The macroeconomic effects of bank regulation: New evidence from a high-frequency approach*

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Abstract

Bank regulation supports financial stability, but might constrain economic activity. This paper estimates the macroeconomic effects of bank regulation using a high-frequency identification approach. We measure market surprises in a bank stock price index during a narrow time window around Federal Reserve speeches that discuss the US banking system and its regulation. We then develop a sign restriction procedure to elicit the variation in these market surprises that can be interpreted as *news about bank regulation*. News that bank regulation will be tighter than expected mitigates risk in the banking sector, but reduces economic activity by increasing banks' funding costs and tightening loan supply. A 10 basis point regulation-induced peak reduction in bank risk premiums is accompanied by a 15 basis point peak increase in the unemployment rate. Compared to previous studies, these magnitudes suggest a relatively high macroeconomic cost of tightening bank regulation, at least in the short run.

Keywords: Federal Reserve; Bank regulation; Macroprudential policy; Financial stability; High-frequency identification; Sign restrictions.

JEL Classification: E44, E51, E52, E58, G28.

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"Now—a decade from the onset of the crisis and nearly seven years since the passage of the Dodd-Frank Act and international agreement on the key banking reforms—a new question is being asked: Have reforms gone too far, resulting in a financial system that is too burdened to support prudent risk-taking and economic growth?"

Janet Yellen at the Jackson Hole Economic Symposium 2017

1 Introduction

Bank regulation supports financial stability, but might constrain economic activity, at least in the short run. For example, while stronger capital buffers protect banks against losses, mandating high capital ratios can lower banks' return on capital. In turn, less attractive return prospects might suppress bank lending to firms and households, which ultimately slows down economic activity. Understanding and quantifying these trade-offs is critical for policymakers to build a regulatory environment that balances risk mitigation with economic dynamism.

Empirically studying how changes in bank regulation affect risk and economic activity is a challenge. Financial regulation does not occur randomly, but typically changes in response to shifts in the macroeconomic environment. For example, the financial deregulation of the 1980s was implemented against the backdrop of stagflation, while the Dodd-Frank Act of 2010 was a response to the Global Financial Crisis (GFC). The simultaneity between bank regulation and macroeconomic outcomes makes it extremely difficult to determine causal relationships.

This paper is the first to employ a high-frequency identification approach to study the macroeconomic effects of bank regulation in the United States. Previous studies of bank regulation have typically used quantitative models, micro data and quasi-experimental designs, or cross-country data (see our review of the bank regulation literature further below). Our high-frequency approach estimates effects at the macroeconomic level, captures the combined impact of various regulatory instruments, and incorporates general equilibrium effects.

The idea of the high-frequency approach is that in a narrow time window around a public announcement about bank regulation, the reaction of financial markets reveals the new information contained only in that announcement. As tighter than expected bank regulation arguably decreases bank profitability, a fall in bank stock prices inside the window signals that new information about tighter regulation was revealed. By the same logic, an increase in bank stock prices conveys news about looser than expected regulation.[1] Importantly, in the same narrow time window, information about other aspects of the economy arguably does not arrive. A financial crisis may be the reason for new bank regulation, but information about the crisis itself should already be priced in before the new regulation announcement.

High-frequency approaches have been successfully applied to assess the effects of changes in monetary policy (Gürkaynak, Sack, and Swanson, 2005; Gertler and Karadi, 2015; Nakamura and Steinsson, 2018; Swanson, 2021), oil supply (Känzig, 2021), or fiscal policy (Hazell and Hobler, 2024). One of the contributions of our paper is to apply insights from these papers to the space of financial regulation.

Our specific strategy consists of estimating market surprises around Federal Reserve speeches that discuss the US banking system and its regulation. While the US Congress passes legislation that underlies bank regulation, the Fed, as one of the supervisory authorities, implements it. In speeches, the Fed informs the public about the details of its implementation. It also comments on ongoing or future regulation by Congress. Focusing our analysis on the US context has the advantage that the Fed has been a bank supervisor over a long time span. This is more complicated in other countries, where supervisory responsibilities moved back and forth between institutions. Since the Fed is not the only regulator, we include speeches by senior leadership of the Federal Deposit Insurance Corporation (FDIC) in additional tests.

Our methodology follows three steps. In the first step, we measure changes in a US bank stock price index in a narrow time window around speeches by Fed officials that primarily discuss bank-related topics. To select relevant speeches, we use natural language processing (NLP) techniques. Among over 8,000 speeches that we retrieve from the St. Louis Fed's FRASER database, we identify around 3,000 speeches that are primarily about banks and regulation.[2] We construct the bank stock price index by aggregating tick data covering stock prices of individual US banks. Our analysis sample starts in 1998, when tick data on bank stocks become available.

We refer to the bank stock price changes around those speeches as "raw" market surprises. Without additional refinements, it is not clear whether these surprises exclusively capture news about bank regulation. For example, they could also

[1]It is possible that some types of regulation, when tightened, increase instead of decrease bank profitability. In the main text, we discuss the role and plausibility of this assumption.

[2]Fed speeches have previously been exploited to extract market surprises about monetary policy by Jayawickrema and Swanson (2023). These authors point out that many Fed speeches are not about monetary policy and discard them. We do the opposite instead. We focus only on Fed speeches that discuss the US banking system and its regulation, discarding speeches about monetary policy.

contain news, revealed inside the narrow time window, about the Fed's assessment of the banking sector's health, rather than about regulatory policy. This potential "contamination" has a direct analogy in the literature on monetary policy surprises. In that literature, authors have pointed out that a surprise change in interest rates could contain news about both the Fed's policy as well as the Fed's view of economy's overall health, known as the "Fed information effect" (Romer and Romer, 2000; Nakamura and Steinsson, 2018).

In the second step of our methodology, we address the potential contamination of raw surprises by eliciting only that portion of their variation that can plausibly be interpreted as *news about bank regulation*. To do so, we develop a sign restriction procedure. The idea is to also exploit movements in a market-based measure of bank risk, specifically banks' distance to default, around Fed speeches. The joint dynamics of bank stock prices and bank distance to default can then be used to distinguish different types of surprises. Our sign restriction procedure is inspired by Jarocinski and Karadi (2020), who apply sign restrictions to distinguish monetary policy shocks from Fed information shocks.

Specifically, we posit that while news about tighter than expected bank regulation lowers expectations about bank profitability, and thereby reduce bank stock prices, the news simultaneously reduces expectations about future default probabilities, thus increasing banks' distance to default. Instead, worse than expected *news about bank health* also reduces bank stock prices, but decreases rather than increases banks' distance to default. Put simply, tighter regulation news lowers returns and lowers risk, while poor health news lowers returns and increases risk. Based on this logic, we select the subset of raw surprises that leads to a negative comovement between the bank stock price index and the bank distance to default measure. As an alternative, we use bank credit default swap (CDS) premiums as a measure of risk.

