literature (e.g., Iyer et al., 2019; Carletti et al., 2024). In particular, the fact that the coefficient is negative and significant for the medium-sized banks (Column 3) is consistent with these uninsured depositors having more resources and capabilities to process banks' disclosures than depositors at smaller banks, while at the same time suffering from the real threat of losing their money (unlike depositors of larger and too-big-to-fail institutions).

5. *Conclusion*

Despite the unresolved decade-long debate about the role of accounting for financial stability, little is known about whether banks' accounting disclosure is used by depositors for monitoring purposes. In this paper, I provide new empirical evidence suggesting that depositors do monitor banks through accounting information, and that this monitoring is associated with their deposit decisions. In particular, I find a negative and significant relation between monitoring of bank fundamentals (via Form 10-K and Form 10-Q), which is concentrated in quarters where depositors learn negative news about bank performance. This finding is in line with theoretical models which show that depositors are mainly concerned about "downside" risks (they lose money if the bank fails, but they do not gain if the bank performs well). Further tests reveal that the effect of monitoring is not driven by the *financial crisis*, but that it evolved differently across the different phases of the crisis. More specifically, greater monitoring of banks' fundamentals is associated with lower uninsured deposit flows in the quarters preceding the government intervention, but with higher uninsured deposit flows in the quarters after. Additional tests reveal that the effect of depositor monitoring varies by *bank size*, and is concentrated among mid-sized banks. Overall, this paper informs the debate about the role of accounting information in the unfolding of bank runs, providing large-scale evidence of a negative association between *depositor monitoring* and future uninsured deposits.

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A. *Variable definitions*

Variable	Definition	Source
Dependent variables		
Δ Dep	Change in total deposits from quarter t to t+2 as a percentage of total assets (in %, annualized). (Total Deposits$_{i,t+2}$ - Total Deposits$_{i,t}$)/Asset$_{i,t}$ $\times$ 200%. *Total deposits*: RCON2200 (total domestic deposits) + RCFN2200 (total foreign deposits).	Call Reports
Δ Dep^I	Change in insured deposits from quarter t to t+2 as a percentage of total assets (in %, annualized): (Insured Deposits$_{i,t+2}$ - Insured Deposits$_{i,t}$)/Asset$_{i,t}$ $\times$ 200%. *Insured deposits*: RCON2702 (before 2006Q2); RCONF049 + RCONF045 (from 2006Q2). *Total assets*: RCFD2170.	Call Reports
Δ Dep^U	Change in uninsured deposits (total deposits – insured deposits) from quarter t to t+2 as a percentage of total assets (in %, annualized): (Uninsured Deposits$_{i,t+2}$ - Uninsured Deposits$_{i,t}$)/Asset$_{i,t}$ $\times$ 200%.	Call Reports
Independent variables		
Ln(downloads)$_{dep}$	Natural logarithm of (1 + total EDGAR downloads) originated by depositors for filings of bank i in quarter t.	EDGAR log files
Ln(downloads)$_{depUS}$	Natural logarithm of (1 + total EDGAR downloads) originated by depositors from the U.S. for filings of bank i in quarter t.	EDGAR log files
Ln(downloads)$_{depglobal}$	Natural logarithm of (1 + total EDGAR downloads) originated by depositors from countries other than the U.S. for filings of bank i in quarter t.	EDGAR log files
Ln(downloads)$_{corpdepUS}$	Natural logarithm of (1 + total EDGAR downloads) originated by U.S. corporate depositors for filings of bank i in quarter t.	EDGAR log files
Ln(downloads)$_{retdepUS}$	Natural logarithm of (1 + total EDGAR downloads) originated by U.S. retail depositors for filings of bank i in quarter t.	EDGAR log files
Ln(downloads)$_{dep,10K+10QUS}$	Natural logarithm of (1 + total EDGAR downloads) originated by U.S. depositors for Form 10-K and Form 10-Q filings of bank i in quarter t.	EDGAR log files
Ln(downloads)$_{dep,8K}$	Natural logarithm of (1 + total EDGAR downloads) originated by depositors for Form 8-K filings of bank i in quarter t.	EDGAR log files
Ln(downloads)$_{dep,other}$	Natural logarithm of (1 + total EDGAR downloads) originated by depositors for filings other than Form 10-K, Form 10-Q and Form 8-K of bank i in quarter t.	EDGAR log files
ROE	ROE in quarter t (in %, annualized): Net Income$_{i,t}$ / Equity$_{i,t-1}$ $\times$ 400%. Net income: RIAD4300 (year-to-date reporting is adjusted to within quarter). Equity: RCFD3210.	Call Reports
Deposit Rate	Average interest rate on total deposits over the two quarters t, t+1 (in %, annualized): (Deposit interest expense$_{i,t}$ + Deposit interest expense$_{i,t+1}$)/(Avg. deposit balance in quarter t and t+1)) $\times$ 400%). *Deposit quarterly interest expense*: RIADA517 + RIAD4508 + RIAD0093 + RIADA518. *Deposit balance*: RCONA514 + RCON3485 + RCONB563 + RCONA529.	Call Reports
Std Write Off	Standard deviation of loan write-offs to lagged equity ratio over quarter t-11 through quarter t. *Loan write-offs*: RIAD4635(year-to-date reporting is adjusted to within quarter). *Equity*: RCFD3210.	Call Reports
Capital Ratio	Equity (RCFD3210) divided by total assets (RCFD2170).	Call Reports
Wholesale Funds	Wholesale funds divided by total assets. *Wholesale funds*: RCON2604 + RCFN2200 + RCFD3200 + RCONB993 + RCFDB995 + RCFD3190. *Total assets*: RCFD2170.	Call Reports

