Measuring Bank Regulations: A Text-Based Approach*

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Abstract

I introduce a novel text-based measure of U.S. banking regulation intensity from historical newspapers spanning 1926–2023. The Bank Regulation Index tracks changes around crucial events like Glass–Steagall's introduction and repeal. Deregulation displays a boom-bust pattern: increased bank stock returns and lending in the short term, followed by higher crisis likelihood in longer horizons. Decomposing the BRI into topics shows that credit-specific regulation reliably predicts future banking distress beyond well-established leading indicators. This pattern, confirmed across five other anglophone countries, underscores how monitoring credit deregulation through text-based analysis offers policymakers an *even earlier* warning indicator for detecting financial instability before crises materialize.

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

*A previous version of this paper was titled "The Long and Short of U.S. Bank Regulations: From the Great Depression to the 2023 Bank Failures". I am grateful to my committee members Gustavo Cortes, Mark Flannery, Joost Impink and Marc Weidenmier for their guidance and support. I am also thankful to Efraim Benmelech (Discussant), Charles Calomiris, Murillo Campello, Silvio Contessi, Isarin Durongkadej (Discussant), Neal Galpin, Seyed Kazempour, Maher Kooli, Nitish Kumar, Van Son Lai (Discussant), Boyuan Li, Alejandro Lopez-Lira, Nimal Mahendrarajah, Lyndon Moore, Karsten Muller, Rajesh Narayanan, R. Kelley Pace, Dimuthu Ratnadiwakara, Raghuram Rajan, Gary Sanger, Wei-Ling Song, Gertjan Verdickt, Junbo Wang, Mengbo Zhang (Discussant) and seminar participants at the University of Florida (Warrington Colege of Business), Louisiana State University (E. J. Ourso College of Business), Monash University (Monash Business School), Université du Québec à Montréal (ESG UQAM), University of Technology Sydney (UTS Business School), Southeast Missouri State University (Harrison College of Business & Computing), Federal Deposit Insurance Corporation (FDIC) 23rd Annual Bank Research Conference (Poster Session), Frontier Risks, Financial Innovation and Prudential Regulation of Banks (J. Fin. Intermediation-CFAR-UNC-Gothenburg Conference), Bank of Finland Conference on AI and Systemic Risk Analytics, 2024 Eastern Finance Association, 2024 Issues in Financial Markets and Banking (IFMB) Conference and 2024 Southwestern Finance Association for helpful feedback. Lakhani Bharat provided excellent research assistance.

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Banking crises have been a recurring feature of economic history, prompting scholars to examine the role of regulatory frameworks in financial stability. A long-standing literature investigates how banking regulations influence boom-bust cycles and financial crises (Kindleberger et al. (2005), Calomiris and Haber (2014)). These studies highlight how regulatory environments shape financial institutions' risk-taking behavior and affect systemic stability. Additionally, a significant body of research has identified credit growth as a key predictor of financial crises (Jordà et al. (2017), Jordà et al. (2021)). Schularick and Taylor (2012) demonstrates that credit booms often precede banking sector distress, while Baron et al. (2021) show that credit expansions predict crashes in bank equity prices. However, a fundamental gap in this literature has been establishing the connection between regulatory frameworks and the credit dynamics that lead to financial instability.

This paper proposes a novel text-based method to identify changes in banking regulations using historical newspaper coverage. I introduce the Bank Regulation Index (BRI), constructed from newspaper articles covering nearly a century of U.S. banking history. To complement this regulatory measure, I hand-collect stock price data from the Commercial and Financial Chronicle, the Wall Street Journal, and the New York Times, along with balance sheet information from Moody's Manuals and FR Y9-C filings. This data collection yields an unprecedented panel dataset spanning almost a century of U.S. banking. I extend this approach internationally, constructing comparable BRIs for five additional anglophone countries (United Kingdom, Canada, New Zealand, Australia, and Ireland) using each nation's newspaper coverage of significant *statutory* banking regulations.

This paper provides three main sets of findings. First, I introduce a novel approach to quantifying and decomposing banking regulations. Existing approaches rely heavily on survey-based measures that capture regulatory frameworks at specific points in time (Abiad et al. (2010), Barth et al. (2013)). While valuable, these survey-based measures typically provide only snapshots of regulatory regimes, making it difficult to track the dynamic evolution of financial regulation over long periods and account for the multi-dimensional nature of banking regulations. Using historical newspaper coverage spanning nearly a century, I construct a Bank Regulation Index (BRI) that captures the flow of regulatory and deregulatory changes. This index serves as an *early warning of an early warning indicator*, identifying changes in the regulatory environment that precede the build-up of traditional crisis predictors, such as excessive credit growth. Banking regulations are inherently multidimensional, encompassing various aspects from capital requirements to permissible and non-permissible activities. To disentangle these different dimensions, I employ Latent Dirichlet Allocation (LDA) on the newspaper text to decompose the BRI into distinct regulatory components. This decomposition reveals subindices related to different regulatory topics, notably a Credit Regulation Index (CRI) that quantifies credit or lending-related bank regulations and shows particularly strong predictive power for future banking distress.

The second key finding is to identify the effects of regulation at the bank level across different time horizons. While existing studies rely on 10-K filings that begin only in the 1990s or Earnings Call transcripts, we lack measures of bank-level regulatory exposure for most of the twentieth century — a period that includes crucial episodes like the Great Depression, the Savings and Loan crisis, and numerous regulatory reforms. To fill this gap, I hand-collect stock price data from the Commercial and Financial Chronicle, the Wall Street Journal, and the New York Times to construct a nearly century-long panel of bank-level responses to regulatory changes. Using stock price reactions to regulatory news, I construct a measure of bank-level regulatory exposure — a "regulatory beta" — that captures each bank's sensitivity to regulatory changes. Employing local projection methods (Jordà (2005)), I reveal a distinct temporal pattern: while deregulation initially generates positive effects on stock returns, profitability, and other bank fundamentals, these benefits systematically reverse over longer time horizons. More importantly, deregulatory periods precede persistent drops in liquidity and rises in loan-to-deposit ratios, suggesting that decreased bank resilience follows regulatory rollbacks. This bank-level evidence complements the aggregate analysis by demonstrating how regulatory changes reshape individual bank behavior and risk-taking over time.

The third finding is that regulatory changes are a leading indicator for future credit growth and banking crises. By decomposing the BRI into distinct components using topic modeling, I find that changes in credit and lending regulations, captured by the Credit Regulation Index (CRI), show a strong statistical association with subsequent banking distress. The relationship follows a distinct temporal pattern: while recent regulatory changes show little relationship with bank failures, changes from earlier periods strongly predict banking sector distress. Notably, the CRI predicts future mortgage and loan growth over the medium term. Periods of credit deregulation correspond with subsequent credit expansion, which then builds into credit booms over longer horizons (Gorton and Ordonez (2014, 2020)). The CRI's predictive ability is orthogonal to established early warning indicators such as credit growth and financial liberalization measures. Together, these results demonstrate that tracking the evolution of credit-related regulations, while accounting for their gradual impact, can significantly enhance our ability to identify the build-up of systemic risks. This pattern is consistent with Krishnamurthy and Muir (2017), who find that pre-crisis periods are characterized by falling spreads and expanding credit supply, suggesting that credit supply expansions are important precursors to crises.

To provide cross-sectional validation of these findings, I construct comparable Bank Regulation Indices for five additional anglophone countries (the United Kingdom, Canada, New Zealand, Australia, and Ireland). Using the same methodology, I create a panel dataset that enables a more robust analysis of these relationships with greater statistical power. The results reveal similar patterns. For instance, UK deregulations around the 1986 Financial Services Act particularly preceded banking sector instability. Using this cross-country panel, I document that changes in credit regulatory intensity predict future credit growth and subsequent banking sector distress, suggesting these relationships are not unique to the US institutional environment. These patterns across countries with different institutional frameworks strengthen the robustness of the results.

The *Bank Regulation Index* (*BRI*) is constructed for each country to measure the flow of banking regulations after classifying banking laws as regulatory or deregulatory. For the US, statutory banking laws span about a century: from the McFadden Act of 1927 to the Economic Growth, Regulatory Relief and Consumer Protection Act of 2018 (EGRRCPA). Similarly, for the UK, the analysis covers significant regulatory changes from the Banking Act of 1979 through the Payment Services Regulations of 2017. For all countries, news articles are short-listed based on consistent criteria to ensure they provide a measure of the temporal importance of each law around the time of its implementation. This methodology allows for cross-country comparison while accounting for institutional differences in regulatory frameworks.

This cross-national empirical framework reveals consistent patterns in regulatory cycles, prompting a deeper analysis: which specific dimensions or topics of banking regulation are most consequential for financial stability? The rich multi-country dataset I've constructed allows for a granular investigation of how different regulatory components affect banking sector outcomes. By decomposing regulations into distinct topics through LDA analysis, I can systematically examine whether certain regulatory dimensions—from capital requirements to liquidity standards, geographic branching restrictions to investment banking activities, disclosure requirements to consumer protections, and lending restrictions—have differential impacts on financial stability. This decomposition helps address several fundamental questions about banking regulation: Does Kane's (1981, 1988) "regulatory dialectic" of cycles in regulation and deregulation systematically relate to future banking crises? Which specific aspects of banking regulation matter most for preventing future crises?

This paper shows that credit deregulations specifically show the strongest association with subsequent banking distress, highlighting the critical importance of maintaining robust oversight of lending activities. By documenting how credit deregulation precedes banking sector instability and credit booms, this paper provides policymakers with evidence supporting more persistent regulatory oversight of lending standards and credit provision, even during periods of apparent financial calm when deregulatory pressures are strongest. These findings have significant implications for regulatory policy, particularly regarding credit-related regulations. The temporal mismatch between immediate regulatory costs and delayed stability benefits creates challenges for policymakers, as pressure for deregulation often mounts during periods of apparent stability. Since regulatory benefits materialize gradually while costs are immediately visible, pressure for deregulation often mounts during periods of apparent stability, precisely when maintaining regulatory vigilance is most crucial.

This paper contributes to multiple literature streams. First, it enhances micro-level evidence on regulatory impacts. Favara and Imbs (2015) document how US bank branching deregulations led to credit expansion affecting house prices, while Di Maggio and Kermani (2017) show federal preemption of national banks from predatory lending laws in 2004 preceded a house price boom-bust via credit expansion. Cortes et al. (2022) demonstrate that their bank stock index explained industrial production, credit, and debt default during the Great Depression. This study extends this work by showing how bank-level *regulatory beta* explains post-deregulation rise and reversal in stock returns, loan-to-deposit ratios, and distance-to-default.

Second, this paper advances the cross-country literature on regulatory changes, building on evidence that credit booms precede busts (Schularick and Taylor (2012); Mian et al. (2017); Baron and Xiong (2017); Baron et al. (2021)) and financial liberalization precedes crises (Demirgüç-Kunt and Detragiache (1998); Kaminsky and Reinhart (1999); Henry (2000)). It goes beyond survey-based measures and single-episode analyses by introducing a text-based approach to quantify banking regulations from newspaper coverage across six anglophone countries. The paper's topic modeling methodology captures the credit component of banking regulations and reveals crisis associations not explained by established measures. This approach aligns with modern literature using text analysis to measure economic uncertainty (Baker et al. (2016)), news-implied volatility (Manela and Moreira (2017)), partisan conflict (Azzimonti (2018)), economic sentiment (van Binsbergen et al. (2024)), and public attention to environmental and social issues (Houston et al. (2024)).

1 Data and Methodology

1.1 Bank Regulation Index

The foundation for constructing the bank regulation index involves the compilation of relevant regulatory and deregulatory *statutory* banking laws. For 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.

The starting point of the analysis is the set of consequential banking, housing, and securities laws, compiled by Tabor, Di Lucido and Zhang (2021) and Conti-Brown and Ohlrogge (2022).[1] Tabor, Di Lucido and Zhang (2021) provides a history of US financial regulations and reviews 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 (Banking) and Title 15 (Securities) laws. According to their metrics, 5 out of the top 10 most important Title 12 laws are Housing Acts. However, as mentioned earlier, this study concerns laws directly affecting banks. This necessitates the exclusion of housing and securities laws. Appendix A shows the list of these laws for the US, UK, Ireland, New Zealand, Australia, and Canada.

Constructing these indices from newspaper coverage rather than official regulatory documents like the Federal Register offers several methodological advantages. First, news-

[1] I thank Peter Conti-Brown for sharing the list of laws used in Conti-Brown and Ohlrogge (2022).

papers provide superior timing benefits—articles appear at informative moments when laws are being formulated and their effects are initially realized. In contrast, the Federal Register follows a sequential pipeline of notice, proposed rule, and final rule, with most market-relevant information often already incorporated by the time of the final publication. Second, the distribution of newspaper attention serves as a natural weighting mechanism that measures the relative importance of different laws. Simple word- or page-counting approaches in the Federal Register fail to accurately capture regulatory intensity or discriminate between more consequential and less impactful regulations. Third, and particularly relevant for the text-based decomposition of bank regulations in this paper, newspaper articles discuss laws using more accessible and topic-focused language. While text in the Federal Register often contains specialized jargon that may dilute the presence of subject-specific keywords, newspapers tend to emphasize the most relevant topics in more straightforward terms. For example, articles covering a credit-related regulation will prominently feature credit-related terminology if that represents the law's primary focus, enabling more effective topic extraction through natural language processing techniques.

I construct the index using the following steps:

1. Identification of Popular Nicknames: I used Google search to identify widely recognized nicknames or abbreviations (4 letters or more) associated with each law. For example, the Garn-St Germain Depository Institutions Act of 1982 is often referred to as just the Garn Act.

2. Obtaining the corpus of newspaper articles: For consistency, I retain only those newspapers that have coverage availability for the full period in ProQuest (for the US). 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. These newspapers have been used in influential studies such as Baker, Bloom and Davis (2016) and, more recently, Hirshleifer, Mai and Pukthuanthong (2024). I use popular financial news sources for other countries that have sufficient coverage

in Factiva. Table A3 mentions the newspaper sources for all countries. The following criteria are then used to shortlist news articles:

- Temporal Relevance: Articles within a window of five years from the date of enactment of the respective law are selected. This ensures that the corpus of news articles remains contemporaneous with the regulatory landscape.
- Name References: The articles explicitly mention the law's full name, any popular nickname, or a 4-letter or more abbreviation.
- 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 yielded a set of more than 16,000 news articles. Thus, in a given country i and year t, $NR_{i,t}$ and $ND_{i,t}$ are the number of articles that mention the regulatory laws and the deregulatory laws, respectively. The index is calculated as:

$$BRI_{i,t} = \ln(NR_{i,t} + 1) - \ln(ND_{i,t} + 1) = \ln\left(\frac{NR_{i,t} + 1}{ND_{i,t} + 1}\right)$$

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 distribution. Taking the logarithm accentuates the importance of deregulatory and regulatory laws that receive disproportionately less media attention. Additionally, using a ratio provides several advantages: first, it makes the measure agnostic to yearly variations in overall news volume, creating a relative rather than absolute metric; second, it facilitates cross-country comparisons by normalizing for differences in media coverage intensity across national contexts; and third, it measures the overall regulatory direction by directly comparing the strength of tightening versus loosening forces, providing a single measure of the net regulatory environment.

The BRI provides valuable insights into the regulatory cycles that characterize banking history. Figure 1 plots the BRI against Bank Failures, defined as the deposits of failed banks as a percentage of total deposits, for the US from 1926 to 2023. Bank Failures serve as a measure of banking crisis severity and highlight four major episodes: the Great Depression of the 1930s, the Savings and Loans Crisis of the 1980s, the Great Recession of 2007-09, and the regional banking crisis of 2023. Similar patterns can be observed in the other five countries in the panel dataset, as shown in Figure A1, supporting the generalizability of these findings beyond the US institutional context.

Each episode of banking crisis in the US is followed by a spike in the BRI, showing a strong regulatory response. Foundational banking regulations of the 1930s followed the Great Depression. 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). This period of stability was disrupted by deregulations of 1979-82, including the Monetary Control Act of 1980 and the Garn-St Germain Act of 1982. Another episode of regulatory laws in 1989-1991 (i.e., Financial Institutions Reform, Recovery, and Enforcement Act of 1989) 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.

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, Schularick and Taylor (2017)) 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, Kohler and Upper (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." Jordà et al. (2022) shows that corporate debt overhang has different implications than household credit booms, with corporate debt resolution frictions leading to slower recoveries. Moreover, Baron, Verner and Xiong (2021) shows that severe declines in bank equity are associated with substantial credit contractions and output gaps even in the absence of bank panics. More notably, Bernanke (1983) argued that bank failures of the Great Depression exacerbated the crisis through eroding capital availability. Therefore, banks provide an ideal ground to study how regulatory frameworks interact with the functioning of the banking sector in different time horizons.

Given the severe economic costs of banking crises, understanding a more complete temporal dimension of regulatory impacts becomes crucial. Although regulatory effects are often evaluated over short horizons, their complete beneficial and adverse implications typically unfold gradually over different periods. This temporal complexity was highlighted by Kane (1988), who noted the scholarly *"insistence on thinking about regulatory adjustments that affect financial firms as exogenous disturbances"* rather than endogenous responses to evolving financial conditions. Significant contributions by Calomiris, Mamaysky and Yang (2020) and Kalmenovitz, Lowry and Volkova (2022) have advanced our understanding by developing sophisticated firm-level measures of regulatory exposure using earnings call transcripts and analyzing the short-term costs associated with regulatory fragmentation, respectively. These valuable insights into the immediate consequences of regulation provide a basis for exploring longer-term dynamics. This paper extends this literature by examining regulatory impacts across multiple time horizons, from immediate market reactions to long-term stability outcomes, while also considering the endogenous nature of regulatory cycles. By spanning nearly a century of data, this approach not only allows analysis of how regulatory changes respond to past and potentially precede future crises but also enables a deeper decomposition of regulatory dimensions to identify which specific aspects most significantly impact financial stability.