The third step of our methodology consists of estimating impulse response functions (IRFs) of macroeconomic and financial variables. After refining our raw surprises with sign restrictions, we interpret the time series of selected surprises as "news shocks" that reveal information about bank regulation, relative to what the market expected. To construct IRFs to these shocks, we estimate local projections.

Our findings are as follows. News about tighter than expected bank regulation is associated with a persistent decline in bank stock prices, which continue to fall for several years. Following the news, bank lending drops persistently. A 1% reduction in bank stock prices leads to a reduction in the volume of total bank loans in the US economy of between 0.5% and 1%. The reduction in lending activity is associated with a rise in unemployment. The unemployment rate reaches a level that is about 10 basis points (bp) higher after 2 to 3 years.

News about tighter than expected bank regulation is mildly inflationary over the medium term, after a small reduction in consumer prices on impact. The 1% reduction in bank stock prices is associated with an increase in the PCE price index of close to 0.1% after several years. The Federal Funds Rate falls with a delay of almost two years after the news shock, likely reflecting a monetary policy easing in reaction to the uptick in unemployment and potentially leading to the rise in consumer prices.

In the IRFs, the negative comovement between bank stock prices and bank distance to default (imposed only on impact) persists for almost two years. The 1% reduction in bank stock prices is associated with an increase in banks' distance to default of 0.05 to 0.1 standard deviations. When we use CDS premiums as an alternative measure of bank risk, we estimate a reduction of roughly 5 bp. While these magnitudes are sizable, the reduction in bank risk after tighter bank regulation news is less durable than the responses of other variables. After about two years, bank risk actually starts rising. This reversal effect could reflect general equilibrium channels. For example, the rise in unemployment might make existing loans on banks' balance sheets riskier and ultimately lead to more bank default risk.

All results are estimated with high statistical precision. As Jayawickrema and Swanson (2023) explain, the large number of Fed speeches increases statistical power relative to previous high-frequency studies of Fed announcements.

We investigate the economic mechanisms underlying our findings. In response to tighter bank regulation news, loan interest margins charged by banks rise. Since loan volumes fall, but loan prices increase, banks appear to actively reduce loan *supply* in response to the news shock. This insight connects our results to the literature that studies employment effects of credit supply shocks (Chodorow-Reich, 2014; Huber, 2018). Furthermore, we find that an important transmission channel of bank regulation news is the immediate response in banks' funding costs. Banks' weighted average cost of capital increases as investors into banks learn that regulation is tighter than expected. Bank regulation news also leads to an increase in firm exit, a potential driver behind the strong unemployment effect. Finally, we cannot detect a response of lending by nonbanks after bank regulation news. This result suggests that nonbank lenders cannot make up for the reduction in credit by banks, a substitution mechanism often discussed in the bank regulation literature.

We present an in-depth discussion of the quantitative tradeoff between financial stability and economic activity implied by our results. In our IRFs, a 10 bp peak reduction in bank CDS premiums is accompanied by a 15 bp peak increase in the unemployment rate. A 10 bp reduction is equivalent to an 16.67 bp lower annual probability of default of the average US bank. Since the average probability of default priced in the CDS market in our sample is 1.5%, with a standard deviation of 1.2%, 16.67 bp is a meaningful gain in financial stability. However, the 15 bp increase in the unemployment rate is also a significant hit to economic activity and thus constitutes a significant cost of regulation, at least in the short run.

Although direct comparisons are difficult, our estimates of the economic costs of bank regulation are sizable relative to existing studies, which we review in our discussion of the quantitative tradeoff. While our estimates capture short-run effects, an argument for tighter regulation is that a stable financial sector supports growth in the long run, despite short-run costs (see e.g. Mendicino et al. (2020)). We think that our estimates can be useful to discipline the short-run dynamics of structural models that can speak to longer-term economic effects.

We provide a variety of additional results and validation exercises. First, in "Placebo" tests, we construct bank stock price surprises in randomly selected time windows, rather than around our selected speeches. These Placebo surprises are not associated with changes in any macroeconomic and financial variables, which confirms that there is relevant economic information in our selected speeches.

Second, we rule out that the surprises we elicit from speeches contain systematic information about monetary policy. We also show that they are uncorrelated with empirical estimates of other macroeconomic shocks from the literature and with information about the overall state of the economy.

Third, our main analysis sample starts in 1998, due to the availability of tick data for bank stock prices. This is a common constraint in the high-frequency literature, but raises the concern that the GFC period dominates our result. We therefore analyze the sensitivity of our results to specific shocks and time periods, for example using a leave-one-out strategy. Moreover, we also estimate a daily version of our bank surprises for a longer sample beginning in 1971. In the daily setup, we employ identification via heteroskedasticity. We obtain results broadly similar to those obtained with tick data.

Fourth, instead of bank regulation news shocks as our main object of interest, we study bank health news shocks. Both shocks contract lending activity. However, while regulation news shocks look like aggregate supply disruptions (increase in unemployment and inflation), health news shocks look like aggregate demand disruptions (increase in unemployment, decrease in inflation).

Fifth, we present results for individual banks to characterize cross-sectional heterogeneity in how regulation news impacts banks. For example, the stock price of Citigroup falls relatively quickly, while the stock price of Goldman Sachs actually rises on impact, but declines strongly and persistently after about two years.

Literature. The consequences of bank regulation are widely studied using structural models. Examples include Corbae and D'Erasmo (2021), Begenau and Landvoigt (2021), Elenev et al. (2021). Empirical estimates are typically at the microeconomic level, often based on quasi-experimental designs. Jiménez et al. (2017) study the impact of macroprudential policy in Spain and find that regulation supports firms in bad times. Huber (2021) studies the effects of larger banks on economic outcomes using a quasi-experimental design in Germany and discusses implications for (de)regulation.[3] In contrast to both of these approaches, we assess the effects of bank regulation using macroeconomic data and an identification approach that is inspired by the empirical literature in monetary economics. Our macroeconomic estimates can capture the combined impact of different regulatory instruments and account for general equilibrium effects that micro-level estimates might miss.

Empirical studies of the macro-level impact of financial regulation include Jordà et al. (2021), who examine the relationship between capital ratios and financial crises using country-level panel data, and Richter et al. (2019), who investigate the effects of raising loan-to-value ratios on output and inflation. Sufi and Taylor (2022) show that financial liberalizations lead to credit expansion. Akinci and Olmstead-Rumsey (2018) study macroprudential policies and their effects across countries. While all of these studies use cross-country variation, we provide new macro-level evidence on the economic effects of bank regulation in the United States over time.[4]

[3] Other examples of quasi-experimental studies include Jayaratne and Strahan (1996), Behn et al. (2016), and Gropp et al. (2019). Fraisse et al. (2020) and Irani et al. (2020) exploit institutional features of the implementation of Basel bank regulation that differentially affected banks in the cross section. Bouwman et al. (2018) exploit size thresholds of the Dodd-Frank Act.

