The Long and Short of U.S. Bank Regulations: From the Great Depression to the 2023 Bank Failures*

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Abstract

Leveraging a unique century-long dataset of U.S. bank balance sheets and stock prices, I uncover a dichotomy of how bank regulation impacts financial intermediaries in the short and long run. I introduce a novel Bank Regulation Index (BRI) based on historical newspaper articles. In the short term, regulations are costly and perceived as bad news by stock market investors, while a Machine Learning analysis of news texts reveals that *deregulations* consistently get positive media coverage. Despite such short-term costs, aggregate and bank-level evidence demonstrate that regulations make banks safer and more profitable in the long term. I show that the BRI predicts future banking crises over and above well-established predictors such as credit growth, mostly due to gauging deregulations 5–10 years before crises. Decomposing the BRI into intuitive topics using the LDA algorithm reveals that *Lending* regulations matter the most for crisis predictability. Finally, using Earnings Calls transcripts, I measure bank-level exposure to *Lending* regulation—using LDA trained on the Federal Register—and show that it produces sizeable alphas. A long-short portfolio of the least and most exposed banks generates a monthly return of 0.84% and an alpha of up to 0.75%.

Keywords: Bank Regulation, Banking Stability, Financial Stability, Financial Crises
JEL Classification: E30, N12

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1 Introduction

The ever-evolving landscape of regulatory measures has become a focal point in economic research, given its profound impact on firms' operational dynamics, innovation and financial performance (Aghion et al. (2021), Ash et al. (2021), Al-Ubaydli and McLaughlin (2017)). As the body of literature concerning the costs of regulations at the firm level continues to grow, recent studies have turned to innovative textual analysis techniques to discern and quantify the implications of regulatory policies (i.e. Kalmenovitz et al. (2022), Calomiris et al. (2020), Davis (2017)). Notably, a prevailing trend in this recent literature lies in its predominant focus on the costs of regulations, manifested in relatively limited time frames.

Most of the aforementioned literature has notably omitted the analysis of financial firms in their examination of regulatory effects. This omission highlights a crucial gap in the current research landscape, leaving the evaluation of regulatory impacts on financial firms largely unexplored. This paper seeks to address this gap by focusing on banks as an exemplary arena to meticulously assess the multifaceted consequences of regulations, both in the short-term and long-term contexts. Recognized as one of the most rigorously regulated sectors within the economy, the banking industry offers a compelling laboratory for such an analysis.

The rationale behind robust bank regulations is firmly grounded in the substantial harm that banking crises can inflict upon the broader economic landscape. Bräuning and Sheremirov (2023) use the Macrohistory database (Jordà et al. (2017, 2021)) to document that systemic banking crises have 2-4 times larger contractionary effects on output and unemployment as compared to other financial crises. Previously, Cecchetti et al. (2009) identified 40 systemic banking crises since 1980 and documented that most crises "coincide with a sharp contraction in output from which it took several years to recover." Moreover, Baron et al. (2021) actually show that even in the absence of panics, large bank equity declines are associated with substantial credit contractions and output gaps. More notably, Bernanke (1983) argued that bank failures of the Great Depression exacerbated the crisis through eroding capital availability.[1] Therefore, banks provide an ideal ground to study how regulatory frameworks interact with the functioning of the banking sector in different time horizons.

[1] However, Miron and Rigol (2013) disagree with this view and find little evidence for bank failures having a substantial impact on output.

Regulatory policies and their impact on industries, particularly the banking sector, often exhibit intricate and evolving dynamics that become fully apparent only over extended periods. A long-term perspective is required to capture the gradual unfolding of these effects, enabling a more comprehensive understanding of both intended and unintended consequences. Moreover, a common assumption in the existing literature is the *"insistence on thinking about regulatory adjustments that affect financial firms as exogenous disturbances"* (Kane (1988)). For instance, Calomiris et al. (2020), using text from 10-Ks and Earning Calls, and Davis (2017), using 10-Ks, make firm-level measures of regulatory impact and show negative short-term (one-year ahead) impacts associated with it. Kalmenovitz et al. (2022) explores a regulatory fragmentation caused by different agencies regulating the same topic and show short-term costs for firms exposed to such a fragmentation. However, the justifications behind the regulations remain unexplored, and as Kane (1988) pointed out, these studies treat regulation as an exogenous variation.

This paper uses almost a century (1926–2023) of hand- and digitally collected data on banking regulations, banks' balance-sheet items, and stock prices to explore the unanswered questions about regulations, particularly in the banking context. For instance, this paper asks if the short-term costs of regulation are so evident, then what predicts the increase in regulation? Also, are there any long-term benefits (costs) associated with regulation (deregulation)? As implied by Kane's (1981, 1988) "regulatory dialectic," are there any cycles of regulation and deregulation in the banking context? Can regulatory changes help predict future banking crises?

This paper provides three main sets of findings. First, it quantifies banking regulations into a latent variable: Bank Regulation Index (BRI). Banking regulations encompass many different topics, ranging from reserve requirements to activities banks can and cannot engage in. The BRI resolves this multidimensional nature of banking regulations by creating a latent variable that captures the flow of banking regulations and deregulations for about a century using text from newspaper articles.

The second key finding of this paper is the identification of a distinct dichotomy in the impact of banking regulations over the short and long term. Utilizing the BRI to trace the cycles of banking regulations and crises, the study reveals a pattern: regulations often intensify following banking crises but lead to periods of stability in the longer term. This is explored further through the development of a bank-level measure of regulatory exposure, termed 'Regulatory

Beta,' which is derived from banks' price reactions to regulatory changes. The analysis shows that, in the short term, regulations tend to exert negative effects, such as reduced profitability and lower stock returns. However, these initial impacts are not enduring and reverse later on. Longer timeframes help document the stabilizing influence of regulations. This is evidenced by the reduced bank leverage, lower Loan-to-Deposit Ratios (LDR), and increased liquidity or cash ratios in the long-term. These findings reveal the mechanisms through which regulations contribute to banking system stability over extended periods.

The third significant contribution of this study is the demonstration of the BRI's predictive power regarding future banking crises. The BRI not only offers insights into past and current regulatory trends but also proves effective in forecasting future banking crises, surpassing known indicators like credit growth. This predictive capability is further enhanced when the BRI is decomposed into specific regulatory topics using Latent Dirichlet Allocation (LDA). This decomposition shows that certain types of deregulation, particularly those related to lending, are especially indicative of impending crises. Hence, the BRI emerges not just as a historical measure but as a valuable tool for anticipating future banking failures.

Here the Federal Register is explored for identifying regulatory topics via Latent Dirichlet Allocation (LDA), as a robustness check. The Federal Register has inconsistent layout across different years and textual methods (e.g., regular expressions) are employed to standardize documents from 1936 to 1993 (1994 onwards is available in a machine-readable format). Focusing on Final Rules issued by FSOC-member agencies, the study decomposes the corpus into six topics. Validation through a probit model analysis confirms the *Lending* topic's predictive power on macro-financial conditions to be the highest. This finding aligns with the newspaper-based analyses, illustrating the importance of lending/credit regulations in economic forecasting.

Similar to Kalmenovitz et al. (2022), I apply the LDA model trained with Federal Register on the earnings calls text. This gives a weight for the *Lending* topic for each earnings call report. Banks stocks in the following quarter are sorted into deciles according the weight of the *Lending* topic. A portfolio with long position in the lowest and short position in the highest decile generates a monthly alpha of 0.61% (t-stat = 2.01) to 0.75% (t-stat = 2.37), depending on the factor model used.

This paper constructs data from a century of balance sheets and market-based variables to examine the impact of the regulatory environment on bank performance. The data for bank balance sheet items was hand-collected for a sample of the largest 20 banks (by deposits) in each year for the 1926-1985 time period from Moody's Manual. Since bank stocks were mostly traded over the counter, the stock price data was hand-collected from three main sources: Commercial and Financial Chronicle (CFC), New York Times (NYT), and Wall Street Journal (WSJ) stock quote sections. Following 1986, the bank balance sheet data is from the FR Y9-C filings, and the stock price data is from CRSP. Section 2.2 provides additional details on the data collection process.

This paper constructs a *Bank Regulation Index* (BRI_t) to measure the flow of banking regulations after classifying a set 50 banking laws as regulatory or deregulatory. The laws span about a century: starting from McFadden Act of 1927 to the Economic Growth, Regulatory Relief and Consumer Protection Act of 2018 (EGRRCPA). News articles are short-listed using ProQuest that meet a criteria to ensure that they give a measure of the importance of the law around the time it was passed. Section 2.1 gives details on the construction of the index and the criteria.

The media's portrayal of regulatory shifts, especially in banking, can shape investor sentiment, public perception, and even policy outcomes (Sinclair and Xie (2021)). Hence, examining the press coverage of deregulatory and regulatory laws is crucial for understanding the broader narrative and sentiment surrounding these legislative changes. I analyze this media discourse by leveraging advanced textual analysis techniques—FinBERT and Latent Dirichlet Allocation (LDA). My findings reveal that deregulatory laws consistently receive more favorable coverage in newspapers, underscoring the public's and possibly the financial sector's short-term positive reception of such measures. FinBERT is an innovative advancement in the realm of textual analysis for finance-related inference. Designed to discern and quantify sentiment, this is a BERT model trained on a vast corpus of financial texts (Araci (2019), Huang et al. (2023)). In the context of news articles, sentiment assessment is conducted within a concise window surrounding the explicit mention of the laws. The investigation shows a discernible divergence in press coverage between deregulatory and regulatory laws. Notably, an unequivocally positive bias is evident in the portrayal of deregulatory laws, contrasting starkly with the treatment of regulatory counterparts, even after the topical context of the article is controlled for.

A pivotal contribution of this study lies in its documentation of the cyclical pattern inherent in banking regulations within the United States throughout the past century. Contrary to prevailing research, which often treats regulatory shocks as exogenously imposed disruptions with significant repercussions for firms, this paper undertakes an analysis of the determinants underpinning banking regulations. It turns out that banking crises are the strongest predictor of bank regulations, and periods of stability follow strong regulatory responses. This cyclicality is clearly visible in Figure 1. This plots the BRI and $BankFailures$, defined as the deposits of failed banks as a percentage of total deposits. $BankFailures$ is a measure of the severity of the banking crises and shows four episodes since 1926: the Great Depression of 1930s, the Savings and Loans Crisis of 1980s, the Great Recession of 2007-09 and the recent bank failures of 2023. Each of these episodes of banking crises is followed by a spike in the BRI, showing a strong regulatory response. Foundational banking regulations of the 1930s followed the Great Depression. Another episode of regulatory laws in 1989-1991[2] followed the Savings and Loans Crisis. Dodd-Frank Act followed the Great Recession of 2007-09. Each episode of strict regulatory reform is followed by a period of stability with no banking panics, which, in turn, is followed by a deregulatory episode. Deregulations of 1979-82[3], of late 1990s and early 2000s[4] and of 2018[5] were followed by banking crisis within a period of 5-10 years.

In the sphere of banking regulations, an important question arises: ex-ante, is it clear whether increased regulations or deregulations should carry more substantial short-term impacts? This uncertainty underscores the critical need to delve deeper into the nuances of regulatory dynamics. Addressing this question, we deconstruct the Bank Regulation Index (BRI_t) into two primary components: the Increasing Regulation Index (IRI_t) and the Decreasing Regulation Index (DRI_t). This bifurcation allows for a precise evaluation of the effects of both regulatory and deregulatory laws.

Utilizing a diverse set of bank-level variables, this research offers a holistic assessment of the *immediate* costs associated with regulations and the potential benefits derived from deregulatory actions. The empirical results narrate an insightful story. Heightened regulatory measures manifest in discernible short-term costs, such as a diminished loan-to-deposits ratio, increased liquidity in the form of cash reserves, a decline in profitability, and an increase in idiosyncratic volatility in the subsequent year. Nevertheless, it becomes paramount to differentiate between the distinct consequences of increasing and decreasing regulations.

[2]Financial Institutions Reform, Recovery, and Enforcement Act of 1989; Federal Deposit Insurance Corporation Improvement Act of 1991

[3]Monetary Control Act of 1980, Garn-St Germain Act of 1982

[4]Interstate Act of 1994, Gramm-Leach-Bliley Act of 1999, BAPCPA of 2005

[5]Economic Growth, Regulatory Relief and Consumer Protection Act of 2018

A critical insight emerges when dissecting the regulation index into its foundational elements: the short-term effects of deregulation overshadow those of increased regulation. In particular, while heightened regulations introduce noticeable *adjustment costs*, the immediate advantages derived from deregulations prove to be both economically and statistically more profound. This differentiation elucidates the intricate relationship between regulatory changes and their subsequent economic ramifications. However, it remains important to explore the long-term impacts increasing and decreasing regulations.

I then use Vector Autoregressions (VARs) to document the long-term implications of regulatory and deregulatory interventions within the banking sector. By employing a dataset encompassing annual observations and adopting a lag structure comprising a decade, this study effectively shows the long-term interplay between regulations and crises.

Specifically, I delve into the dynamic relationship between the Bank Regulation Index (BRI_t) and bank failures ($BankFailures_t$). The empirical analysis reveals a compelling correlation: an escalated BRI_t is distinctly associated with a notable reduction in $BankFailures_t$ over the following decade. This observation underscores the significant role that robust regulatory measures play in engendering stability within the banking sector. Conversely, negative impulses brought about by banking deregulations imply a subsequent rise in bank failures. This finding accentuates the fragility that can ensue from a lax regulatory environment, substantiating the imperative for a balanced approach to regulatory reforms.

Furthermore, this paper delves into the reciprocal relationship between banking regulations and failures, unraveling a noteworthy observation. It becomes evident that banking crises serve as a catalyst for robust regulatory responses, setting the stage for intensified regulatory frameworks in the years that follow. Conversely, periods characterized by few bank failures appear conducive to future deregulatory shifts. The empirical evidence aptly attests to the interconnectedness of these dynamic forces, contributing a nuanced perspective to our understanding of the historical evolution of banking regulations.

2 Data and Methodology

2.1 Bank Regulation Index

The foundation for constructing the bank regulation index is established through a comprehensive compilation of relevant *regulatory* and *deregulatory* banking laws. For the purposes of this paper, a *regulatory* law is defined as one that increases the government's influence over the banking sector. This can be in the form of disallowing them from certain activities (i.e. Glass-Steagall Act of 1933), requiring a minimum capital ratio (FIRREA 1989, FDICIA 1991), or requiring stress tests (Dodd-Frank). *Deregulatory* laws do the opposite and provide banks with greater power. It is essential to discern that while a piece of legislation might impact the banking sphere indirectly, it does not necessarily fall into either of these two categories. For instance, the National Housing Act of 1934 shaped the housing landscape by establishing the Federal Housing Administration (FHA) and introducing mortgage insurance. Thus, while it is undeniably significant, it does not fit within the purview of the regulation index because it neither regulates nor deregulates banks directly.

I commence with the set of consequential banking, housing, and securities laws, thoughtfully curated by Tabor et al. (2021) and Conti-Brown and Ohlrogge (2022).[6] Tabor et al. (2021) (Federal Reserve Board Discussion Paper) provides a history of US financial regulations and review a list of 70 critical laws since 1791 (61 since 1927). I complement this list with that of Conti-Brown and Ohlrogge (2022), who use different metrics (such as US Court citations) to measure the importance of Title 12 and Title 15 laws. According to their metrics, 5 out of the top 10 most important Title 12 (Banks and Banking) laws are Housing Acts. However, as mentioned earlier, this study is concerned with laws that directly affect banks.

The purview of this study necessitates a deliberate exclusion of housing and securities laws. The process entails a thorough review of the laws within these titles, culminating in the curation of a list comprising 50 pivotal banking laws. These selected statutes distinctly align with the explicit criteria of being inherently regulatory or deregulatory in nature. This filtration ensures that the resultant bank regulation index encompasses a focused and relevant set of laws, facilitating an analysis of the dynamic interplay between regulatory shifts and the banking sector. Table A.1 shows the list of these laws. I construct the index using the following steps:

[6] I am very grateful to the authors of the latter study for sharing their list of laws with me.

1. Identification of Popular Nicknames: I use Google search to identify widely recognized nicknames associated with each law. This step ensures a comprehensive compilation of colloquial references that contribute to the multifaceted characterization of each law.

2. Obtaining the corpus of newspaper articles: I use ProQuest to retrieve news articles that mention the selected laws. I begin with the same newspapers used in Baker et al. (2016). However, 4 out of 10 newspapers do not have a sufficiently long coverage in ProQuest. Therefore, I use the following six newspapers: (*i*) Chicago Tribune, (*ii*) Los Angeles Times, (*iii*) New York Times, (*iv*) USA Today, (*v*) Wall Street Journal, and (*vi*) The Washington Post. I then use the following criteria to short-list news articles:

   - Temporal Relevance: Articles are meticulously selected within a precise temporal window of five years from the date of enactment of the respective law. This ensures that the corpus of news articles remains contemporaneous with the regulatory landscape.
   - Name References: A comprehensive criterion entails that the articles explicitly reference the law's full name, any popular nickname, or a 4-letter abbreviation. Table A.1 mentions the other name references.
   - Relevance to the banking sector: The articles are further filtered to include only those directly connected to the banking sector. This is achieved by ensuring the article includes the word "bank."

This procedure yields a set of more than 6,000 news articles. Thus, in a given year t, NR_t and ND_t are the number of articles that mention the regulatory laws and the deregulatory laws, respectively. The index is calculated as:

$$BankRegIndex_t = \ln\left(\frac{NR_t + 1}{ND_t + 1}\right) = \ln(NR_t + 1) - \ln(ND_t + 1)$$

The justification for taking the natural logarithm of the ratio of articles mentioning regulatory laws to deregulatory laws is, (i) a disproportionately high number of articles mention regulatory laws, and (ii) the large positive skewness of the distrubution (i.e. about one-third of the articles mention the Dodd-Frank Act). Taking the logarithm accentuates the importance of deregulatory and regulatory laws that receive disproportionately less media attention.

2.2 Balance Sheet

Undertaking an extensive research endeavor spanning nearly a century (1926-2020) presents a formidable challenge due to the inherent scarcity of historical data. To surmount this hurdle, this study meticulously gathers data on bank-level balance sheet variables from the Moody's Manuals. The research methodology entails a sample selection of the 20 largest banks each year, comparable to other historical studies (e.g., Cortes et al. (2022)). I use Gross Deposits as a measure of bank size to determine the largest 20.

The process of data collection involves a detailed extraction of pertinent balance sheet and income statement elements for the largest 20 banks. This includes a compilation of variables such as total loans (or loans and discounts), total assets, cash, deposits, total income, net earnings, EPS, net income, total equity, government bonds, cash held in banks, capital stock, surplus, undivided profits, Book Value per share, other bonds and other securities. The scope of this data compilation spans six decades, from 1926 to 1985, thereby providing a rich historical context.

Subsequently, the study transitions to utilizing bank-holding company data derived from FR Y9-C filings. Post-1985, this paper selects commercial banks within the sample in alignment with the methodology established by Gandhi and Lustig (2014).