The Latent Dirichlet Allocation (LDA) analysis decomposes the corpus of banking regulation news articles into six distinct topics (see Appendix B for details). The topics are categorized as *Bank Activities*, *Systemic Risk*, *Credit*, *Legalese*, *Government*, and *Monetary*. This topic categorization approach is applied consistently across all six countries in the panel to ensure comparability. To identify the laws most strongly associated with each topic, I calculate the average topic distribution for news articles referencing the law. This produces a topic distribution for each law, as shown in Table A2.

Figure 2 highlights the key terms within each topic. For example, the *Systemic Risk* topic, derived primarily from Dodd-Frank era regulations, encapsulates concerns about financial stability. Key terms include 'risk', 'regulatory', 'firm', and 'market'. This topic predominantly relates to post-crisis regulatory legislation, with a notable share for the Dodd-Frank Act of 2010 (0.63), reflecting the emphasis on macro-prudential regulation and systemic risk oversight.[2] The *Credit* topic centers on consumer credit, featuring terms such as 'loan', 'mortgage', 'borrower', and 'lender'. It is significantly represented in both post-crisis regulations, such as the Credit CARD Act (2009) and FDICIA (1991), and pre-crisis deregulatory measures like DIDMCA (1980) and BAPCPA (2005). Further, the *Government* topic captures the legislative process, with terms like 'president', 'congress', and 'senate'. It is most strongly associated (0.53) with oversight legislation, exemplified by the Bank Secrecy Act (1970).

The outputs of LDA are two distributions: a probability weight distribution of each article j over each topic T, and a distribution of each topic T on terms associated with that topic. This weight is defined as $w_{j,T}$ (so for a given news article j, $\sum w_{j,T} = 1$). For each topic T, for articles dated in year t and country i, the value of the time series plot is calculated as $BRI_{i,t,T}$:

$$BRI_{i,t,T} = BRI_{i,t} \times \left(\frac{\sum_{j \in t} w_{j,T}}{N_{j \in t}} \right) = \ln \left(\frac{NR_{i,t} + 1}{ND_{i,t} + 1} \right) \times \left(\frac{\sum_{j \in t} w_{j,T}}{N_{j \in t}} \right) \tag{1}$$

The Credit Regulation Index (CRI) is the BRI subindex or component associated with the *Credit* topic. Figure 3 presents the decomposed time-series plot for each subindex.

[2] If the Dodd-Frank Act is decomposed into different topics based on the LDA distribution of the news articles mentioning it, the *Systemic Risk* topic alone will have 63% share with the remaning 37% allocated to other topics.

1.2 Stock Prices

Because bank stocks were traded over-the-counter (OTC) (Cortes et al. (2022)), rendering their stock price data inaccessible through the CRSP database, I collected the stock prices of over-the-counter securities from multiple sources. For the initial year of 1926 and beyond, the Commercial and Financial Chronicle (CFC) is the primary source, offering a comprehensive coverage of bank stocks. The data collection methodology involves the 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 calculated 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 price for that month. I then compute stock returns as the monthly price change. One challenge in using OTC stocks is that severe stale prices may limit the informativeness of stock price movements. Recognizing this pervasive data concern for the earlier part of the sample, I follow Cortes et al. (2022) and focus on the 20 largest banks ranked by total gross deposits. Cortes et al. (2022) show that this solution broadly addresses the potential for data inaccuracies arising from stale prices. It also ensures I focus on banks with significant news coverage and accounting information quality. Another challenge is the intermittent data availability for specific banks across all periods. I utilize the most recently available price when data is missing.

Coverage within the *Commercial and Financial Chronicle* dataset ends in 1963. Yet, comprehensive coverage within the CRSP database only begins in the late 20th century. I use stock price data from CRSP starting in 1977. To bridge this temporal gap and ensure data continuity, I utilize 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 get the price for that specific month.

1.3 Bank Balance Sheets

The bank balance sheet data spans nearly a century (1926-2020) and is sourced from Moody's Manuals and the Federal Reserve's Y9-C filings. The use of Y9-C data, which provides consolidated financial information at the bank holding company level, is preferred over Call reports as it better captures the complete operations of large banking organizations, aligns with the regulatory framework studied, enables appropriate risk analysis across broader banking activities, and corresponds directly with market-based measures used in this analysis (Adrian and Brunnermeier (2016)). This consolidated view at the holding company level is particularly important for examining the effects of major banking regulations like the Dodd-Frank Act and EGRRCPA, analyzing systemic risk that emerges from diverse banking activities beyond traditional deposit-taking, and matching financial data with stock market returns that are typically issued at the holding company level rather than individual bank subsidiaries. For the earlier part of the sample (1926-1984), I selected the 20 largest banks each year. This is comparable to other studies (e.g., Begley et al. (2017), Cortes, Taylor and Weidenmier (2022)). I use Gross Deposits to measure bank size to determine the sample.

The process of amassing the data used in this paper involves the hand-collection of balance sheets and income statement items. These include 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. Subsequently, I use 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).

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

To measure bank risk, I follow Gelman, Goldstein and MacKinlay (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:

$$ret_{i,t} - RF_t = \alpha_0 + \beta_1 \cdot MKTRF_t + \beta_2 \cdot SMB_t + \beta_3 \cdot HML_t + \varepsilon_{i,t} \tag{2}$$

where $MKTRF_t$ is the market return minus risk-free rate, and RF_t, SMB_t, and HML_t are risk-free rate, 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 (2) for bank i for the months $t-37$ to $t-1$. Using the factor exposures from that regression, I compute abnormal returns as:

$$abret_{i,t} = ret_{i,t} - \hat{\beta}_1 \cdot MKTRF_t - \hat{\beta}_2 \cdot SMB_t - \hat{\beta}_3 \cdot HML_t$$

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]

I follow Bharath and Shumway (2008) to construct a 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. Table 1 shows the summary statistics for the main variables used in the paper.

2 Results and Discussion

2.1 Determinants 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. To predict regulation, I use the following specification:

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

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. This variable is not lagged to match the party in year t with the regulations passed in year t. 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.

Table 2 shows a strong correlation between prior-year bank failures and the ensuing year's Bank Regulation Index (BRI). Turning to a partisan dimension, Column (2) shows an inclination toward deregulation during Republican tenures, exemplified by legislative shifts during the Reagan, Bush, and Trump eras. This may point toward political factors underpinning bank regulatory cycles. These findings align with broader evidence on political cycles in financial regulation. Notably, Columns (3) and (4) show that bank failures are the best and the only significant predictors of bank regulations. The non-significance of political and economic variables shows that bank regulation cycles are largely independent of political and economic cycles.

[INSERT TABLE 2 ABOUT HERE]

Given these short-term correlations, the long-term determinants and implications of banking regulations become important. Vector Autoregressions (VARs) can capture dynamic temporal relations across time series and offer invaluable insights into long-term regulatory impacts. I employ a bivariate Vector Autoregression (VAR), including bank failures and BRI, 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 $p = 10$ based on the Akaike Information Criterion (AIC).

Figure 4A 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. 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 is followed by an extended period of stability. Figure 4A shows how regulations respond to crisis. As evident from this figure and the regressions in Table 2, 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 2 reveals an asymmetry in regulatory dynamics: the explanatory variables strongly predict increased regulations but show little predictive power for deregulation in the short run (Column (6)). This observation suggests that deregulatory actions may stem from different factors altogether. Prolonged banking sector stability may foster regulatory complacency that leads to deregulatory impulses. The Impulse Response Function (IRF) in Figure 4B supports this interpretation, as the Decreased Regulation Index (DRI) exhibits a negative response to shocks in *Bank Failures*, indicating that extended periods without significant bank failures precede increased deregulatory measures. Importantly, the consequences of such deregulation unfold not immediately but over the medium to long term—Figure 4B demonstrates that surges in deregulation are typically followed by substantial increases in bank failures within approximately a decade, a pattern consistent with the historical regulatory cycles as shown in Figure 1.

2.2 The Short-Term and Long-Term Dichotomy of Regulations

Bank-specific exposures to regulatory risk are quantified by computing the equity beta of each bank with respect to innovations in the BRI, a methodology that can be applied across countries to capture institutional differences in regulatory response. 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 a 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 every month 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. I utilize data available up to year t to avoid potential endogeneity and forward-looking bias. Specifically, for each bank i and year t, the following regression is used over the period $t-5$ to $t-1$ to estimate regulatory exposure from stock returns:

$$ret_{i,t} - rf_t = \beta_0 + \beta_1 \cdot BRI_t + \beta_2 \cdot MKTRF_t + \beta_3 \cdot SMB_t + \beta_4 \cdot HML_t + \epsilon_{i,t} \tag{6}$$

From this regression, the exposure of bank i to regulations is the standardized $\beta^{reg}_{i,t}$ (*Regulatory Exposure*), which I define as $\beta^{reg}_{i,t} \equiv -\beta_1$ for a more intuitive interpretation. 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.[3] This approach (of using $\beta^{reg}_{i,t}$ as the time-varying *Regulatory Exposure*) aligns with how regulatory changes influence bank stock prices.

To study how different bank characteristics explain the *Regulatory Exposure*, I use the following regression:

$$\beta^{reg}_{i,t} = \gamma_0 + \mathbf{X}_{t-1} + \delta_i + \gamma_t + \epsilon_{i,t} \tag{7}$$

$\mathbf{X}_{t-1}$ are *LDR*, ln(*Total_Assets*), Leverage and Cash Ratio of year $t-1$. δ_i are bank fixed effects, γ_t are decade fixed effects. $\beta^{reg}_{i,t}$ is estimated over the period t to $t+5$ to ensure that there is no look-ahead bias in explaining bank-level regulatory exposure.

[3] 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.

[Insert Table 3 About Here]

Table 3 shows the coefficient estimates from this regression. The table reveals several important bank characteristics that help explain cross-sectional variation in regulatory exposure. The most economically and statistically significant predictor is bank size, with smaller banks showing substantially higher sensitivity to regulatory changes. Specifically, doubling total assets is associated with a 0.27 standard deviation decrease in regulatory exposure (column 5). This relationship is intuitive for several reasons. Smaller banks typically have less sophisticated compliance departments and fewer resources to adapt to new regulatory requirements. They may also lack the economies of scale that help larger institutions absorb compliance costs.

The results also show that banks with weaker fundamentals tend to be more exposed to regulatory changes. Banks with lower cash buffers (measured by $Cash/TA$) exhibit higher regulatory exposure. This aligns with the expectation that better-capitalized banks with stronger liquidity positions are better equipped to handle regulatory shifts without significant operational disruption. Profitability also plays an important role — banks with lower ROE show greater sensitivity to regulatory changes. This suggests that more profitable banks have more capacity to absorb regulatory compliance costs while maintaining their business models. The role of risk is captured through several metrics. Banks with higher idiosyncratic volatility and lower distance-to-default scores show increased regulatory exposure. This indicates that riskier banks are more sensitive to regulatory changes, consistent with the notion that regulations often target risk-taking behavior.

Collectively, these results convey a consistent idea: smaller, less profitable banks with weaker balance sheets and higher risk profiles tend to be most exposed to regulatory changes. This aligns with economic intuition, as such banks typically have less financial and operational flexibility to adapt to new regulatory requirements. The findings also help explain why regulatory changes often have heterogeneous effects across the banking sector, with some banks better positioned to weather regulatory shifts than others.

The following local projections (Jordà (2005), Barnichon and Brownlees (2019), Ferreira et al. (2023)) are then used to study the short-term and long-term impact of regulations:

$$Y_{i,t\to t+10} = \gamma_0 + \gamma_1 \cdot \beta_{i,t}^{reg} + BankControls + MacroControls + \delta_i + \gamma_t + \epsilon_{i,t}$$

where δ_i are unit fixed effects, γ_t are time fixed effects, $Y_{i,t}$ is outcome, 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). and *BankControls* are *LDR*, $\ln(Total\_Assets)$, Cash Ratio, and Leverage of year $t-1$.

[Insert Table 4 About Here]

The impact of banking regulations on bank profitability in Table 4 exhibits a clear dichotomy between short-term and long-term effects. Leading values of ROE from years t to $t+10$ show a reversal from negative to positive impacts as a result of regulatory exposure ($\beta_{i,t}^{reg}$). This reveals that over time, deregulatory shocks are linked to a reversal and later decline in profitability (in the long term).[4]

The pattern in abnormal returns further reinforces this temporal dichotomy. Banks more exposed to regulatory changes (higher $\beta_{i,t}^{reg}$) experience significantly negative abnormal returns in the immediate term, consistent with markets initially viewing regulations as costly. However, this negative effect dissipates over the medium term before reversing to significantly positive abnormal returns in 6 to 8 years ahead. This reversal suggests that markets initially underestimate the long-term benefits of regulatory oversight, leading to a systematic correction in bank valuations as these benefits materialize over time.

The implications of regulatory changes for bank risk, measured by idiosyncratic volatility as delineated by Gelman et al. (2022), also exhibit a clear short-term versus long-term dichotomy. In the short term, banks more exposed to regulatory changes experience increased idiosyncratic volatility, which intensifies in the following two years. However, this

[4]This is further supported by the Impulse Response Function (IRF) analysis in Figure 4E. In summary, this analysis highlights a transition from short-term benefits to long-term costs in the wake of deregulatory changes in the banking sector.

initial volatility spike reverses direction around year $t+4$, leading to significant reductions in idiosyncratic volatility by years $t+6$ and $t+8$. This pattern suggests that while regulatory changes may initially disrupt bank operations and create uncertainty, they ultimately lead to more stable risk profiles over longer horizons. The evolution of idiosyncratic volatility aligns with the notion that the short-term costs of regulatory adjustment are outweighed by the long-term benefits of enhanced stability and risk management.

Examining cash holdings relative to assets (Cash/TA) in Table 4, banks more exposed to regulatory changes show no immediate significant adjustment, but substantially increase their liquidity positions over the medium term, peaking at year $t+4$. This delayed build-up in liquidity buffers suggests that banks require time to adjust their asset composition in response to regulatory changes.[5]

Simultaneously, the impact on lending behavior, measured through the Loan-to-Deposit Ratio (LDR), displays a more immediate and sustained response. Banks with higher regulatory exposure significantly reduce their LDR starting from the current year, with the effect strengthening over the medium term and reaching its peak four years ahead of the shock. This substantial reduction in lending intensity persists through year $t+6$ before gradually normalizing.[6] Together, these results suggest that regulatory changes induce banks to adopt more conservative balance sheet positions by simultaneously building liquidity buffers and restraining lending growth, with these effects materializing gradually over several years.

The impact of regulations on bank stability is crucial for financial policy decisions. A salient metric that captures this stability is the distance-to-default (DD). Derived from structural models of credit risk, DD serves as a metric indicating the buffer a bank has against potential default. Similar to the profitability and abnormal returns variables, the

[5] The Impulse Response Functions in Figure 4F corroborate this pattern, showing a persistent rise in aggregate cash ratios following regulatory shocks.

[6] The IRF analysis in Figure 4C and Figure 4D supports this finding, showing that regulatory shocks lead to a persistent decline in the aggregate Loans/GDP and Leverage ratios.

local projections in Table 4 show that the Distance-to-Default coefficient of banks exposed to regulations reverses from negative to positive over longer time horizons.

Regulatory exposure exhibits a nuanced relationship with bank stability, as measured by the Distance-to-Default (DD), a key metric derived from structural models of credit risk that captures a bank's buffer against potential default. The local projections in Table 4 show that while banks more exposed to regulatory changes initially show a significant decline in year $t + 2$, suggesting an initial period of adjustment costs. However, this pattern reverses in subsequent years, with DD increasing significantly from years $t + 4$ through $t + 8$. This transition from short-term vulnerability to long-term resilience suggests that while regulatory changes may temporarily strain banks' stability metrics, they ultimately strengthen their buffers against default risk, supporting the view that regulatory oversight enhances bank safety over longer horizons.

3 What Type of (De)Regulation precedes Banking Crises?

Banking regulations are complex and multi-dimensional, spanning capital requirements, geographic restrictions, credit standards, disclosure rules, and consumer protection. Therefore, a critical question for both policymakers and financial institutions is which specific regulatory dimensions matter for financial stability. The Bank Regulation Index (BRI) constructed in this paper captures the overall regulatory environment, but regulations are not monolithic. Different facets of banking oversight may have vastly different impacts on banking sector stability, with some potentially serving as leading indicators of distress while others having negligible predictive power. Is it regulation on capital standards that directly affects bank stability? Investment and commercial banking activity restrictions that constrain risk-taking? Or lending standards that shape credit provision? Identifying the most consequential regulatory domains is essential for designing effective financial stability frameworks.

To empirically address this question, I first examine how changes in the overall regulatory environment from year $t-10$ to $t-5$ affect bank failures at time t using the following regression specification:

$$BankFailures_t = \alpha_0 + \beta \cdot \Delta_{t-10\rightarrow t-5} BRI + \mathbf{X}_{t-1} + \epsilon \tag{8}$$

where $BankFailures_t$ is measured as the deposits of failed banks as a percentage of total deposits, and $\mathbf{X}_{t-1}$ is a vector of macroeconomic controls including GDP growth, inflation, and interest rate. The results in Table 5 reveal that changes in the overall BRI significantly predict bank failures. Notably, when decomposing the BRI into its regulatory (IRI) and deregulatory (DRI) components, the predictive power primarily stems from deregulatory actions. The coefficient on $\Delta_{t-10\rightarrow t-5} DRI$ is 0.415 and statistically significant, while $\Delta_{t-10\rightarrow t-5} IRI$ shows no significant relationship with subsequent failures. This asymmetry suggests that banking deregulations are a particularly powerful predictor of future banking sector distress.