(Continued on next page)

(continued)

Real Estate Loans	Loans secured by real estate (RCFD1410) divided by total assets (RCFD2170).	Call Reports
Ln(Assets)	Natural logarithm of total assets (RCFD2170).	Call Reports
Unused Commitments	Unused commitments (RCFD3814 + RCFD3816 + RCFD3817 + RCFD3818 + RCFD6550 + RCFD3411) divided by the sum of loans (RCFD1400) and unused commitments.	Call Reports

Tables

Table 1: Sample construction.

Panel A: EDGAR sample

	Tot. downloads	%	
EDGAR downloads (a)	20,896,494,385	100%	
EDGAR human downloads (b)	906,776,768	4.3%	(b)/(a)
of which: EDGAR bank downloads (c)	69,612,703	7.7%	(c)/(b)
EDGAR sample = (c)			

Panel B: Regression sample

	Tot. downloads	%	N. of CIKs
EDGAR bank downloads (c)	69,612,703	100%	2,610
of which: matched with U.S. Call Reports (d)	30,772,734	44.2%	935
of which: non-missing controls + sample cleaning (e)	25,331,430	36.4%	697
Regression sample = (e)			

This table presents the sample construction process. Panel A describes the construction process for the EDGAR sample. Panel B describes the construction process for the regression sample (EDGAR data matched with U.S. Call Reports data). Both samples cover the period 2003-2016.

Table 2: Downloads of banks' SEC filings.

Panel A: Downloads of banks' SEC filings by year.

Year	Tot. downloads	Mean	Min	p1	p25	Median	p75	p99	Max	Sd
2003	866,839	120	1	1	8	41	112	1,495	8,176	331
2004	1,704,519	225	1	1	10	78	221	2,410	16,483	604
2005	1,010,117	148	1	1	5	31	148	1,611	12,509	441
2006	915,033	147	1	1	4	30	148	1,651	12,013	457
2007	1,823,460	237	1	1	6	56	213	2,639	28,583	823
2008	2,974,988	376	1	1	7	57	282	4,685	43,149	1,694
2009	4,641,339	561	1	1	8	55	459	6,994	87,429	2,451
2010	5,113,184	594	1	1	8	52	510	6,736	57,716	2,442
2011	5,721,581	664	1	1	8	49	556	7,531	82,560	2,889
2012	5,879,547	672	1	1	8	46	528	6,824	130,239	3,560
2013	9,094,788	1,001	1	1	12	65	689	10,688	253,631	6,730
2014	9,941,011	1,081	1	1	11	63	718	12,066	223,622	6,688
2015	9,748,339	1,054	1	1	10	57	605	10,095	228,232	7,646
2016	10,177,958	1,072	1	1	13	74	613	9,900	263,067	8,031
Total	69,612,703	607	1	1	8	53	340	6,827	263,067	4,485

Panel B: Downloads of banks' SEC filings by user type.