In order to construct the $BankFailures_t$ index, the data for deposits of failed banks is available at the FDIC website starting 1934. Following Miron and Rigol (2013), I get data for bank failures during the Great Depression from Federal Reserve (1937). The data for total deposits is obtained from Jordà et al. (2017) database, augmented by the FRED data. $BankFailures_t$ is defined as the deposits of failed banks as the percentage of total deposits. This variable provides a measure of severity of the financial crisis, that is not captured by a metric with just the number of banks. The deposits of three bank failures of 2023 (First Republic Bank, Silicon Valley and Signature Bank) represent 1.7% of the total deposits and this can be distinctly seen in Figure 1. This is the fourth such time over the last century that $BankFailures_t$ reached above 0.3%. The three earlier crises are identified as the Great Depression (1929-1933), Savings and Loans Crisis (1986-1992) and the Great Recession (2008-2010).

2.3 Stock Price

In light of the fact that bank stocks were traded over-the-counter (OTC), rendering their stock price data inaccessible through the CRSP database, this study adopts an alternative approach by sourcing stock prices of over-the-counter securities from multiple sources. For the inception year of 1926 and beyond, the Commerical and Financial Chronicle (CFC) emerges as a pivotal resource, offering a comprehensive coverage of bank stocks. The data collection methodology entails entry of bid and ask quotes at a monthly frequency for each bank. The banks are identified through their names and respective cities, as delineated within the CFC dataset. The price $prc_{i,t}$ for bank i in a given month t is ascertained as the midpoint between the bid and ask quotes. In cases where one of the quotes is absent, the available quote is utilized as the prevailing price for that month. This rigorous data compilation process yields a structured dataset that forms the foundation for subsequent analyses.

For the purpose of computing stock returns, a precise definition is formulated.[7] Specifically, the stock return for bank i in a given month t is defined as the percentage change in price from the previous month's recorded price: $ret_{i,t} = \frac{prc_{i,t} - prc_{i,t-1}}{prc_{i,t-1}} \times 100$. The challenge of stale pricing is a recognized and pervasive data concern in earlier stock market data. This issue underscores the potential for data inaccuracies arising from the usage of outdated prices. Another challenge is the intermittent availability of data for specific banks across distinct periods. This sporadic data presence can significantly impact the integrity and comprehensiveness of the dataset. Specifically, I utilize the most recently available price when facing missing price data.

Coverage within the *Commercial and Financial Chronicle* (CFC) dataset terminates in the year 1963. Yet, a comprehensive coverage within the CRSP database only begins in the 1980s and 1990s (see, e.g., Cortes et al. (2022)). To bridge this temporal gap and ensure a seamless continuity of data, this study utilizes two primary sources: the stock quote segments of the New York Times (NYT) and the Wall Street Journal (WSJ). The latest available stock quote within a given month is employed to derive the price for that specific month.

To study the impact of regulations on bank risk, I follow Gelman et al. (2022) in using idiosyncratic risk as a measure of bank risk. I employ Fama and French's (1993) three-factor model to calculate idiosyncratic volatility in month t. The model is defined as follows:

$$ret_{i,t} - r_{f,t} = \alpha_0 + \beta_1 \cdot (MKT_t - r_{f,t}) + \beta_2 \cdot SMB_t + \beta_3 \cdot HML_t + \varepsilon_{i,t} \tag{1}$$

[7] This definition is not based on holding period return because the dividend information is not available in the historical part of the sample.

where SNP_t is the market factor, defined by the S&P composite index, and SMB_t and HML_t are size and value factors from French's website. The idiosyncratic volatility of year $\sigma(\varepsilon_{i,t})$ is defined as the standard deviation of $\varepsilon_{i,t}$. To calculate the abnormal return for bank i in month t, I run Equation (1) for bank i for the months $t-37$ to $t-1$. Using the factor exposures from that regression, I compute abnormal returns as:

$$abret_{i,t} = ret_{i,t} - \hat{\beta}_1 \cdot (MKT_t - r_{f,t}) - \hat{\beta}_2 \cdot SMB_t - \hat{\beta}_3 \cdot HML_t$$

The annual abnormal return is then calculated similarly by compounding monthly abnormal returns: $AR_{i,T} = \prod_{t=1}^{12}(1 + abret_{i,t}) - 1$.

[INSERT TABLE 1 ABOUT HERE]

3 U.S. Banking Crises and Regulations in Historical Perspective

The relationship between banking crises and regulatory measures in the U.S. has been a pivotal aspect of the nation's financial history, offering significant insights into the broader implications of financial governance. As documented by Bräuning and Sheremirov (2023), Cecchetti et al. (2009), and Bernanke (1983), banking crises precipitate notable economic downturns, highlighting the crucial need for rigorous banking regulations to ensure sustained economic stability.

In contextualizing this relationship, a thorough historical examination is paramount. It elucidates the complex interplay and cyclical nature of banking crises, regulatory enactments, and subsequent deregulation phases. Figure 1 complements this historical discussion by presenting a graphical plot of the Bank Regulation Index with the *BankFailures* metric, defined as the deposits of failed banks as a percentage of total deposits.

3.1 Pre-Depression Banking and Post-Depression Regulations

The pre-Depression structure of unit banking in the US left banks vulnerable to runs, as evidenced by the bank panics of 1873, 1884, 1890, 1893, and 1907. The Federal Reserve Act of 1913 established the Fed to address these bank panics and promote a more stable banking system. Unit banking's fragility led to the need for deposit insurance. States with unit banking support favored federal insurance, notably in rural areas. Democrats' 1930 victory led to control of the House, and Otis

Wingo's death resulted in Henry Steagall leading the House Banking and Currency Committee. Wingo was open to branch limits in the *McFadden Act of 1927*,[8] while Steagall demanded complete branch elimination, showcasing their differing approaches. Figure 1 shows *BRI* at 3.09 in 1927.[9]

Senator Carter Glass vocally opposed federal deposit insurance in the US but strongly advocated for separating commercial and investment banking. After the Great Depression's bank failures, urban bankers faced blame. Pecora hearings' results, later contested by scholars (e.g., Kroszner and Rajan (1994)), gained media attention. A compromise with Steagall emerged: he backed deposit insurance in return for commercial-investment banking separation (*Banking Acts of 1933 and 1935*). These post-crisis regulations provided the foundational framework for modern US banking. *BRI* reaches its highest at 7.1 in 1934 (Figure 1). Calomiris (2000) opens his book by remarking that, *"From the mid-1930s through the 1970s the fundamental institutional and regulatory features of the US banking system were taken for granted as permanent and mainly beneficial by most policymakers and economists"* (chapter 1, page 1).

3.2 The Post-Regulatory Stability: From the Mid-1930s to the 1970s

However, several important regulatory laws reinforced and modernized existing regulatory norms. For example, *Federal Deposit Insurance Act (FDIA) of 1950* expanded the coverage and benefits of the Federal Deposit Insurance Corporation (FDIC) and increased deposit insurance from $5,000 to $10,000. The *Bank Holding Company Act of 1956* (BHCA) defined a bank holding company (BHC) as any company that controls more than 25% of the voting shares of two or more banks and prohibited it from engaging in certain non-banking activities, such as insurance underwriting and real estate development, and acquiring banks in other states. This was later revised when the *BHCA Amendments of 1970* extended the Fed's authority to single-bank holding companies (Avraham et al. (2012)) in response to concerns about the growing concentration of economic power in the banking industry and prohibited bank holding companies from owning more than 5% of the voting shares of another bank (Lichtenstein (1991)). The *Community Reinvestment Act of 1977* further increased regulatory powers by establishing mechanisms for evaluating and rating banks' performance in meeting underprivileged communities' credit needs. Overall, this period was marked by the maintenance

[8] Rajan and Ramcharan (2016) show that representatives from districts with concentrated landholdings and higher credit costs exhibited a significantly greater tendency to oppose the act.

[9] For reference, *BRI* has a mean of 1.61 and a standard deviation of 2.64.

and expansion of the post-Depression regulatory framework and low bank failures. The average value of BRI from 1935 to 1979 was 2.32, compared to a 1.61 overall mean (Figure 1).

3.3 Deregulations of 1979-82, S&L Crisis and Regulatory Response

The *Monetary Control Act of 1980* and the *Garn-St. Germain Act of 1982* were critical deregulatory reforms in the US banking sector after almost a half-century of stability (Kaufman et al. (1981)). The former abolished the *Regulation Q* ceiling on interest rates set in place during the 1930s. While the latter allowed the S&L institutions to engage in risky lending practices. BRI drops to -3.09 by 1984 (Figure 1). These deregulations were followed by the S&L Crisis in late 1980s (Kane (1989), Garcia (2013), Burge (2018), Gray (1990)).

Financial Regulators responded to the banking crisis by the *Financial Institutions Reform, Recovery, and Enforcement Act (FIRREA) of 1989* and *Federal Deposit Insurance Corporation Improvement Act (FDICIA) of 1991*. BRI reaches 3.9 in 1990 (Figure 1). These regulatory interventions helped build up bank capital during the 1990s and another period of stability followed (Flannery and Rangan (2008)). Moreover, these laws helped banks generate more loans (increase their loan-to-deposits ratio) by allowing banks that held at least 10 percent of their assets in residential mortgage loans to become members of the Federal Home Loan Banks (FHLBs) system (Disalvo et al. (2017)).

3.4 Deregulations of 1990s, Great Recession & Dodd-Frank Act

While the 1990s was a period of consolidation of bank balance sheets, it was also marked by significant deregulations. The *Riegle-Neal Interstate Banking and Branching Efficiency Act of 1994* repealed the *McFadden Act of 1927* and allowed banks to branch across state lines (Mulloy and Lasker (1995)). Perhaps the most consequential was the *Gramm-Leach-Bliley Act of 1999*, which partially repealed the separation of investment and commercial banking established by the *Glass-Steagall Act of 1933*.

Other notable deregulations in the early 2000s included the *Bankruptcy Abuse Prevention and Consumer Protection Act (BAPCPA) of 2005*, which imposed stricter bankruptcy filing requirements on consumers. The *Financial Services Regulatory Relief Act (FSRRA) of 2006* aimed to alleviate regulatory burdens on financial institutions. For example, it raised the threshold for once in 18-month mandatory on-site examination of banks from $250 million to $500 million or less in total assets (Federal Reserve (2011)). BRI averages -2.71 for the 1999-2007 period (Figure 1). However, these deregulatory measures were soon followed by the Great Recession of 2007-09 (Grant (2009), Flynn (2015)). In response, the Dodd-Frank Act was enacted, marking one of the most significant pieces of banking legislation in US history. *BRI* reaches 6.73 in 2011 (Figure 1).

3.5 EGRRCPA and the 2023 Bank Failures

The Dodd-Frank Act placed sweeping reforms to address *systemic risk* and ensure that banks, especially those deemed too-big-to-fail (TBTF), are capitalized enough to endure capital shortfalls. It introduced the Comprehensive Capital Analysis and Review (CCAR) program to subject banks with assets above $50 Billion to stress testing. García and Steele (2022) show that stress-testing reduces moral hazard and does not come at the cost of lower lending as lending concentration increased. However, this does not reduce small-business lending as small banks increase lending in areas formerly reliant on stress-tested BHCs (Cortés et al. (2020)).

Nevertheless, the *Economic Growth, Regulatory Relief, and Consumer Protection Act (EGRRCPA) of 2018* partially repealed the stipulations of the Dodd-Frank Act by increasing the threshold for stress-testing to $250 Billion from $50 Billion. *BRI* drops to -2.71 in 2018 (Figure 1). This was followed by the second to fourth largest bank failures in US history in 2023: First Republic Bank ($229B in assets at time of failure)[10], Silicon Valley Bank ($209B)[11] and Signature Bank ($118B)[12]. The assets of these banks fall within the $50-$250 Billion range, and several recent papers have linked the deregulatory reform to these failures (e.g., Al-Sowaidi and Faour (2023), Heinrich (2023), Kupiec (2023)). Figure 1 shows that the *BRI* falls into negative region in 2023. This is not because of any deregulatory reforms but because of news articles mentioning the EGRRCPA 2018 after the collapse of these banks. Since these news articles satisfy the 5-year window criteria, they are included in the index construction.

4 Results and Discussion

In this section, the principal findings of this research are elucidated and critically examined. Beginning with a textual analysis of news articles spanning a century, it becomes evident that deregulatory banking laws consistently receive markedly favorable media coverage. Delving

[10]"JPMorgan Chase Bank, National Association, Columbus, Ohio Assumes All the Deposits of First Republic Bank, San Francisco, California." FDIC.

[11]"Silicon Valley Bank Fails After Run on Deposits." The New York Times. ISSN 0362-4331.

[12]https://www.federalreserve.gov/newsevents/pressreleases/monetary20230312b.htm

deeper into the determinants of banking regulations, empirical evidence demonstrates that banking crises emerge as the predominant predictor.

Subsequently, the analysis bifurcates to consider banking regulations' long-term and short-term ramifications. Over the past century, there has been a discernible pattern: banking crises often trail periods of deregulation, highlighting the pivotal role of stringent regulations in ensuring sectoral stability. Conversely, in the short-term, mirroring findings from extant literature, regulations seem to entail costs, while deregulations appear beneficial. Notably, the short-term effects of deregulations profoundly overshadow those of regulations. This dichotomy underscores the imperative of adopting extended time horizons when assessing the implications of regulatory shifts, especially in the context of the banking industry.

4.1 Deregulation and Media Sentiment

The media's portrayal of banking regulations holds significance in shaping public and market sentiment. This section delves into this relationship, providing empirical evidence on how various bank regulations are covered in the news. Utilizing the dataset of news articles, the study leverages the Latent Dirichlet Allocation (LDA) method to identify distinct topics within the corpus and employs the FinBERT model to assess the sentiment surrounding these regulations.

I follow Calomiris et al. (2020) and employ LDA (Latent Dirichlet Allocation) to decompose the corpus into six distinct topics (see Appendix B to see how LDA is implemented). These are labelled as *BankActivities, DoddFrank, Lending, Legalese, Government,* and *Monetary*. LDA provides two different distributions: a distribution of each document on the topics and a distribution of each topic on a set of words or terms (Figure 2). In order to examine, which laws each of the topics load most heavily on, I take the mean of distribution for topic for each news article that mentions a particular law. As a result, there is a topic distribution for each law. Table 2 shows the laws that have a high share of each topic.

[Insert Table 2 About Here]

In order to calculate sentiment, I identify the mention of a law (or its nickname or a abbreviation) within an article, a 3-sentence window around the mention is extracted. The sentiment of this window is then gauged using FinBERT, which provides a tripartite output vector consisting of the probabilities for positive, negative, and neutral sentiments. The dependent variable, in this context, represents the net sentiment, obtained by computing the difference between the positive and negative probabilities. The regression model is:

$$Sentiment_i = \beta_0 + \beta_1 \cdot Dereg_i + \sum_{j=1}^{6} \gamma_j \cdot Topic_{i,j} + \epsilon_i, \tag{2}$$

where $Sentiment_i$ is the net sentiment from FinBERT for the mention of the law in article i; $Dereg_i$ is a dummy indicating a deregulatory law; and $Topic_{i,j}$ is the distribution share of topic j in article i. Table 3 showcases the findings from this test. Deregulatory laws (*Dereg*) consistently receive more positive media coverage. With the mean of the dependent variable at 0.05, the coefficient of *Dereg* suggests a nearly 100% increase in sentiment, underscoring the media's positive bias towards deregulatory laws.

[INSERT TABLE 3 ABOUT HERE]

The regression incorporates month-fixed effects, controlling for any time-specific shocks or seasonality in the media's portrayal of bank regulations. This ensures that the coefficients capture the effect of the variables of interest and are not confounded by monthly variations. Moreover, standard errors in the regression are double-clustered by Year and by Law. Clustering the standard errors adjusts for potential heteroskedasticity and autocorrelation within each cluster, providing more robust estimates. This is especially relevant in the context of news articles, where responses to regulations might exhibit temporal patterns or specific regulations might garner consistent media attention over time. The double clustering ensures that the standard errors are robust to both time-specific shocks and specific characteristics of individual laws.

This analysis incorporates topic variables derived from Latent Dirichlet Allocation (LDA) as control measures. The adoption of LDA is instrumental, given its capacity to discern the intricate thematic compositions inherent within news articles. This refined control is pivotal for effectively segregating the influence of regulations on the sentiment. Notably, the topic designated as *Legalese* emerges with significance, attracting a negative coefficient, as evidenced in Table 3. The visual representation in Figure 2 offers word clouds for each topic, with *Legalese* in Figure 2D. A temporal time-series analysis, as demonstrated in Figure 10D, indicates a concentration of news articles with a pronounced *Legalese* loading during the post-Depression era, specifically the regulatory landscape of the 1930s.

This nuanced exploration accentuates the intricate dynamics between bank regulations and their portrayal in media. The data underscores a discernible proclivity in media narratives favoring deregulatory measures. Furthermore, with the incorporation of month-specific controls and a clustering approach to standard errors, the findings presented are both methodologically robust and substantively compelling. Most LDA-derived topics are observed to be orthogonal to the sentiment of their corresponding news coverage, with the notable exception of *Legalese*, which consistently evokes negative sentiment.

4.2 Determinants and Long-term Impacts of Bank (De)Regulation

Understanding the determinants of bank regulation is pivotal for both policymakers and scholars. This section presents empirical evidence on various factors predicting the Bank Regulation Index (BRI) for the subsequent year. In order to predict regulation, I use the following specification:

$$BRI_t = \alpha + \beta_1 \cdot BankFailures_{t-1} + \beta_2 \cdot Republican_t + \beta_3 \cdot \Delta GDP_{t-1} + \beta_4 \cdot \pi_{t-1} + \beta_5 \cdot r_{t-1} + \varepsilon_t \quad (3)$$

Here BRI_t is the Bank Regulation Index for year t. $BankFailures_{t-1}$ represents the deposits of failed banks as a percentage of total deposits in year $t-1$. $Republican_t$ is a dummy variable indicating a Republican-led government. ΔGDP_{t-1}, π_{t-1}, and r_{t-1} are the growth rate of GDP, the inflation rate, and the short-term interest rate for the previous year, respectively. ε_t is the error term.[13]

In Table 4, a pronounced correlation emerges between prior year bank failures and the ensuing year's Bank Regulation Index (BRI). This underscores a pattern wherein a surge in bank failures typically precedes intensified regulatory measures. Nevertheless, a pressing question remains: How does $BankFailures_{t-1}$ fare as a predictor vis-à-vis other potential determinants? Evidently, as highlighted in Column (2), the prior year's short-term interest rate stands out as a consequential predictor for subsequent bank regulations. A negative, statistically significant coefficient suggests an inverse relationship between interest rates and regulatory intensity, pointing to higher rates as potential harbingers of deregulation. Historical trends support this inference. For instance, the

[13]This table uses Newey and West (1987) standard errors, adjusted for 12 lags. Newey-West standard errors are designed to provide consistent standard error estimates when there is potential autocorrelation and heteroskedasticity in the residuals. Economic data often exhibit temporal dependencies, which can invalidate the standard assumptions of OLS regressions. The use of Newey-West standard errors ensures robustness against such serial correlation and heteroskedasticity, providing more reliable inference. Given the dynamic nature of bank regulations and their potential lagged effects, ensuring robustness against serial correlation is particularly important in this context. The remainder of the paper continues to calculate standard errors in this fashion.

dramatic interest rate hikes of the late 1970s, primarily to counter prevailing inflationary pressures, subjected banks to significant fiscal duress. This fiscal environment catalyzed regulators to liberalize borrowing and lending norms, evident in subsequent legislative measures like the *DIDMCA of 1980* and the *Garn-St. Germain Act of 1982*. A parallel can be drawn with the early 2000s when constricted interest rate spreads, following rate augmentations, culminated in deregulatory legislations such as the *BAPCPA of 2005* and *FSRRA of 2006*.