[4] Eickmeier, Kolb, and Prieto (2025) use a narrative approach to study changes in capital requirements within the US. They find that tighter capital requirements reduce lending and economic activity. Variation within the US is also used by Cascaldi-Garcia and Iacoviello (2026), who employ artificial intelligence to measure deregulation from newspaper articles. Albuquerque et al. (2025) focus on identifying macroprudential policy shock for multiple countries, including the US.

Our paper contributes to the literature on high-frequency identification. In many cases, this approach uses Federal Funds Rate futures data to identify monetary policy shocks around Fed announcements (e.g. Gürkaynak, Sack, and Swanson (2005), Gertler and Karadi (2015), Nakamura and Steinsson (2018), Swanson (2021) and Bauer and Swanson (2023)). Känzig (2021) studies oil supply news and Hazell and Hobler (2024) deficit news. Relative to this literature, our approach identifies a new type of shock, news about bank regulation. Very few papers have attempted something similar, with Bluwstein and Patozi (2024) studying macroprudential policy announcements by the Bank of England and Duprey and Tuzcuoglu (2025) by the Bank of Canada.[5] We are the first to focus on US bank regulation.

Some studies identify broader types of "financial shocks" with methods other than high-frequency ones, e.g. in VARs with sign restrictions (Furlanetto et al., 2017). We aim to identify a financial shock that has a specific interpretation as regulatory news. Our refinement of high-frequency surprises is based on sign restrictions and uses ideas from Jarocinski and Karadi (2020).

Two recent contributions are particularly related to ours. First, Jayawickrema and Swanson (2023) also study the high-frequency impact of Fed speeches, but focus on monetary policy. They exclude speeches that discuss bank regulation, while we put them at the center of our analysis. Similarly to Jayawickrema and Swanson (2023), we can use a large number of speeches which enhances the statistical power of our estimated shock. Second, Ottonello and Song (2025), also study high-frequency surprises in bank stock price data. While we focus on Fed speeches and bank regulation news, they identify news about bank-level net worth revealed through the release of financial statements. Thus, the shocks estimated by Ottonello and Song (2025) are closer to what we refer to as bank health news shocks in our analysis.

2 Dataset construction

2.1 Speeches

We collect speeches by Fed and FDIC policymakers. We employ an NLP approach to select speeches that primarily discuss the US banking system and its regulation.

[5] Aikman et al. (2024) use a high-frequency approach to study credit controls in Britain after World War 2. They argue that these can be viewed as similar to present-day macroprudential policies.

2.1.1 Institutional background: relation between speeches and regulation

The laws underlying US bank regulation are passed by Congress. The Federal Reserve and the FDIC, as major US supervisory authorities, interpret and implement these laws. This section explains two distinct ways in which speeches by these authorities reveal news about future regulation to financial markets. We focus our discussion on Fed speeches.

First, Fed speeches communicate to the public about the implementation of regulation that has been passed by Congress. At the implementation stage, important details of regulation are left open for the Fed to decide. Fed Chair Ben Bernanke explains in a February 2011 speech that "*The (Dodd Frank) act gives the Federal Reserve important responsibilities both to make rules to implement the law and to apply the new rules. In particular, the act requires the Federal Reserve to complete more than 50 rule makings and sets of formal guidelines.*" Bouwman et al. (2018) provide specific examples from the Dodd-Frank Act. For example, banks with assets above 50 bn USD "*must limit their aggregate credit exposure to an unaffiliated company to no more than 25% of its capital stock and surplus, or lower if decided by the Federal Reserve.*" A more recent example is a December 2019 speech by Randal Quarles about the implementation of Economic Growth, Regulatory Relief, and Consumer Protection Act of 2018.

Second, Fed speeches reveal recommendations to Congress on how legislation should be designed while the legislative process in Congress is ongoing. For example, in an October 2009 speech, Bernanke emphasizes "*(...) we are working with our fellow regulatory agencies toward the development of capital standards and other supervisory tools (...). Options under consideration in this area include requiring systemically important institutions to hold aggregate levels of capital above current regulatory norms or to maintain a greater share of capital in the form of common equity or instruments with similar loss-absorbing attributes (...).*" These ideas were later implemented in the Dodd-Frank Act. In an April 2017 speech, Dan Tarullo demands legal reform from Congress: "*I believe we should be moving toward a much simpler capital regime for community banks. (...) it may be helpful to amend the law so as to make clear that the agencies would have the flexibility to create a simple capital regime applicable only to community banks.*"

Institutionally, our focus on the US has the advantage that the Fed and FDIC have been bank supervisors over a long period of time. Supervisory responsibilities tend to be more complex in other countries. For example, in several countries the central bank only became a bank supervisor after the GFC.

2.1.2 Data source for speeches

We retrieve speeches from FRASER, a digital library maintained by the Federal Reserve Bank of St. Louis, and from the website of the Board of Governors. We include speeches by Fed Chairs, members of the Board of Governors, and Presidents of Federal Reserve Banks. We also consider speeches by key Fed staff members that are in regulatory roles, as well as speeches by FDIC leadership. Speeches include, for example, presentations at banking associations or universities. They also consist of official testimony before Congress. For each speech, we obtain the full text content, along with relevant metadata such as the date of the speech, the speaker name, and title. As we do not focus on monetary policy, we do not include FOMC statements or minutes. Note that Fed speeches usually occur outside of FOMC weeks.

We start our speech dataset in 1971, which is the longest sample we use across the paper, including validation exercises at daily frequency. We retrieve a total of 8,155 speeches. For speeches delivered after January 1998, when tick data for bank stock prices index become available, we also collect the precise time stamp of the speech.[6]