	Tot. downloads	%
Downloads by unclassified IPs	27.256.523	39.2%
Downloads by manually classified IPs	42,356,180	60.8%
of which:		
Depositors	**20,790,158**	**29.9**%
Retail *(telecommunication)*	17,500,773	25.1%
Corporate *(non-financial companies)*	3,289,385	4.8%
Other users	12,220,344	17.55%
Financial - bank	4,823,802	6.9%
Audit/rating/law	2,523,334	3.6%
Financial - non bank	1,892,025	2.7%
Other[(a)]	1,669,985	2.4%
Information intermediary	990,684	1.4%
Regulator/state	320,514	0.5%
n.a.[(b)]	9,345,678	13.4%
Total downloads	69,612,703	100%

Panel C: *Depositors*' downloads of banks' SEC filings by filing type.

	Depositors downloads	%
Periodic filings	**5,481,013**	**26.4**%
Form 10-Q	*2,822,840*	*13.6*%
Form 10-K	*2,658,173*	*12.8*%
Current filings (Form 8-K)	3,068,592	14.8%
Other filings	12,210,952	58.7%
n.a.	29,601	0.1%
Total downloads	20,790,158	100%

This table shows descriptive statistics of downloads of banks' SEC filings as recorded in the EDGAR log file. Panel A shows bank filings downloads by year. Panel B shows bank filings downloads by user type and is based on the classification od the top 5,000 IP addresses by number of downloads, accounting for 60.8% of total EDGAR bank downloads. [(a)] is a residual category which includes all the IP addresses not classified in the other categories (e.g., universities). [(b)] includes IPs that were registered after the sample period end (2016) and IPs that cannot be traced to any owner because the IP range belongs to different users. Panel C shows depositors' downloads of banks' SEC filings by type of filing.

Table 3: Summary statistics (regression sample).

Panel A: Summary statistics.

	N	mean	sd	p25	median	p75
Dependent variables						
Δ Dep	19,870	5.78	12.15	-0.85	4.11	10.11
Δ Dep^U	19,870	2.60	10.59	-1.23	2.61	7.19
Δ $\text{Dep}^{\ I}$	19,870	3.28	10.49	-1.67	1.04	4.90
Independent variables (EDGAR log files)						
$\text{Ln(downloads)}_{tot}$	19,871	5.81	1.82	5.00	6.08	6.97
$\text{Ln(downloads)}_{dep}$	19,871	4.52	1.83	3.50	4.71	5.83
$\text{Ln(downloads)}_{depglobal}$	19,871	3.35	1.91	2.08	3.30	4.86
$\text{Ln(downloads)}_{depUS}$	19,871	4.04	1.70	3.14	4.28	5.22
$\text{Ln(downloads)}_{corp.dep(US)}$	19,871	2.12	1.57	0.69	2.08	3.26
$\text{Ln(downloads)}_{ret.dep(US)}$	19,871	3.86	1.67	3.00	4.08	5.00
$\text{Ln(downloads)}_{dep,10K+10Q(US)}$	19,871	2.96	1.67	1.79	3.14	4.19
Control variables						
ROE	19,871	6.66	14.21	5.45	8.92	12.41
Deposit Rate	19,871	1.59	1.18	0.59	1.33	2.29
Std Write Off	19,871	1.02	1.49	0.20	0.47	1.12
Capital Ratio	19,871	0.10	0.02	0.09	0.10	0.11
Wholesale Funds	19,871	0.24	0.10	0.16	0.23	0.30
Real Estate Loans	19,871	0.32	0.28	0.00	0.39	0.56
Ln(Assets)	19,871	14.34	1.49	13.31	13.98	15.04
Unused Commitments	19,871	0.13	0.22	0.00	0.08	0.15
Deposits (% Assets)	19,871	0.78	0.08	0.74	0.80	0.84
% Foreign Deposits	19,871	0.01	0.06	0.00	0.00	0.00
% Uninsured Deposits	19,871	0.40	0.17	0.28	0.39	0.50

Panel B: Pearson correlation.