The multi-dimensional nature of banking regulation, however, raises a deeper question: which specific regulatory topics drive this predictive relationship? To answer this, I decompose the BRI into distinct regulatory topics using Latent Dirichlet Allocation (LDA). This unsupervised machine learning technique identifies latent themes within the corpus of regulatory news coverage, allowing for a granular examination of which regulatory dimensions matter most for financial stability (see Appendix B for details). The estimated model is:

$$BankFailures_t = \alpha + \sum_{j=1}^{6} \beta_j \Delta_{t-10\rightarrow t-5} Topic_j + \gamma \mathbf{X}_{t-1} + \epsilon_t \tag{9}$$

where $Topic_j$ represents the six regulatory topics identified through LDA, and $\mathbf{X}_{t-1}$ is a vector of macroeconomic controls.

[Insert Table 5 About Here]

The results in Table 5 reveal a striking pattern: among all regulatory dimensions, the *credit*-related regulatory topic carries the strongest predictive power for future banking crises, with a coefficient of -2.65 (t-stat = -2.39). This finding is economically significant, suggesting that deregulation of lending practices and credit standards is particularly consequential for banking system stability. Laws regulating lending to consumers, such as the Credit CARD Act of 2009 (0.87), the Bankruptcy Abuse Prevention and Consumer Protection Act of 2005 (0.65), and the Monetary Control Act of 1980 (0.49), have a high share on this topic, underscoring the importance of credit-related regulations in maintaining financial stability. This shows that regulating (or deregulating) bank lending (especially to high-risk borrowers) carries significant implications for the future stability of the financial system. Relatedly, Gorton and Ordonez (2014, 2020) develop a *"Good Booms, Bad Booms"* model in which a crisis happens when a credit boom transitions 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, Gorton and Holmström (2020)). The predictive results in Table 5 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.

The insights from the U.S. analysis are further validated in the broader international context: Table A4 presents evidence that the credit regulation component carries the strongest predictive power (highest t-statistic). This cross-country evidence powerfully reinforces the finding that credit-related regulatory changes have uniquely consequential implications for financial stability. Table A5 shows that this association is robust across different crisis databases (JST refers to the Jordà et al. (2017) database, BVX refers to the Baron et al. (2021) database, and LV refers to the Laeven and Valencia (2012) database). Even when controlling for country-specific characteristics through fixed effects, changes in credit regulation maintain a robust relationship with subsequent banking distress (Table A6).

[Insert Table 6 About Here]

To further explore the association between credit regulations and banking crises, I examine how changes in credit regulation predict future credit growth. Table 6 shows that changes in the Credit Regulation Index (CRI) significantly predict future changes in both mortgages-to-GDP and loans-to-GDP ratios over a 5-year horizon.[7] These findings provide direct evidence that regulatory changes influence future credit growth, especially in mortgage markets, establishing a key channel through which regulatory changes can affect banking stability.

This relationship extends beyond the U.S. context. As shown in Table A7, the same pattern holds across our six-country panel, where credit regulation changes consistently predict future credit growth even after controlling for country and year fixed effects. This international evidence strengthens the conclusion that credit deregulation leads to credit expansion—particularly in mortgage markets—across diverse financial systems, suggesting this mechanism represents a fundamental economic relationship rather than a country-specific phenomenon.

This predictive relationship exhibits important temporal dynamics. Table A8 shows how the predictive power of credit regulation changes varies with different lag structures. Recent changes in credit regulations (2-7 years or 3-8 years ago) show no significant relationship with current bank failures, with coefficients close to zero and statistically insignificant. However, the predictive power emerges and strengthens as we look at more distant regulatory changes, with the strongest effects observed for changes from 5-10 years ago. This pattern suggests that the impact of credit regulation takes significant time to manifest in banking sector stability.

Table 7 provides evidence on the relationship between credit-related regulations and future banking crises.

[7] A one unit decrease (1.4 standard deviations) in CRI (indicating deregulation) is associated with a 2.115 percentage point increase in the mortgages-to-GDP ratio over the subsequent five years. This effect remains robust and even strengthens to 2.154 percentage points when controlling for macroeconomic conditions. The relation with overall loans-to-GDP is also significant but somewhat smaller in magnitude, suggesting that credit deregulation particularly affects mortgage lending.

[Insert Table 7 About Here]

Credit regulation changes show strong predictive power for future bank failures. Column (1) shows that the lagged change in the credit-related regulatory index ($\Delta_{t-10 \to t-5} CRI$) is a significant predictor, with a coefficient of -2.494 (t-stat = -2.261). This predictive power remains robust when controlling for macroeconomic conditions in Column (2), with the coefficient becoming slightly more negative at -2.647 (t-stat = -2.386).

I explore how this relationship competes with various measures of credit expansion. Columns (3) and (4) show that the loans-to-GDP ratio significantly predicts bank failures, with a stronger result after including macro controls, consistent with earlier findings from Jordà, Richter, Schularick and Taylor (2021) that credit growth is a significant predictor of financial crises. Importantly, the credit regulation index maintains its significant predictive power in these specifications, suggesting it captures additional information beyond simple credit growth measures.

Following Mian et al. (2017), I examine mortgage-specific credit expansion in Columns (5) and (6). The mortgage-to-GDP ratio shows strong predictive power with a coefficient of 3.357 (t-stat = 2.535), increasing to 3.635 (t-stat = 3.030) with macro controls. Recent work by Diebold and Richter (2023) shows that the source of credit financing matters, with foreign-financed household credit expansions being particularly predictive of lower future GDP growth and higher crisis risk. Finally, Columns (7) and (8) demonstrate that the loan-to-deposit ratio (LDR) is also a significant predictor, though its statistical significance weakens when including macro controls.

Notably, the credit regulation index maintains its economic and statistical significance across all specifications, with coefficients ranging from -2.270 to -2.665. This persistence suggests that changes in credit-related regulations play a fundamental role in the build-up of banking sector vulnerabilities. The 5-10 year lag in the predictive power of regulatory changes aligns with Greenwood and Hanson (2013), who document that credit supply shocks correlate with subsequent household debt booms, suggesting that the effects of credit regulation changes take time to materialize through the banking system.

Furthermore, as shown in Table A9, this relationship is not limited to the U.S. or a single measure of financial distress. The panel analysis across six countries reveals that the CRI's predictive power remains robust across different institutional environments and using various crisis definitions. This cross-country validation significantly strengthens the case that credit regulation changes represent a fundamental driver of financial system vulnerability that transcends national institutional differences.[8]

The strong indicativeness of credit-related regulations for both future credit growth (Table 6) and banking crises (Table 7) characterizes this relationship: periods of deregulation are associated with subsequent credit expansion, particularly in mortgage markets, and these periods show a higher incidence of banking crises. This sequence is particularly evident in the mortgage market, where regulatory changes have the most substantial impact on credit growth and where the mortgage-to-GDP ratio shows the highest predictive power for banking crises. The timing of these relationships—with regulatory changes predicting credit growth over a 5-year horizon and banking crises over a 5-10 year horizon—suggests a gradual build-up of vulnerabilities through the credit channel, consistent with the theoretical framework of Greenwood and Hanson (2013) and the empirical findings of Mian, Sufi and Verner (2017).

3.1 Controlling for Financial Liberalization

To further examine the text-based Credit Regulation Index (CRI), I compare it with established measures of financial liberalization. I estimate the following specification:

$$\begin{aligned} BankFailures_t = {} & \alpha + \beta_1 \Delta_{t-10\to t-5} CRI + \beta_2 FinLib_{t-1} \\ & + \beta_3 FinReform_{t-1} + \beta_4 ISBRI_{t-1} + \gamma X_{t-1} + \epsilon_t \end{aligned} \tag{10}$$

[8] The lag structure analysis in Table A8 provides additional insight into this mechanism. The progressive strengthening of the relationship between credit regulation changes and bank failures as the lag increases from 2-7 years (insignificant) to 5-10 years (significant at -2.647) suggests that the build-up of vulnerabilities through credit expansion is a gradual process. This aligns with both credit growth findings in Table 6, which shows effects over a 5-year horizon, and the broader literature on credit cycles. The timing pattern suggests a sequential process where regulatory changes are followed by shifts in lending patterns, with credit booms often observed in subsequent periods.

where $FinLib_{t-1}$ is the Demirgüç-Kunt and Detragiache (1998) financial liberalization index based on policy changes, $FinReform_{t-1}$ is the IMF's financial reform index from Abiad, Detragiache and Tressel (2010), and $ISBRI_{t-1}$ is the intra-state bank branching restriction index from Kroszner and Strahan (1999), calculated as the number of states with branching restrictions in year t. X_{t-1} represents macroeconomic controls, including GDP growth, inflation, and short-term interest rates. Table 8 presents the results. Column (1) shows the baseline specification where $\Delta_{t-10\rightarrow t-5}CRI$ significantly predicts bank failures. In Column (2), I add the Demirgüç-Kunt and Detragiache (1998) measure, which enters positively and significantly, while the CRI measure maintains its significance and magnitude. This suggests that the text-based measure captures different aspects of regulatory changes than the policy-based measure. When I incorporate the IMF's financial reform index in Column (3), both the CRI measure and Demirgüç-Kunt and Detragiache (1998)'s index remain significant, while the financial reform index shows marginal significance with a negative coefficient. The negative coefficient suggests that broader financial reforms may have stabilizing effects, in contrast to specific credit deregulations captured by our measure.

[Insert Table 8 About Here]

Column (4) adds the intrastate branching restriction index ($ISBRI_{t-1}$), which captures the geographic component of banking deregulation. The coefficient is negative and significant. Importantly, the CRI measure remains significant even after controlling for this geographic dimension of deregulation. The full specification in Column (5) includes macroeconomic controls and confirms the robustness of all regulatory measures. The explanatory power of the model increases substantially from an R-squared of 0.151 in the baseline to 0.636 in the full specification, suggesting that these different measures capture complementary aspects of financial sector regulation. These results validate the text-based CRI measure as a distinct and valuable indicator of banking distress, complementing existing measures of financial liberalization. While policy-based measures capture discrete regulatory changes and branching restrictions reflect geographic deregulation, the text-based CRI measure appears to capture broader changes in credit-related regulations that may not be fully reflected in explicit policy changes or specific deregulatory actions.

4 Concluding Remarks

I examine nearly a century of banking history in the U.S. and five other anglophone countries to understand the complex relationship between regulation and financial stability. Using my novel text-based approach to quantify regulatory intensity and decompose it into different topics, I demonstrate that while periods following new regulations are associated with increased bank costs, they ultimately precede long-term stability and resilience. I observe this pattern consistently across all six countries in my sample, suggesting a robust trade-off between short-term regulatory costs and long-term financial system benefits. This recurring dynamic helps me explain the cyclical pattern of banking regulation and deregulation.

I make three main contributions. First, I develop a Bank Regulation Index (BRI) using historical newspaper coverage across multiple countries, revealing regulatory cycles where deregulation precedes crises, triggering regulatory responses that create stability until deregulatory pressures build again. Second, I analyze hand-collected historical bank data to show that while regulations initially reduce profitability, they enhance long-term stability, with "regulatory betas" demonstrating deregulation's short-term benefits but long-term disadvantages, including higher leverage and volatility. Third, I decompose the BRI and identify that a Credit Regulation Index (CRI) effectively predicts banking crises beyond established warning indicators, including credit growth.

I reveal a recurring cycle in which deregulation precedes financial crises, suggesting policymakers should exercise caution when considering regulatory rollbacks, especially for credit-related regulations. I identify a policy-relevant temporal mismatch: regulation's costs are immediate while benefits emerge gradually. These costs generate political pressure for deregulation during stable periods that ultimately leads to instability, a pattern I find consistently across multiple countries.

These findings have significant implications for regulatory policy, particularly credit-related regulations. This century-long, cross-country evidence confirms that credit deregulation consistently precedes banking crises across different institutional frameworks. The historical perspective highlights the value of taking long-term views when assessing financial regulations and underscores the importance of maintaining robust lending oversight even during stable periods.

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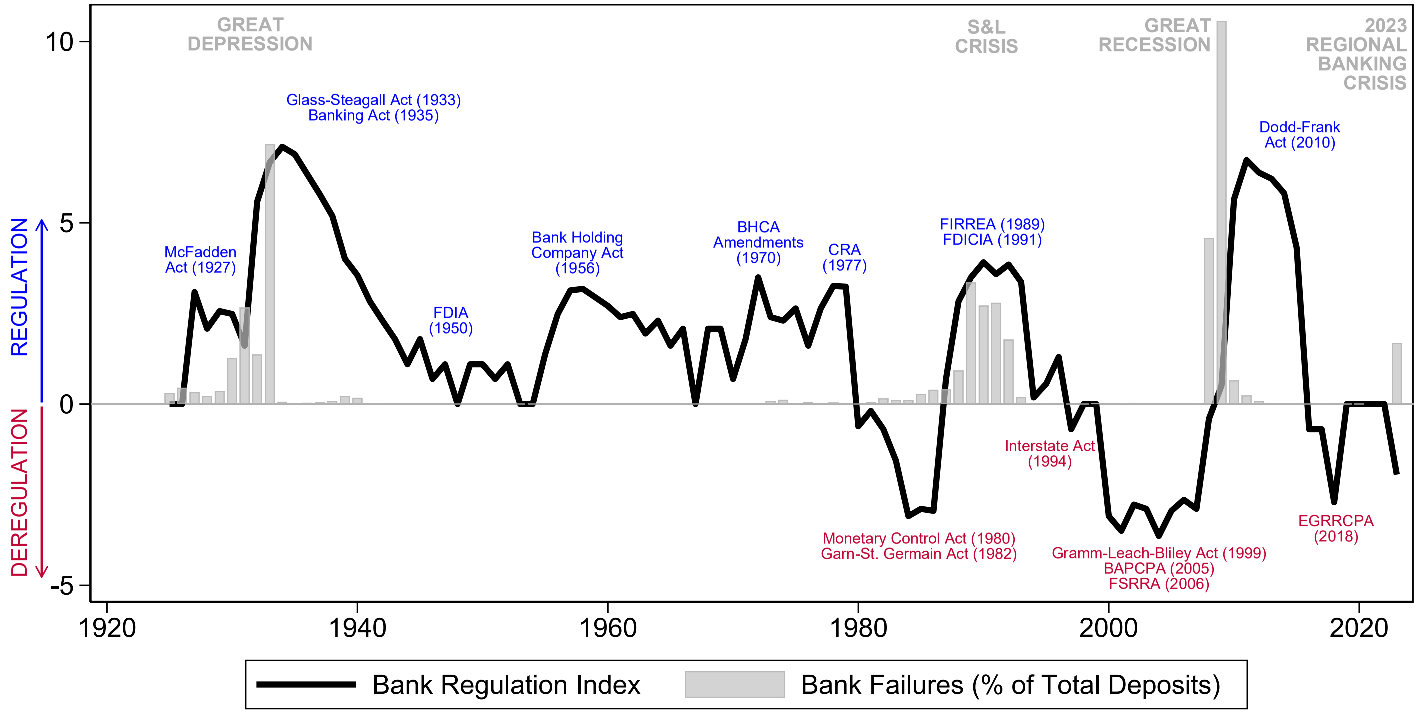


Figure 1. Bank Regulation Index and Banking Crises. The figure illustrates the relationship between *BRI* and *BankFailures*, where *BankFailures* represents the proportion of deposits in failed banks to total deposits. The plot highlights four distinct peaks in *BankFailures* since 1926. The initial 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.