Yet, while this association between interest rates and deregulation seems plausible at first glance, empirical scrutiny reveals caveats. Columns (4) and (6) of Table 4 indicate the predictive efficacy of short-term interest rates diminishes in the presence of other determinants. Turning to the partisan dimension, Column (3) unearths a discernible inclination towards deregulation during Republican tenures, exemplified by legislative shifts during the Reagan, Bush, and Trump eras. However, much akin to the interest rate dynamics, the partisan predictor's efficacy wanes when raced with a broader set of determinants, as evidenced in Columns (4)–(6). Notably, Columns (4) and (5) accentuate the singular reliability of banking crises in predicting imminent regulatory stringency. In contrast, Column (6) underscores the apparent unpredictability of short-term deregulations.

[Insert Table 4 About Here]

Given these intricate short-term correlations, it becomes imperative to delve deeper into the long-term determinants and implications of banking regulations. Vector Autoregressions (VARs) can capture dynamic temporal interdependencies across multivariate time series and offer invaluable insights into enduring regulatory impacts. I employ a bivariate Vector Autoregression (VAR), including bank failures and changes in regulations, to discern the dynamic interplay between these two factors. The bivariate VAR model is specified as:

$$BRI_t = \alpha_1 + \sum_{i=1}^{p} \phi_{1i} \cdot BRI_{t-i} + \sum_{i=1}^{p} \theta_{1i} \cdot BankFailures_{t-i} + \varepsilon_{1t} \tag{4}$$

$$BankFailures_t = \alpha_2 + \sum_{i=1}^{p} \phi_{2i} \cdot BRI_{t-i} + \sum_{i=1}^{p} \theta_{2i} \cdot BankFailures_{t-i} + \varepsilon_{2t}, \tag{5}$$

where BRI_t represents the Bank Regulation Index at time t; $BankFailures_t$ denotes bank failures at time t; ε_{1t} and ε_{2t} are the error terms. The lag order is set at $p = 10$ to allow for a full decade of time series variation.

Figure 3A depicts the impulse responses of bank failures to shocks in regulations. Following the methodology of Sims and Zha (1999, 2006), I observe 68% and 90% confidence bands. The impulse response function (IRF) illustrates the reaction of bank failures to a one-unit shock in the Bank Regulation Index (BRI) while holding other shocks to zero. An immediate increase in the BRI leads to a trivial surge in bank failures in the initial period. This could be attributed to the immediate *adjustment costs* and disruptions associated with the implementation of new or stricter regulations. As regulators respond to an episode of bank failures, this can also represent the lagging effects of the crisis. However, as time progresses and banks adapt to the new environment, the regulatory shock results in an extended period of stability. Figure 3B shows how regulations respond to crisis. As evident from this figure and from the regressions in Table 4, regulators are swift to respond to banking crises. This shows the short-term and long-term dichotomy in how regulations and crises relate to each other.

Column (5) in Table 4 presents an intriguing aspect of regulatory dynamics: the predictive power of our explanatory variables is notably evident for increased regulations, yet conspicuously absent when it comes to deregulation in the short run (Column (6)). This differential predictability prompts a deeper inquiry into the determinants of deregulatory actions.

A plausible hypothesis emerges from this observation: prolonged stability within the banking sector, rather than ensuring sustained resilience, might foster a sense of complacency, thus paving the way for deregulatory impulses. The Impulse Response Function (IRF) delineated in Figure 4A lends credence to this conjecture. Specifically, the Decreased Regulation Index (DRI) exhibits a negative response to shocks in $BankFailures$. This suggests that extended intervals characterized by minimal bank failures act as precursors to heightened deregulatory measures. Furthermore, the ramifications of such deregulatory measures manifest not in immediate disruptions, but in the medium to long term. As evidenced in Figure 4B, a surge in deregulation is invariably followed by a substantial uptick in bank failures within a span of a decade. This empirical finding resonates with historical patterns of regulatory cycles, as elaborated in Section 3.

Several pivotal banking legislations have emphasized enhancing capital requirements, with a particular focus on prominent financial institutions. Notably, the Financial Institutions Reform, Recovery, and Enforcement Act (FIRREA) of 1989 and the Federal Deposit Insurance Corporation Improvement Act (FDICIA) of 1991 were enacted in the wake of the Savings and Loans crisis, underscoring the necessity of robust capital buffers. Similarly, the Dodd-Frank Act imposed stringent capital requirements on larger banks, further solidifying this regulatory trajectory. The Impulse Response Function (IRF) depicted in Figure 5 illuminates the relationship between regulatory upticks and subsequent banking leverage. As banking regulations intensify, there's a discernible decline in bank leverage in ensuing years. This contraction in leverage bolsters the banks' capital reserves, enhancing their resilience against potential asset downturns and thereby contributing to the systemic stability of the banking sector.

4.3 Short-Term and Long-Term Dichotomy in the Impact of Regulations

I use regressions of the following form to measure the short-term impact of bank regulations.

$$Y_{i,t} = \gamma_0 + \gamma_1 \cdot BRI_{t-1} + Controls + \delta_i + \epsilon_{i,t} \tag{6}$$

$$Y_{i,t} = \gamma_0 + \gamma_1 \cdot IRI_{t-1} + \gamma_2 \cdot DRI_{t-1} + Controls + \delta_i + \epsilon_{i,t} \tag{7}$$

where BRI_{t-1} is the lagged value of annual Bank Regulation Index. Similarly, IRI_{t-1} and DRI_{t-1} are lagged values of Increased Regulation Index and Decreased Regulation Index, respectively. δ_i are bank fixed effects. Bank-level $Controls$ are LDR, $\ln(Total\_Assets)$, Leverage and Cash Ratio of year $t-1$. Macro $Controls$ are ΔGDP_{t-1} (last year's GDP growth), π_{t-1} (last year's inflation), r_{t-1} (last year's short-term interest rate). Here $Y_{i,t}$ represents different bank-level outcomes.

I now quantify bank-specific exposures to regulatory risk by computing the equity beta of each bank with respect to innovations in the BRI. Stock prices are forward-looking and encapsulate the collective assessment of market participants about a bank's future performance, risk, and the discount rate applied to bank's future cash flows. Thus, they serve as an encompassing measure of the various risks, including regulatory ones, that might influence a bank's valuation. This high-frequency responsiveness of stock prices provides the granularity needed to delineate the nuances of regulatory risk exposures with precision.

To achieve a more detailed analysis, the BRI is reconstructed at a monthly frequency, with articles aggregated on a monthly basis instead of annually. A bank i's heightened exposure to regulatory risk should manifest as an elevated beta when its monthly stock returns are regressed against changes in the BRI. To control for other market risks, the regression incorporates the FF3 factors. We utilize data available up to year t to avoid potential endogeneity and forward-looking bias. Specifically, for each bank i and year t, the first-stage regression is formulated over the period $t-5$ to $t-1$:

$$ret_{i,t} - rf_t = \beta_0 + \beta_1 \cdot BRI_t + \beta_2 \cdot MKTRF_t + \beta_3 \cdot SMB_t + \beta_4 \cdot HML_t + \epsilon_{i,t} \tag{8}$$

From this regression, the exposure of bank i to regulations is the standardized $\beta_{i,t}^{reg}$ (*Regulatory Exposure*), which I define as $\beta_{i,t}^{reg} \equiv -\beta_1$ for a more intuitive interpretation[14]. The following is the second-stage regression:

$$Y_{i,t} = \gamma_0 + \gamma_1 \cdot \beta_{i,t}^{reg} + BankControls + MacroControls + \delta_i + \gamma_t + \epsilon_{i,t}$$

where δ_i are bank fixed effects, γ_t are time fixed effects, $Y_{i,t}$ is outcome, *MacroControls* are GDP growth, inflation and short-term interest rate of year $t-1$. and *BankControls* are *LDR*, $\ln(Total\_Assets)$, Cash Ratio, and Leverage of year $t-1$. In the regression analysis, the focus is on the negative of β_1 to accurately capture the banks' response to regulatory changes, reflected inversely in their stock prices. Consider the example of two banks, ABC and XYZ, reacting to a deregulatory shift, indicated by a 5 point drop in the BRI. If ABC's stock price increases by 5%, its β_1 is -1, whereas XYZ, experiencing a 10% stock price increase, has a β_1 of -2. These negative β_1 values demonstrate an inverse relationship between stock price movements and regulatory dynamics. For a clearer understanding of the banks' sensitivities to regulatory changes, translating these negative values to their positive equivalents is insightful. By applying the negative of β_1, ABC's value becomes +1, and XYZ's becomes +2, more accurately reflecting their respective exposures to regulatory shifts. This approach of using $\beta_{i,t}^{reg}$ as the time-varying *Regulatory Exposure* aligns the analysis with the actual influence of regulatory changes on bank stock prices. Figure A.2 plots the *Regulatory Exposure* or $\beta_{i,t}^{reg}$ values for sample of 6 large banks for the past century.

The impact of banking regulations on bank profitability exhibits a clear dichotomy between short-term and long-term effects. In the short term, as shown in Table 5, increased regulation,

[14] In order to study how different bank characteristics explain the *Regulatory Exposure*, I use the following regression:

$$\beta_{i,t}^{reg} = \gamma_0 + BankControls_{t-1} + MacroControls_{t-1} + \delta_i + \gamma_t + \epsilon_{i,t} \tag{9}$$

Bank *Controls* are *LDR*, $\ln(Total\_Assets)$, Leverage and Cash Ratio of year $t-1$. Macro *Controls* are ΔGDP_{t-1} (last year's GDP growth), π_{t-1} (last year's inflation), r_{t-1} (last year's short-term interest rate). δ_i are bank fixed effects. γ_t are decade fixed effects. Figure A.1 shows the coefficient estimates from this regression.

indicated by a rise in the Bank Regulation Index (BRI), is associated with a decrease in banks' Return on Equity (ROE). This suggests that regulatory measures initially dampen profitability. The effect is even more pronounced in the case of deregulatory shocks, where reduced regulation leads to a significant immediate impact on ROE.

[Insert Table 5 About Here]

In contrast, the long-term implications present a different picture. The Impulse Response Function (IRF) analysis in Figure 7 reveals that over time, regulatory shocks are linked to an increase in profitability (in long-term). This is further supported by the findings in Table 7, where leading values of ROE from years t to $t + 10$ show a reversal from negative to positive impacts as a result of regulatory exposure ($\beta^{reg}_{i,t}$). In summary, this analysis highlights a transition from short-term challenges to long-term benefits in the wake of regulatory changes in the banking sector. While regulations may initially constrain profitability, they eventually contribute to stronger financial performance over time.

Table 5 explores the interplay between bank regulatory dynamics and their ensuing impact on stock returns. Regulatory changes are known to influence stock returns in both positive and negative directions. Table 6 uses interaction with a dummy variable for Large Banks and shows that short-term impacts of regulations are attenuated for large banks (regulations have heavier impacts of smaller banks).

[Insert Table 6 About Here]

According to Calomiris et al. (2020), enhanced compliance risks from regulations could initially restrict growth but might also lead to higher future expected returns. The logic here is multifaceted: increased risks often result in reduced investments, impacting growth; the elevated distress risk from compliance obligations diminishes the attractiveness of debt's tax benefits, leading to lower leverage; and companies might need to offer greater returns to equity investors to compensate for this heightened risk. Analysis of the BRI_{t-1} coefficient reveals that regulations in the previous year are somewhat linked to increased stock returns in the following year, especially when macroeconomic factors are considered. Delving deeper, the IRI_{t-1} and DRI_{t-1} coefficients suggest that both regulatory intensifications and relaxations are predictors of higher future stock returns, with deregulation having a more pronounced effect. This ties back to the compliance risk theory proposed by Calomiris et al. (2020).

Furthermore, Table 7 helps to explain short-term and long-term outcomes. It shows that while returns can be positive in the short term following deregulation, they tend to turn negative in the years that follow. This nuanced understanding of the temporal dynamics between regulation and stock returns provides valuable insights into the complex nature of regulatory impacts on bank performance.

[Insert Table 7 About Here]

Table 5 provides an examination of the implications of regulatory dynamics on the idiosyncratic volatility of banks, a pivotal metric of bank risk as delineated by Gelman et al. (2022). The coefficient on BRI_{t-1} is positive and statistically significant across various model specifications. This suggests that an increase in the overall bank regulation index from the preceding year is associated with elevated idiosyncratic volatility in the subsequent year. Intriguingly, this positive coefficient on BRI_{t-1} can be understood in the context of the negative and statistically significant coefficient on DRI_{t-1} (Panel B). Given that DRI_{t-1} represents the decreased regulation index, its negative coefficient implies that deregulation in the previous year leads to a reduction in idiosyncratic volatility, a manifestation of reduced bank risk, and reinforces the notion that alleviation of regulatory burdens translates into a more stable risk profile for banks in the short-term.

The coefficient on IRI_t offers additional insights. In the initial model specification, IRI_t carries a negative and statistically significant coefficient, indicating that increased regulations from the prior year contribute to reduced idiosyncratic volatility. However, this relationship becomes statistically insignificant as control variables are incorporated into the model. This attenuation in statistical significance suggests that the initial negative relationship between increased regulation and idiosyncratic volatility is potentially confounded by other bank-specific and macroeconomic factors. Once these factors are accounted for, the distinct impact of increased regulation on idiosyncratic volatility becomes less discernible.

The relationship between banking regulations and liquidity, as indicated by cash holdings relative to assets, mirrors a similar trend observed with other financial metrics. Banks are compelled to enhance their liquidity reserves in response to tighter liquidity regulations, as measured by the $Cash/TA_t$ ratio. As shown in Column (4), an increase in regulation tends to augment liquidity in the short term, whereas deregulation has the opposite effect. Notably, this impact is predominantly driven by deregulatory actions, as the IRI_{t-1} is not significant in Panel B. These findings underscore the adjustment costs associated with new regulations and the time lag required for these regulations to manifest their effects thoroughly. Furthermore, an uptick in banking regulations in the year $t-1$ is correlated with a reduced Loan-to-Deposits Ratio (LDR_t) in the subsequent year. Both regulatory and deregulatory components of the index independently influence this outcome, with deregulation exerting a stronger impact. When controlling for macroeconomic variables such as the previous year's GDP growth, inflation, and interest rates, the influence of IRI_t diminishes and ceases to be significant (Column (6)). This suggests that the observed lower LDR_t is primarily a consequence of deregulation-induced increases in the LDR in the short term.

Figure 8 and Figure 6 further reinforce this understanding, demonstrating that regulatory shocks correlate with a lower $Loans/GDP$ ratio and higher cash ratios over the long term. This is substantiated by Table 7, which confirms that future values of lending (LDR) and Cash Ratio are indeed lower and higher, respectively, for banks more exposed to regulatory shocks. This dynamic between regulation, liquidity, Loan/GDP and loan-to-deposit ratios across different time frames provides a comprehensive view of the nuanced effects of banking regulations.

Regulatory implications on bank stability are of paramount significance in the landscape of financial policymaking. A salient metric that captures this stability is the distance-to-default (DD). Derived from structural models of credit risk, DD serves as a barometer indicating the buffer a bank has against potential default. I follow Bharath and Shumway (2008) to make the Distance-to-Default (DD) measure. First, Bharath and Shumway (2008) document that their simplified DD measure performs slightly better than the structural DD derived from Merton's (1974) model. Second, the naïve DD is well-suited for my data limitations. It is defined as:

$$DD_{i,t} = \frac{\ln(\frac{E+D}{D}) + (r_{i,t-1} - \frac{1}{2}\sigma_V^2)T}{\sigma_V\sqrt{T}},$$

where E is Equity, D is Total Liabilities, $r_{i,t-1}$ is last year's equity return, $T=1$ and σ_V is a weighted average of debt and equity volatility, as they suggest.

An initial reading of Table 5 may give rise to a seemingly paradoxical observation: both regulatory intensifications (IRI_t) and deregulations (DRI_t) appear to amplify the short-term distance-to-default. The empirical evidence reveals that both regulatory and deregulatory shocks are associated with positive short-term stock returns. Given the proportionality of the DD measure with the preceding year's stock returns (positively) and stock volatility (negatively), the observed positive link between the regulatory changes and subsequent DD becomes elucidated.

However, it is crucial to conflate these immediate repercussions with long-term systemic stability. The narrative flips when one extends the temporal lens, as evinced in Figure 5. Over protracted durations, heightened regulations typically curtail leverage, reinforcing the buffers of bank stability. In contrast, deregulatory impulses tend to elevate leverage, potentially ratcheting systemic vulnerabilities. This accentuates the pivotal role of astute regulatory oversight in controlling the risk and maintaining resilience of the banking sector.

Therefore, it should not come as surprise that studies that use short time windows to study the effects of regulations mostly find negative outcomes. This paper makes the case that much longer time frames should be used to evaluate the costs and benefits of regulations. Moreover, the short-term attractiveness of deregulatory impacts should be approached with caution because they can lead to crises in the medium to long term.

5 Predicting Banking Crises

Given the profound and long-lasting economic repercussions of banking crises, as evidenced by historical data and scholarly research, it becomes imperative to establish predictive indicators for such events. Studies have consistently demonstrated that the negative impacts of systemic banking crises on output and employment far exceed those of other financial disturbances. Notably, the Macrohistory database, elaborated by Jordà et al. (2017, 2021), provides substantial evidence of the severe contractionary effects banking crises have, which can be up to four times more intense than those of non-banking financial crises. This is further corroborated by Cecchetti et al. (2009), who, upon examining 40 systemic banking crises since 1980, observed that such events typically coincide with acute downturns in economic output from which recovery is often protracted. Baron and Xiong (2017) show that expansions in private debt predict a crash in bank equity prices. Additionally, Baron et al. (2021) find that significant declines in bank equity, even in the absence of outright panics, are closely linked with notable contractions in credit and consequent output gaps. The seminal work of Bernanke (1983) goes as far as to suggest that the bank failures during the Great Depression not only mirrored the economic downturn but actively exacerbated it by depleting capital resources.

In light of these insights, the necessity for robust leading indicators to forecast banking crises becomes clear. Such indicators would not only be crucial for preemptive measures and policy formulation but also for mitigating the profound and pervasive economic distress that banking crises can unleash. The section ahead endeavors to build upon this foundation, emphasizing the vital importance of regulations and refining tools that can accurately signal impending banking sector crises.

Using long-run historical data from advanced economies, Schularick and Taylor (2012) have highlighted credit growth as a key predictor of banking crises. Subsequent studies, including Jordà et al. (2021), expanded this understanding by identifying the loan-to-deposit ratio (LDR) as another indicator while noting that capital ratios are not as predictive. Studies by Baron and Xiong (2017) and Fahlenbrach et al. (2018) further reveal a tendency for over-optimism and risk neglect during credit booms, which often precede bank failures. These insights are critical as banking crises are known to cause more severe economic downturns than other financial indicators.