2.1.3 Speech classification with natural language processing

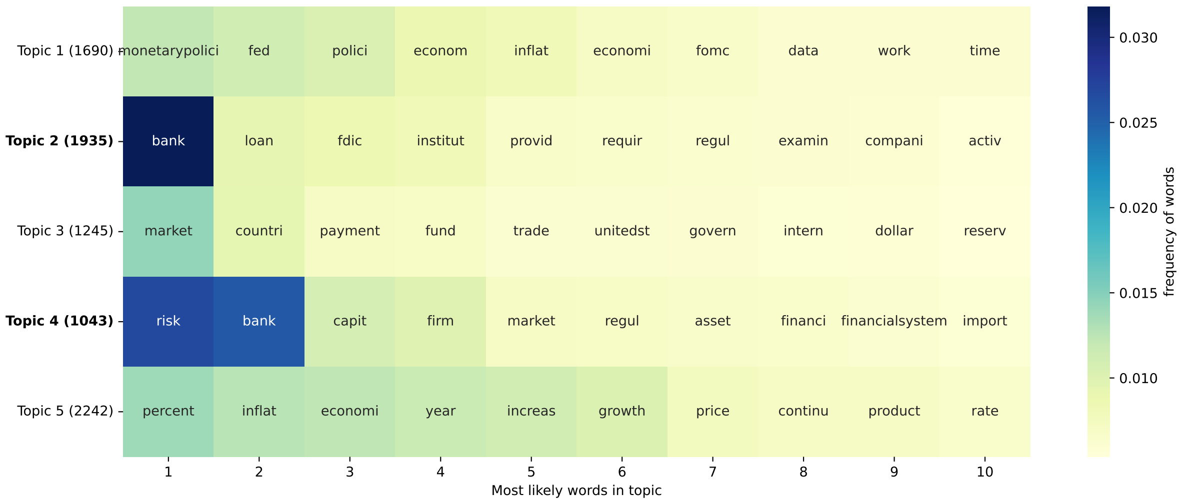
To select the subset of speeches that focus primarily on the banking system and its regulation, we follow the approach of Hansen, McMahon, and Prat (2018). These authors develop a Latent Dirichlet Allocation (LDA) algorithm to uncover latent topics in Fed texts. LDA assumes that a document is composed of a mixture of several topics and that each topic generates a specific probability distribution over words. Observing the frequency of words in the document, it is possible to estimate the relative importance of latent topics. Training an LDA algorithm requires setting the number of latent topics K. Typically, a smaller K enhances interpretability, while a larger K improves the statistical fit. We prioritize the interpretability of the algorithm output and set a relatively small number of topics, $K = 5$.[7]

Figure 1 presents the results of the LDA algorithm applied to our full speech database. Each row represents one of the five latent topics. The cells in each row

[6]The release time is usually stated on the first page of a speech transcript. When it is not available, we discard the speech unless it is by the Fed Chair. In that case, we collect the time stamp from additional sources such as news articles. This ensures that we include as many Chair speeches as possible, as these are closely watched by markets (Jayawickrema and Swanson, 2023). The release time was not available for FDIC speeches, so we only use those in the validation using daily data.

[7]When setting larger values, there is greater room for arbitrariness when judging which topics are relevant. The Online Appendix shows results for $K = 10$ and $K = 20$ to illustrate this point.

Figure 1: Topics and associated word stems in speeches



Notes: Topics are shown in separate rows. Columns represents the word stems with the top 10 highest probabilities of belonging to a given topic. Darker shadings represent higher probabilities. The number in parentheses for each topic indicates the number of speeches classified into that topic.

show the word stems with the 10 highest probabilities of belonging to a topic. Darker shadings correspond to higher probabilities. Topic 1 is characterized by words such as "monetary policy" and "inflation", indicating a clear focus on monetary policy. 1,690 speeches are mainly associated with that topic. Topic 3 is related to international economic developments, with 1,245 associated speeches. Finally, the 2,242 speeches associated with Topic 5 discuss the overall state of the US economy, with word stems such as "infla" and "'growth". This topic is probably closely connected to the Fed's conduct of monetary policy as well.

We consider Topics 2 and 4, with 1,935 and 1,043 speeches, to be primarily related to banking. They are characterized by words such as "bank", "loan" and "fdic". Both topics are directly related to regulation, as both contain the word "regul". Topic 4 also contains "capit" which we verified is mostly about bank capital regulation. This body of 2,978 speeches is matched with financial market data for our high-frequency analysis. It is a large number of speeches, especially considering that they have been discarded by the previous high-frequency literature, which has focused exclusively on monetary policy related speeches. Of course, it is not clear at this stage whether the speeches we select contain *only* news about bank regulation. Instead, these speeches might also convey other information. We address this issue in detail in our methodology section. The NLP-based speech selection step here should simply be regarded as a first broad sorting step within the large body of available speeches.

2.1.4 Further restrictions to match speeches with financial market data

Table 1 summarizes our speech classification with additional breakdowns. The column labeled *Long sample* shows the number of speeches in the longest analysis sample we use in the paper, starting in 1971. We sort this into all topics, monetary policy related (Topics 1 and 5 from Figure 1) and bank related (Topics 2 and 4 from Figure 1). We further break down how many of those speeches have been given by specific policy-makers, such as the Fed Chair or the Vice Chair. This breakdown reveals, for example, that the Fed Chair gives a higher share of speeches about monetary policy than other speakers.

The columns labeled *Tick data sample* show the number of speeches used in our main analysis sample, for which bank stock price tick data are available. This sample starts in January 1998. We further break this down by speeches that have a time stamp and those within and outside trading hours. Both the availability of a time stamp and the release inside trading hours thus restrict the number of speeches that can be used for our analysis based on intraday market prices.

The last two columns show the number of speeches that can be matched to our two analysis samples. For the period with intraday price data, 321 speeches are suitable for analysis. These are the ones related to banking, excluding those without time stamps and those outside of trading hours. This can be considered a relatively large number of observations in the context of the high-frequency monetary policy literature. Jayawickrema and Swanson (2023) discuss the statistical power gained by using Fed speeches in addition to FOMC announcements. For the daily sample that we use in additional validation exercises, we can use as many as 2,978 speeches.

2.1.5 Sanity check for our speech classification

Jayawickrema and Swanson (2023) use a procedure to select speeches that is different from our LDA algorithm. Therefore, it is helpful to check whether similar speech selections are obtained. The sample period considered by Jayawickrema and Swanson (2023) is 1988–2023. Their dataset contains 927 speeches by the Fed Chair. For the same period, our dataset contains 856 speeches by the Chair. Their selection procedure picks 411 speeches related to monetary policy (which they keep). Our LDA algorithm selects 481 speeches related to monetary policy (which we remove). Thus, although the aim of our algorithm is not to identify speeches on monetary policy specifically, our selection procedure appears to yield outcomes comparable to theirs.