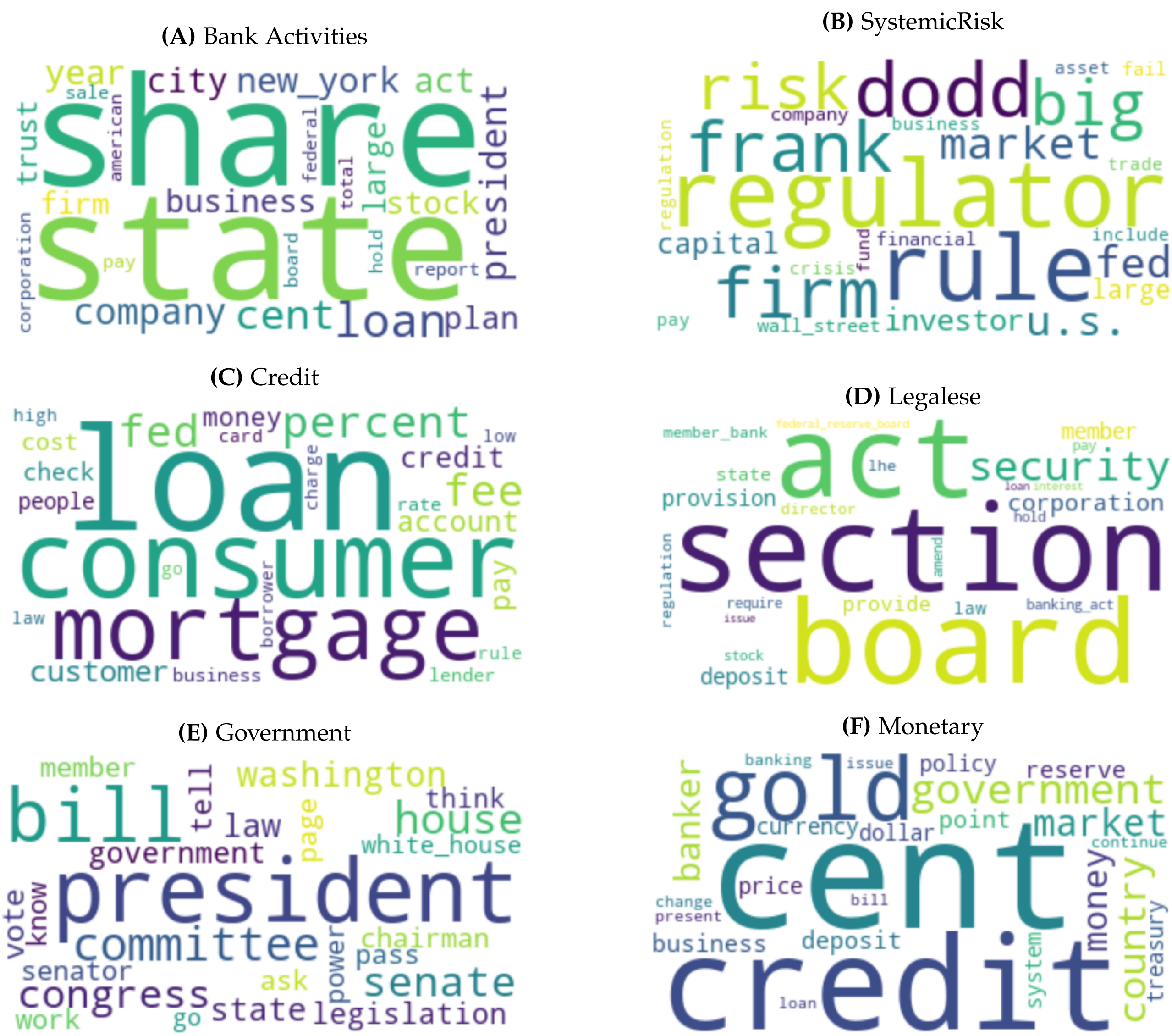


Figure 2. Word Clouds for LDA Topics. LDA provides two different distributions: a distribution of each document on the topics and a distribution of each topic on a set of words or terms. See Appendix B for details on the LDA procedure. The term distribution of each topic can be used to create the word clouds associated with the topic. The size of each term in the image is proportionate to the score it receives in the LDA distribution.

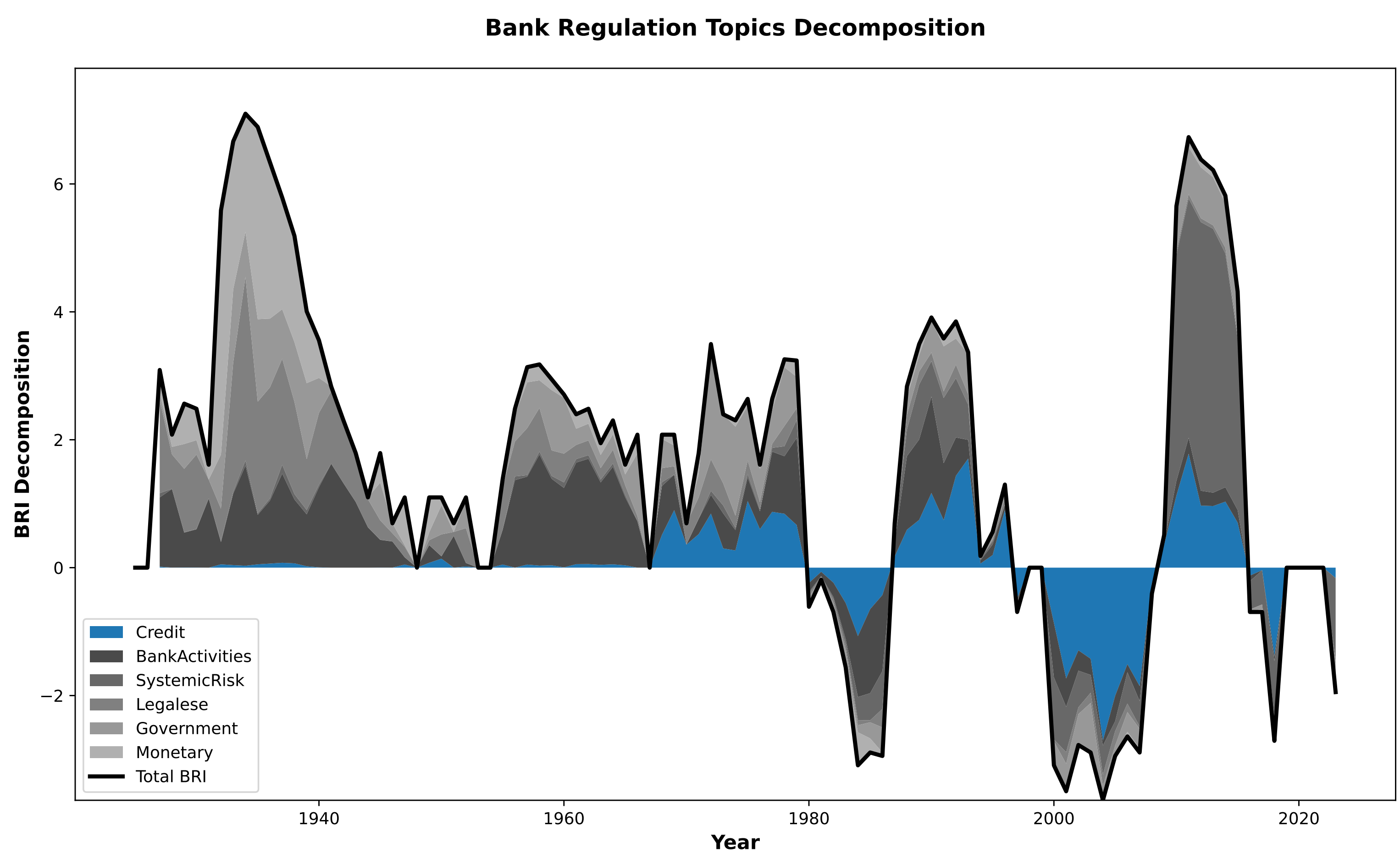
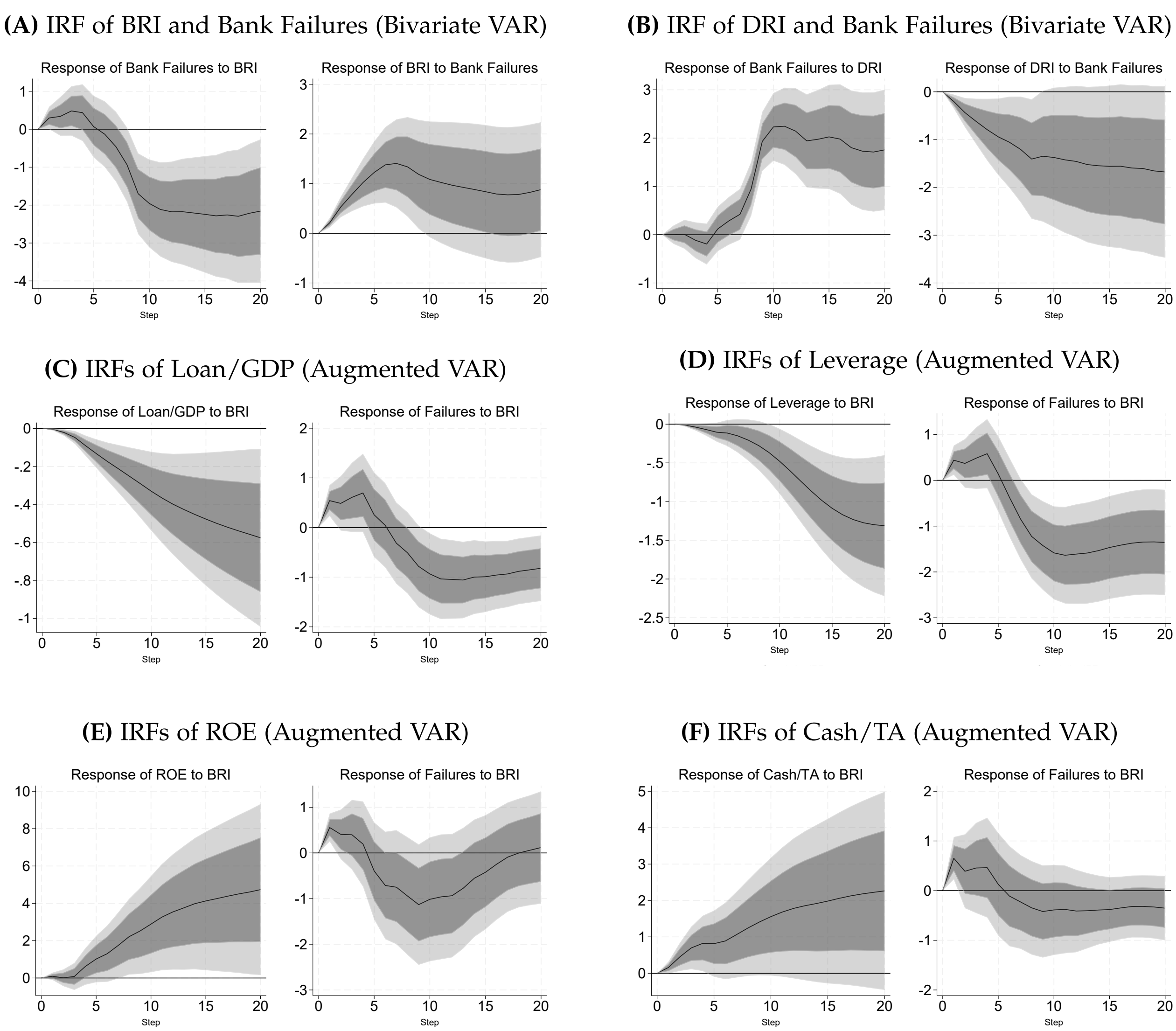


Figure 3. Bank Regulation Index: LDA-based Decomposition. The LDA preprocessing steps include tokenization, removal of stopwords and special characters, and lemmatization using NLTK and spaCy libraries. Using gensim.LdaModel, I obtain probability weights $w_{i,t}$ for each article i over topic t. The topic-specific Bank Regulation Index for year T is then:

$$BRI_{t,T} = BRI_T \times \left(\frac{\sum_{i \in T} w_{i,t}}{N_{i \in T}} \right)$$



(A) IRF of BRI and Bank Failures (Bivariate VAR)

(B) IRF of DRI and Bank Failures (Bivariate VAR)

(C) IRFs of Loan/GDP (Augmented VAR)

(D) IRFs of Leverage (Augmented VAR)

(E) IRFs of ROE (Augmented VAR)

(F) IRFs of Cash/TA (Augmented VAR)

Figure 4. Impulse Response Functions of BRI on Banking and Economic Outcomes. VAR-estimated impulse-response functions with 68% (dark gray) and 90% (light gray) confidence bands following Sims and Zha (1999) and Sims and Zha (2006).

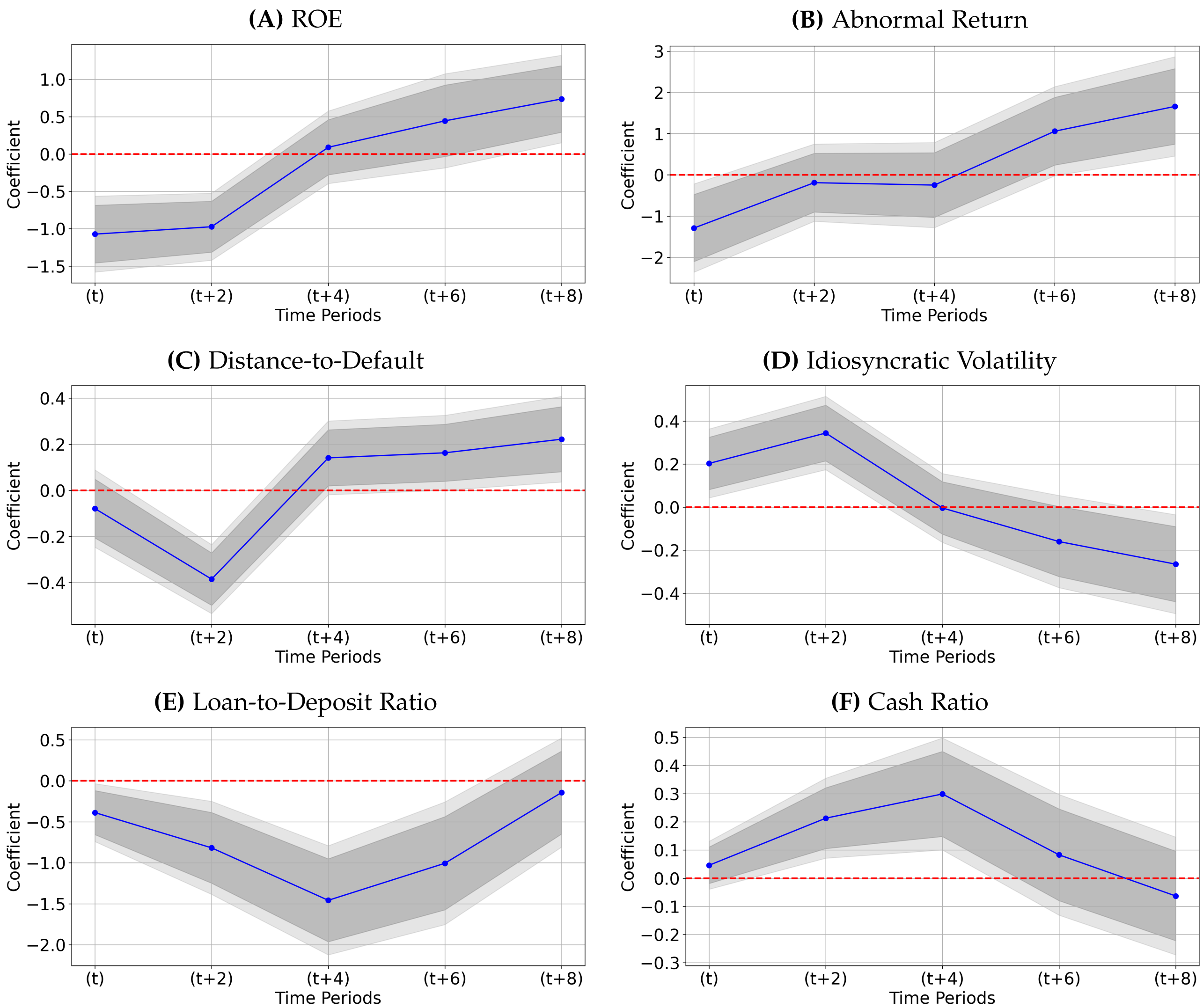


Figure 5. Local Projections of Bank-Level Outcomes. This figure plots the estimated coefficients from local projections (Table 4) of various bank-level outcomes on regulatory exposure (β^{reg}) over a longer horizon. The blue line represents point estimates, while the light and dark gray shaded areas indicate 95% and 99% confidence intervals, respectively.

Table 1. Summary Statistics

This table presents the summary statistics for the main variables. $BRI_{i,t}$, the value of annual Bank Regulation Index. $CRI_{i,t}$ is the credit subindex of $BRI_{i,t}$ calculated using Latent Dirichlet Allocation (LDA) based on newspaper text from six anglophone countries (Appendix B). $\Delta GDP_{i,t}$ is GDP growth, $\pi_{i,t}$ is inflation and $r_{i,t}$ is short-term interest rate, $Loans/GDP_{i,t}$ and $Mortgages/GDP_{i,t}$ is Total Loans and Mortgages, respectively, as percentage of GDP from Jordà et al. (2017) of country i in year t. $LDR_{i,t}$, $Cash/TA_{i,t}$, Lev_t, $\ln(TA_{i,t})$ are Loan-to-Deposit Ratio, Cash Ratio, Leverage and log of Total Assets (in $ Millions) for year t. $ROE_{i,t}$ is Net Income as a % of Equity. AR_t is annual abnormal return. $\sigma(R_{i,t})$ 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
A. Country-Year Level					
$BRI_{i,t}$	1.69	2.40	0.00	1.61	3.37
$CRI_{i,t}$	0.23	0.58	0.00	0.05	0.53
$Loans/GDP_{i,t}$	0.70	0.41	0.41	0.59	0.86
$Mortgages/GDP_{i,t}$	0.35	0.23	0.16	0.31	0.46
$\Delta GDP_{i,t}$	0.06	0.06	0.04	0.06	0.09
$\pi_{i,t}$	2.26	3.62	0.04	1.80	3.39
$r_{i,t}$	4.99	4.02	1.78	4.28	6.59
B. US 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
$AR_{i,t}$	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. 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 and West (1987) robust z-statistics with 12 lags are shown in parentheses.

	BRI_t			IRI_t	DRI_t
	(1)	(2)	(3)	(4)	(5)
$BankFailures_{t-1}$	0.597***		0.488**	0.417**	-0.071
	(3.432)		(2.050)	(2.397)	(-0.888)
$Republican_t$		-1.853**	-1.453	-1.148	0.305
		(-1.971)	(-1.531)	(-1.638)	(0.645)
ΔGDP_{t-1}			0.025	0.010	-0.015
			(0.735)	(0.278)	(-1.364)
π_{t-1}			-0.148	-0.115	0.033
			(-1.194)	(-1.095)	(0.702)
r_{t-1}			-0.072	0.044	0.117
			(-0.837)	(0.579)	(1.393)
Observations	95	96	95	95	95
R-squared	0.111	0.125	0.264	0.238	0.201

Table 3. Determinants of Regulatory Exposure

The dependent variable is the standardized Regulatory Exposure ($\beta^{reg}_{i,t\to t+5}$), estimated using the year t to $t+5$ window. $LDR_{i,t-1}$, $DD_{i,t-1}$ and $Cash/TA_{i,t-1}$ are Loan-to-Deposit Ratio, Distance-to-Default and Cash Ratio for year $t-1$. $ROE_{i,t-1}$ is Net Income as a % of Equity. $AR_{i,t-1}$ and $\sigma(\epsilon_{i,t-1})$ are annual abnormal return and the idiosyncratic volatility for bank i in year $t-1$, respectively. Newey and West (1987) robust z-statistics with 12 lags are shown in parentheses.