Following this line of research, Mian et al. (2017) shows that Shock to the household debt to GDP ratio in a country leads to a three- to four-year rise of household debt, which then subsequently reverts. However, the same is not true for nonfinancial firm debt, which is associated with a smaller and more immediate negative effect on GDP. They argue the following as the factors driving a credit boom: the influx of foreign capital (Favilukis et al. (2017), Justiniano et al. (2015)), economic sentiment (Greenwood et al. (2016)), and deregulations. The contribution of this paper is to quantify regulations and examine how a regulation-based measure (BRI_t) performs in the prediction of future crises compared to these known indicators.

As argued earlier and shown in Figure 3 and Figure 4, regulations take time to have real effects. These figures show that an increase (decrease) in regulations takes about 5 to 10 years to have an impact on the banking system's stability. Therefore, this paper explores how regulatory changes 5 to 10 years ago, predict bank failures today. To measure this change, $\frac{1}{5}(BRI_{t-5} - BRI_{t-10})$ is the average change in the BRI_t from year $t-10$ to $t-5$. Following, Jordà et al. (2021), I use a probit regression model and assume the probability of a crisis conditional on the vector of observables $\mathbf{X}_t$ that can be represented as:

$$\mathbb{P}[I_t = 1 | \alpha_0, \mathbf{X}_t] = \phi(\alpha_0 + \beta \mathbf{X}_t), \tag{10}$$

where I_t is a dummy variable that takes value 1 when $BankFailures_t$ reach a certain threshold (0.5% for baseline). Similar to Jordà et al. (2021), $\mathbf{X}_t$ includes average annual change of the ratio of credit to gross domestic product (GDP) over the previous 5-year window (denoted $\Delta_5 Loans/GDP$), following Schularick and Taylor (2012), Loan-to-Deposit Ratio and Capital Ratio lagged by one year.

Table 8 (Column 1) confirms the results of Jordà et al. (2021). The main dependent variable is taken to be $I(BankFailures_t > 0.5\%)$, a dummy variable indicating that deposits of failed banks in year t amounted to more than 0.5% of total deposits. It confirms that while the credit growth of the last five years is significant in predicting future bank failures, the capital ratio is not. Column (2) of the table augments the probit regression with lagged changes in BRI, and it shows that not only does it significantly predict future crises, but it also explains the predictive power of the known indicators. This makes the case that bank regulations are an important piece in the puzzle of predicting bank failures: while credit growth over the last five years explains banking crises, the regulatory changes in the preceding period explain the credit growth itself. In other words, deregulatory changes fuel credit booms (by allowing banks to lend to riskier borrowers) that are subsequently associated with banking crises. This relates to Greenwood and Hanson (2013), who show that a measure of credit supply shocks, based on the quantity of credit origination to low-credit-quality firms in the United States, is positively correlated with household debt booms. Column (5) shows that a rise in mortgages (as a share of GDP) also predicts future bank failures, but the predictive power of this measure is also explained by the regulatory changes that precede it (Column 6).

[Insert Table 8 About Here]

Here, it is important to distinguish between the predictive power of regulatory versus deregulatory changes. Table 9 replaces the BRI with lagged changes in Increased Regulation Index (IRI_t) and Decreased Regulation Index (DRI_t). It turns out that both increasing and decreasing regulatory changes provide predictive power. Higher (lower) regulation is associated with a lower (higher) probability of bank failures after other known predictors are controlled for.

[Insert Table 9 About Here]

These results are robust to different specifications. Table A.2 uses a more stringent cut-off, i.e., that deposits of failed banks in year t amounted to more than 1% of total deposits. Baron et al. (2021) show that banking panics (i.e., equity declines below -30% for banks) without crises (i.e., widespread bank failures) are also associated with output declines. Since my definition of crises does not include years of large equity declines (without crises), Table A.3 shows that the results are robust to including their years. Moreover, Table A.4 uses several different lag orders, and the predictive results remain robust. This table shows that regulatory changes in the recent past do not carry as much predictive power as those in a more distant past—results get more significant in higher lag orders. This again confirms the hypothesis that regulatory changes take time to have an effect, and 5-10 years turns out to be an effective lag duration.

5.1 Regulatory Topics by Latent Dirichlet Allocation (LDA)

Bank regulations are multi-dimensional. There are regulations on many different topics, such as the activities banks can and cannot engage in, determining lending to consumers, the amount of capital and other reserves (such as cash) the banks are required to maintain, disclosure, transparency, the BRI_t is a latent variable: it resolves the multi-dimensional nature of bank regulations into a single variable. This approach has the advantage of using this index to measure the impact of regulations and predict future crises. However, this does not explain which type of regulations are more informative about future states of the world. To this end, I use Latent Dirichlet Allocation (LDA) to decompose the corpus of news articles on six different topics. Appendix B provides details on how the process is implemented.

Appendix B explains that using the topic distributions, the BRI can be decomposed into six different indices, one for each topic. Figure 10 plots these indices. In order to determine which type of laws are the most predictive, Table 10 uses the lags of changes in these indices to predict future crises.

[Insert Table 10 About Here]

Separately, each of the indices is predictive (Columns 1 to 6). However, when they are employed in the same regression, *Lending* turns out to be the most predictive. Laws regulating lending to consumers such as the Credit CARD Act of 2009 (0.87), Bankruptcy Abuse Prevention and Consumer Protection Act of 2005 (0.65) and Monetary Control Act of 1980 (0.49) have a high share on this topic. This shows that regulating (or deregulating) the scope of permissible banking operations and lending (especially to high-risk borrowers) carries significant implications for the future stability of the banking system. Relatedly, Gorton and Ordonez (2014) and Gorton and Ordonez (2020) develop a *"Good Booms, Bad Booms"* model in which a crisis happens when a credit boom transits toward an information regime with careful examination of collateral. A financial crisis, therefore, is a switch from information-insensitive debt to information-sensitive debt when agents produce information about the backing collateral (Dang et al. (2020)). The predictive results in Table 8 to Table 10 characterize the *good booms* and *bad booms*. They show that *bad booms* are empirically preceded by lax regulatory environments that allow banks to engage in risky lending activities. This results in credit expansions (as shown by higher LDR after deregulatory shocks) that are followed by banking crises.

6 Federal Register and Earnings Call Transcripts

This section employs the Federal Register as an alternative dataset to identify regulatory topics through Latent Dirichlet Allocation (LDA). The register's machine-readable format, accessible via an API for documents post-1994, and .txt files for 1936-1993 from HathiTrust, presents a challenge due to its inconsistent layout over the years. I employ various methods, including regular expressions, to standardize these documents for the historical (1936-1993) period. The focus is on Final Rules issued by Financial Stability Oversight Council (FSOC)-member regulatory agencies, as shown in Figure A.3 (Labonte (2017)).

LDA techniques, similar to those applied to newspaper texts, decompose the Federal Register corpus from 1936-2021 into six distinct topics. Word clouds associated with these topics are displayed in Figure 11, with a notable "Lending" topic characterized by terms like "loan", "creditor", "mortgage", and "lender". To validate the significance of the "Lending" topic, Table A.5 replicates the probit model analysis of Table 10. Initial bivariate regressions reveal that only the "Lending" topic exhibits significant predictive power. Even when incorporating all six topics in a single regression model, regulations pertaining to "Lending" maintain their prominent predictive role.

This robustness check confirms the initial findings derived from newspaper sources, asserting that regulations concerning lending practices are pivotal indicators of future macro-financial conditions. The consistency of these results, despite the shift from newspaper to Federal Register data, underscores the critical role of lending regulations in shaping broader economic conditions.

Further, I obtain Earning Calls transcripts from Capital IQ for 2007-2020. Kalmenovitz et al. (2022) train an LDA model on the Federal Register and apply it on firms' 10-Ks to measure regulatory exposure. On the other hand, Calomiris et al. (2020) uses LDA on earnings calls transcripts.

Similar to Kalmenovitz et al. (2022), I train LDA model on the almost century-long corpus of Federal Register text of rules passed by FSOC-member agencies (keeping six topics to be consistent). The result decomposes each earning call into six topics and gives the weight distribution.

Next, I match bank-month level returns data with weights obtained from earnings call of the previous quarter. In each quarter, I sort bank stocks into deciles according to weight of the *Lending* topic. The long-short portfolio takes a long position in the lowest and short position in the highest decile. Figure 13 shows the performance of the long and short legs of this portfolio with the market portfolio.

[Insert Table 11 About Here]

The alphas and R2 of *Lending* exposure portfolios are reported in Table 11. The table shows time-series regressions of monthly returns with different factors. Sample is Sep-2007 to Dec-2020. Four different models are considered: the CAPM model, Four-Factor model (market ($MKTRF$), size (SMB), value (HML) and momentum (MOM)), Five-Factor model (market ($MKTRF$), size (SMB), value (HML), robust-minus-weak (RMW) and conservative-minus-aggressive (CMA)) and Four-Factor model with robust-minus-weak (RMW) and conservative-minus-aggressive (CMA). All alphas are expressed in percentages.

The alphas range from 0.61% (t-stat = 2.10) for the 4-factor model to 0.75% (t-stat = 2.37) for the CAPM model. The 6-factor model (Four-Factor model with robust-minus-weak (RMW) and conservative-minus-aggressive (CMA)) generates an alpha of 0.64% (t-stat = 2.07). This implies a 7.96% annualized return.

7 Concluding Remarks

Banks are one of the most rigorously regulated sectors. In recent times, there has been a surge in literature highlighting the costs associated with regulations. Many of these studies rely on short time windows and do not exclusively focus on banks, potentially missing the broader implications of regulatory changes. I gathered data from various sources to address this limitation, crafting a comprehensive century-long panel of bank-level variables and their stock returns. Using newspapers as a primary data source, I constructed the Bank Regulation Index (BRI), offering a refined measure of regulatory changes over time.

A key insight from this research is the recognition of a clear dichotomy in the effects of banking regulations in the short and long term. Using the BRI, my analysis uncovers a cyclical pattern where regulations tend to intensify following financial crises, leading to periods of subsequent stability. However, these periods of calm often give rise to deregulatory trends, potentially setting the stage for future instabilities. This cyclical nature of regulations and their long-term ramifications are further explored through the *Regulatory Exposure*, a measure derived from banks' price reactions to regulatory changes. This measure illuminates how regulations, while initially burdensome in terms of profitability and stock returns, eventually manifest as stabilizing forces, reducing bank leverage, lowering Loan-to-Deposit Ratios (LDR), and increasing liquidity ratios. The third significant conclusion of this study is showcasing the BRI's predictive prowess in forecasting future banking crises. The BRI's predictive capacity is especially potent when decomposed into specific regulatory topics using Latent Dirichlet Allocation, highlighting the predictive significance of (de)regulations on credit and lending.

The Federal Register serves as an alternative data source to model regulatory topics through Latent Dirichlet Allocation (LDA). Employing a probit model elevates the *Lending* topic as the most predictive of macro-financial conditions. This outcome is congruent with findings from newspaper-based assessments, underscoring the critical role of lending and credit regulations in economic prediction.

This paper applies an LDA model, originally trained on Federal Register documents, to the text of earnings calls. This approach assigns a specific weight to the *Lending* topic within each report. By categorizing bank stocks based on their *Lending* topic exposure in subsequent quarters and constructing portfolios accordingly—taking long positions in the lowest decile and short positions in the highest—the strategy yields monthly alphas ranging from 0.61% to 0.75%, depending on the factor model applied.

In conclusion, while short-term analyses often underscore the immediate costs of regulatory changes, they fall short of capturing the long-term implications. This study steps beyond this limitation by illustrating regulations' enduring, stabilizing influence across extended periods. The BRI serves as an effective tool for historical and current regulatory analysis and emerges as a predictive metric for future banking crises. Its ability to resolve multi-dimensional regulatory changes into a latent measure provides a deeper understanding of banking regulations' cyclical nature.

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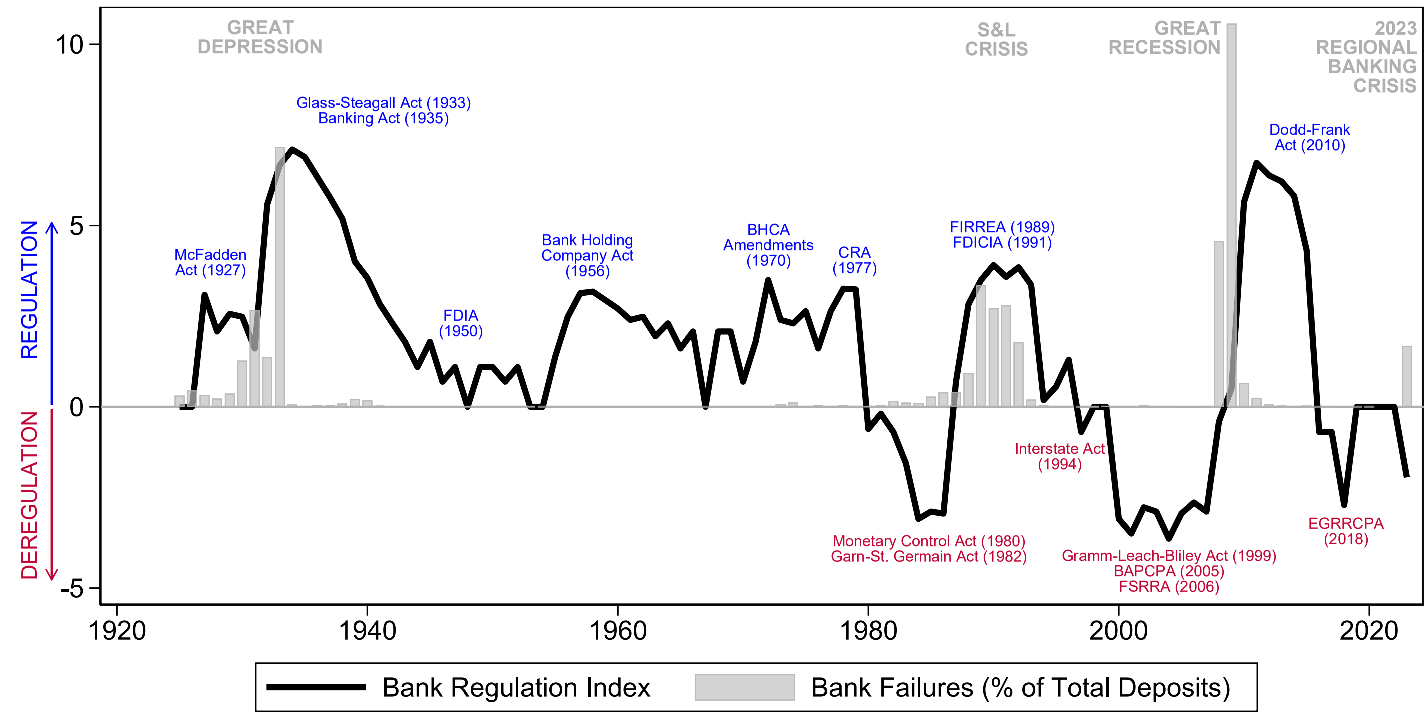


Figure 1. Bank Regulation Index and Banking Crises

The figure illustrates the relationship between *BRI* and *BankFailures*, where *BankFailures* represents the proportion of deposits in failed banks to total deposits. The plot highlights four distinct peaks in *BankFailures* since 1926. The initial surge corresponds to the Great Depression of the 1930s. In response, stringent banking regulations were instituted, leading to a subsequent decline in *BankFailures*. A period of deregulation during 1979-82 set the stage for the next notable peak, representing the Savings and Loans Crisis of the 1980s. Regulatory reforms between 1989 and 1991 then followed. A subsequent deregulatory phase from the late 1990s to early 2000s paved the way for the Great Recession of 2007-09, which triggered the enactment of the Dodd-Frank Act. This recurring pattern of regulatory interventions post-crisis, followed by deregulatory periods, with the Economic Growth, Regulatory Relief, and Consumer Protection Act of 2018 leading to the most recent increase in *BankFailures* by 2023. The cyclical trajectory of *BRI* against *BankFailures* underscores a consistent narrative: post-crisis regulatory measures often transition into deregulatory phases, resulting in bank failures. The 2023 decline in *BRI* is attributed to mentions of the EGRRCPA following the recent bank failures.

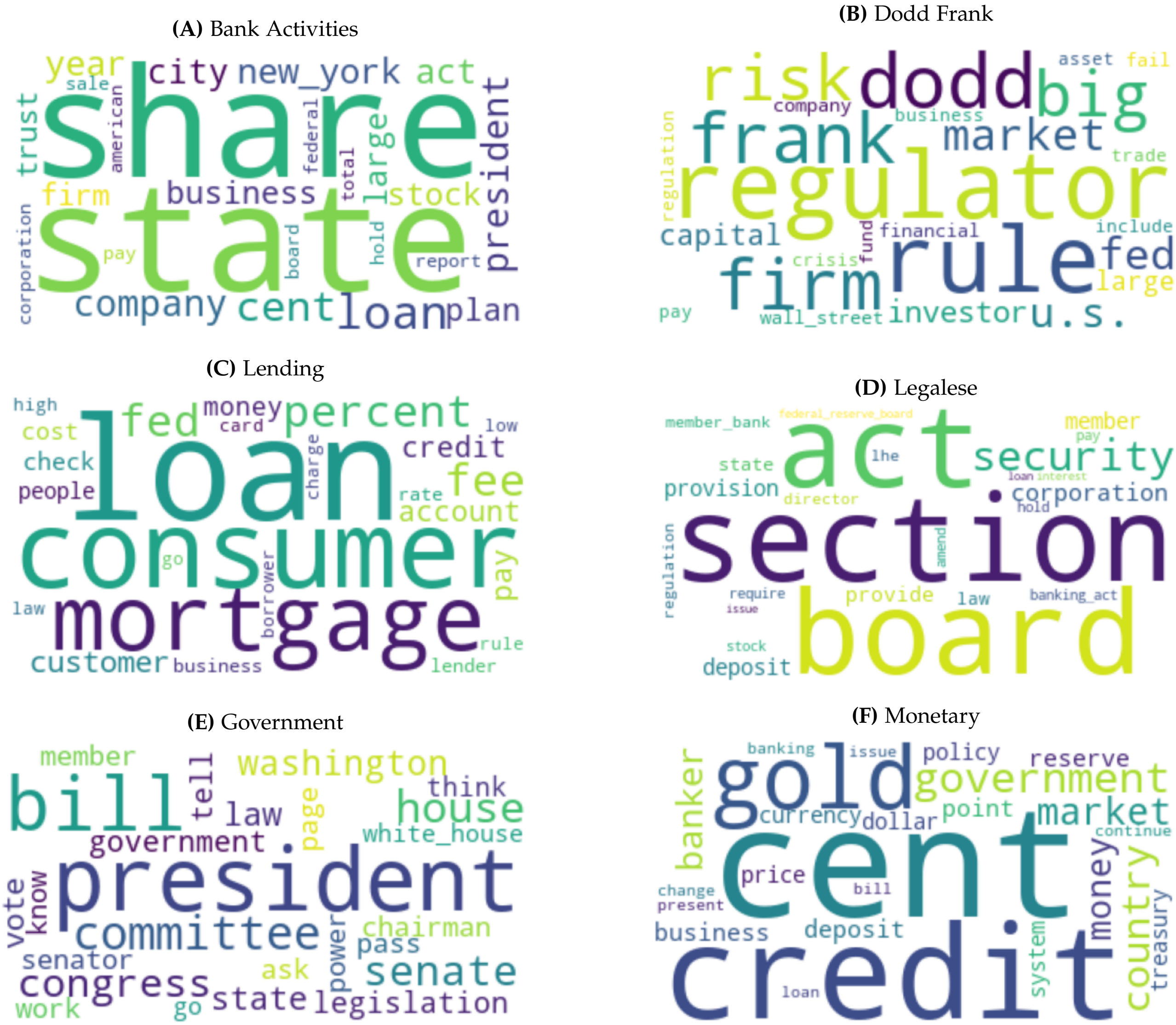
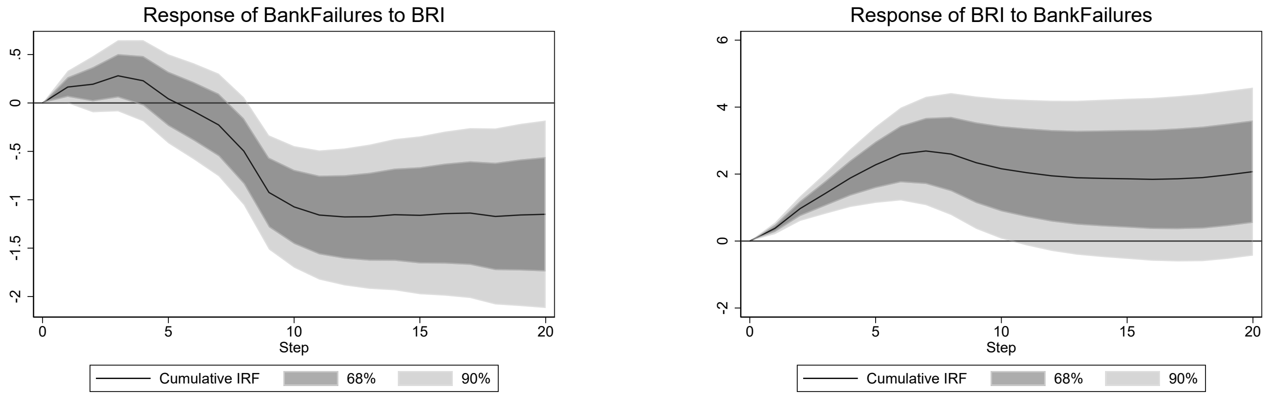