	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**	**(11)**	**(12)**	**(13)**	**(14)**	**(15)**	**(16)**
(1) Δ Dep^U	1.00															
(2) Ln(dwlds)_*tot*	**-0.07**	1.00														
(3) Ln(downloads)_*dep*	**-0.07**	**0.96**	1.00													
(4) Ln(downloads)_*depglobal*	**-0.05**	**0.84**	**0.91**	1.00												
(5) Ln(downloads)_*depUS*	**-0.08**	**0.94**	**0.96**	**0.80**	1.00											
(6) Ln(downloads)_*corp.dep(US)*	**-0.03**	**0.76**	**0.81**	**0.76**	**0.82**	1.00										
(7) Ln(downloads)_*ret.dep(US)*	**-0.08**	**0.92**	**0.95**	**0.79**	**0.99**	**0.75**	1.00									
(8) Ln(downloads)_$dep, 10K + 10Q(US)$	**-0.07**	**0.86**	**0.90**	**0.80**	**0.92**	**0.79**	**0.91**	1.00								
(9) ROE	**0.10**	-0.01	-0.00	0.00	-0.01	0.00	-0.01	0.00	1.00							
(10) Deposit Rate	**-0.11**	**-0.34**	**-0.38**	**-0.46**	**-0.31**	**-0.37**	**-0.30**	**-0.43**	**-0.07**	1.00						
(11) Std Write Off	**-0.11**	**0.10**	**0.10**	**0.08**	**0.11**	**0.07**	**0.11**	**0.10**	**-0.15**	**-0.12**	1.00					
(12) Capital Ratio	**0.04**	**0.21**	**0.24**	**0.27**	**0.22**	**0.25**	**0.22**	**0.24**	**0.07**	**-0.20**	**-0.14**	1.00				
(13) Wholesale Funds	**-0.05**	**-0.07**	**-0.11**	**-0.17**	**-0.07**	**-0.11**	**-0.06**	**-0.12**	**-0.05**	**0.44**	-0.01	**-0.22**	1.00			
(14) Real Estate Loans	**-0.12**	**-0.33**	**-0.39**	**-0.51**	**-0.29**	**-0.38**	**-0.27**	**-0.43**	**-0.08**	**0.70**	**-0.10**	**-0.21**	**0.27**	1.00		
(15) Ln(Assets)	0.00	**0.54**	**0.52**	**0.47**	**0.54**	**0.53**	**0.55**	**0.53**	**0.03**	**-0.18**	**-0.08**	**0.21**	**0.07**	**-0.19**	1.00	
(16) Unused Commitments	-0.02	**-0.03**	**-0.09**	**-0.18**	**-0.03**	**-0.10**	-0.01	**-0.10**	-0.00	**0.30**	**-0.12**	**-0.09**	**0.18**	**0.33**	**0.24**	1.00

This table shows summary statistics (Panel A) and correlation coefficients (Panel B) for the main variables used in the regression analyses. Correlation coefficients in bold: *p-value* $<$ .01. Detailed variable definitions are available in Appendix A.

Table 4: Depositor monitoring and uninsured deposit flows.