	$\beta^{reg}_{i,t\to t+5}$					
	(1)	(2)	(3)	(4)	(5)	(6)
$\ln(Total\,Assets)_{i,t-1}$	-0.080***	-0.117***	-0.115***	-0.176***	-0.271***	-0.267***
	(-4.176)	(-4.961)	(-4.837)	(-5.093)	(-6.746)	(-6.667)
$Cash/TA_{i,t-1}$		-0.013**	-0.013**		-0.012*	-0.012**
		(-2.209)	(-2.230)		(-1.892)	(-1.991)
$DD_{i,t-1}$		-0.007***	-0.006**		-0.005**	-0.003
		(-2.942)	(-2.333)		(-2.149)	(-1.314)
$LDR_{i,t-1}$		0.000	0.001		0.000	0.000
		(0.389)	(0.483)		(0.272)	(0.434)
$ROE_{i,t-1}$		-0.005***	-0.006***		-0.004**	-0.005**
		(-2.997)	(-3.242)		(-2.505)	(-2.546)
$\sigma(\epsilon)_{i,t-1}$			0.005			0.008*
			(1.065)			(1.755)
$AR_{i,t-1}$			0.002***			0.002***
			(3.929)			(4.012)
Observations	7,583	5,861	5,861	7,583	5,861	5,861
R-squared	0.007	0.014	0.018	0.008	0.020	0.024
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Decade FE	No	No	No	Yes	Yes	Yes

Table 4. 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 2.2. $ROE_{i,t}$, 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. Newey and West (1987) robust z-statistics with 12 lags are shown in parentheses.

	(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
	(-5.442)	(-5.592)	(0.479)	(1.820)	(3.247)	(1.367)
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
	(-3.108)	(-0.523)	(-0.620)	(2.525)	(3.555)	(1.144)
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
	(-1.215)	(-6.638)	(2.274)	(2.587)	(3.083)	(-0.653)
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
	(3.274)	(5.212)	(-0.065)	(-1.928)	(-2.978)	(0.111)
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
	(-2.832)	(-3.718)	(-5.651)	(-3.469)	(-0.554)	(1.326)
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
	(1.394)	(3.873)	(3.883)	(1.000)	(-0.778)	(-1.635)
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

Table 5. Bank Failures and Regulatory Changes

This table shows regression results where the dependent variable is bank failures. DRI and IRI are the Deregulation and Regulation components of the BRI. Variables with prefix $\Delta_{t-10\rightarrow t-5}$ represent average changes from *t-10* to *t-5*. Macro control variables include GDP growth, inflation, and short-term interest rate, all lagged by one year. Newey and West (1987) robust z-statistics with 12 lags are shown in parentheses.

	$BankFailures_t$							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\Delta_{t-10\rightarrow t-5}BRI$	-0.195***							
	(-2.870)							
$\Delta_{t-10\rightarrow t-5}DRI$		0.415**						
		(2.297)						
$\Delta_{t-10\rightarrow t-5}IRI$		-0.019						
		(-0.353)						
$\Delta_{t-10\rightarrow t-5}$BankActivities			-1.108					
			(-1.446)					
$\Delta_{t-10\rightarrow t-5}$SystemicRisk				-1.249*				
				(-1.666)				
$\Delta_{t-10\rightarrow t-5}$Credit					-2.647**			
					(-2.386)			
$\Delta_{t-10\rightarrow t-5}$Legalese						-0.650		
						(-0.837)		
$\Delta_{t-10\rightarrow t-5}$Government							-1.614*	
							(-1.685)	
$\Delta_{t-10\rightarrow t-5}$Monetary								-0.157
								(-0.333)
Observations	86	87	86	86	86	86	86	86
R-squared	0.167	0.159	0.052	0.054	0.187	0.035	0.051	0.032
Macro Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 6. Predicting Future Changes in Mortgages and Loans to GDP

This table presents regression results examining how changes in Credit Regulation Index (CRI) predict future changes in mortgages and loans as a percentage of GDP. The dependent variables are 5-year forward changes in mortgages-to-GDP ratio ($\Delta_{t\rightarrow t+5}Mortgages/GDP$) and loans-to-GDP ratio ($\Delta_{t\rightarrow t+5}Loans/GDP$). $\Delta_{t-5\rightarrow t}CRI$ represents the change in CRI over the previous 5 years. Control variables include GDP growth (ΔGDP), inflation (π), short-term interest rate (r), FDI (Foreign Direct Investment), and consumer sentiment (UMCSENT) from University of Michigan. Newey and West (1987) robust z-statistics with 12 lags are shown in parentheses.

	$\Delta_{t\rightarrow t+5}Mortgages/GDP$			$\Delta_{t\rightarrow t+5}Loans/GDP$		
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta_{t-5\rightarrow t}CRI$	-2.115***	-2.154***	-2.015***	-1.719*	-1.871*	-2.342*
	(-4.078)	(-3.871)	(-2.743)	(-1.806)	(-1.841)	(-1.789)
ΔGDP_t		0.004	-0.048		0.023	-0.039
		(0.176)	(-1.510)		(0.501)	(-0.901)
r_t		-0.034	-0.019		-0.102*	-0.109
		(-1.143)	(-0.333)		(-1.674)	(-0.976)
π_t		0.095	0.021		0.199*	-0.019
		(1.537)	(0.290)		(1.789)	(-0.204)
FDI_t			-0.000			-0.000
			(-0.434)			(-0.858)
$UMCSENT_t$			0.015			-0.005
			(0.757)			(-0.189)
Observations	86	86	64	86	86	64
R-squared	0.164	0.267	0.382	0.040	0.238	0.275

Table 7. Credit Growth and Bank Failures

This table shows regression results where the dependent variable is bank failures. $\Delta_{t-10 \to t-5} CRI$ represents average change in credit regulation topic from $t-10$ to $t-5$ (Appendix B). $Loans/GDP_{t-1}$ and $Mortgages/GDP_{t-1}$ are loan-to-GDP and mortgage-to-GDP ratios lagged by one year, respectively. LDR_{t-1} is loan-to-deposit ratio lagged by one year. Macro control variables include GDP growth, inflation, and short-term interest rate, all lagged by one year. Newey-West robust z-statistics are shown in parentheses.

	$BankFailures_t$							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\Delta_{t-10 \to t-5} CRI$	-2.494**	-2.647**	-2.351**	-2.665***	-2.270**	-2.562***	-2.514***	-2.572***
	(-2.261)	(-2.386)	(-2.256)	(-2.651)	(-2.342)	(-2.740)	(-2.609)	(-2.699)
$Loans/GDP_{t-1}$			2.040**	2.363***				
			(2.259)	(2.654)				
$Mortgages/GDP_{t-1}$					3.357**	3.635***		
					(2.535)	(3.030)		
LDR_{t-1}							1.433**	1.519*
							(2.165)	(1.764)
Observations	89	86	87	86	87	86	86	86
R-squared	0.151	0.187	0.194	0.235	0.211	0.248	0.204	0.222
Macro Controls	No	Yes	No	Yes	No	Yes	No	Yes

Table 8. Validation of CRI Against Alternative Measures

This table presents regression results validating the Credit Regulation Index (CRI) against alternative regulatory measures. The dependent variable is bank failures across all specifications. $FinLib_{t-1}$ represents the Demirgüç-Kunt and Detragiache (1998) financial liberalization index, $FinReform_{t-1}$ is the IMF financial reform index from Abiad, Detragiache and Tressel (2010), and $ISBRI_{t-1}$ is the bank branching restriction index from Kroszner and Strahan (1999). Control variables include GDP growth, inflation, and short-term interest rate, all lagged by one year. Newey and West (1987) robust z-statistics with 12 lags are shown in parentheses.

	$BankFailures_t$				
	(1)	(2)	(3)	(4)	(5)
$\Delta_{t-10\rightarrow t-5}CRI$	-2.494**	-2.515**	-1.368**	-2.197**	-2.319***
	(-2.261)	(-2.258)	(-2.213)	(-2.412)	(-2.896)
$FinLib_{t-1}$		0.598*	0.892***	1.087***	0.760***
		(1.738)	(3.012)	(4.928)	(5.516)
$FinReform_{t-1}$			-0.031*	-0.429***	-0.522***
			(-1.699)	(-3.288)	(-3.709)
$ISBRI_{t-1}$				-0.077***	-0.092***
				(-3.446)	(-3.060)
ΔGDP_{t-1}					-0.066*
					(-1.669)
π_{t-1}					-0.053
					(-1.163)
r_{t-1}					0.114**
					(2.016)
Sample	1935-2023	1935-2023	1973-2005	1973-2005	1973-2005
Observations	89	89	33	33	33
R-squared	0.151	0.182	0.317	0.584	0.636

A Appendix

Measuring Bank Regulations: A Text-Based Approach

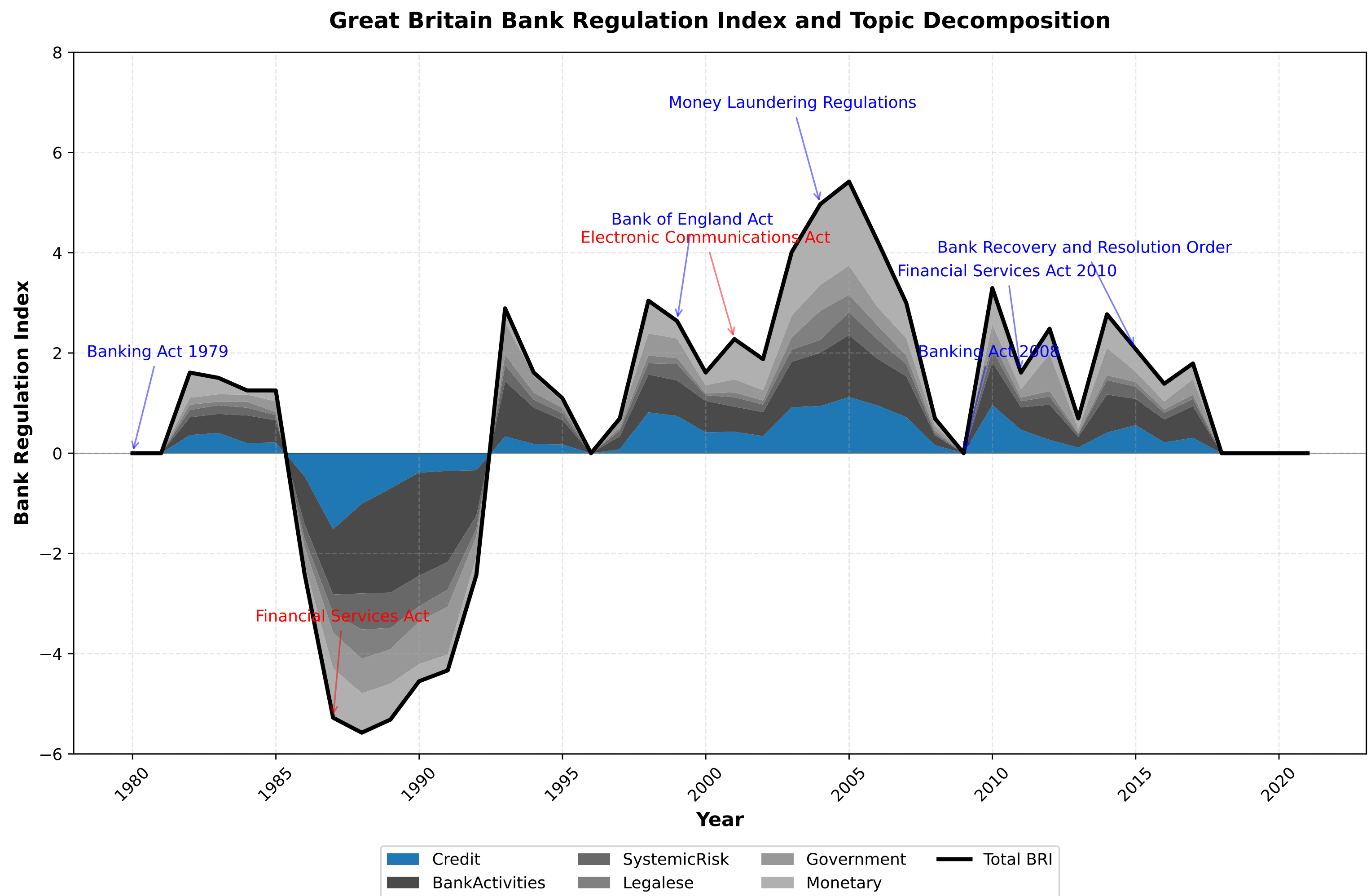


Figure A1. Great Britain - Bank Regulation Index & LDA-based Decomposition. This figure plots the Great Britain BRI. The BRI is constructed using the newspaper coverage (Table A3) of statutory banking laws (Appendix A). The text of news corpus is decomposed into different topics using Latent Dirichlet Allocation (LDA). The LDA preprocessing steps include tokenization, removal of stopwords and special characters, and lemmatization using NLTK and spaCy libraries. Using gensim.LdaModel, I obtain probability weights $w_{i,t}$ for each article i over topic t. The topic-specific Bank Regulation Index for year T is then:

$$BRI_{t,T} = BRI_T \times \left(\frac{\sum_{i \in T} w_{i,t}}{N_{i \in T}} \right)$$

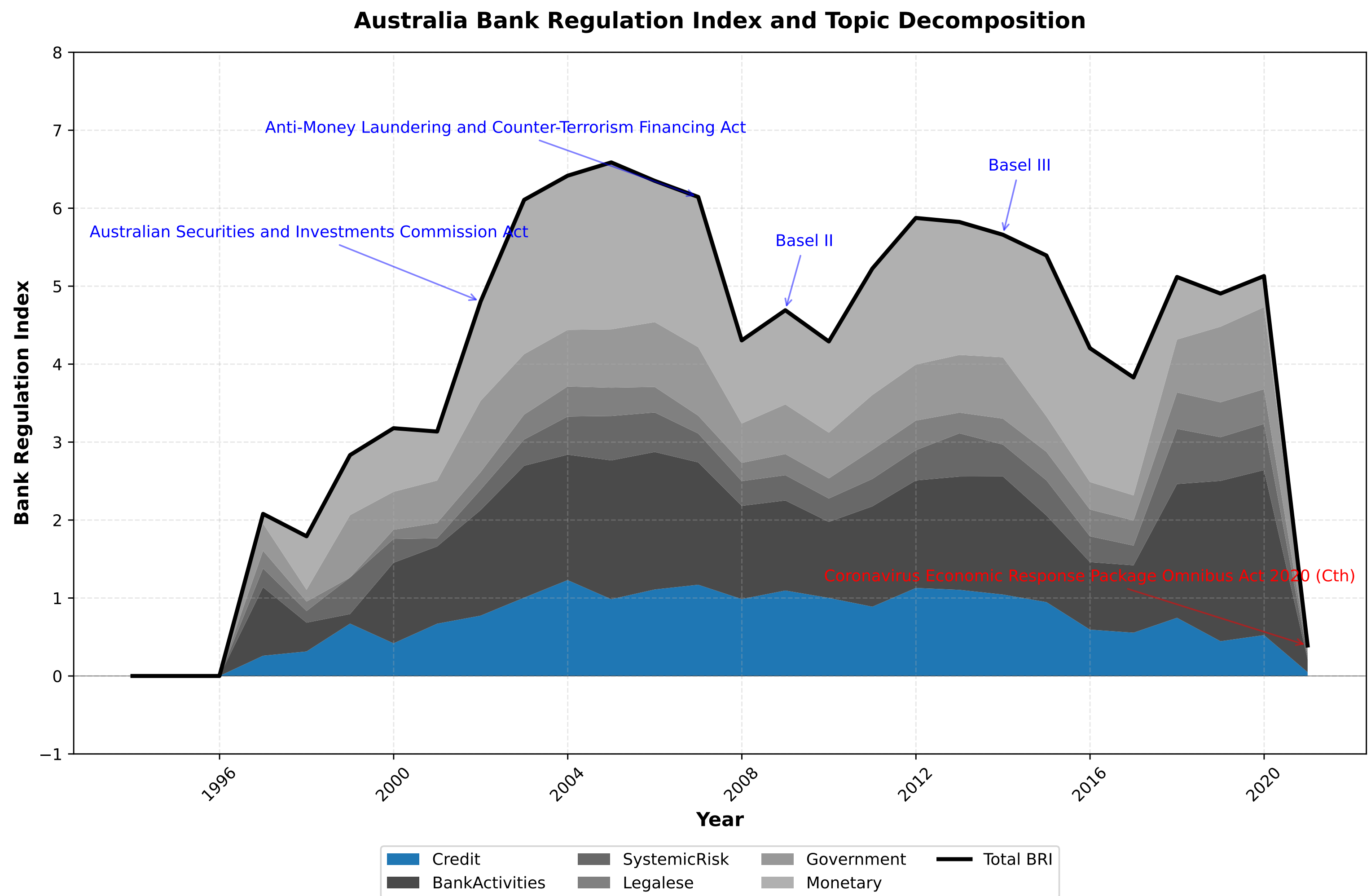


Figure A1. Australia - Bank Regulation Index & LDA-based Decomposition. This figure plots the Australia BRI. The BRI is constructed using the newspaper coverage (Table A3) of statutory banking laws (Appendix A). The text of news corpus is decomposed into different topics using Latent Dirichlet Allocation (LDA). The LDA preprocessing steps include tokenization, removal of stopwords and special characters, and lemmatization using NLTK and spaCy libraries. Using gensim.LdaModel, I obtain probability weights $w_{i,t}$ for each article i over topic t. The topic-specific Bank Regulation Index for year T is then:

$$BRI_{t,T} = BRI_T \times \left(\frac{\sum_{i \in T} w_{i,t}}{N_{i \in T}} \right)$$