Table 1: Number of speeches, broken down by different categories and samples

Speaker	Topic	Full sample (1971–2023)	Tick data sample (Jan 1998–Aug 2023)					Matched to:	
			All	Time stamp		Trading hour		Daily	Intraday
				Yes	No	Yes	No	Prices	Prices
All speakers	all topics	8155	4443	1319	3124	905	414	–	–
	mon. policy	3932	2447	691	1756	479	212	–	–
	bank	2978	1561	458	1103	321	137	**2978**	**321**
Chair	all topics	1208	590	582	8	406	176	–	–
	mon. policy	681	355	350	5	256	94	–	–
	bank	254	133	132	1	93	39	254	93
Vice Chair	all topics	580	360	216	144	138	78	–	–
	mon. policy	246	190	113	77	67	46	–	–
	bank	230	137	86	51	59	27	230	59
FDIC	all topics	1164	564	0	564	0	0	–	–
	mon. policy	84	55	0	55	0	0	–	–
	bank	1072	508	0	508	0	0	1072	0
Other speakers	all topics	5203	2929	521	2408	361	160	–	–
	mon. policy	2921	1847	228	1619	156	72	–	–
	bank	1422	783	240	543	169	71	1422	169

2.1.6 Why not use LLMs?

We employ a rather traditional NLP method to process speeches. Recent advances in large language models (LLMs) suggest that these models are useful for processing text in great detail and at large scale. However, the main component of our empirical strategy is not the language processing part, but the high-frequency identification. While LLMs can potentially give us a detailed interpretation for each speech, they cannot tell us which parts of the speech were *unexpected by financial markets*. This information is only conveyed through surprise movements in asset prices, which is our basis for identification. In fact, if we asked an LLM which sentences in a given speech were unexpected, it probably would give us some answer. However, this answer would not be useful for inference, as the LLM has already been trained on future information. This phenomenon is known as 'lookahead bias' of LLMs (Sarkar and Vafa, 2024). Instead, the NLP component in our procedure represents only a simple sorting step to exclude speeches that are not about bank regulation. An easy and transparent NLP algorithm is all we need for that initial step.

2.2 High-frequency financial market data

In constructing our market price dataset, we follow the high-frequency literature in monetary economics (Gürkaynak et al., 2005; Gertler and Karadi, 2015; Nakamura and Steinsson, 2018; Bauer and Swanson, 2023). However, we consider US bank stock prices, instead of Federal Funds Rate futures.

2.2.1 Bank stock price index data

We retrieve tick prices for the stocks of 18 large US banks, in 15-minute intervals. The data source is the Trade and Quote (TAQ) database, accessed through Wharton Research Data Services. The data are available starting from January 1998, providing the longest available tick data for the widest set of US bank stock prices that we are aware of. The largest banks in the sample are well known names, such as JP Morgan Chase, Citi, Bank of America and Wells Fargo. The smallest banks are Northern Trust, Bankboston, First Chicago and Ameriprise Financial. The same data is used by Ottonello and Song (2025) (see e.g. their Table 1). We aggregate individual stock prices to an index, using the market capitalization as aggregation weights, obtaining tick data for a bank stock price index from January 1998 to August 2023.[8]

2.2.2 Bank distance to default

For our sign restriction procedure, we require a measure of bank risk. For the same 18 banks and the same time period as for the stock price data, we construct *distance to default* following Merton's methodology. The idea of this measure is to interpret bank equity as a contingent claim on underlying assets and measure the buffer against insolvency implied by market prices. It is computed using data on equity prices, option-implied equity volatility, and the book value of bank liabilities. A higher distance to default indicates a larger buffer against insolvency and therefore lower default risk. Distance to default measures are widely used in empirical studies, for example for nonfinancial firms in Ottonello and Winberry (2020). The underlying data comes from Option Metrics and Compustat-CRSP. We again aggregate bank-level measures to an index based on market capitalization.

[8]There are bank stock price indices for which tick price data is available directly, but these are available for shorter time spans. For example, tick data for the SPDR S&P Bank ETF is available only from 2005. We verified that our index correlates strongly with other bank stock price indices in overlapping samples and at lower frequencies.

2.2.3 Bank CDS

As an alternative to distance to default, we use banks' CDS spreads. Following the literature that uses such spreads (Eichengreen et al., 2012), we obtain data for 5-year CDS, the most liquid in the market. Our data source is Bloomberg's generic prices (CBGN), from which we obtain daily data for the six largest US banks (JP Morgan Chase, Bank of America, Citigroup, Wells Fargo, Goldman Sachs, and Morgan Stanley). We aggregate the CDS data of individual banks by calculating the simple average of these banks' CDS spreads. The data period for this aggregated bank CDS premium begins in November 2002, later than our distance to default data. It is also available for fewer banks. Therefore, distance to default is our preferred risk measure.

2.3 Monthly macroeconomic and financial market data

We study the responses of several monthly macroeconomic and financial market variables to bank regulation news shocks. These come from a variety of sources, including FRED, the Federal Reserve's US Financial Accounts, and Bloomberg. We explain the sources for each series in the results section.

3 Methodology

We proceed in three steps. First, we measure high-frequency bank stock price surprises around speeches about bank regulation. Second, we use sign restrictions to refine the "raw" surprises. These refinements elicit variation that plausibly reflects news only about bank regulation. Third, we estimate IRFs using local projections.

3.1 Step 1: construct "raw" surprises

Let $\{(\tau_1, h_1), ..., (\tau_N, h_N)\}$ denote combinations of the day τ_i and the release time h_i of a speech i. We retrieve our tick price data in 15-minute intervals, so, to be precise, h_i represents the closest 15-minute time interval that occurs before the time stamp of the speech. We define the raw intraday surprise by speech i as

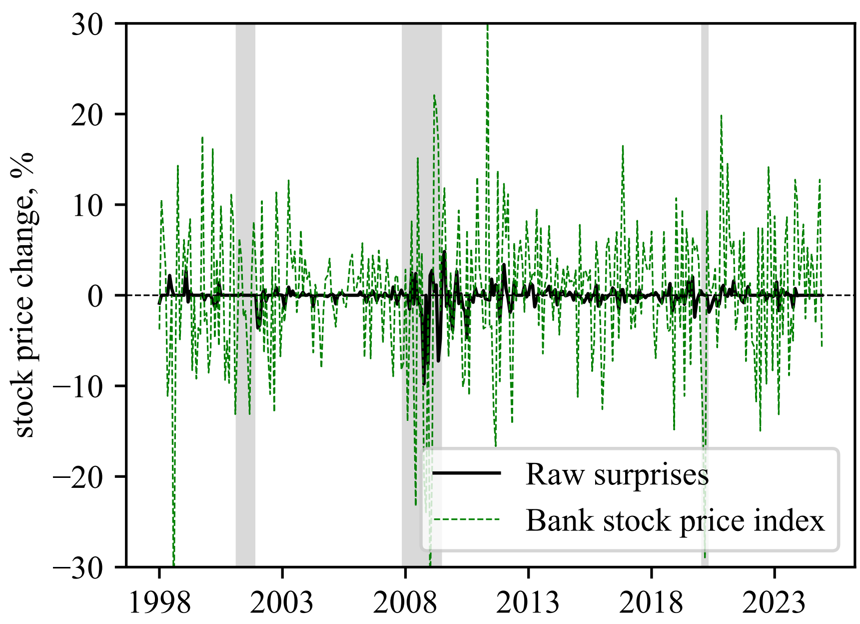
$$s_i = \log p_{\tau_i, h_i+\Delta_i} - \log p_{\tau_i, h_i} \tag{1}$$

where $p_{\tau,h}$ denotes the tick price of the bank stock price index at date τ and time h. Δ_i is the time window. We use a 2-hour window for speeches and a 3.5-hour window for congressional testimony, following Jayawickrema and Swanson (2023).[9] We exclude speeches outside trading hours.