Figure 2. Word Clouds for LDA Topics

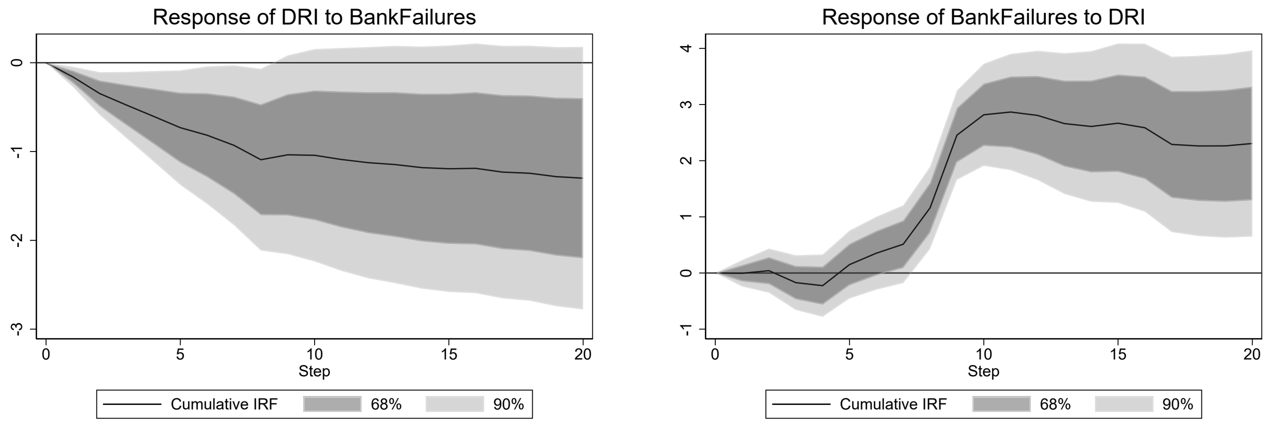
LDA provides two different distributions: a distribution of each document on the topics and a distribution of each topic on a set of words or terms. See Appendix B for details on the LDA procedure. The term distribution of each topic can be used to create the word clouds associated with the topic. The size of each term in the image is proportionate to the score it receives in the LDA distribution.



(A) Impulse (BRI) **(B)** Impulse (BankFailures)

Figure 3. IRF of BRI and Bank Failures

VAR-estimated impulse-response functions for BankFailures and Bank Regulation Index. 68% and 90% confidence bands are used following Sims and Zha (1999) and Sims and Zha (2006). Identification is based on ten lags. The VAR model is specified in Section 4.2.



(A) Impulse (BankFailures)

(B) Impulse (DRI)

Figure 4. IRF of DRI and Bank Failures

VAR-estimated impulse-response functions for BankFailures and Decreased Regulation Index. 68% and 90% confidence bands are used following Sims and Zha (1999) and Sims and Zha (2006). Identification is based on ten lags. The VAR model is specified in Section 4.2.

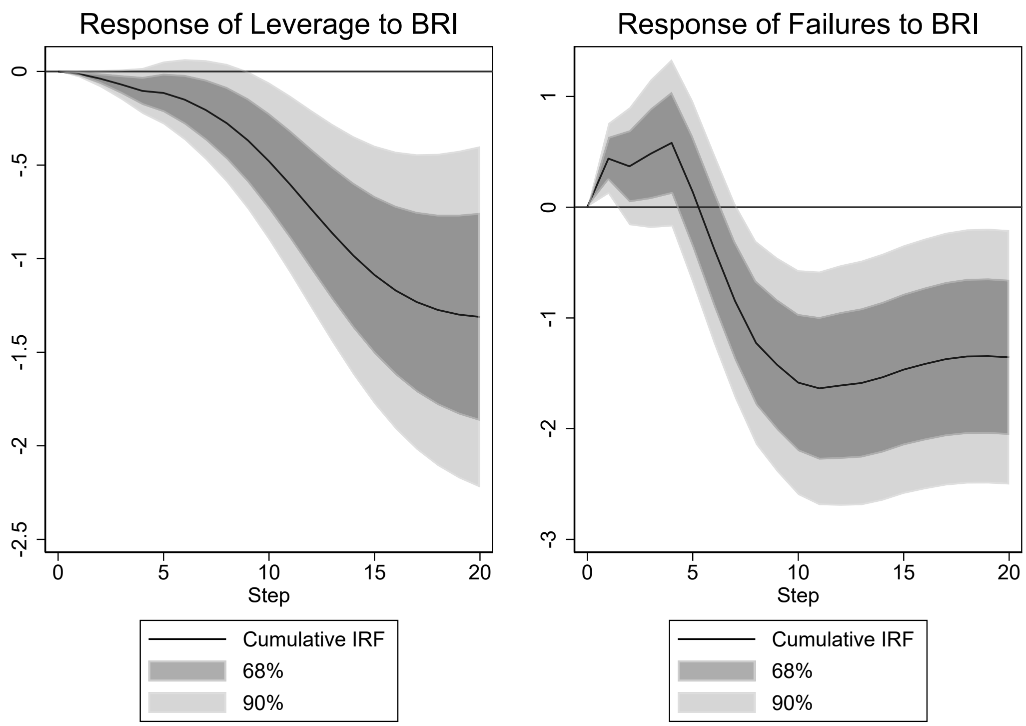


Figure 5. IRFs of Leverage

Augmented VAR-estimated impulse-response functions for Leverage and Bank Regulation Index. 68% and 90% confidence bands are used following Sims and Zha (1999) and Sims and Zha (2006). Data for Leverage is from Jordà et al. (2017). Identification is based on ten lags.

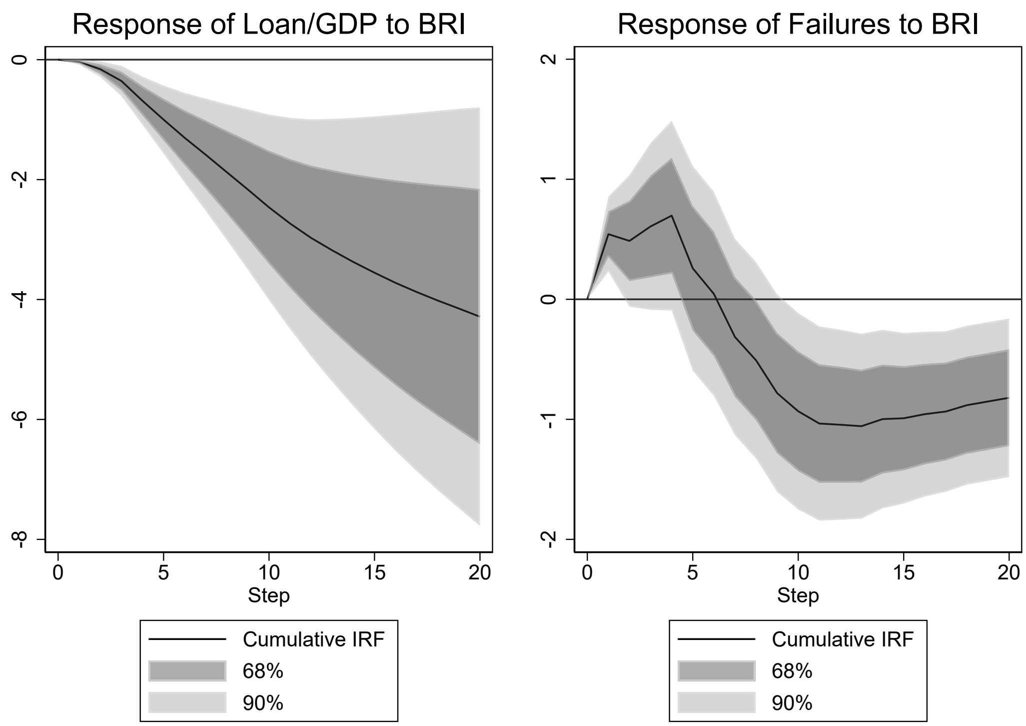


Figure 6. IRFs of Loan/GDP

Augmented VAR-estimated impulse-response functions for Loan/GDP and Bank Regulation Index. 68% and 90% confidence bands are used following Sims and Zha (1999) and Sims and Zha (2006). Data for Leverage is from Jordà et al. (2017). Identification is based on ten lags.

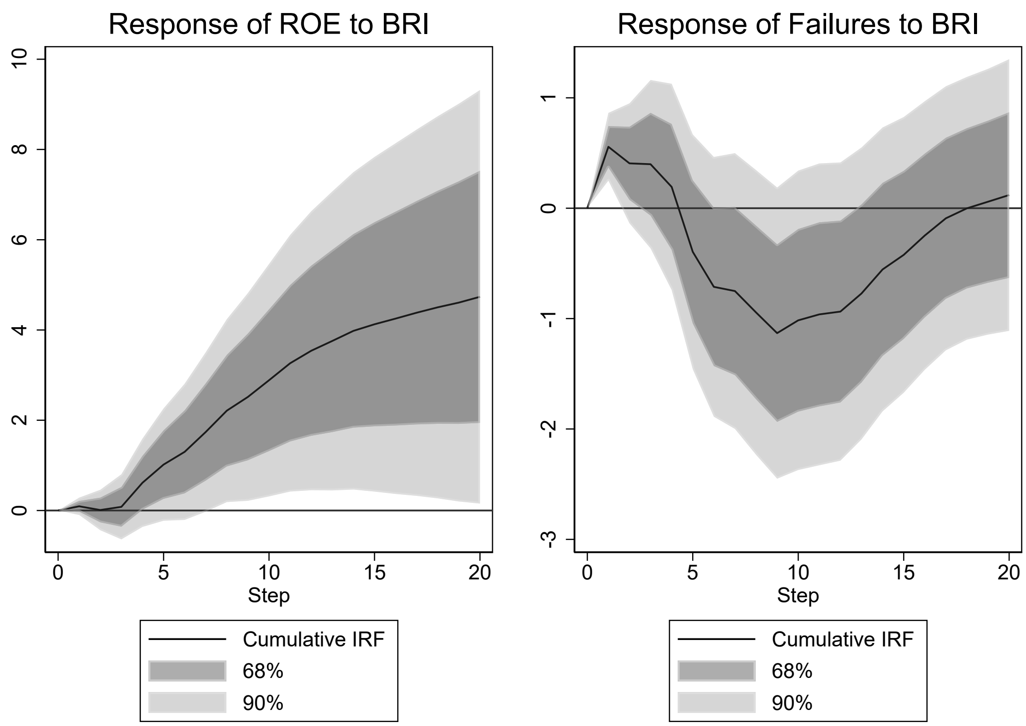


Figure 7. IRFs of ROE

Augmented VAR-estimated impulse-response functions for Return-on-Equity and Bank Regulation Index. 68% and 90% confidence bands are used following Sims and Zha (1999) and Sims and Zha (2006).

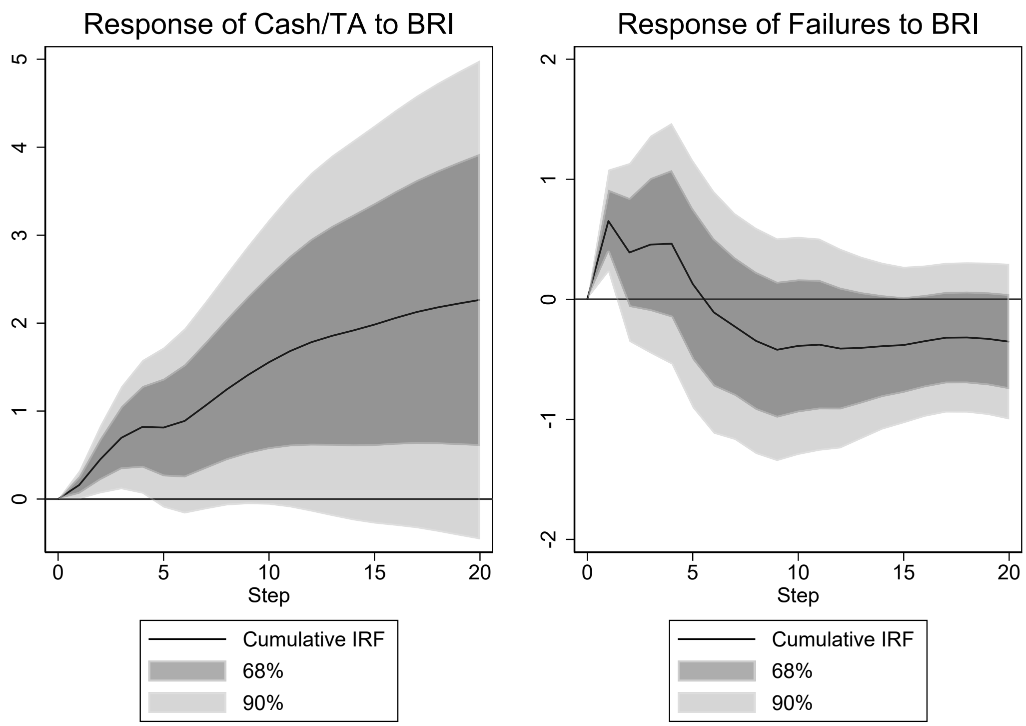


Figure 8. IRFs of Cash/TA

Augmented VAR-estimated impulse-response functions for Cash Ratio and Bank Regulation Index. 68% and 90% confidence bands are used following Sims and Zha (1999) and Sims and Zha (2006). Data for Leverage is from Jordà et al. (2017). Identification is based on ten lags.

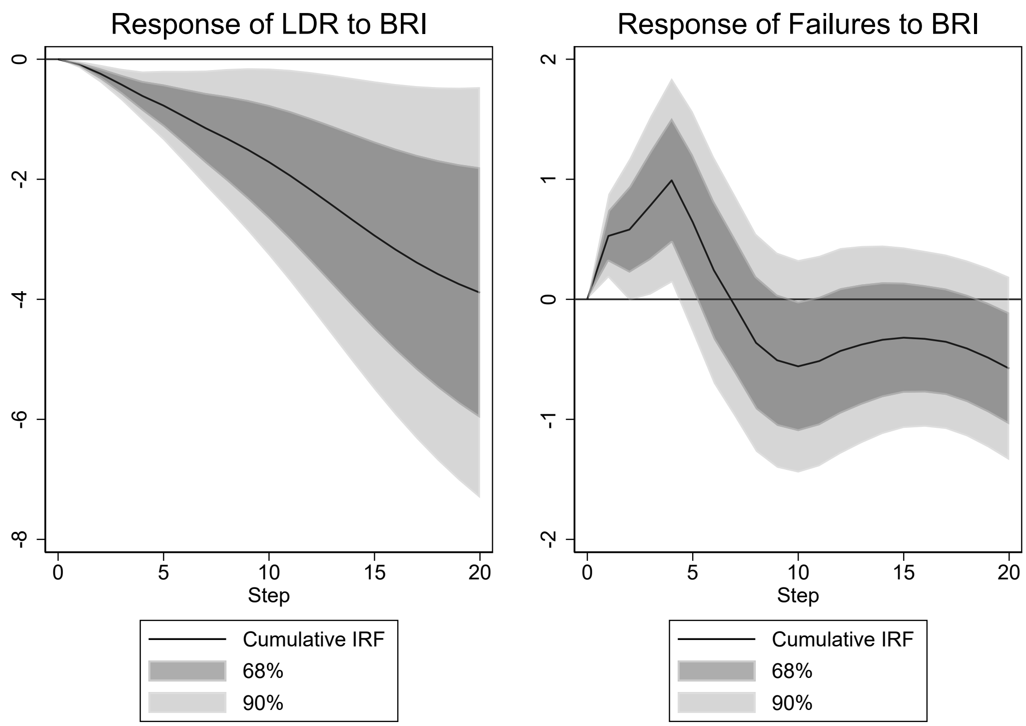


Figure 9. IRFs of LDR

Augmented VAR-estimated impulse-response functions for IRF Augmented by Loan-to-Deposit Ratio and Bank Regulation Index. 68% and 90% confidence bands are used following Sims and Zha (1999) and Sims and Zha (2006). Data for Leverage is from Jordà et al. (2017). Identification is based on ten lags.