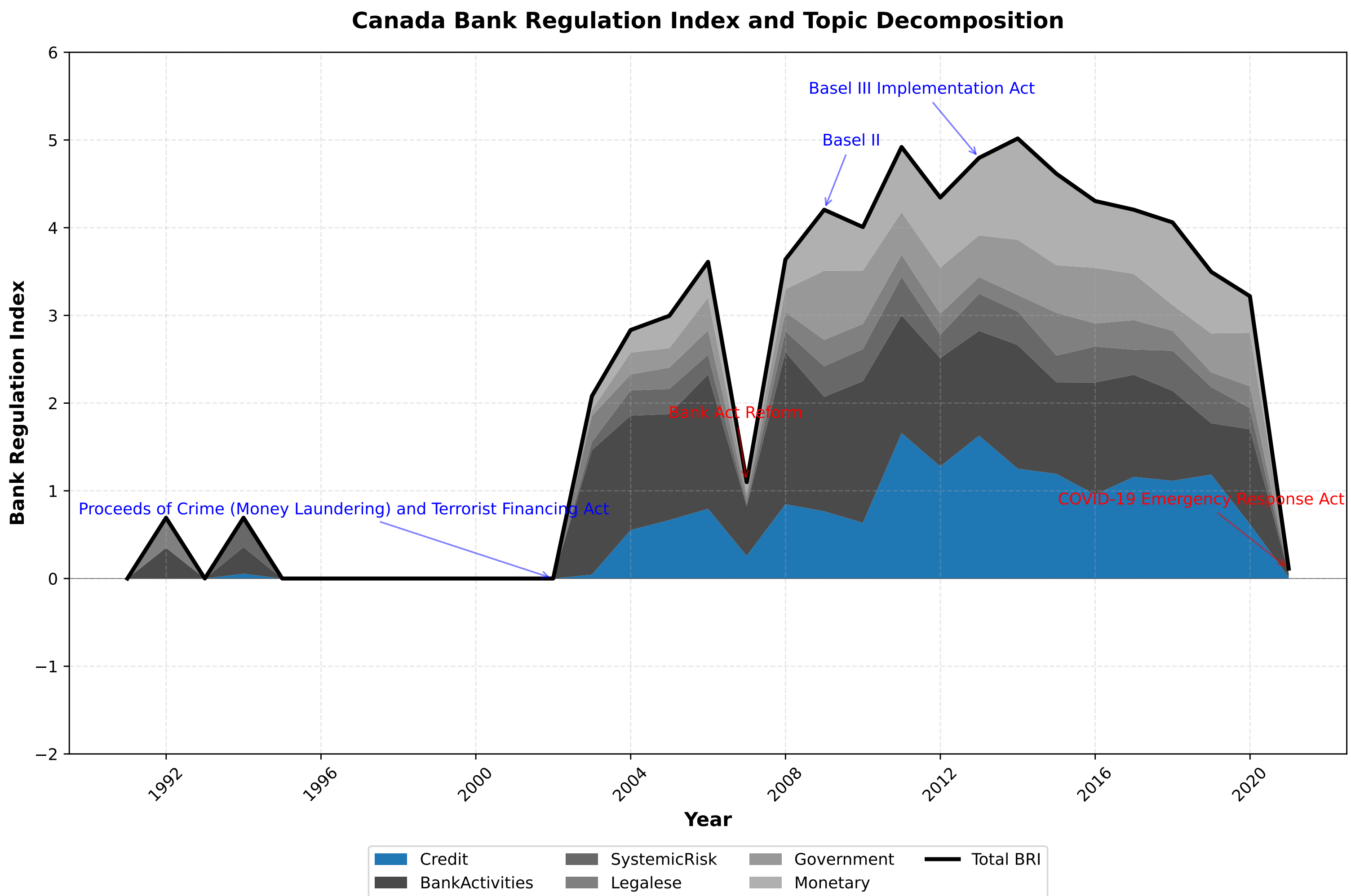


Figure A1. Canada - Bank Regulation Index & LDA-based Decomposition. This figure plots the Canada BRI. The BRI is constructed using the newspaper coverage (Table A3) of statutory banking laws (Appendix A). The text of news corpus is decomposed into different topics using Latent Dirichlet Allocation (LDA). The LDA preprocessing steps include tokenization, removal of stopwords and special characters, and lemmatization using NLTK and spaCy libraries. Using gensim.LdaModel, I obtain probability weights $w_{i,t}$ for each article i over topic t. The topic-specific Bank Regulation Index for year T is then:

$$BRI_{t,T} = BRI_T \times \left(\frac{\sum_{i \in T} w_{i,t}}{N_{i \in T}} \right)$$

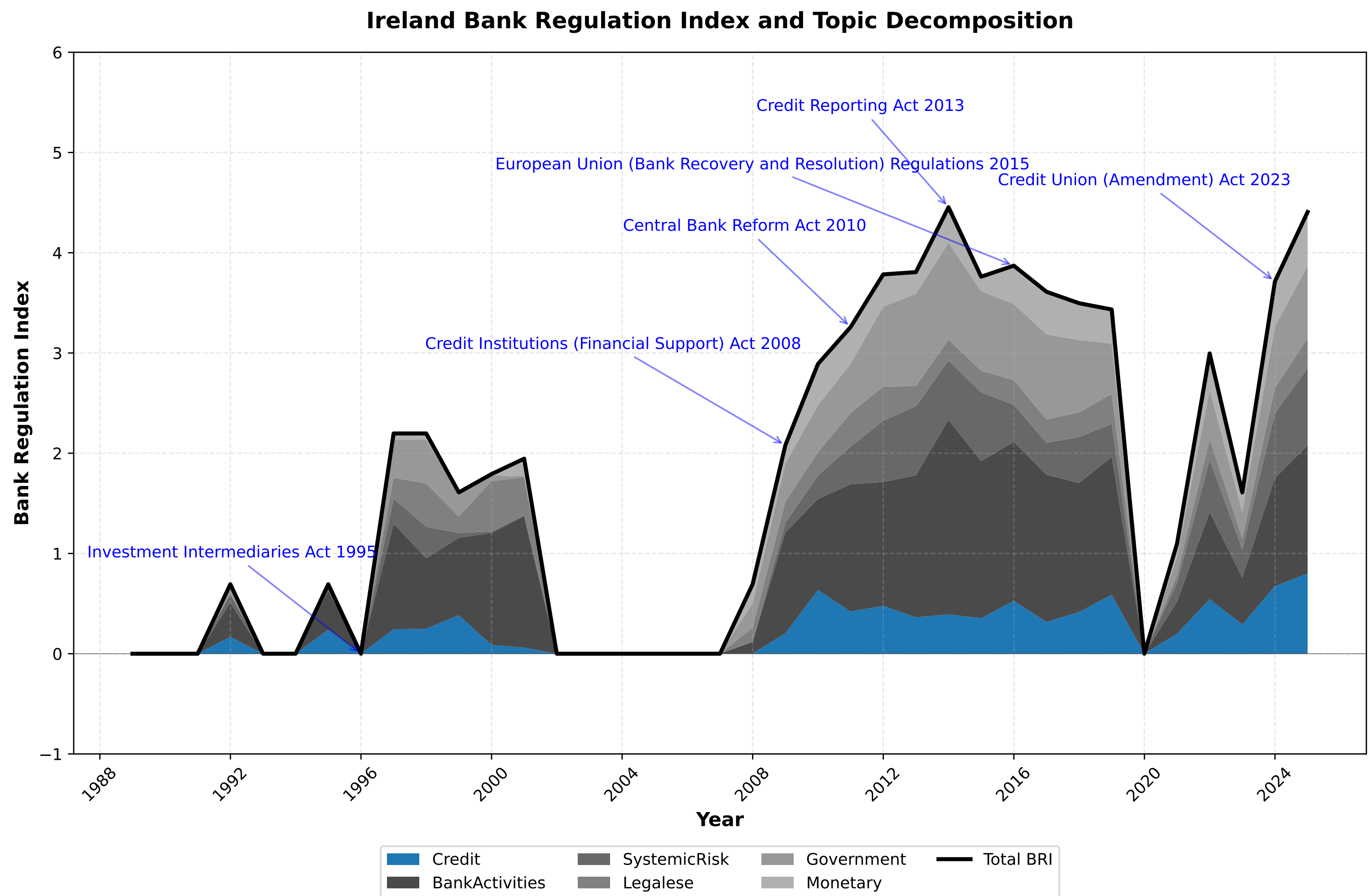


Figure A1. Ireland - Bank Regulation Index & LDA-based Decomposition. This figure plots the Ireland BRI. The BRI is constructed using the newspaper coverage (Table A3) of statutory banking laws (Appendix A). The text of news corpus is decomposed into different topics using Latent Dirichlet Allocation (LDA). The LDA preprocessing steps include tokenization, removal of stopwords and special characters, and lemmatization using NLTK and spaCy libraries. Using gensim.LdaModel, I obtain probability weights $w_{i,t}$ for each article i over topic t. The topic-specific Bank Regulation Index for year T is then:

$$BRI_{t,T} = BRI_T \times \left(\frac{\sum_{i \in T} w_{i,t}}{N_{i \in T}} \right)$$

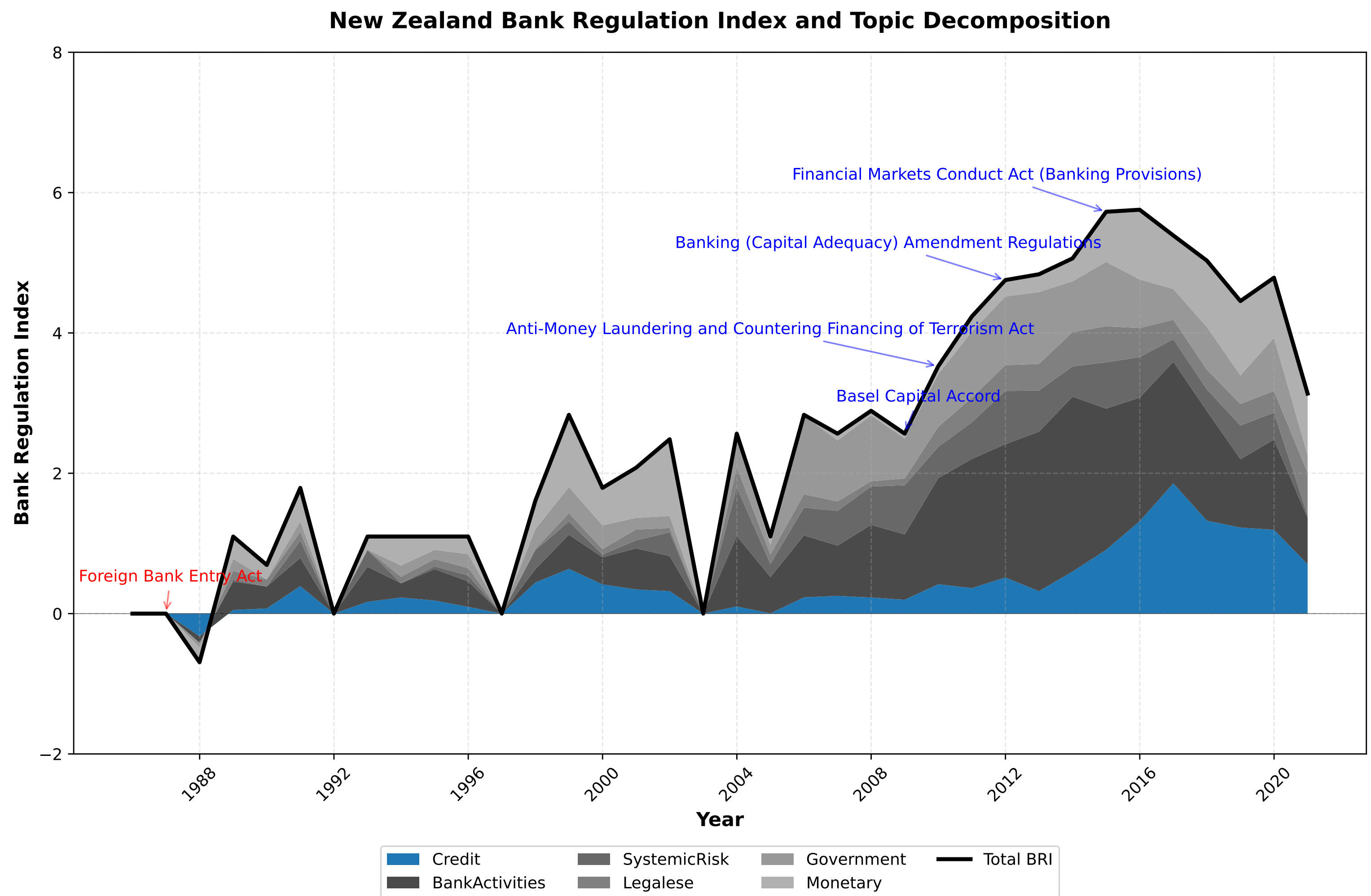


Figure A1. New Zealand - Bank Regulation Index & LDA-based Decomposition. This figure plots the New Zealand BRI. The BRI is constructed using the newspaper coverage (Table A3) of statutory banking laws (Appendix A). The text of news corpus is decomposed into different topics using Latent Dirichlet Allocation (LDA). The LDA preprocessing steps include tokenization, removal of stopwords and special characters, and lemmatization using NLTK and spaCy libraries. Using gensim.LdaModel, I obtain probability weights $w_{i,t}$ for each article i over topic t. The topic-specific Bank Regulation Index for year T is then:

$$BRI_{t,T} = BRI_T \times \left(\frac{\sum_{i \in T} w_{i,t}}{N_{i \in T}} \right)$$

Table A1. List of Banking Laws

This table presents compilation of banking and financial regulatory laws across multiple countries, including the United States, United Kingdom, Ireland, New Zealand, Australia, and Canada. For each law, the table indicates the country of origin, year of enactment, full name of the legislation (including common abbreviations), and whether the law is classified as regulatory or deregulatory in nature. Regulatory laws increase government influence over the banking sector, while deregulatory laws provide banks with greater power and flexibility. The US laws are compiled based on Tabor et al. (2021) and Conti-Brown and Ohlrogge (2022). This compilation forms the foundation for the bank regulation index discussed in Section 1.1.

Country	Year	Law Name	Type
US	1927	McFadden Act	Regulatory
US	1932	Federal Home Loan Bank Act; FHLBA	Regulatory
US	1933	Emergency Banking Relief Act	Regulatory
US	1933	State Bank Aid Act	Regulatory
US	1933	Banking Act of 1933; Glass-Steagall	Regulatory
US	1934	Federal Credit Union Act	Regulatory
US	1935	Banking Act of 1935	Regulatory
US	1939	Export-Import Bank Extension Act	Regulatory
US	1939	Glass Federal Reserve Note Act	Regulatory
US	1945	Export-Import Bank Act of 1945	Regulatory
US	1950	Federal Deposit Insurance Act; FDIA	Regulatory
US	1956	Bank Holding Company Act of 1956; BHCA, BHC Act	Regulatory
US	1959	Spence Act (Savings and Loan Holding Companies); Spence Act	Regulatory
US	1962	Bank Service Company Act; BSCA	Regulatory
US	1966	Financial Institutions Supervisory Act of 1966; FISA	Regulatory
US	1968	Truth in Lending Act; TILA	Regulatory
US	1968	Bank Protection Act of 1968	Regulatory
US	1970	Bank Secrecy Act of 1970	Regulatory
US	1970	Bank Holding Company Act Amendments of 1970; BHCA	Regulatory
US	1973	Federal Financing Bank Act of 1973	Regulatory
US	1974	Real Estate Settlement Procedures Act of 1974; RESPA	Regulatory
US	1977	Community Reinvestment Act; Housing and Community Development Act of 1977	Regulatory
US	1977	Federal Reserve Reform Act of 1977; FRRA	Regulatory
US	1978	International Banking Act of 1978	Regulatory
US	1978	Financial Institutions Regulatory and Interest Rate Control Act of 1978; FIRA	Regulatory
US	1980	Monetary Control Act of 1980; DIDMCA, Depository Institutions Deregulation Act of 1980	Deregulatory
US	1981	Cash Discount Act	Deregulatory
US	1981	International Banking Facility Deposit Insurance Act	Deregulatory
US	1982	Export Trading Company Act of 1982	Deregulatory
US	1982	Garn-St Germain Depository Institutions Act of 1982; Garn-St Germain Act, Garn Act	Deregulatory
US	1987	Competitive Equality Banking Act of 1987; CEBA	Regulatory
US	1989	Financial Institutions Reform, Recovery, and Enforcement Act of 1989; FIRREA	Regulatory
US	1991	Resolution Trust Corporation Refinancing, Restructuring, and Improvement Act of 1991	Regulatory
US	1991	Federal Deposit Insurance Corporation Improvement Act of 1991; FDICIA, Truth in Savings Act	Regulatory
US	1994	Riegle Community Development and Regulatory Improvement Act of 1994	Deregulatory
US	1994	Riegle-Neal Interstate Banking and Branching Efficiency Act of 1994; Interstate Act, Riegle-Neal	Deregulatory
US	1996	Deposit Insurance Funds Act of 1996	Deregulatory
US	1997	Riegle-Neal Amendments Act of 1997	Regulatory
US	1999	Gramm-Leach-Bliley Act; GLB Act, GLBA	Deregulatory