	(1)	(2)	(3)
Dependent variable:	Δ $\text{Dep}^U_{i,t+1}$	Δ $\text{Dep}^U_{i,t+1}$	Δ $\text{Dep}^U_{i,t+1}$
		Δ ROE	
	Full Sample	*Positive*	*Negative*
$\text{Ln(downloads)}_{USdep,10K+10Q}$	**-0.257***	0.057	**-0.529*****
	(0.057)	(0.757)	(0.001)
$\text{Ln(downloads)}_{USdep,8K}$	0.180	0.020	0.330**
	(0.134)	(0.902)	(0.035)
$\text{Ln(downloads)}_{USdep,other}$	0.468***	0.248*	0.614***
	(0.000)	(0.097)	(0.000)
ROE	0.024***	0.009	0.045***
	(0.000)	(0.535)	(0.000)
Deposit Rate	-1.602***	-1.806***	-1.491***
	(0.000)	(0.001)	(0.002)
Std Write Off	-0.619***	-0.585***	-0.552***
	(0.000)	(0.000)	(0.000)
Capital Ratio	22.156***	19.467*	21.195**
	(0.007)	(0.063)	(0.019)
Wholesale Funds	3.188	1.727	4.564*
	(0.159)	(0.527)	(0.072)
Real Estate Loans	-0.802	-1.387	-0.475
	(0.523)	(0.358)	(0.732)
Ln(Assets)	-6.533***	-5.943***	-6.858***
	(0.000)	(0.000)	(0.000)
Unused Commitments	2.135***	2.166**	2.064**
	(0.010)	(0.024)	(0.013)
Observations	19871	8726	11095
Unique banks	697	660	678
Adj. R-squared	0.339	0.364	0.315
Within R-squared	0.035	0.029	0.041
Control variables	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes
Year-quarter FE	Yes	Yes	Yes

Notes: *, ** and *** represent significance (two-sided) at the 10%, 5%, and 1% levels, respectively. P-values are reported in parentheses. Detailed variable definitions are available in Appendix A.

Table 5: Depositor monitoring and uninsured deposit flows during the Global Financial Crisis.

Dependent variable:	(1) Δ $\text{Dep}^{U}_{i,t+1}$	(2) Δ $\text{Dep}^{U}_{i,t+1}$
	Non-Crisis Period	*Full Sample*
	(1)	(2)
$\text{Ln(downloads)}_{USdep,10K+10Q}$	**-0.316****	**-0.263***
	(0.025)	(0.057)
$\text{Ln(downloads)}_{USdep,8K}$	0.259**	0.162
	(0.040)	(0.178)
$\text{Ln(downloads)}_{USdep,other}$	0.479***	0.462***
	(0.000)	(0.000)
$\text{2007q3=1}\times\text{Ln(downloads)}_{USdep,10K+10Q}$		0.157
		(0.755)
$\text{2007q4=1}\times\text{Ln(downloads)}_{USdep,10K+10Q}$		-0.297
		(0.539)
$\text{2008q1=1}\times\text{Ln(downloads)}_{USdep,10K+10Q}$		0.107
		(0.836)
$\text{2008q2=1}\times\text{Ln(downloads)}_{USdep,10K+10Q}$		**-0.976****
		(0.042)
$\text{2008q3=1}\times\text{Ln(downloads)}_{USdep,10K+10Q}$		-0.315
		(0.459)
$\text{2008q4=1}\times\text{Ln(downloads)}_{USdep,10K+10Q}$		0.957
		(0.118)
$\text{2009q1=1}\times\text{Ln(downloads)}_{USdep,10K+10Q}$		**1.580*****
		(0.004)
$\text{2009q2=1}\times\text{Ln(downloads)}_{USdep,10K+10Q}$		-0.297
		(0.401)
Observations	16,972	19,871
Unique banks	697	697
Adj. R-squared	0.189	0.340
Within R-squared	0.034	0.037
Control variables	Yes	Yes
Bank FE	Yes	Yes
Year-quarter FE	Yes	Yes

Notes: *, ** and *** represent significance (two-sided) at the 10%, 5%, and 1% levels, respectively. P-values are reported in parentheses. Detailed variable definitions are available in Appendix A.

Table 6: Depositor monitoring and uninsured deposit flows by bank size.