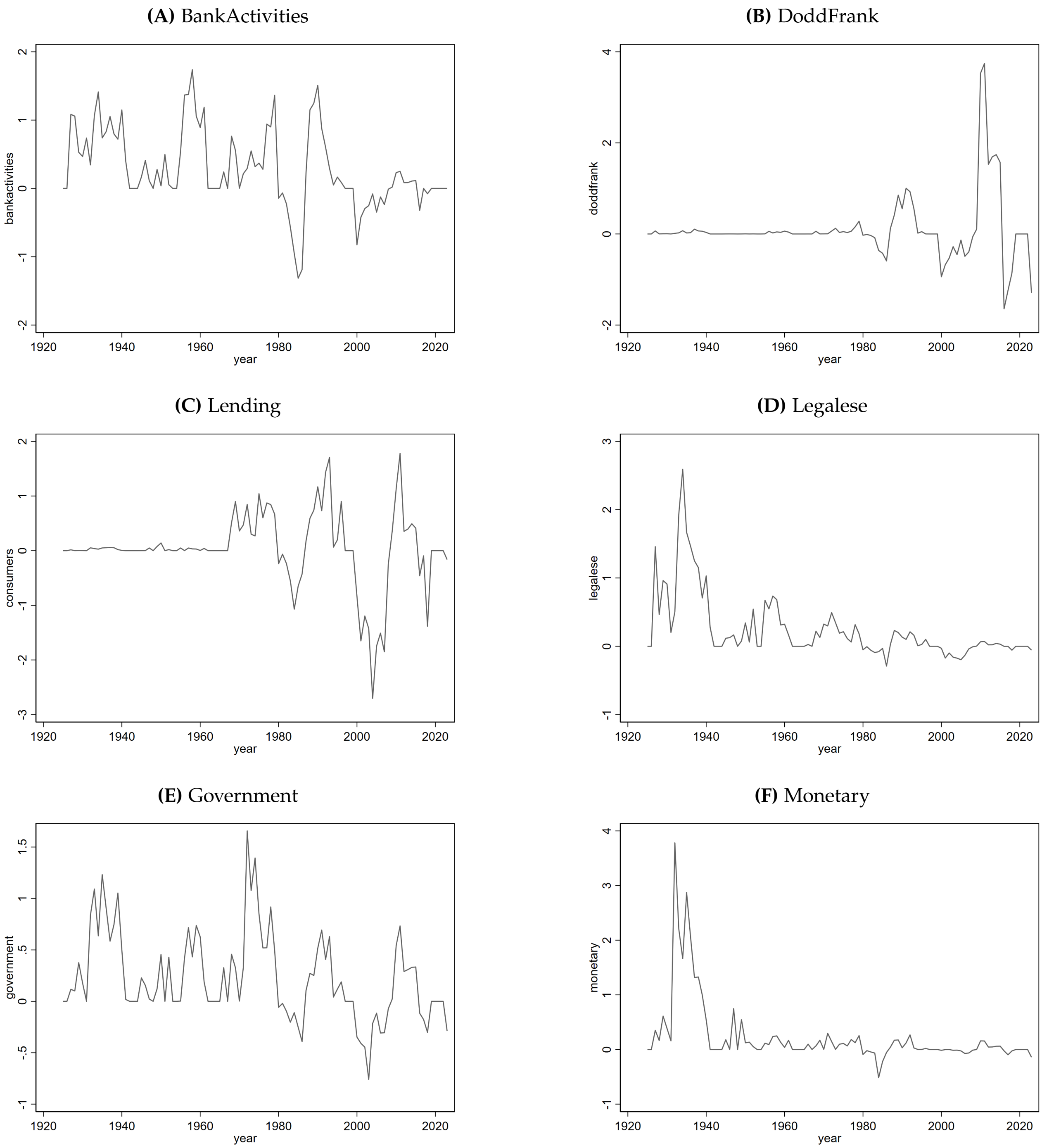
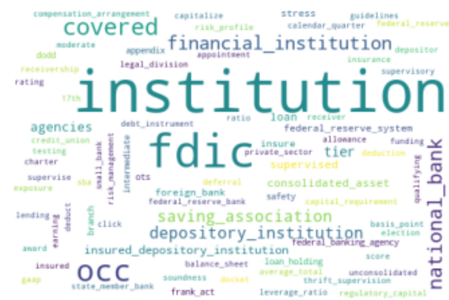


Figure 10. Time-Series Plots for LDA Topics

This figure plots the sub-index associated with each topic obtained from LDA (Appendix B).

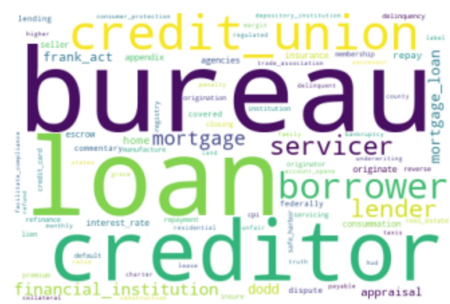
(A) Exposure

(B) Institutions



(C) Banking Entity

(D) Lending



(E) Credit Rating

(F) Accounting

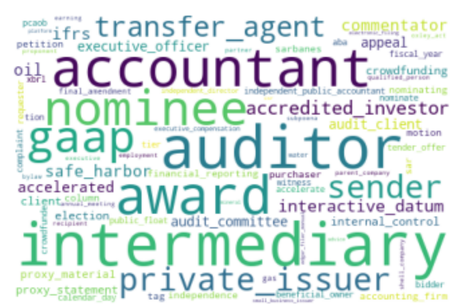


Figure 11. Federal Register: Word Clouds for LDA Topics

LDA provides two different distributions: a distribution of each document on the topics and a distribution of each topic on a set of words or terms. These word clouds, associated with each topic, are obtained by applying Latent Dirichlet Allocation (LDA) on Federal Register text. See Appendix B for details on the LDA procedure. The term distribution of each topic can be used to create the word clouds associated with the topic. The size of each term in the image is proportionate to the score it receives in the LDA distribution.

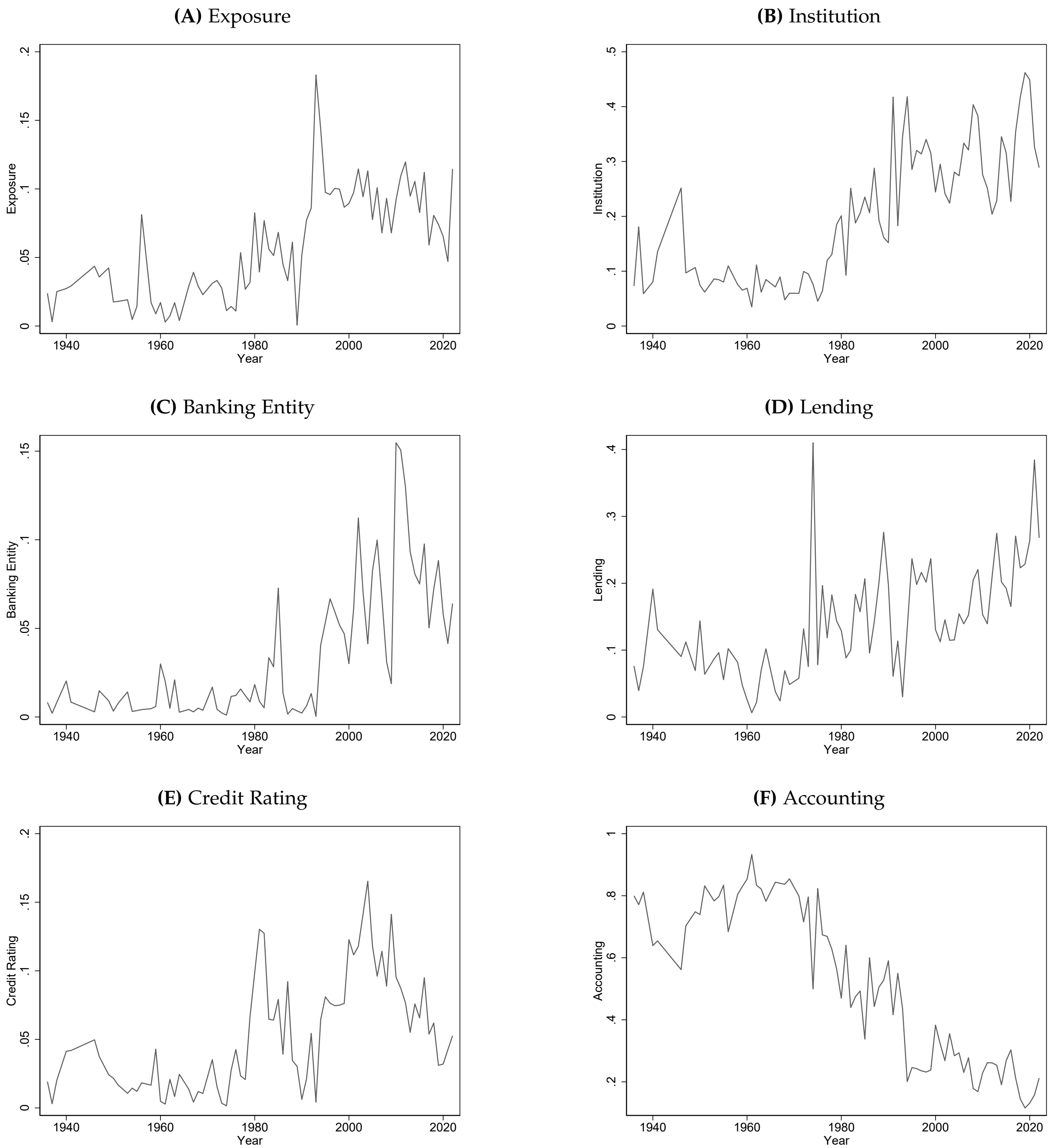


Figure 12. Time-Series Plots for Federal Register LDA Topics

This figure plots the weight associated with each topic obtained from LDA (Section 6).

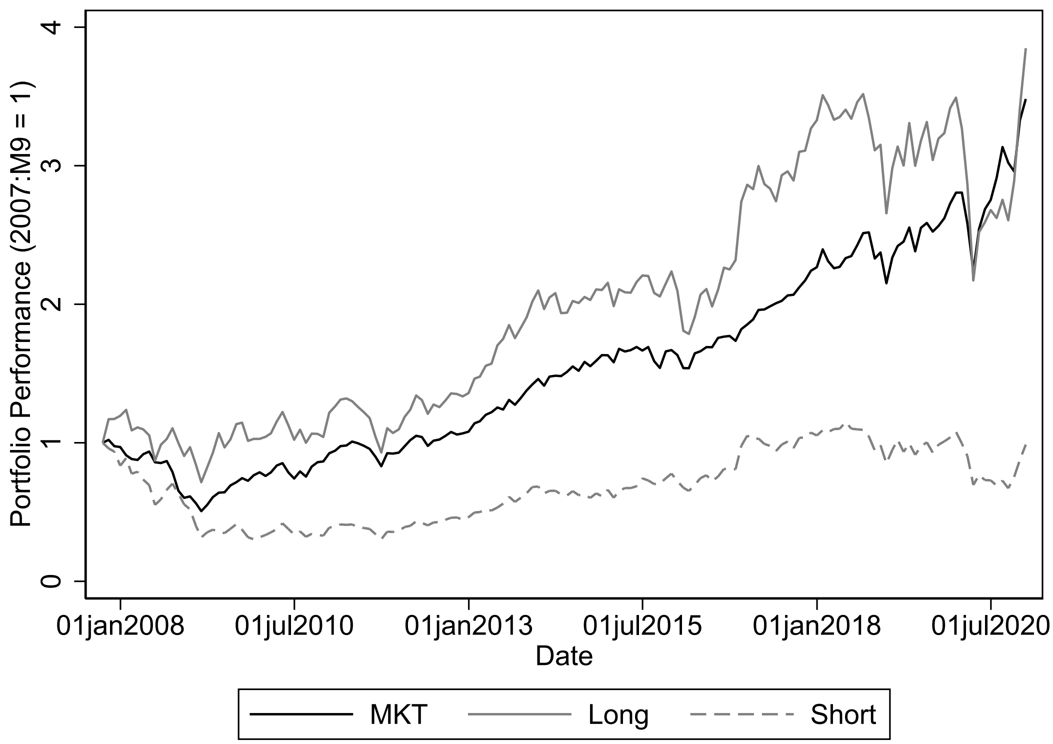


Figure 13. Performance of Long and Short Portfolios

This figure plots the performance of $1 invested in the long, market, and short portfolios. LDA model, trained on the Federal Register, is applied to the earnings call text, yielding weight for the *Lending* topic. Bank stocks in the following quarter are sorted into deciles by weight of the *Lending* topic (Section 6). *Long* and *Short* show the performance of a portfolio of bank stocks in the lowest and highest decile, respectively.

Table 1. Summary Statistics

BRI_t, the value of annual Bank Regulation Index. Similarly, IRI_t and DRI_t are values of Increased Regulation Index and Decreased Regulation Index, respectively. ΔGDP_t is GDP growth, π_t is inflation and r_{t-1} is short-term interest rate from Jordà et al. (2017). $LDR_{i,t}$, $Cash/TA_{i,t}$, Lev_t, $\ln(TA_{i,t})$ are Loan-to-Deposit Ratio, Cash Ratio, Leverage and log of Total Assets (in $ Millions) for year t. $ROE_{i,t}$ and $ROA_{i,t}$ is Net Income as a % of Equity and Total Assets, respectively. R_t and AR_t are annual stock return and annual abnormal return of year t, respectively. $\sigma(R_{i,t})$ and $\sigma(\epsilon_{i,t})$ volatility of stock return and the idiosyncratic volatility for bank i in year t, respectively.

Variable	Mean	Std. Dev.	P25	P50	P75
Year-Level					
BRI_t	1.61	2.64	0.00	1.79	3.18
IRI_t	1.98	1.97	0.00	1.61	3.26
DRI_t	0.80	1.30	0.00	0.00	1.61
ΔGDP_t	6.44	6.15	3.97	5.96	9.04
π_t	2.96	3.43	1.35	2.49	4.16
r_t	3.92	3.32	1.16	3.11	5.66
Bank-Year Level					
$LDR_{i,t}$	85.51	26.59	72.52	85.20	97.21
$Cash/TA_{i,t}$	5.89	6.82	2.10	3.26	5.99
$\ln(TA_{i,t})$	7.70	1.65	6.51	7.39	8.63
Lev_t	12.13	4.56	9.43	11.33	13.69
$ROE_{i,t}$	8.57	11.05	6.84	10.24	13.41
$ROA_{i,t}$	0.79	0.81	0.61	0.92	1.18
$R_{i,t}$	11.10	31.74	-8.45	8.34	29.39
$AR_{i,t}$	4.36	25.91	-9.39	0.58	17.79
$\sigma(\epsilon_{i,t})$	7.15	3.73	4.54	6.24	8.74
$\sigma(R_{i,t})$	7.54	3.79	4.88	6.72	9.32
$DD_{i,t}$	3.25	4.44	0.20	2.98	6.12

Table 2. LDA: Topic and Laws

Latent Dirichlet Allocation (LDA) is a machine-learning technique that analyzes sets of documents — in this case, a corpus of newspaper articles — to provide a distribution of each document over a specified number of topics, which in our study is set to six. It also determines how frequently certain words are associated with these topics, as illustrated in the accompanying word cloud visualizations (Figure 2). Given that LDA assigns a distribution of topics to each article, we can calculate the mean topic distribution for each piece of legislation mentioned within these articles. The table resulting from this analysis categorizes each topic and provides examples of laws. These examples are accompanied by the proportion (in third column) that denotes the extent to which a particular law is representated by a given topic.

Topic	Laws	Share
BankActivities	Bank Holding Company Act of 1956	0.51
	Community Reinvestment Act of 1977	0.42
	Garn-St Germain Depository Institutions Act of 1982	0.42
	Riegle-Neal Interstate Banking and Branching Efficiency Act of 1994	0.36
DoddFrank	Dodd-Frank Wall Street Reform and Consumer Protection Act of 2010	0.63
	Jumpstart Our Business Startups of 2012	0.65
	Economic Growth, Regulatory Relief, and Consumer Protection Act of 2018	0.47
	Financial Services Regulatory Relief Act of 2006	0.52
Lending	Credit CARD Act of 2009	0.87
	Bankruptcy Abuse Prevention and Consumer Protection Act of 2005	0.65
	Federal Deposit Insurance Corporation Improvement Act of 1991	0.56
	Monetary Control Act of 1980	0.49
Legalese	McFadden Act of 1927	0.43
	Federal Deposit Insurance Act of 1950	0.37
Government	Bank Secrecy Act of 1970	0.53
	Bank Holding Company Act Amendments of 1970	0.47
	Federal Credit Union Act of 1934	0.47
	Bank Protection Act of 1968	0.32
Monetary	Banking Act of 1933	0.41
	Federal Financing Bank Act of 1973	0.36
	Banking Act of 1935	0.34
	Export-Import Bank Act of 1945	0.33

Table 3. News about Bank Regulations, Topics and Sentiment

The dependent variable is the Sentiment of the news text calculated using FinBERT. *dereg* is a dummy variable indicating the mentioned Law is of deregulatory nature. Sentiment is calculated using a 3-sentence window around the mention of the Law Name, nickname or (4-letter or more) abbreviation in the news text. *BankActivities, DoddFrank, Lending, Legalese, Government, and Monetary* are assigned labels of six topics obtained from LDA. Standard Errors reported in brackets are double-clustered by Year and by Law.

	FinBERT Sentiment						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
dereg	0.056***	0.055***	0.055***	0.055***	0.055***	0.055***	0.055***
	(0.011)	(0.012)	(0.012)	(0.012)	(0.012)	(0.013)	(0.013)
BankActivities	0.025***						0.005
	(0.009)						(0.012)
DoddFrank		0.011					0.016
		(0.007)					(0.021)
Lending			-0.003				0.010
			(0.012)				(0.025)
Legalese				-0.071***			-0.071***
				(0.009)			(0.014)
Government					-0.004		-0.011
					(0.021)		(0.020)
Monetary						0.037***	
						(0.011)	
Observations	6,261	6,261	6,261	6,261	6,261	6,261	6,261
R-squared	0.112	0.111	0.111	0.115	0.111	0.112	0.115
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Clusters	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Law Clusters	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Robust standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 4. Determinants of Bank Regulation

The dependent variable is BRI_t, the value of annual Bank Regulation Index. Similarly, IRI_t and DRI_t are values of Increased Regulation Index and Decreased Regulation Index, respectively. ΔGDP_{t-1} is last year's GDP growth. π_{t-1} is last year's inflation. r_{t-1} is last year's short-term interest rate. $BankFailures_{t-1}$ are defined as Deposits of failed banks as a percentage of total deposits in year $t-1$. $Republican_t$ is a dummy variable indicating Government being held by the Republican Party. Newey-West Standard Errors with 12 lags are reported in brackets.

	(1)	(2)	(3)	(4)	(5)	(6)
	BRI_t	BRI_t	BRI_t	BRI_t	IRI_t	DRI_t
$BankFailures_{t-1}$	0.597***			0.488**	0.417**	-0.071
	(0.174)			(0.238)	(0.174)	(0.080)
$Republican_t$			-1.853**	-1.453	-1.148	0.305
			(0.940)	(0.949)	(0.701)	(0.473)
ΔGDP_{t-1}		0.012		0.025	0.010	-0.015
		(0.041)		(0.034)	(0.036)	(0.011)
π_{t-1}		-0.144		-0.148	-0.115	0.033
		(0.135)		(0.124)	(0.105)	(0.047)
r_{t-1}		-0.184**		-0.072	0.044	0.117
		(0.076)		(0.086)	(0.076)	(0.084)
Constant	1.331**	2.654***	2.523***	2.660***	2.733***	0.073
	(0.543)	(0.707)	(0.701)	(0.784)	(0.722)	(0.260)
Observations	95	96	96	95	95	95
R-squared	0.111	0.121	0.125	0.264	0.238	0.201
Std. Err.	NW	NW	NW	NW	NW	NW

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 5. Regulations' Short-term Impact on Banks

The dependent variable is shown in column title for year t. BRI_{t-1} is the lagged value of annual Bank Regulation Index. Similarly, IRI_{t-1} and DRI_{t-1} are lagged values of Increased Regulation Index and Decreased Regulation Index, respectively. $LDR_{i,t}$, $DD_{i,t}$ and $Cash/TA_{i,t}$ are Loan-to-Deposit Ratio, Distance-to-Default and Cash Ratio for year t. $ROE_{i,t}$ is Net Income as a % of Equity. AR_t and $\sigma(\epsilon_{i,t})$ are annual abnormal return and the idiosyncratic volatility for bank i in year t, respectively. Bank-level $Controls$ are LDR, $\ln(Total\_Assets)$, Leverage and Cash Ratio of year $t-1$. Newey-West Standard Errors with 12 lags are reported in brackets.