Continued on next page

Country	Year	Law Name	Type
US	2002	FHA Downpayment Simplification Act of 2002	Regulatory
US	2003	Check Clearing for the 21st Century Act; Check 21 Act	Deregulatory
US	2005	Bankruptcy Abuse Prevention and Consumer Protection Act of 2005; BAPCPA	Deregulatory
US	2006	Financial Services Regulatory Relief Act of 2006; FSRRA	Deregulatory
US	2009	Credit CARD Act of 2009; CARD Act	Regulatory
US	2010	Dodd-Frank Wall Street Reform and Consumer Protection Act; Dodd-Frank	Regulatory
US	2014	Insurance Capital Standards Clarification Act of 2014; Insurance Capital Standards Clarification Act	Deregulatory
US	2014	American Savings Promotion Act	Deregulatory
US	2018	Economic Growth, Regulatory Relief, and Consumer Protection Act; EGRRCPA	Deregulatory
US	2019	RBIC Advisers Relief Act of 2018; RBIC Advisers Relief Act	Deregulatory
UK	1935	Bank Notes Act; Bank Notes (Scotland) Act 1935	Regulatory
UK	1946	Bank of England Act; Bank of England Act 1946	Regulatory
UK	1947	Exchange Control Act; Exchange Control Act 1947	Regulatory
UK	1954	Bank Notes Act	Regulatory
UK	1956	Finance Act	Regulatory
UK	1963	Protection of Depositors Act	Regulatory
UK	1969	Bank of England Act Amendment	Regulatory
UK	1979	Banking Act 1979	Regulatory
UK	1986	Financial Services Act	Deregulatory
UK	1986	Building Societies Act	Deregulatory
UK	1987	Banking Act 1987	Regulatory
UK	1992	Banking Coordination Regulations; Banking Coordination (Second Council Directive) Regulations	Deregulatory
UK	1998	Bank of England Act	Regulatory
UK	2000	Financial Services and Markets Act	Regulatory
UK	2000	Electronic Communications Act	Deregulatory
UK	2001	Anti-Terrorism, Crime and Security Act	Regulatory
UK	2003	Money Laundering Regulations	Regulatory
UK	2008	Banking Act 2008; Banking (Special Provisions) Act	Regulatory
UK	2008	Counter-Terrorism Act	Regulatory
UK	2009	Banking Act 2009	Regulatory
UK	2010	Financial Services Act 2010	Regulatory
UK	2012	Financial Services Act 2012	Regulatory
UK	2013	Financial Services Act 2013; Financial Services (Banking Reform) Act	Regulatory
UK	2014	Bank Recovery and Resolution Order	Regulatory
UK	2017	Payment Services Regulations	Regulatory
Ireland	1971	Central Bank Act 1971; Banking Licence Act	Regulatory
Ireland	1985	Finance Act 1985; Tax Compliance Act	Regulatory
Ireland	1989	Central Bank Act 1989; Banking Control Act	Regulatory
Ireland	1995	Investment Intermediaries Act 1995; Investment Services Act	Regulatory
Ireland	2007	Markets in Financial Instruments and Miscellaneous Provisions Act 2007; MiFID I Implementation Act	Regulatory
Ireland	2008	Credit Institutions (Financial Support) Act 2008	Regulatory
Ireland	2009	Anglo Irish Bank Corporation Act 2009; Anglo Nationalization Act	Regulatory
Ireland	2009	Financial Emergency Measures in the Public Interest Act 2009; Banking Stabilization Act	Regulatory
Ireland	2010	Criminal Justice (Money Laundering and Terrorist Financing) Act 2010; AML Legislation	Regulatory
Ireland	2010	Central Bank Reform Act 2010; Unified Regulator Act	Regulatory
Ireland	2012	Consumer Protection Code 2012; Amended 2024	Regulatory
Ireland	2013	Credit Reporting Act 2013; Credit Bureau Act	Regulatory
Ireland	2013	Central Bank (Supervision and Enforcement) Act 2013; Enhanced Powers Act	Regulatory
Ireland	2015	European Union (Bank Recovery and Resolution) Regulations 2015; BRRD Implementation	Regulatory

Continued on next page

Country	Year	Law Name	Type
Ireland	2021	Criminal Justice (Money Laundering and Terrorist Financing) Amendment Act 2021; AML Amendment Act	Regulatory
Ireland	2023	Central Bank (Individual Accountability Framework) Act 2023; SEAR/IAF Act	Regulatory
Ireland	2023	Credit Union (Amendment) Act 2023; Credit Union Modernization Act	Regulatory
Ireland	2023	Screening of Third Country Transactions Act 2023; Foreign Investment Screening Act	Regulatory
Ireland	2023	Consumer Protection Code (Revised 2024); CPC 2024	Regulatory
Ireland	2024	Finance Act 2024; Pillar Two Implementation Act	Regulatory
New Zealand	1986	Foreign Bank Entry Act; Reserve Bank of New Zealand Amendment Act 1986	Deregulatory
New Zealand	1989	Reserve Bank of New Zealand Act 1989; The Central Bank Independence Act	Regulatory
New Zealand	1991	Banking Supervision Amendment Act; The Disclosure Regime Act	Regulatory
New Zealand	1995	Banking (Capital Adequacy) Regulations; The Capital Rules	Regulatory
New Zealand	1996	Payment Systems and Netting Act 1996; The Settlement Act	Regulatory
New Zealand	2001	Anti-Money Laundering Guidelines Act; The AML Act	Regulatory
New Zealand	2003	Reserve Bank Amendment Act 2003; The Bank Registration Act	Regulatory
New Zealand	2008	Basel Capital Accord; Basel II	Regulatory
New Zealand	2008	Reserve Bank Amendment Act 2008	Regulatory
New Zealand	2009	Anti-Money Laundering and Countering Financing of Terrorism Act; The Enhanced AML Act	Regulatory
New Zealand	2010	Banking (Liquidity Requirements) Order; The Liquidity Rules	Regulatory
New Zealand	2011	Banking (Capital Adequacy) Amendment Regulations; The Basel III Rules	Regulatory
New Zealand	2013	Non-bank Deposit Takers Act; The NBDT Act	Regulatory
New Zealand	2014	Financial Markets Conduct Act (Banking Provisions); The Conduct Rules	Regulatory
New Zealand	2016	Banking (Outsourcing) Policy; The Outsourcing Rules	Regulatory
New Zealand	2017	Banking (Capital Review) Framework; The Capital Review	Regulatory
New Zealand	2018	Financial Services Legislation Amendment Act; The Financial Advice Act	Regulatory
New Zealand	2020	Financial Market Infrastructures Act; The FMI Act	Regulatory
New Zealand	2022	Financial Markets (Conduct of Institutions) Amendment Act; The Conduct of Institutions Act	Regulatory
New Zealand	2023	Deposit Takers Act 2023; The Deposit Takers Act	Regulatory
Australia	1975	Foreign Acquisitions and Takeovers Act; FATA	Regulatory
Australia	1998	Payment Systems (Regulation) Act; PSRA	Regulatory
Australia	1998	Australian Prudential Regulation Authority Act	Regulatory
Australia	2001	Australian Securities and Investments Commission Act	Regulatory
Australia	2001	Corporations Act	Regulatory
Australia	2001	Financial Services Reform Act	Regulatory
Australia	2006	Anti-Money Laundering and Counter-Terrorism Financing Act	Regulatory
Australia	2007	Financial Sector Legislation Amendment (Simplifying Regulation and Review) Act	Regulatory
Australia	2008	Basel II	Regulatory
Australia	2011	Stronger Super Reform Package	Regulatory
Australia	2012	Treasury Legislation Amendment (Unclaimed Money and Other Measures) Act	Regulatory
Australia	2013	Basel III	Regulatory
Australia	2018	Treasury Laws Amendment (Banking Executive Accountability Regime) Act	Regulatory
Australia	2019	Treasury Laws Amendment (Design and Distribution Obligations and Product Intervention Powers) Act	Regulatory
Australia	2019	Financial Sector Reform (Hayne Royal Commission Response) Act	Regulatory
Australia	2020	Coronavirus Economic Response Package Omnibus Act	Deregulatory
Australia	2022	Financial Accountability Regime Bill	Regulatory
Australia	2024	Financial Market Infrastructure Regulatory Reforms	Regulatory
Canada	1992	Office of the Superintendent of Financial Institutions Act; OSFI Act	Regulatory
Canada	2001	Proceeds of Crime (Money Laundering) and Terrorist Financing Act; PCMLTFA	Regulatory
Canada	2002	Financial Consumer Protection Framework; FCAC Act	Regulatory
Canada	2006	Bank Act Reform	Deregulatory
Canada	2008	Basel II	Regulatory
Canada	2010	Payment Card Networks Act; PCNA	Regulatory
Canada	2012	Basel III Implementation Act	Regulatory

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Country	Year	Law Name	Type
Canada	2012	Financial System Review Act	Regulatory
Canada	2016	Bank Recapitalization (Bail-in) Regime	Regulatory
Canada	2018	New Financial Consumer Protection Framework	Regulatory
Canada	2020	COVID-19 Emergency Response Act	Deregulatory
Canada	2021	Retail Payments Activities Act; RPAA	Regulatory
Canada	2021	Consumer Privacy Protection Act	Regulatory
Canada	2022	Financial Innovation Act	Deregulatory
Canada	2024	Criminal Interest Rate Amendment; Usury Reform Act	Regulatory

Table A2. 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
SystemicRisk	Dodd-Frank Wall Street Reform and Consumer Protection Act of 2010	0.63
	Economic Growth, Regulatory Relief, and Consumer Protection Act of 2018	0.47
	Financial Services Regulatory Relief Act of 2006	0.52
Credit	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 A3. Newspaper Sources by Country

This table documents the comprehensive newspaper sources used to construct the Bank Regulation Index (BRI) for each of the six countries in our panel. For the United States analysis, we collected articles from six major national newspapers through ProQuest, while for the United Kingdom, Canada, Ireland, Australia, and New Zealand, we gathered comparable media coverage through Factiva. This multi-country approach ensures consistent application of our text-based methodology across different institutional environments while maintaining appropriate coverage of each country's financial news landscape. The diversity of sources helps capture the full spectrum of regulatory discussions in each national context.

Country	Newspapers	Source
US	Chicago Tribune, Los Angeles Times, New York Times, USA Today, Wall Street Journal, The Washington Post	ProQuest
UK	The Times, The Daily Telegraph, The Guardian, Daily Mail, Financial Times	Factiva
CA	The Globe and Mail, Canada NewsWire, CBC.ca, Mondaq Business Briefing, National Post	Factiva
IE	The Irish Times, Irish Independent, Mondaq Business Briefing, The Irish Examiner, RTE.ie	Factiva
AU	The Australian Financial Review, The Australian, The Sydney Morning Herald, Australian Government News, Mondaq Business Briefing	Factiva
NZ	New Zealand Exchange Company Announcements, The New Zealand Herald, Reuters, Scoop.co.nz, The Press, Dominion Post, Fuseworks Media, ForeignAffairs.co.nz, BusinessDesk, Waikato Times	Factiva

Table A4. Decomposing BRI: Credit Regulations and Crisis Prediction

This table examines how different components of banking regulation predict financial crises. The dependent variable in all specifications is the JST banking crisis indicator from Jordà et al. (2017). Column (1) shows the baseline specification with the Bank Regulation Index (BRI). Columns (2)-(7) decompose BRI into specific regulatory topics identified through Latent Dirichlet Allocation: Credit, Legalese, Bank Activities, Monetary, Systemic Risk, and Government (see Appendix B for details). $\Delta_{t-10\to t-5}BRI$ represents the change in BRI from t-10 to t-5. $\Delta_{t-10\to t-5}Topic$ represents the change in the specific topic component from t-10 to t-5. Control variables include lagged GDP growth ($\Delta GDP_{i,t-1}$), lagged short-term interest rate ($r_{i,t-1}$), and lagged inflation ($\pi_{i,t-1}$). All specifications include country fixed effects. Robust z-statistics are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

	(1) BRI	(2) Credit	(3) Legalese	(4) Activities	(5) Monetary	(6) S. Risk	(7) Government
$\Delta_{t-10\to t-5}Topic$	-1.189*	-4.545**	-9.330**	-1.723	-2.328	-7.267	-6.855*
	(-1.701)	(-2.160)	(-2.092)	(-0.726)	(-0.552)	(-1.258)	(-1.828)
$\Delta GDP_{i,t-1}$	0.002	-0.002	-0.002	-0.008	-0.005	0.002	-0.002
	(0.052)	(-0.069)	(-0.071)	(-0.256)	(-0.101)	(0.049)	(-0.063)
$r_{i,t-1}$	0.152*	0.152*	0.151*	0.175*	0.146	0.152*	0.155*
	(1.839)	(1.803)	(1.745)	(1.771)	(1.610)	(1.791)	(1.802)
$\pi_{i,t-1}$	0.026	0.061	-0.010	-0.011	0.064	0.026	0.020
	(0.261)	(0.561)	(-0.084)	(-0.090)	(0.501)	(0.261)	(0.192)
Observations	210	210	210	210	210	210	210
AUC	0.778	0.811	0.816	0.794	0.741	0.801	0.782

Table A5. Credit Regulation and Financial Crisis Prediction

This table presents logistic regression results examining how changes in Credit Regulation Index (CRI) predict future financial crises. Dependent variables are binary indicators for different types of financial crises: JST banking crisis (columns 1-2), BVX bank failure crisis (columns 3-4), and LV banking crisis (columns 5-6). The Credit Regulation Index (CRI) is constructed by decomposing the text of newspaper coverage into granular regulatory topics, using topic modeling with Latent Dirichlet Allocation (LDA), for statutory banking regulations from 6 countries: United States, Great Britain, New Zealand, Australia, Ireland and Canada (see Appendix B for details). $\Delta_{i,t-10\to t-5}CRI$ represents the change in CRI from t-10 to t-5 for country i. JST refers to Jordà et al. (2017) database, BVX refers to Baron et al. (2021) database, and LV refers to Laeven and Valencia (2012) database. Control variables include lagged GDP growth ($\Delta GDP_{i,t-1}$), lagged inflation ($\pi_{i,t-1}$), and lagged short-term interest rate ($r_{i,t-1}$). Robust z-statistics clustered by year are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

	JST Banking Crisis		BVX Banking Failure		LV Banking Crisis	
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta_{i,t-10\to t-5}CRI$	-4.834**	-4.545**	-4.212**	-4.478**	-4.188***	-3.904**
	(-2.251)	(-2.274)	(-2.152)	(-2.238)	(-2.776)	(-2.533)
$\Delta GDP_{i,t-1}$		-0.005		-0.097		0.011
		(-0.104)		(-0.815)		(0.348)
$r_{i,t-1}$		0.154*		0.262*		-0.036
		(1.831)		(1.649)		(-0.328)
$\pi_{i,t-1}$		0.069		-0.224		0.092
		(0.546)		(-0.989)		(0.447)
Observations	210	210	210	201	132	123
AUC	0.678	0.811	0.711	0.741	0.768	0.779

Table A6. Credit Regulation and Financial Crisis Prediction with Country Fixed Effects

This table presents logistic regression results examining how changes in Credit Regulation Index (CRI) predict future financial crises with country fixed effects. Dependent variables are binary indicators for different types of financial crises: JST banking crisis (columns 1-2), BVX bank failure crisis (columns 3-4), and LV banking crisis (columns 5-6). The Credit Regulation Index (CRI) is constructed by decomposing the text of newspaper coverage into granular regulatory topics, using topic modeling with Latent Dirichlet Allocation (LDA), for statutory banking regulations from 6 countries: United States, Great Britain, New Zealand, Australia, Ireland and Canada (see Appendix B for details). $\Delta_{i,t-10\rightarrow t-5}CRI$ represents the change in CRI from t-10 to t-5 for country i. Control variables include lagged GDP growth ($\Delta GDP_{i,t-1}$), lagged inflation ($\pi_{i,t-1}$), and lagged short-term interest rate ($r_{i,t-1}$). JST refers to Jordà et al. (2017) database, BVX refers to Baron et al. (2021) database, and LV refers to Laeven and Valencia (2012) database. Country fixed effects are included in all specifications. Standard errors using Driscoll-Kraay methodology Driscoll and Kraay (1998) with 10-period lag structure are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

	JST Banking Crisis		BVX Banking Failure		LV Banking Crisis	
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta_{i,t-10\rightarrow t-5}CRI$	-0.119*	-0.096	-0.142*	-0.118*	-0.125**	-0.126**
	(-1.944)	(-1.634)	(-1.901)	(-1.719)	(-2.644)	(-2.125)
$\Delta GDP_{i,t-1}$		-0.000		-0.004		-0.001
		(-0.448)		(-1.563)		(-0.772)
$r_{i,t-1}$		0.005**		0.009**		-0.001
		(2.414)		(2.542)		(-0.464)
$\pi_{i,t-1}$		0.002		-0.006		0.002
		(0.575)		(-0.832)		(0.351)
Observations	210	210	210	201	132	123
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
AUC	0.678	0.816	0.710	0.732	0.768	0.779

Table A7. Credit Regulation Impact on Credit Growth

This table presents regression results examining how changes in Credit Regulation Index (CRI) predict future changes in loans and mortgages as a percentage of GDP. The dependent variables are loans-to-GDP ratio ($Loans/GDP$) in columns 1-3 and mortgages-to-GDP ratio ($Mortgages/GDP$) in columns 4-6. $\Delta_{t-5\rightarrow t}CRI$ represents the 5-year change in the credit component of the regulation index. $\Delta_{t-5\rightarrow t}BRI$ represents the 5-year change in the overall Bank Regulation Index. Control variables include lagged GDP growth ($\Delta GDP_{i,t-1}$), lagged short-term interest rate ($r_{i,t-1}$), and lagged inflation ($\pi_{i,t-1}$). All specifications include country fixed effects. Columns 2, 3, 5, and 6 also include year fixed effects. Standard errors clustered by year are shown in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

	$Loans/GDP$			$Mortgages/GDP$		
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta_{i,t-5\rightarrow t}CRI$	-0.024**	-0.035***	-0.058*	-0.014*	-0.014*	-0.027*
	(-2.046)	(-2.965)	(-1.778)	(-1.700)	(-1.893)	(-1.734)
$\Delta_{i,t-5\rightarrow t}BRI$			0.039			0.022
			(0.838)			(0.931)
$\Delta GDP_{i,t-1}$	-0.016***	-0.014**	-0.014**	-0.009***	-0.006**	-0.006**
	(-4.190)	(-2.472)	(-2.276)	(-4.181)	(-2.569)	(-2.267)
$r_{i,t-1}$	-0.024***	-0.009	-0.008	-0.020***	-0.009	-0.008
	(-5.399)	(-0.773)	(-0.728)	(-7.027)	(-1.478)	(-1.460)
$\pi_{i,t-1}$	0.021*	0.009	0.008	0.012*	0.001	0.001
	(1.978)	(0.486)	(0.437)	(1.946)	(0.158)	(0.091)
Observations	255	200	200	255	200	200
R-squared	0.719	0.782	0.782	0.656	0.793	0.793
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	No	Yes	Yes	No	Yes	Yes

Table A8. Predicting Bank Failures: Lags of Credit Regulation Index

This table presents a regression model where the dependent variable is $BankFailures_t$, defined as the percentage of deposits in failed banks over total deposits in year t. The table includes different lags of changes in credit indicators (denoted as CRI) and macroeconomic variables as explanatory variables. Newey and West (1987) robust z-statistics with 12 lags are shown in parentheses.