Dependent variable	(1) Δ Dep$^U_{i,t+1}$	(2) Δ Dep$^U_{i,t+1}$	(3) Δ Dep$^U_{i,t+1}$	(4) Δ Dep$^U_{i,t+1}$	(5) Δ Dep$^U_{i,t+1}$
	Bank size				
	Quintile 1	*Quintile 2*	*Quintile 3*	*Quintile 4*	*Quintile 5*
Ln(downloads)$_{USdep,10K+10Q}$	-0.306	0.075	**-0.498****	-0.418	0.368
	(0.302)	(0.786)	(0.039)	(0.185)	(0.295)
Ln(downloads)$_{USdep,8K}$	-0.475*	0.087	0.214	0.438	0.331
	(0.053)	(0.748)	(0.375)	(0.118)	(0.305)
Ln(downloads)$_{USdep,other}$	0.521**	0.094	0.141	0.774***	0.747***
	(0.023)	(0.698)	(0.565)	(0.004)	(0.008)
ROE	0.010	0.030**	0.028**	0.027**	0.029**
	(0.364)	(0.012)	(0.023)	(0.035)	(0.024)
Deposit Rate	-1.771**	-1.069	-2.652***	-3.001***	-0.365
	(0.034)	(0.155)	(0.003)	(0.000)	(0.706)
Std Write Off	-0.524***	-0.689***	-0.829***	-0.490***	-0.729***
	(0.000)	(0.001)	(0.000)	(0.008)	(0.000)
Capital Ratio	26.565*	9.817	8.591	14.881	20.797
	(0.058)	(0.561)	(0.657)	(0.436)	(0.321)
Wholesale Funds	3.660	1.873	2.955	6.072	9.754
	(0.442)	(0.677)	(0.589)	(0.198)	(0.107)
Real Estate Loans	-0.494	1.094	-0.963	3.749	-2.505
	(0.892)	(0.739)	(0.811)	(0.274)	(0.230)
Ln(Assets)	-8.509***	-6.140***	-6.104***	-6.025***	-7.789***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Unused Commitments	-1.337	6.477*	5.589**	1.462	2.250**
	(0.808)	(0.065)	(0.035)	(0.424)	(0.020)
Observations	3867	4001	4009	4007	3987
Unique banks	165	141	137	118	136
Adj. R-squared	0.359	0.339	0.371	0.373	0.265
Within R-squared	0.048	0.027	0.039	0.043	0.045
Bank FE	Yes	Yes	Yes	Yes	Yes
Year-quarter FE	Yes	Yes	Yes	Yes	Yes

Notes: Banks are sorted into quintiles based on their average total assets over the sample period. *, ** and *** represent significance (two-sided) at the 10%, 5%,and 1% levels, respectively. Standard errors clustered at the bank level are reported in parentheses. Detailed variable definitions are available in Appendix A.