The idea of the high-frequency approach is that inside the narrow time window Δ_i, the reaction of financial markets, encapsulated in the price change from p_{τ_i,h_i} to $p_{\tau_i,h_i+\Delta_i}$, reveals the new information contained only in speech i. In the same narrow time window, arguably no other information about the economy or the banking system is released to investors.

Figure 2 presents the raw surprises we obtain with this procedure. To construct this figure, we aggregate the surprise time series to monthly frequency (denoted s_t, where t is a month) and plot it together with the actual change in the stock price index over the same month ($\log p_t - \log p_{t-1}$). The surprise series is shown as the thicker solid line and the changes in the actual price index as the thin dashed line. As expected, only a subset of the variation in the bank stock price index can be attributed to surprises triggered by Fed speeches.

Figure 2: Raw bank stock price index surprises around speeches



[9]We noticed that the authors slightly changed these settings across different versions of their paper. We follow the version presented at the NBER Summer Institute in 2023.

3.1.1 Returns vs. excess returns

An alternative way to construct the raw surprises would be to calculate the change in the bank stock price index and subtract the change in a general stock price index. This would amount to constructing a surprise in the *excess* return, rather than the return, on bank stocks. Whether this excess-return version is preferable depends on the desired interpretation. The excess return version effectively controls for the movement in the prices of stocks of nonfinancial firms. The change in these stock prices reflects general equilibrium transmission channels of bank regulation news. For example, investors might sell stocks of manufacturing firms exactly because they understand that more tightly regulated banks will harm the credit supply to those firms. This effect is part of the economic mechanism of interest. Therefore, we opt for not subtracting changes in the overall stock market in our empirical strategy. In the Online Appendix, we show that the relation between return surprises and excess returns surprises is strong, with a correlation coefficient of 0.86.

3.2 Step 2: elicit bank regulation news shocks with sign restrictions

Even if a speech is the only new piece of information for markets inside a narrow window, it is not clear whether the raw surprises contain *only* regulatory news. When policymakers talk about bank regulation or banks in general, they typically also discuss the health of the banking system. News about bank regulation and news about the health of banks could trigger different macroeconomic responses. A similar issue arises in the literature on monetary policy surprises, where monetary policy announcements by the Fed might also convey information about the Fed's assessment of the economy (Romer and Romer, 2000; Nakamura and Steinsson, 2018). See also Bauer and Swanson (2023) and Acosta (2026) for further discussion.

To address this identification challenge, we use a refinement procedure. The idea is to elicit only that portion of the variation in the raw surprises that can plausibly be interpreted as news about bank regulation. In other words, we remove potential "contamination" in our raw surprises. The refinement procedure uses sign restrictions and is inspired by Jarocinski and Karadi (2020) who restrict the signs of interest rates and stock prices to separate monetary policy shocks from central bank information shocks. It takes advantage of additional information on the response of banks' perceived riskiness to regulation. We measure risk as distance to default in our main specification, and through CDS premiums in an alternative specification.

Table 2: Sign restrictions to separate different news shocks contained in the raw surprises

Panel (a): main specification	Bank stock price index	Bank distance to default
Bank regulation news shocks	−	+
Bank health news shocks	−	−

Panel (b): alternative specification	Bank stock price index	Bank CDS premium
Bank regulation news shocks	−	−
Bank health news shocks	−	+

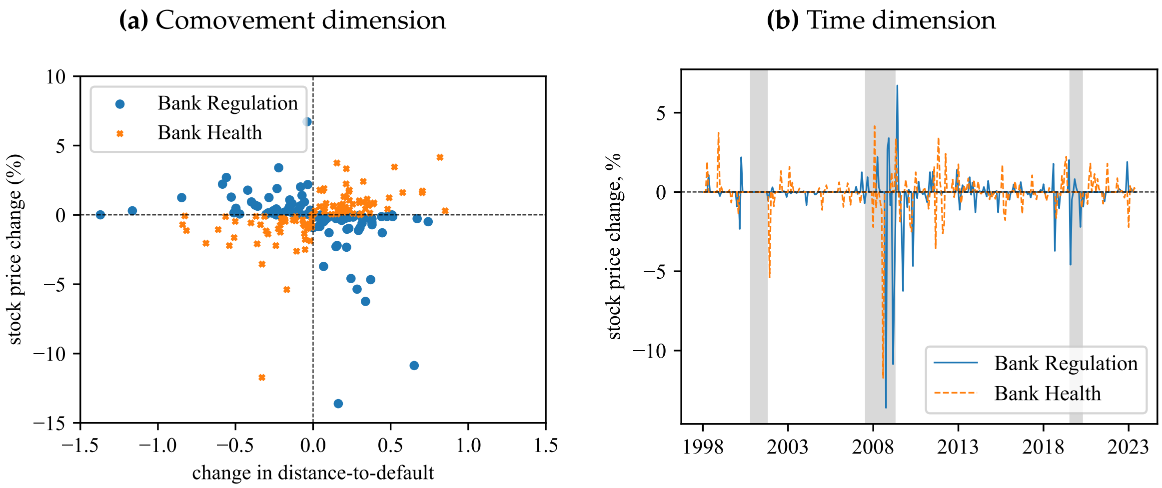
To distinguish bank regulation news shocks from bank health news shocks, we posit the following logic. The news of tightening bank regulation arguably lowers expectations about bank profitability and therefore reduces bank stock prices. Tighter bank regulation should also reduce future default probabilities, so it increases banks' distance to default. News about worse bank health, on the other hand, also reduces bank stock prices, but decreases rather than increases banks' distance to default. This is because when the Fed speaks of poor bank health, the market should interpret this as a higher likelihood of bank default. We provide additional discussion of the assumptions behind this comovement further below.

Table 2, Panel (a) summarizes the sign restrictions implied by this logic. Of course, bank regulation news shocks and bank health news shocks can be positive or negative, implying tighter vs. looser regulation and sound vs. poor bank health. What the restrictions imply is that bank regulation news shocks move stock prices and distance to default in the opposite direction, while bank health news shocks imply a positive comovement between stock prices and distance to default.[10] Panel (b) shows the specification of the sign restrictions when we use CDS premiums as an alternative to distance to default. The logic is exactly the same, except that higher risk implies higher CDS premiums instead of lower distance to default.