	$BankFailures_t$					
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta_{2\to7}CRI$	0.375					
	(0.457)					
$\Delta_{3\to8}CRI$		0.117				
		(0.242)				
$\Delta_{4\to9}CRI$			-1.313			
			(-1.631)			
$\Delta_{5\to10}CRI$				-2.647**		
				(-2.386)		
$\Delta_{6\to11}CRI$					-2.076***	
					(-3.061)	
$\Delta_{7\to12}CRI$						-2.338***
						(-2.734)
Observations	89	88	87	86	85	84
R-squared	0.134	0.132	0.071	0.187	0.127	0.152
Macro Controls	Yes	Yes	Yes	Yes	Yes	Yes

Table A9. Credit Regulation, Credit Growth, and Financial Crisis Prediction

This table presents logistic regression results examining how changes in Credit Regulation Index (CRI) and loan-to-GDP ratios predict future financial crises. Dependent variables are binary indicators for different types of financial crises: JST banking crisis (columns 1-2), BVX bank failure crisis (columns 3-4), and LV banking crisis (columns 5-6). The Credit Regulation Index (CRI) is constructed by decomposing the text of newspaper coverage into granular regulatory topics, using topic modeling with Latent Dirichlet Allocation (LDA), for statutory banking regulations from 6 countries: United States, Great Britain, New Zealand, Australia, Ireland and Canada (see Appendix B for details). $\Delta_{i,t-10\rightarrow t-5}CRI$ represents the change in CRI from t-10 to t-5 for country i. $\Delta_{i,t-5\rightarrow t}Loans/GDP$ represents the 5-year change in loans-to-GDP ratio. Control variables include lagged GDP growth ($\Delta GDP_{i,t-1}$), lagged inflation ($\pi_{i,t-1}$), and lagged short-term interest rate ($r_{i,t-1}$). JST refers to Jordà et al. (2017) database, BVX refers to Baron et al. (2021) database, and LV refers to Laeven and Valencia (2012) database. Robust z-statistics clustered by year are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

	JST Banking Crisis		BVX Banking Failure		LV Banking Crisis	
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta_{i,t-10\rightarrow t-5}CRI$	-5.232**	-5.058**	-4.577**	-5.072*	-4.699**	-4.810**
	(-2.146)	(-2.050)	(-2.033)	(-1.958)	(-2.487)	(-2.364)
$\Delta_{i,t-6\rightarrow t-1}Loans/GDP$	4.895**	5.784**	4.694**	5.522**	4.384**	5.087**
	(2.332)	(2.214)	(2.423)	(2.378)	(1.995)	(2.062)
$\Delta GDP_{i,t-1}$		0.079		0.044		0.101
		(1.082)		(0.485)		(1.401)
$r_{i,t-1}$		0.152**		0.256**		-0.031
		(1.962)		(2.045)		(-0.371)
$\pi_{i,t-1}$		-0.006		-0.323		-0.029
		(-0.062)		(-1.508)		(-0.220)
Observations	210	210	210	201	132	123
AUC	0.781	0.822	0.779	0.809	0.865	0.845

B Topical Decomposition with Latent Dirichlet Allocation (LDA)

LDA is an unsupervised machine-learning method. 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 employs TF-IDF (Term Frequency-Inverse Document Frequency), a numerical measure that assesses the relative importance of words in a document corpus. This technique combines two components: the Term Frequency (TF), which counts how frequently a term appears in a document, and the Inverse Document Frequency (IDF), which measures how unique or rare that term is across all documents. Formally, for a term t in document d within a corpus D:

$$TF(t,d) = \frac{f_{t,d}}{|d|}$$

$$IDF(t,D) = \log\left(\frac{|D|}{|d \in D : t \in d|}\right)$$

$$TF-IDF(t,d,D) = \mathrm{TF}(t,d) \times \mathrm{IDF}(t,D)$$

where $f_{t,d}$ is the frequency of term t in document d, $|d|$ is the total number of terms in document d, $|D|$ is the total number of documents in the corpus, and $|d \in D : t \in d|$ is the number of documents containing term t. This procedure helps identify distinctive terms while down weighting common ones. For example, since the word "bank" appears in all news articles (by selection), its IDF value is log(1) = 0, resulting in a TF-IDF score of zero. I retain only terms with high TF-IDF scores that appear in at least 25 documents to ensure relevance and significance. Using the gensim library, I then create a dictionary of these filtered terms and convert documents to numerical vectors. A challenge in implementing LDA is determining the optimal number of topics. Following standard practice in the literature, I use topic coherence scores to evaluate model interpretability, with higher scores indicating more semantically coherent topics. As shown in Figure B1, coherence scores across different window sizes consistently peak at six topics, suggesting this is the optimal number from both statistical and interpretability perspectives. This approach aligns with Calomiris et al. (2020), who also use six and eight topics in their analysis. While the main analysis of the paper is conducted with a six-topic LDA model, I demonstrate robustness by also implementing an eight-topic model, with results presented in Appendix IA. Finally, I employ gensim's LdaModel to conduct the Latent Dirichlet Allocation analysis.

The outputs of LDA are two distributions: a probability weight distribution of each article i over each topic t, and a distribution of each topic t on terms associated with that topic. This weight is defined as $w_{i,t}$ (so for a given news article i, $\sum w_{i,t} = 1$). For each topic t, for articles dated in year T, the value of the time series plot is calculated as $BRI_{t,T}$:

$$BRI_{t,T} = BRI_T \times \left(\frac{\sum_{i \in T} w_{i,t}}{N_{i \in T}} \right) = \ln \left(\frac{NR_T + 1}{ND_T + 1} \right) \times \left(\frac{\sum_{i \in T} w_{i,t}}{N_{i \in T}} \right) \tag{11}$$

Figure 3 shows the decomposed time-series plot for each subindex. Figure 2 shows the terms in each topic. The topics are labelled as *BankActivities*, *SystemicRisk*, *Credit*, *Legalese*, *Government*, and *Monetary*. 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 A2 shows the laws that have a high share of each topic. The *SystemicRisk* topic (derived from Dodd-Frank era regulations) captures broad financial stability concerns, dominated by terms 'risk', 'regulatory', 'firm', and 'market'. This topic loads heavily on post-crisis regulatory legislations, with strong weight on the Dodd-Frank Act of 2010 (0.63), reflecting the shift toward macro-prudential regulation and systemic risk oversight. The *Credit* topic focuses on consumer credit, characterized by terms 'loan', 'mortgage', 'borrower' and 'lender'. This topic carries high weights in both post-crisis regulations like Credit CARD Act (2009) and FDICIA (1991) and pre-crisis deregulations like DIDMCA (1980) and BAPCPA (2005). The *Government* topic reflects legislative processes, with terms like 'president', 'congress', and 'senate', loading most heavily (0.53) on oversight legislation like the Bank Secrecy Act (1970).

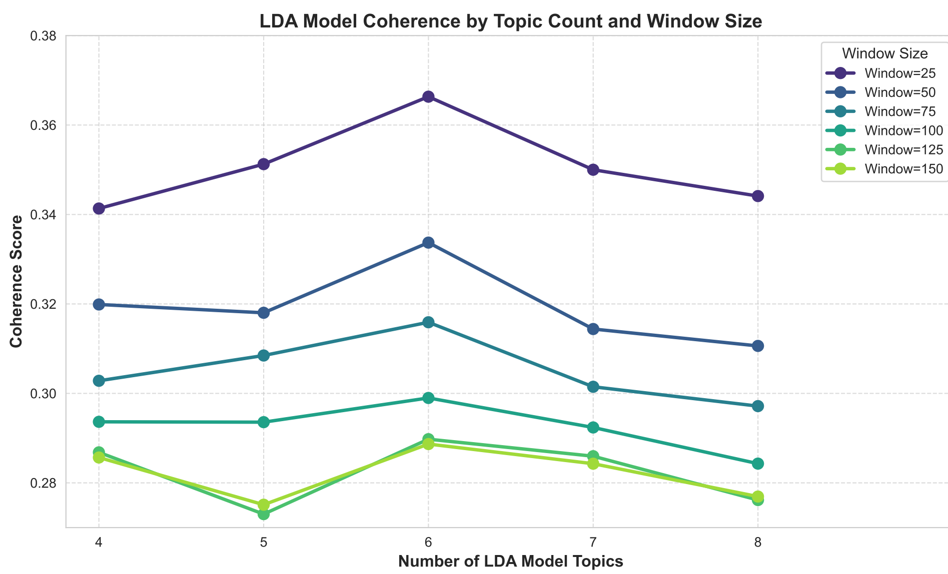


Figure B1. Topic Coherence for Latent Dirichlet Allocation (LDA). Latent Dirichlet Allocation (LDA) is an unsupervised machine learning technique that identifies latent topics within text corpora by modeling documents as distributions over topics and topics as distributions over words. Topic coherence measures the semantic similarity among top words within each topic, with higher scores indicating more interpretable and meaningful topics. This figure displays topic coherence scores across different model specifications, comparing various numbers of topics and context window sizes.

Internet Appendix for
Measuring Bank Regulations: A Text-Based Approach

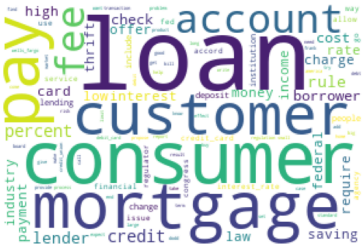
IA Internet Appendix

Table IA1. Summary of Credit Regulation Index Results

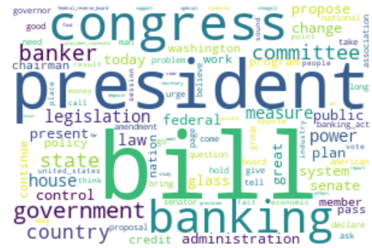
This table summarizes the key findings of the paper across different samples and methodological approaches. The first column presents the main results, while the second column indicates where each finding is documented for the United States sample. The third column shows the corresponding evidence for external validity using a multinational panel of six anglophone countries (US, UK, Canada, Australia, New Zealand, and Ireland). The fourth column references robustness checks using an alternative 8-topic LDA model. The results consistently demonstrate that: (1) the "Credit" topic is the strongest predictor of banking distress, (2) credit deregulation predicts increased credit growth over a 5-year horizon, (3) credit deregulation is associated with higher banking distress over a 5-10 year horizon, and (4) the CRI's predictive power for banking crises remains significant even when controlling for established early warning indicators.

Result	**US Sample**	**External Validity: Multinational Sample (US, UK, CA, AU, NZ and IE)**	**Robustness: Alternate 8-Topic LDA Model**
The LDA-based "Credit" topic is the best regulatory indicator for future banking distress.	Table 5	Table A4	Table IA2
The LDA-based Credit Regulation Index (CRI) shows that credit regulations (deregulations) are associated with lower (higher) credit growth in the medium term (5-year horizon).	Table 6	Table A7	Table IA3
The LDA-based Credit Regulation Index (CRI) shows that credit regulations (deregulations) are associated with lower (higher) banking distress in the long term (5-10 year horizon).	Table 7	Table A5	Table IA4
The CRI's ability to forecast banking crises survives a horse race with well-established early warning indicators, including credit growth.	Table 7	Table A9	Table IA4

(A) Credit



(B) Government



(C) Legalese

(D) Political

(E) Investment

(F) Systemic Risk

(G) Legalese2

(H) Monetary

Figure IA1. 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. This figure shows the word clouds for the 8-topic LDA.

Table IA2. Bank Failures and Regulatory Changes

This table shows regression results where the dependent variable is bank failures. Variables with prefix $\Delta_{t-10\to t-5}$ represent average changes from *t-10* to *t-5* for regulatory topic subindices from 8-topic LDA (Appendix B). Macro control variables include GDP growth, inflation, and short-term interest rate, all lagged by one year. Newey and West (1987) robust z-statistics with 12 lags are shown in parentheses.

	$BankFailures_t$							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\Delta_{t-10\to t-5}$Credit	-2.944***							
	(-2.808)							
$\Delta_{t-10\to t-5}$Monetary		-0.291						
		(-0.176)						
$\Delta_{t-10\to t-5}$Legalese			-2.082**					
			(-2.083)					
$\Delta_{t-10\to t-5}$Systemic Risk				-1.220				
				(-0.962)				
$\Delta_{t-10\to t-5}$Investment					-3.444			
					(-1.205)			
$\Delta_{t-10\to t-5}$Political						-3.111		
						(-1.241)		
$\Delta_{t-10\to t-5}$Legalese2							-0.176	
							(-0.116)	
$\Delta_{t-10\to t-5}$Government								-0.666
								(-0.494)
Observations	86	86	86	86	86	86	86	86
R-squared	0.159	0.100	0.105	0.098	0.092	0.092	0.110	0.106
Macro Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table IA3. Predicting Future Changes in Mortgages and Loans to GDP

This table presents regression results examining how changes in Credit Regulation Index (CRI) from 8-topic LDA (Appendix B) predict future changes in mortgages and loans as a percentage of GDP. The dependent variables are 5-year forward changes in mortgages-to-GDP ratio ($\Delta_{t\rightarrow t+5}Mortgages/GDP$) and loans-to-GDP ratio ($\Delta_{t\rightarrow t+5}Loans/GDP$). $\Delta_{t-5\rightarrow t}CRI$ represents the change in CRI over the previous 5 years. Control variables include GDP growth (ΔGDP), inflation (π), short-term interest rate (r), FDI (Foreign Direct Investment), and consumer sentiment (UMCSENT) from University of Michigan. Newey and West (1987) robust z-statistics with 12 lags are shown in parentheses.

	$\Delta_{t\rightarrow t+5}Mortgages/GDP$			$\Delta_{t\rightarrow t+5}Loans/GDP$		
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta_{t-5\rightarrow t}CRI$	-0.025***	-0.024***	-0.024***	-0.021**	-0.022**	-0.022**
	(-5.676)	(-4.855)	(-5.081)	(-2.044)	(-2.043)	(-2.277)
ΔGDP_t			0.000			0.000
			(1.133)			(0.831)
r_t		0.000	-0.000		-0.000	-0.001*
		(0.637)	(-0.660)		(-0.086)	(-1.951)
π_t			0.001*			0.002*
			(1.692)			(1.888)
Observations	86	86	86	86	86	86
R-squared	0.164	0.267	0.382	0.040	0.238	0.275

Table IA4. Credit Growth and Bank Failures

This table shows regression results where the dependent variable is bank failures. $\Delta_{t-10\rightarrow t-5}CRI$ represents average change in credit regulation topic from $t-10$ to $t-5$ for the 8-topic LDA (Appendix B). $Loans/GDP_{t-1}$ and $Mortgages/GDP_{t-1}$ are loan-to-GDP and mortgage-to-GDP ratios lagged by one year, respectively. LDR_{t-1} is loan-to-deposit ratio lagged by one year. Macro control variables include GDP growth, inflation, and short-term interest rate, all lagged by one year. Newey and West (1987) robust z-statistics with 12 lags are shown in parentheses.

	$BankFailures_t$							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\Delta_{t-10\rightarrow t-5}CRI$	-2.968***	-2.944***	-2.936***	-3.012***	-2.865***	-2.922***	-2.819***	-2.886***
	(-2.769)	(-2.808)	(-2.906)	(-3.023)	(-2.936)	(-3.021)	(-2.711)	(-2.825)
$Loans/GDP_{t-1}$			2.379**	2.450**				
			(2.261)	(2.068)				
$Mortgages/GDP_{t-1}$					3.861***	3.868**		
					(2.775)	(2.485)		
LDR_{t-1}							1.512**	1.604*
							(1.976)	(1.832)
Observations	86	86	86	86	86	86	86	86
R-squared	0.127	0.155	0.193	0.207	0.215	0.224	0.177	0.195
Macro Controls	No	Yes	No	Yes	No	Yes	No	Yes