Figures

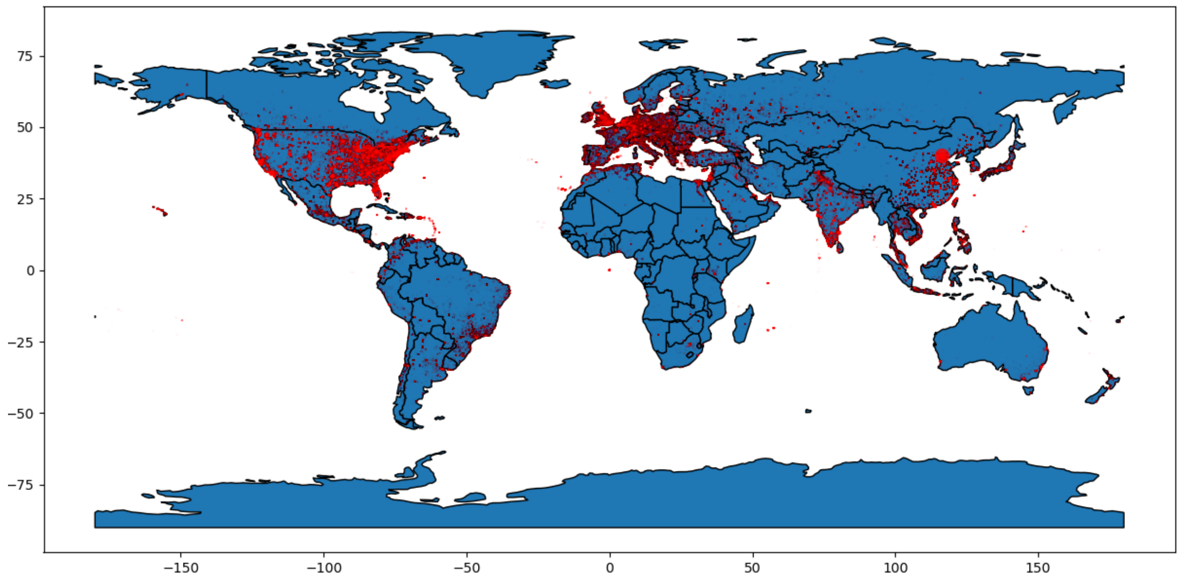

Figure 1: Location of EDGAR bank downloads (2003-2016).
This figure illustrates the global distribution of downloads of banks' filings from the EDGAR filing system between April 1st, 2003, and December 31st, 2016. The figure is constructed based on the geographical location of the IP addresses that generated the 69.6 million EDGAR human downloads related to banks' SEC filings (see Table 1a). Location data is obtained through *IP2Location*. The relative darkness of each point's color indicates the relative number of downloads originating from the estimated latitude and longitude point. Approximately 66% of all downloads originates from the United States.

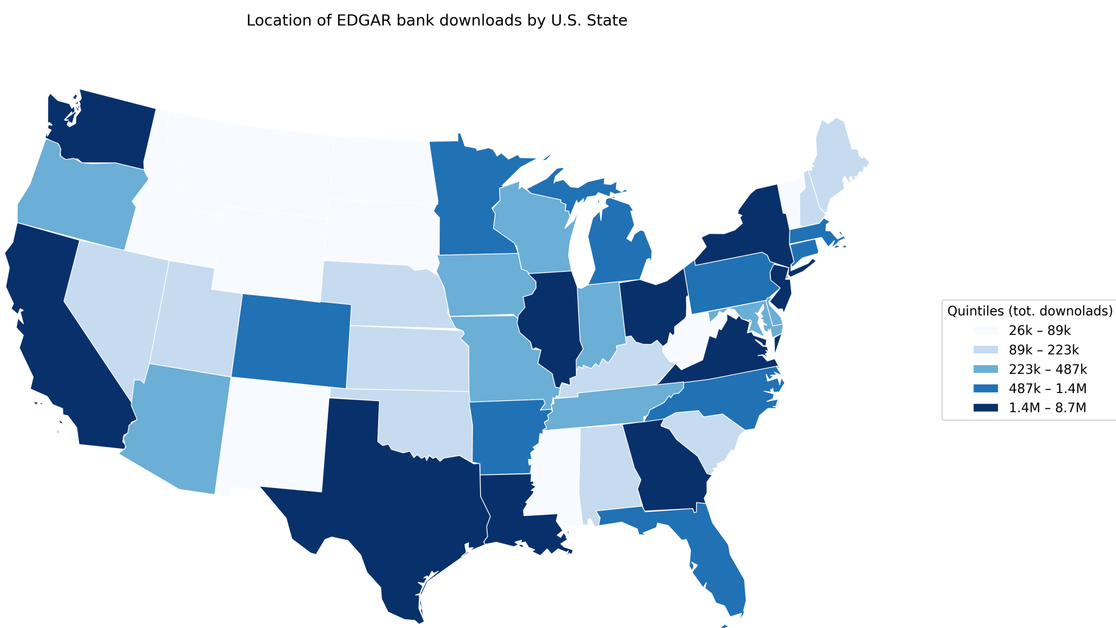

Figure 2: Location of EDGAR bank downloads by U.S. state (2003-2016).
This figure illustrates the distribution of downloads of banks' filings from the EDGAR filing system between April 1st, 2003, and December 31st, 2016 across U.S. sates. The figure is constructed based on the geographical location of the IP addresses that generated the 69.6 million EDGAR human downloads related to banks' SEC filings (see Table 1a). Location data is obtained through *IP2Location*. The relative darkness of each state indicates the quintiles as shown in the legend.