Using the sign restrictions in Table 2, we decompose raw surprises into bank regulation news shocks and bank health news shocks. There are different ways to do so. We follow what Jarocinski and Karadi (2020) call "poor man's sign restrictions." We simply handpick only those raw surprises that satisfy the sign restriction for the bank regulation news shock. As our IRFs are estimated using monthly data in the

[10]Recall that distance to default is computed from equity price, option-implied equity volatility and book value of liabilities. At high frequency, the book value of bank liabilities does not respond to news. Therefore, high-frequency dynamics in distance to default are determined by equity price and equity volatility. As these can respond with different signs, the opposite signs between bank stock prices and bank distance to default, which define the bank regulation news shock, are possible.

Figure 3: Shocks identified by sign restrictions



next step of our methodology, we impose these sign restrictions after aggregating the raw surprises to monthly frequency. For the aggregation, we use a weighted sum within a month, where the weight is higher when a shock occurs earlier in the month, as for example in Ottonello and Winberry (2020). Aggregating the surprises first, and then imposing the sign restrictions, mimics how the signs would restrict the data in a monthly VAR. It is consistent with how Jarocinski and Karadi (2020) describe the implementation of sign restrictions, in particular the "poor man's" version (see e.g. Sections II.A and III.C in their paper).[11]

The distinction between bank regulation news shocks and bank health news shocks is shown in Figure 3, Panel (a), which presents a scatter plot, where each dot represents a month. The plot distinguishes between bank regulation shocks (negative comovement between bank stock prices and bank distance to default, blue dots) and bank health shocks (positive comovement, orange markers).

Panel (b) shows the two shock series in the time dimension. The solid blue line represents bank regulation news shocks and the orange dashed line represents bank health news shocks. Interestingly, the large raw surprises during the Great Recession are attributed to both bank health and bank regulation news. This is plausible as speeches during the GFC actively discussed both the state of US banks as well as what future regulation may look like. We use the blue line of bank regulation news shocks in the next step of our methodology. In a later section, we discuss the specific speeches that give rise to large bank regulation news shocks.

[11]In the case of monetary policy, multiple surprises within one month are less common. But when this is the case, Jarocinski and Karadi (2020) restrict the signs of the *net effect* over the month.

3.3 Step 3: construct impulse response functions

Finally, we assess how macroeconomic and financial variables respond to bank regulation news shocks. To this end, we estimate a set of local projections at monthly frequency, specified as follows:

$$y_{t+h} = \alpha^h + \beta^h \widetilde{s}_t + \gamma^h y_{t-1} + \epsilon_{t+h}, \tag{2}$$

where y_t denotes the outcome variable. We take logs of all outcome variables, except those originally expressed as percentages (such as the unemployment rate). We control for one lag of the left-hand-side variable. $\widetilde{s}_t$ denotes our bank regulation news shock, the subset of raw surprises s_t that satisfy the sign restrictions. We convert the shocks to monthly frequency as described in the previous step of the methodology. β^h represents the horizon-h IRF of variable y_t.

4 Further discussion of the methodology

We wrap up the description of our methodology with a discussion of key assumptions of our approach and the interpretation of bank regulation news shocks.

4.1 Key underlying assumptions

We discuss two underlying assumptions of our approach in more detail. First, an implicit assumption is that a fall in bank stock prices reveals tighter than expected bank regulation, since tighter regulation plausibly decreases bank profitability. By the same logic, an increase in bank stock prices conveys news about looser than expected regulation, due to higher profitability.

It is possible that there are regulations that, when tightened, increase instead of decrease bank profitability. We think, however, that it is reasonable to assume the majority of regulations constrain banks' choices and therefore lower their profitability. In fact, banks spend billions of dollars lobbying against bank regulation (Igan, Mishra, and Tressel, 2012). The assumed relation between regulation and bank stock prices is validated in other empirical studies. Duprey and Tuzcuoglu (2025) study market surprises around macroprudential policy announcements by the Bank of Canada. These authors classify the announcements into tightenings and easings without making restrictions on the stock price response. They find that regulatory tightenings lower bank stock prices, regulatory easings increase stock prices. Cascaldi-Garcia and Iacoviello (2026) find that industry-specific deregulation shocks boost industry stock returns. One of their industries is Finance, which includes banks. The relation between bank regulation and bank stock prices also holds in theoretical models. In Elenev et al. (2021) tighter bank regulation leads to a decline in franchise value, consistent with our assumption (see their Table IV).

A second important assumption is that tighter than expected regulation leads to a reduction in the pricing of risk in the banking sector. Based on this logic, our sign restriction procedure imposes that tighter regulation increases distance to default and decreases CDS spreads. We think this is a reasonable assumption as the goal of bank regulation is to avoid bank failures. For example, this goal is explicitly stated in the Basel Framework for bank regulation. Again, this assumption has empirical support. For example, the negative relationship between regulation and CDS premiums is consistent with evidence provided in Handorf (2017). This author finds that regulation-favored balance sheet ratios imply lower CDS premiums across banks. There is also theoretical support, with risk measures declining in response to tighter regulation in Elenev et al. (2021).

Beyond these arguments in support of our assumptions, it is of course possible that our approach misclassifies regulatory news in instances where the implied asset price comovements contradict the ones we posit. For our methodology to work well, such instances need to be rare and wash out over the sample.

4.2 Interpreting bank regulation news shocks

Our methodology has certain features that make it different from existing approaches. First, our high-frequency strategy should capture the full general equilibrium effects of regulation news. In contrast, estimates at the micro-level miss important macroeconomic transmission channels. For example, if capital requirements are raised for a *subset* of banks, it is of course useful to study their effect at the bank level, say with a diff-in-diff or a regression discontinuity design. However, these estimates could be very different from an increase in capital requirements for *all* banks in the economy. If all banks need to raise more capital, this could, for example, significantly change the cost of capital in funding markets. Such an effect cannot be captured by micro-level estimates. Instead, it requires a macro-level identification strategy such as ours.

Second, our shocks capture the combined effect of news about multiple types of regulatory instruments. When the market learns about how the Fed will enforce new regulatory legislation passed by Congress or when the Fed guides future Congressional action, this might encompass details about new capital requirements, changes in reporting requirements, and changes in the frequency of supervisory audits. The market reaction to a speech in which these details are explained then captures the combined effect of all of them. In other words, we cannot pin down the effects of specific instruments, such as a change in capital requirements, which might be in and of themselves interesting to policymakers. Instead, we estimate the impact of news about the "broad direction" of regulation.