Panel A. Short-term Impact of BRI_{t-1}

	$ROE_{i,t}$	$\sigma(\epsilon_{i,t})$	$\Delta LDR_{i,t}$	ΔCash/TA$_{i,t}$	$DD_{i,t}$	$AR_{i,t}$
BRI_{t-1}	-0.321***	0.118***	-0.141***	0.019*	-0.018	-0.229**
	(0.045)	(0.015)	(0.042)	(0.011)	(0.017)	(0.104)
Observations	8,317	8,668	8,576	8,556	8,535	8,535
R-squared	0.109	0.136	0.161	0.169	0.088	0.088
Bank Controls	Yes	Yes	Yes	Yes	Yes	Yes
Macro Controls	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Std. Err.	NW	NW	NW	NW	NW	NW

Panel B. Separating BRI_{t-1} into IRI_{t-1} and DRI_{t-1}

	$ROE_{i,t}$	$\sigma(\epsilon_{i,t})$	$\Delta LDR_{i,t}$	ΔCash/TA$_{i,t}$	$DD_{i,t}$	$AR_{i,t}$
IRI_{t-1}	-0.242***	0.030	-0.017	-0.010	0.091***	0.858***
	(0.057)	(0.020)	(0.055)	(0.018)	(0.024)	(0.144)
DRI_{t-1}	0.928***	-0.570***	0.814***	-0.227***	0.625***	3.975***
	(0.105)	(0.029)	(0.096)	(0.030)	(0.040)	(0.266)
Observations	8,317	8,668	8,576	8,556	8,535	8,535
R-squared	0.109	0.136	0.161	0.169	0.088	0.088
Bank Controls	Yes	Yes	Yes	Yes	Yes	Yes
Macro Controls	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Std. Err.	NW	NW	NW	NW	NW	NW

Table 6. Regulations' Short-term Impact on Banks

The dependent variable is shown in column title for year t. BRI_{t-1} is the lagged value of annual Bank Regulation Index. Similarly, IRI_{t-1} and DRI_{t-1} are lagged values of Increased Regulation Index and Decreased Regulation Index, respectively. *Large Bank* is a dummy indicating that bank is in top tercile by size for year t. $LDR_{i,t}$, $DD_{i,t}$ and $Cash/TA_{i,t}$ are Loan-to-Deposit Ratio, Distance-to-Default and Cash Ratio for year t. $ROE_{i,t}$ is Net Income as a % of Equity. AR_t and $\sigma(\epsilon_{i,t})$ are annual abnormal return and the idiosyncratic volatility for bank i in year t, respectively. Bank-level *Controls* are LDR, $\ln(Total\_Assets)$, Leverage and Cash Ratio of year $t-1$. Newey-West Standard Errors with 12 lags are reported in brackets.

	$AR_{i,t}$	$ROE_{i,t}$	$\sigma(\epsilon_{i,t})$	$\Delta LDR_{i,t}$	$\Delta\text{Cash/TA}_{i,t}$	$DD_{i,t}$
$IRI_{t-1} \times$ *Large Bank*	-1.494***	0.206**	-0.200***	-0.043	-0.017	0.049
	(0.226)	(0.095)	(0.029)	(0.095)	(0.026)	(0.031)
$DRI_{t-1} \times$ *Large Bank*	-2.601***	-0.574***	0.076	-0.311	0.089**	-0.229***
	(0.405)	(0.153)	(0.049)	(0.190)	(0.042)	(0.058)
Large Bank	5.948***	1.584***	0.045	0.547	-0.090	0.545***
	(1.381)	(0.589)	(0.210)	(0.594)	(0.145)	(0.180)
Observations	9,247	8,798	9,096	9,080	9,059	8,963
R-squared	0.020	0.018	0.048	0.163	0.189	0.019
Bank Controls	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Std. Err.	NW	NW	NW	NW	NW	NW

Table 7. Short- and Long-Term Dichotomy in Impact of Regulations

The dependent variable is shown in row title i in year t. $\beta^{reg}_{i,t}$ are the winsorized (1% and 99%) and standardised values of -β_1 from Section 4.3. $ROE_{i,t}$, AR_t, DD_t, $\sigma(\epsilon_{i,t})$, $Cash/TA_{i,t}$ and $LDR_{i,t}$, are Net Income as a % of Equity, Annual Abnornal Return, Distance-to-Default, Cash Ratio and Loan-to-Deposit Ratio bank i for year t with lead order shown in column number. NW Standard Errors with 12 lags are reported in brackets.

	(t)	$(t+2)$	$(t+4)$	$(t+6)$	$(t+8)$	$(t+10)$
			$ROE_{i,t}$			
$\beta^{reg}_{i,t}$	-1.072***	-0.973***	0.090	0.444*	0.737***	0.354
	(0.197)	(0.174)	(0.188)	(0.244)	(0.227)	(0.259)
Observations	8,239	6,768	5,499	4,483	3,673	2,979
R-squared	0.085	0.097	0.099	0.071	0.063	0.048
			$AR_{i,t}$			
$\beta^{reg}_{i,t}$	-1.290***	-0.190	-0.248	1.058**	1.660***	0.500
	(0.415)	(0.363)	(0.400)	(0.419)	(0.467)	(0.437)
Observations	8,585	7,259	6,002	4,970	4,090	3,344
R-squared	0.037	0.041	0.017	0.011	0.016	0.014
			$DD_{i,t}$			
$\beta^{reg}_{i,t}$	-0.079	-0.385***	0.141**	0.163***	0.222***	-0.049
	(0.065)	(0.058)	(0.062)	(0.063)	(0.072)	(0.075)
Observations	8,425	6,938	5,654	4,625	3,801	3,097
R-squared	0.067	0.103	0.053	0.136	0.128	0.046
			$\sigma(\epsilon_{i,t})$			
$\beta^{reg}_{i,t}$	0.203***	0.344***	-0.004	-0.160*	-0.265***	0.010
	(0.062)	(0.066)	(0.062)	(0.083)	(0.089)	(0.090)
Observations	8,561	7,242	5,980	4,948	4,068	3,325
R-squared	0.100	0.119	0.109	0.123	0.137	0.040
			$LDR_{i,t}$			
$\beta^{reg}_{i,t}$	-0.388***	-0.818***	-1.458***	-1.006***	-0.143	0.382
	(0.137)	(0.220)	(0.258)	(0.290)	(0.258)	(0.288)
Observations	8,424	6,939	5,661	4,633	3,808	3,105
R-squared	0.545	0.211	0.091	0.067	0.067	0.059
			$Cash/TA_{i,t}$			
$\beta^{reg}_{i,t}$	0.046	0.213***	0.299***	0.083	-0.063	-0.170
	(0.033)	(0.055)	(0.077)	(0.083)	(0.081)	(0.104)
Observations	8,404	6,905	5,622	4,587	3,763	3,070
R-squared	0.374	0.106	0.053	0.049	0.026	0.014
Bank Controls	Yes	Yes	Yes	Yes	Yes	Yes
Macro Controls	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Decade FE	Yes	Yes	Yes	Yes	Yes	Yes
Std. Err.	NW	NW	NW	NW	NW	NW

Table 8. Predicting Bank Failures with the Bank Regulation Index

This table shows a probit classification model, where the dependent variable is a dummy that takes the value 1 when $BankFailures_t > 0.5$ and 0 otherwise. $BankFailures_t$ is the percentage of deposits in failed banks over total deposits in year t. Following Jordà et al. (2021), $\Delta_5 Loans/GDP$ is the average change in $Loans/GDP$ ratio over the last 5 years. $\Delta_{t-10\rightarrow t-5}BRI$ is the average change in BRI_t over the years $t-10$ to $t-5$. $CapitalRatio_{t-1}$ is the Capital Ratio lagged by one year. LDR_{t-1} is the Loans-to-Deposits ratio lagged by one year. $Mortgages/GDP_{t-1}$ is the ratio of Mortgages to GDP lagged by one year. These variables are calculated from Jordà et al. (2017) data.

	$Crisis_t$					
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta_{t-10\rightarrow t-5}BRI$		-0.927***		-0.917***		-0.462**
		(0.299)		(0.331)		(0.208)
Known Predictors						
$\Delta_5 Loans/GDP$	0.304**	-0.593*	0.384**	-0.992*		
	(0.152)	(0.332)	(0.195)	(0.552)		
$CapitalRatio_{t-1}$	-4.442	8.627	-1.181	13.795*		
	(3.446)	(6.216)	(3.847)	(7.795)		
LDR_{t-1}			0.043**	0.055		
			(0.018)	(0.049)		
$Mortgages/GDP_{t-1}$					0.049**	0.030
					(0.021)	(0.047)
Constant	-0.644	-3.243**	-4.279***	-8.014*	-2.565***	-2.492*
	(0.579)	(1.299)	(1.621)	(4.617)	(0.655)	(1.497)
Observations	96	87	95	86	95	87
Pseudo-R^2	0.0963	0.550	0.220	0.591	0.0940	0.464

Table 9. Predicting Bank Failures: Decomposing BRI into Regulatory vs. Deregulatory Indices

This table shows probit classification model, where the dependent variable is a dummy that takes the value 1 when $BankFailures_t > 0.5$ and 0 otherwise. $BankFailures_t$ is the percentage of deposits in failed banks over total deposits in year t. Following Jordà et al. (2021), $\Delta_5 Loans/GDP$ is the average change in $Loans/GDP$ ratio over the last 5 years (year $t-6$ to year $t-1$). $\Delta_{10\rightarrow5} IRI$ and $\Delta_{10\rightarrow5} DRI$ is the average change in Increasing and Decreasing Regulation Index over the years $t-10$ to $t-5$. $CapitalRatio_{t-1}$ is the Capital Ratio lagged by one year. LDR_{t-1} is the Loans-to-Deposits ratio lagged by one year. $Mortgages/GDP_{t-1}$ is the ratio of Mortgages to GDP lagged by one year. These variables are calculated from Jordà et al. (2017) data.

	$Crisis_t$					
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta_{t-10\rightarrow t-5} IRI$		-0.852**		-1.133**		-0.329
		(0.377)		(0.536)		(0.254)
$\Delta_{t-10\rightarrow t-5} DRI$		0.964***		0.854**		0.622**
		(0.330)		(0.343)		(0.276)
Known Predictors						
$\Delta_5 Loans/GDP$	0.301**	-0.581*	0.381*	-1.158*		
	(0.152)	(0.342)	(0.196)	(0.665)		
$CapitalRatio_{t-1}$	-4.175	7.964	-0.888	17.709		
	(3.413)	(6.527)	(3.817)	(11.169)		
LDR_{t-1}			0.044**	0.069		
			(0.018)	(0.056)		
$Mortgages/GDP_{t-1}$					0.049**	0.023
					(0.021)	(0.052)
Constant	-0.694	-3.259**	-4.358***	-9.358*	-2.565***	-2.630
	(0.574)	(1.303)	(1.627)	(5.448)	(0.655)	(1.668)
Observations	97	87	96	86	95	87
Pseudo-R^2	0.0963	0.552	0.220	0.598	0.0940	0.481

Table 10. Predicting Bank Failures: Decomposing BRI into Topics through LDA Methods

This table shows probit classification model, where the dependent variable is a dummy that takes the value 1 when $BankFailures_t > 0.5$ and 0 otherwise. $BankFailures_t$ is the percentage of deposits in failed banks over total deposits in year t. This table uses Latent Dirichlet Allocation (LDA) to decompose BRI into different topics, as explained in Appendix B. LDA provides a distribution of each news article over the 6 topics. The BRI of year t is then decomposed into six different topics for year t using distribution provided by LDA for news articles of year t. $\Delta_{t-10\to t-5}$ shows the average change of the subindex from year $t-10$ to year $t-5$. Figure 2 shows Word Cloud associated with each topic.

	$Crisis_t$						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$\Delta_{t-10\to t-5}BankActivities$	-2.001***						-1.347*
	(-3.341)						(-1.711)
$\Delta_{t-10\to t-5}DoddFrank$		-0.791**					0.370
		(-2.234)					(0.664)
$\Delta_{t-10\to t-5}Lending$			-1.286***				-0.974**
			(-3.911)				(-2.116)
$\Delta_{t-10\to t-5}Legalese$				-6.929***			-1.289
				(-3.089)			(-0.394)
$\Delta_{t-10\to t-5}Government$					-3.401***		0.011
					(-3.036)		(0.007)
$\Delta_{t-10\to t-5}Monetary$						-3.489**	-0.138
						(-2.450)	(-0.096)
Constant	-1.431***	-1.365***	-1.722***	-1.444***	-1.460***	-1.278***	-1.819***
	(-5.813)	(-6.703)	(-6.108)	(-5.175)	(-5.165)	(-6.213)	(-4.980)
Observations	89	89	89	89	89	89	89
Pseudo-R^2	0.337	0.0954	0.369	0.311	0.320	0.158	0.498

Table 11. Performance of Lending-Exposure Bank Stock Portfolios

The table shows the alphas, t-statistics, and R^2 of *Lending* exposure bank stock portfolios from time-series regressions of monthly returns with different factors (Section 6). Sample is Sep-2007 to Dec-2020. Four different models are considered: the CAPM model, Four-Factor model (market ($MKTRF$), size (SMB), value (HML) and momentum (MOM)), Five-Factor model (market ($MKTRF$), size (SMB), value (HML), robust-minus-weak (RMW) and conservative-minus-aggressive (CMA)) and Four-Factor model with robust-minus-weak (RMW) and conservative-minus-aggressive (CMA). All alphas are expressed in percentages. t-statistics are shown in brackets.

	Long-Short			
	(1)	(2)	(3)	(4)
ALPHA	0.75	0.61	0.65	0.64
	(2.37)	(2.01)	(2.03)	(2.07)
MKTRF	0.10	0.15	0.18	0.13
	(1.55)	(2.05)	(2.46)	(1.71)
SMB		-0.34	-0.30	-0.33
		(-2.59)	(-2.18)	(-2.48)
HML		-0.35	-0.07	-0.23
		(-2.97)	(-0.51)	(-1.64)
MOM		-0.24		-0.23
		(-3.34)		(-3.18)
RMW			0.09	0.09
			(0.44)	(0.45)
CMA			-0.46	-0.39
			(-1.89)	(-1.62)
Observations	159	159	159	159
R-squared	0.06	0.18	0.14	0.20

A Data Appendix

Table A.1. Complete List of Laws

Law Date	Law Name	Other Names	Reg
2/25/1927	McFadden Act		1
7/22/1932	Federal Home Loan Bank Act	FHLBA	1
3/9/1933	Emergency Banking Relief Act		1
3/24/1933	State Bank Aid Act		1
6/16/1933	Banking Act of 1933	Glass-Steagall	1
6/26/1934	Federal Credit Union Act		1
8/23/1935	Banking Act of 1935		1
3/4/1939	Export-Import Bank Extension Act		1
6/30/1939	Glass Federal Reserve Note Act		1
7/31/1945	Export-Import Bank Act of 1945		1
9/21/1950	Federal Deposit Insurance Act	FDIA	1
5/9/1956	Bank Holding Company Act of 1956	BHCA, BHC Act	1
9/23/1959	Spence Act (Savings and Loan Holding Companies)	Spence Act	1
10/23/1962	Bank Service Company Act	BSCA	1
10/16/1966	Financial Institutions Supervisory Act of 1966	FISA	1
5/29/1968	Truth in Lending Act	TILA	1
7/7/1968	Bank Protection Act of 1968		1
10/26/1970	Bank Secrecy Act of 1970		1
12/31/1970	Bank Holding Company Act Amendments of 1970	BHCA	1
12/29/1973	Federal Financing Bank Act of 1973		1
12/22/1974	Real Estate Settlement Procedures Act of 1974	RESPA	1
10/12/1977	Community Reinvestment Act	Housing and Community Development Act of 1977	1
11/16/1977	Federal Reserve Reform Act of 1977	FRRA	1
9/17/1978	International Banking Act of 1978		1
11/10/1978	Financial Institutions Regulatory and Interest Rate Control Act of 1978	FIRA	1
3/31/1980	Monetary Control Act of 1980	DIDMCA, Depository Institutions Deregulation Act of 1980	-1
7/27/1981	Cash Discount Act		-1
12/26/1981	International Banking Facility Deposit Insurance Act		-1
10/8/1982	Export Trading Company Act of 1982		-1
10/15/1982	Garn-St Germain Depository Institutions Act of 1982	Garn-St Germain Act, Garn Act	-1
8/10/1987	Competitive Equality Banking Act of 1987	CEBA	1
8/9/1989	Financial Institutions Reform, Recovery, and Enforcement Act of 1989	FIRREA	1
12/12/1991	Resolution Trust Corporation Refinancing, Restructuring, and Improvement Act of 1991		1
12/19/1991	Federal Deposit Insurance Corporation Improvement Act of 1991	FDICIA, Truth in Savings Act	1
9/23/1994	Riegle Community Development and Regulatory Improvement Act of 1994		-1
9/29/1994	Riegle-Neal Interstate Banking and Branching Efficiency Act of 1994	Interstate Act, Riegle-Neal	-1
9/30/1996	Deposit Insurance Funds Act of 1996		-1
7/3/1997	Riegle-Neal Amendments Act of 1997		1
11/12/1999	Gramm-Leach-Bliley Act	GLB Act, GLBA	-1
12/4/2002	FHA Downpayment Simplification Act of 2002		1
10/28/2003	Check Clearing for the 21st Century Act	Check 21 Act	-1
4/20/2005	Bankruptcy Abuse Prevention and Consumer Protection Act of 2005	BAPCPA	-1
10/13/2006	Financial Services Regulatory Relief Act of 2006	FSRRA	-1
5/22/2009	Credit CARD Act of 2009	CARD Act	1
7/21/2010	Dodd-Frank Wall Street Reform and Consumer Protection Act	Dodd-Frank	1
4/5/2012	Jumpstart Our Business Startups	JOBS Act	-1
12/18/2014	Insurance Capital Standards Clarification Act of 2014	Insurance Capital Standards Clarification Act	-1
12/18/2014	American Savings Promotion Act		-1
5/24/2018	Economic Growth, Regulatory Relief, and Consumer Protection Act	EGRRCPA	-1
1/3/2019	RBIC Advisers Relief Act of 2018	RBIC Advisers Relief Act	-1

Table A.2. Predicting Bank Failures: Robustness to Alternative Cutoff

This table shows an alternative cutoff of 1% in defining a banking crisis (i.e., when deposits of failed banks in year t amount to more than 1% of total deposits). It uses a probit classification model, where the dependent variable is a dummy that takes the value 1 when $BankFailures_t > 1$ and 0 otherwise. $failures_t$ is the percentage of deposits in failed banks over total deposits in year t. Following Jordà et al. (2021), $\Delta_5 Loans/GDP$ is the average change in $Loans/GDP$ ratio over the last 5 years (year $t-6$ to year $t-1$). $\Delta_{10\rightarrow 5}BRI$ is the average change in BRI_t over the years $t-10$ to $t-5$. $CapitalRatio_{t-1}$ is the Capital Ratio lagged by one year. LDR_{t-1} is the Loans-to-Deposits ratio lagged by one year. $Mortages/GDP_{t-1}$ is the ratio of Mortgages to GDP lagged by one year. These variables are calculated from Jordà et al. (2017) data.

	$Crisis_t$					
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta_5 Loans/GDP$	0.278*	-0.687*	0.336*	-2.428		
	(0.155)	(0.375)	(0.198)	(1.545)		
$CapitalRatio_{t-1}$	-5.657	7.062	-2.790	19.465*		
	(3.739)	(6.393)	(4.123)	(10.648)		
LDR_{t-1}			0.039**	0.224		
			(0.018)	(0.163)		
$Mortages/GDP_{t-1}$					0.036*	0.015
					(0.020)	(0.046)
$\Delta_{10\rightarrow 5}BRI$		-0.906***		-1.426*		-0.448**
		(0.332)		(0.781)		(0.217)
Constant	-0.554	-3.203**	-3.829**	-22.940	-2.281***	-2.189
	(0.612)	(1.349)	(1.680)	(14.651)	(0.631)	(1.414)
Observations	96	87	95	86	95	87
Pseudo-R^2	0.104	0.521	0.209	0.648	0.0559	0.407

Table A.3. Predicting Bank Failures: Robustness to Baron et al. (2021) crises years

This table shows probit classification model, where the dependent variable is a dummy that takes the value 1 when $BankFailures_t > 0.5$, or if the year is included in Baron et al. (2021) definition of banking panics, and 0 otherwise. $failures_t$ is the percentage of deposits in failed banks over total deposits in year t. Following Jordà et al. (2021), $\Delta_5 Loans/GDP$ is the average change in $Loans/GDP$ ratio over the last 5 years (year $t-6$ to year $t-1$). $\Delta_{10\to5}BRI$ is the average change in BRI_t over the years $t-10$ to $t-5$. $CapitalRatio_{t-1}$ is the Capital Ratio lagged by one year. LDR_{t-1} is the Loans-to-Deposits ratio lagged by one year. $Mortages/GDP_{t-1}$ is the ratio of Mortgages to GDP lagged by one year. These variables are calculated from Jordà et al. (2017) data.

	$Crisis_t$					
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta_5 Loans/GDP$	0.116	-0.348**	0.033	-0.490**		
	(0.095)	(0.156)	(0.109)	(0.215)		
$CapitalRatio_{t-1}$	-3.069	3.135	-1.412	6.144		
	(2.941)	(3.948)	(3.097)	(4.609)		
LDR_{t-1}			0.027**	0.027		
			(0.012)	(0.016)		
$Mortages/GDP_{t-1}$					0.044**	0.037
					(0.018)	(0.025)
$\Delta_{10\to5}BRI$		-0.420***		-0.385***		-0.169**
		(0.121)		(0.128)		(0.086)
Constant	-0.519	-1.414*	-2.525**	-3.731**	-2.200***	-2.081**
	(0.490)	(0.723)	(1.012)	(1.685)	(0.553)	(0.813)
Observations	96	87	95	86	95	87
Pseudo-R^2	0.0247	0.258	0.0593	0.310	0.0785	0.215

Table A.4. Predicting Bank Failures: Lag Length Robustness

This table shows probit classification model, where the dependent variable is a dummy that takes the value 1 when $BankFailures_t > 0.5$ and 0 otherwise. $failures_t$ is the percentage of deposits in failed banks over total deposits in year t. This table uses different lags of the changes in BRI as a robustness check.

	$Crisis_t$						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$\Delta_{6\to1}BRI$	0.078						
	(1.212)						
$\Delta_{7\to2}BRI$		-0.030					
		(-0.467)					
$\Delta_{8\to3}BRI$			-0.131*				
			(-1.833)				
$\Delta_{9\to4}BRI$				-0.295***			
				(-3.100)			
$\Delta_{10\to5}BRI$					-0.585***		
					(-3.747)		
$\Delta_{11\to6}BRI$						-0.807***	
						(-3.371)	
$\Delta_{12\to7}BRI$							-0.640***
							(-3.604)
Constant	-1.251***	-1.144***	-1.137***	-1.261***	-1.654***	-2.035***	-1.651***
	(-6.236)	(-6.259)	(-6.240)	(-5.909)	(-4.637)	(-3.589)	(-4.235)
Observations	93	92	91	90	89	88	87
Pseudo-R^2	0.0208	0.00326	0.0581	0.221	0.478	0.575	0.494

Table A.5. Decomposing Federal Register text into Topics through LDA Methods

This table shows probit classification model, where the dependent variable is a dummy that takes the value 1 when $BankFailures_t > 0.5$ and 0 otherwise. $BankFailures_t$ is the percentage of deposits in failed banks over total deposits in year t. This table uses Latent Dirichlet Allocation (LDA) to decompose Federal Register text into different topics, as explained in Appendix B. LDA provides a distribution of each Federal Register document over the 6 topics. The LDA distribution of year t is then used to make six different topic values for year t. $\Delta_{t-10 \to t-5}$ shows the average change of the subindex from year $t-10$ to year $t-5$. Figure 11 shows Word Cloud associated with each topic.

	$Crisis_t$						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$\Delta_{t-10 \to t-5}Exposure$	-0.007						-0.049
	(0.016)						(0.065)
$\Delta_{t-10 \to t-5}Institution$		-0.004					0.019
		(0.008)					(0.020)
$\Delta_{t-10 \to t-5}Banking\ Entity$			0.000				0.051
			(0.014)				(0.033)
$\Delta_{t-10 \to t-5}Lending$				-0.023**			-0.056*
				(0.012)			(0.030)
$\Delta_{t-10 \to t-5}Credit\ Rating$					0.016		0.011
					(0.015)		(0.040)
$\Delta_{t-10 \to t-5}Accounting$						-0.000	0.003
						(0.002)	(0.003)
Constant	-1.057***	-1.045***	-1.069***	-1.120***	-1.109***	-1.070***	-1.311***
	(0.197)	(0.199)	(0.198)	(0.217)	(0.203)	(0.197)	(0.271)
Observations	63	63	63	63	63	63	63
Pseudo-R^2	0.004	0.005	0.000	0.0957	0.020	0.000	0.217

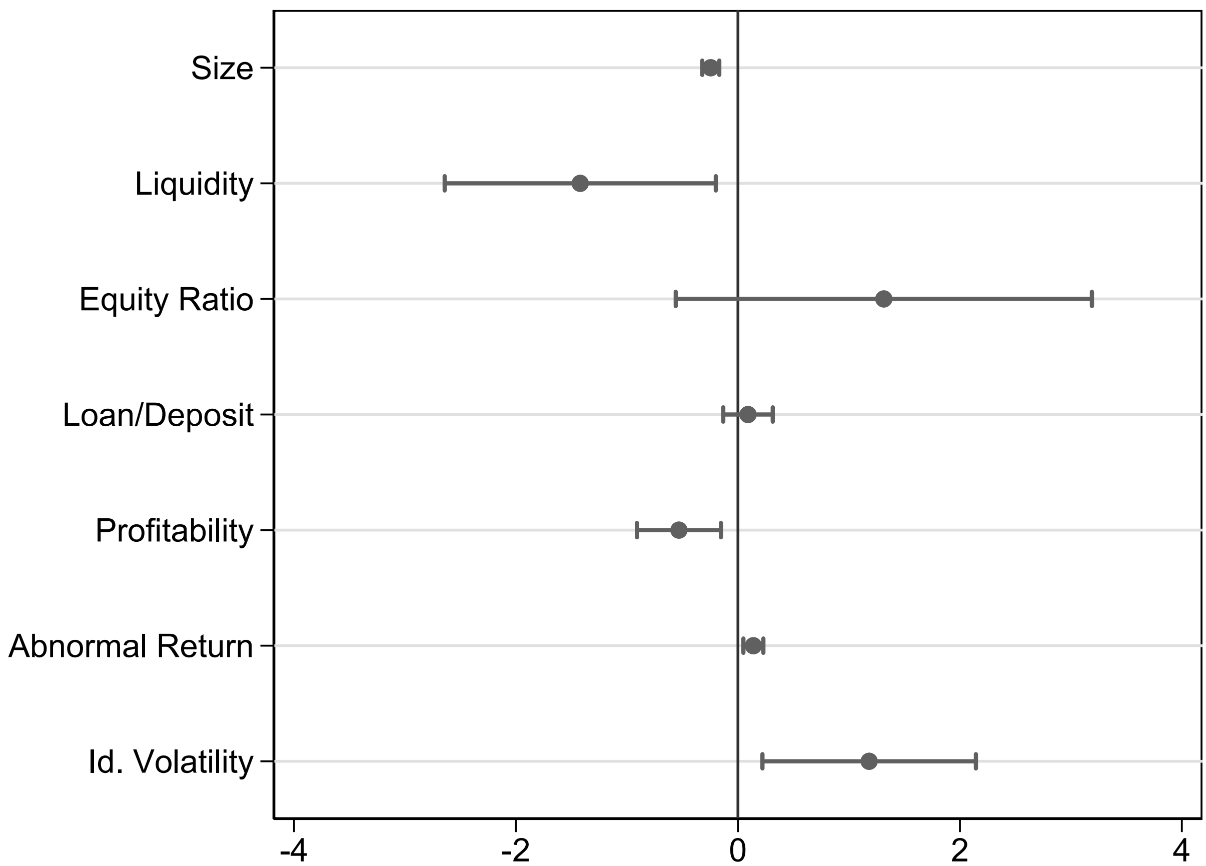


Figure A.1. Regulatory Exposure: Coefficient Plot

This figure plots the coefficients that explain the *Regulatory Exposure*. These estimates are obtained from the following regression:

$$\beta^{reg}_{i,t} = \gamma_0 + BankControls_{t-1} + MacroControls_{t-1} + \delta_i + \gamma_t + \epsilon_{i,t} \tag{12}$$

Bank *Controls* are *LDR*, $\ln(Total\_Assets)$, Leverage and Cash Ratio of year $t-1$. Macro *Controls* are ΔGDP_{t-1} (last year's GDP growth), π_{t-1} (last year's inflation), r_{t-1} (last year's short-term interest rate). δ_i are bank fixed effects. γ_t are decade fixed effects.

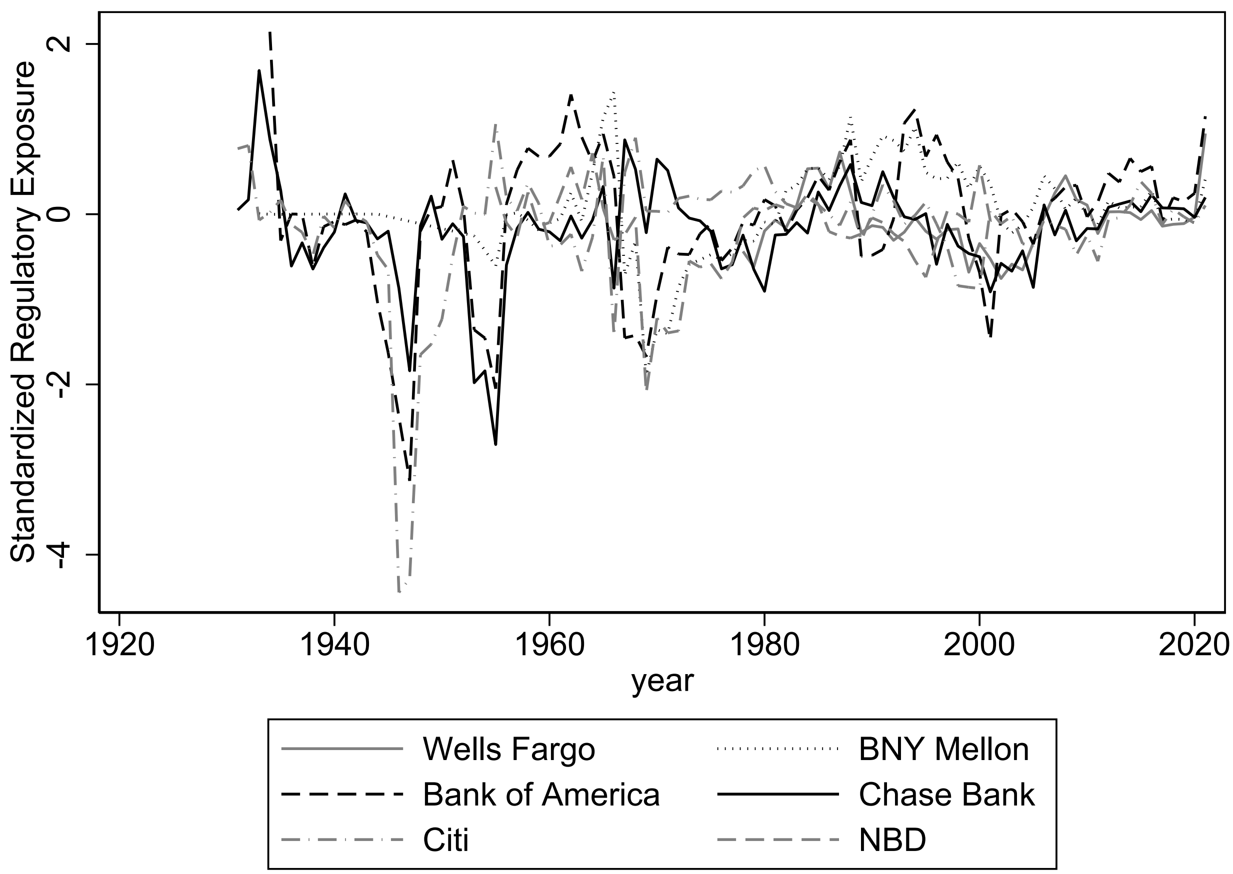
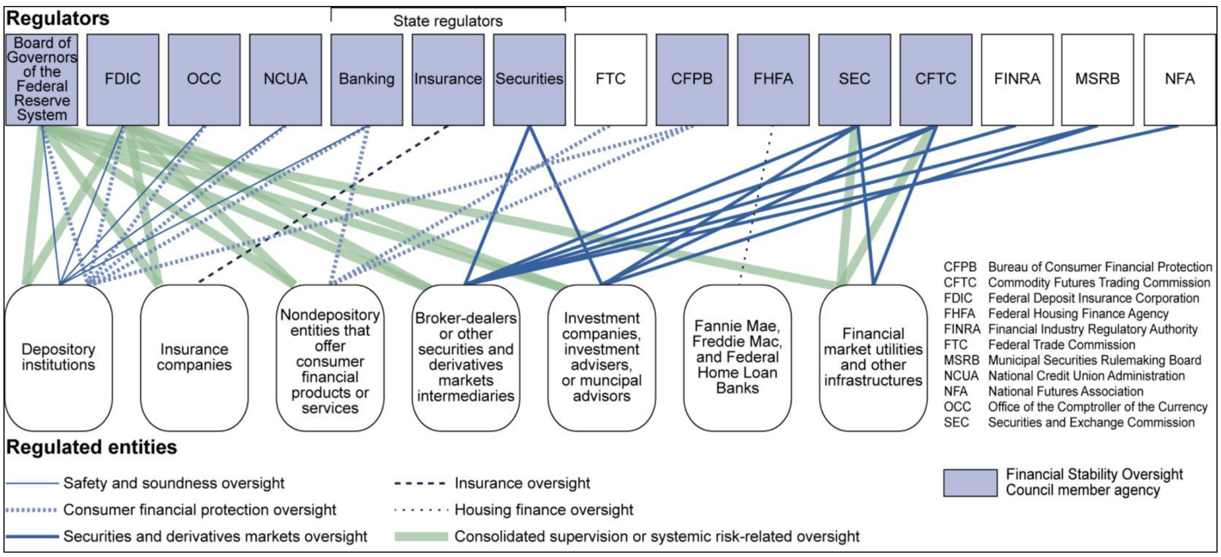


Figure A.2. Regulatory Exposure for Large Banks

This figure plots the *Regulatory Exposure* obtained for a selected sample of 6 large banks.



Source: Government Accountability Office (GAO), *Financial Regulation*, GAO-16-175, February 2016, Figure 2.

Figure A.3. FSOC-Member Agencies

A financial entity can fall under the purview of multiple regulatory bodies due to its involvement in various financial operations, as depicted here (Figure 1 from Labonte (2017)). For instance, a firm could be simultaneously regulated by an institutional overseer and an activity-specific regulator when it partakes in a regulated financial activity, and additionally by a market regulator during its participation in a regulated market. This intricate setup, as demonstrated in this figure, highlights the multifaceted regulatory roles and responsibilities assigned to different overseeing authorities.

B Latent Dirichlet Allocation: Implementation Details

LDA is an unsupervised machine-learning method. A challenge in implementing LDA is to decide the number of topics, as there is no optimal number from an interpretation standpoint. There is always a trade-off between fit statistics and substansive information fit. Following Calomiris et al. (2020), I decide this number to be six. The following steps are then taken in implementing the LDA model.

First, I convert the text to lowercase and use Natural Language Toolkit (NLTK) to *tokenize* the corpus. Then I remove line, paragraph and page breaks. The second step is to remove words that are related to days (Monday, Tuesday, etc), time (month, year etc), distance (miles etc) or numbers (two, thousand, million etc). This list is augmented by stopword list by gensim. Words of length 3 letters or larger are kept and special characters (@, *, etc.) are removed. Words are tagged for their part of speech and I keep adjectives, adverbs, nouns, proper nouns, and verbs. Third, bigrams are created using the NLTK library. Fourth is *lemmtization*, where a word is converted to its root word using spaCy.

The next step is TF-IDF (Term Frequency - Inverse Document Frequency). It is a procedure that scales the frequency of a term in a document by frequency of that term in documents across the corpus. For example, since the word "bank" appears in all news articles (by selection), it gets a low TF-IDF score and I keep terms with scores above a threshold. I keep only those terms that appear in at least 25 documents. Then I use gensim.corpora to create the dictionary and doc2bow to convert documents to vectors. Lastly, I use gensim.Ldamodel to conduct the LDA analysis.

The output of LDA is a distribution of each article i over each topic t. This weight is defined as $w_{i,t}$. Let w^r and w^d denote if the article is about a regulatory or deregulatory law, respectively. For each topic t, for articles dated in year T, the value of the time series plot is calculated as $BRI_{t,T}$:

$$BRI_{t,T} = \ln\left(\frac{\sum_{i\in T} w^r_{i,t} + 1}{\sum_{i\in T} w^d_{i,t} + 1}\right) \tag{13}$$

Figure 10 shows the time-series plot for each subindex.