4.3 Examples of large bank regulation news shocks

To further interpret our estimated shocks, we inspect the speeches that are associated with large shocks. Table 3 presents the ten largest bank regulation news shocks we estimate in their high frequency windows, ranked by the magnitude of the shock in absolute value. The table reports the rank, the date of the speech, the magnitude of the shock (measured in %-change in the bank stock price index), the speaker and the job title of the speaker.[12]

A key insight revealed by the table is the identity of speakers. As in Jayawickrema and Swanson (2023), we find that speeches by the Fed Chair lead to large market movements, with Ben Bernanke prominently appearing in the top 10. However, not only Chair speeches give rise to important bank regulation news shocks. In fact, the other speakers in the table are exactly those that one would plausibly expect to matter for bank regulation. The second largest surprise is caused by a staff member, Roger Cole, the Director of the Division of Banking Supervision and Regulation. Another news shock occurs around a speech given by Randy Quarles, the Fed's Vice Chair for Supervision. Finally, Lael Brainard appears in the top 10 list. At the time of the speech, Brainard served as Chair of the Committee on Financial Stability and the Committee on Federal Reserve Bank Affairs. The fact that we estimate large news shocks around speeches by speakers that are in roles relevant to banking regulation and supervision lends credibility to our identification strategy.

[12] These are the magnitudes of the shocks as they occur inside individual *high-frequency* windows, while the shocks shown as the blue line in Figure 3, Panel (b) are aggregated to *monthly* frequency.

Table 3: Largest shocks and associated speeches

Rank	Date	Shock (%)	Speaker name	Speaker title (at time of speech)
1	3/24/2009	4.03	Ben Bernanke	Chairman of the Federal Reserve
2	3/18/2009	3.58	Roger T. Cole	Director, Banking Supervision and Regulation
3	6/19/2008	1.96	Donald L. Kohn	Vice Chair of the Federal Reserve
4	12/3/2009	-1.89	Ben Bernanke	Chairman of the Federal Reserve
5	10/14/2008	-1.89	Ben Bernanke	Chairman of the Federal Reserve
6	7/9/2019	1.54	Randal Quarles	Vice Chair for Supervision
7	7/10/2008	1.53	Ben Bernanke	Chairman of the Federal Reserve
8	3/23/2021	-1.26	Lael Brainard	Member of the Board of Governors
9	4/8/2010	1.24	Ben Bernanke	Chairman of the Federal Reserve
10	6/3/2010	-1.22	Ben Bernanke	Chairman of the Federal Reserve

Beyond what is displayed in the Table 3, we can look into the language content of each individual speech. There are limits to how useful such an analysis can be. As we read a specific speech, we cannot know what financial markets expected to be said. Therefore, we cannot detect the *news* in the language of a speech, which is why we rely on high-frequency asset prices reactions to begin with. Keeping this in mind, we describe the content of a few selected speeches from Table 3 as an illustration.

Ben Bernanke on March 24, 2009. This speech consists of testimony before the Committee on Financial Services. The topic is the near-failure of the finance and insurance company AIG six months earlier. Bernanke signals a strong commitment to a regulatory environment with systemic backstops. He also argues for structured resolution regimes instead of bankruptcy. The market reacts to these remarks in a way consistent with an easing in financial regulation. A plausible interpretation is that Bernanke does not advocate tighter ex ante constraints, such as balance sheet restrictions. Instead, he favors ex post safety nets and resolution mechanisms. These regulatory elements likely support bank profitability and lower bank default risk.

Roger T. Cole on March 18, 2009. This speech consists of testimony before two subcommittees related to banking and financial markets. It is a detailed discussion of risk management practices in the banking industry and their role in the financial crisis. Cole explains that the Fed aims to systematically incorporate the lessons learned into future regulatory oversight. The market reacts to these remarks in a way consistent with news of an easing in financial regulation. The reason could be that there is little concrete action announced by Cole. The remarks are largely diagnostic and procedural, but do not propose new, sharply defined policy changes.

It is conceivable that markets were worried about more onerous rule changes and the statements reassured them that those would not occur, raising bank valuations.

Randal Quarles on July 9, 2019. Since the two examples above are from the GFC period, we also describe a speech from 2019. In a research conference at the Federal Reserve Bank of Boston, the Vice Chair for Supervision talks about bank stress testing. He reviews the ideas behind stress testing and emphasizes its success in the preceding decade. He then turns to recent proposed reforms of stress testing. While Quarles is sympathetic to reforms, he emphasizes efficiency and credibility rather than tightening stringency. He argues that "banks have now built enough capital to withstand a severe recession" and "given the huge strides that the banks have made (...), I view the risk of banks backsliding in this regard to be minimal". Overall, the speech indicates that Quarles is opposed to making the stress testing framework more burdensome for banks. The market reaction is an increase in the bank stock price index, reflecting a looser than expected regulation.

Ben Bernanke on June 3, 2010. Since the above examples are all regulatory easing episodes, we also discuss speech that triggers a tightening news shock. In this case, Bernanke speaks in Detroit, Michigan about small business lending. He emphasizes the importance of bank credit for small businesses. "(...) lenders should do all they can to meet the legitimate needs of creditworthy borrowers." The decline in bank stock prices following the speech likely reflects that it is interpreted as regulatory pressure, with concerns about supervisory judgment of what qualifies as "creditworthy". Bernanke says the Fed has "conducted extensive training programs for our bank examiners, with the message that encouraging lending to small businesses that are well positioned to repay is positive, not negative, for the safety and soundness of our banking system", a statement that might be viewed as regulatory interference with lending decisions lowering bank valuations.

5 The macro effects of bank regulation news shocks

This section presents our findings on the macroeconomic effect of bank regulation news shocks. We present the main results, additional results that help better understand the economic mechanism, as well as several validation exercises. A deeper discussion of the quantitative magnitudes follows in a separate section.

5.1 Main results

To construct IRFs of monthly macroeconomic variables, we estimate equation (2). Figure 4 presents the results. The shock is normalized to reduce the bank stock price index by one percent.[13] The shaded areas represent 68% and 90% confidence bands based on heteroskedasticity and autocorrelation consistent (HAC) standard errors. For comparison, the dashed black lines superimpose the responses associated with a raw surprise, before our sign restriction refinement is implemented.[14]

News about tighter than expected bank regulation is associated with a persistent decline in bank stock prices. While the initial decline arises by construction, the bank stock price response to regulation news remains significantly negative for the following four years, when it still stands at roughly -1%. By construction, the response of banks' distance to default is positive on impact, meaning that default risk among banks declines. The response builds up for the first year and reaches a peak of 0.05 to 0.1 units, where a unit corresponds to one standard deviation relative to the asset-value threshold implied by the Merton framework. After reaching its peak, bank distance to default eventually starts declining. At the three to four year horizon, we in fact see a reduction in distance to default. This increase in bank risk at longer horizons might reflect general equilibrium effects coming from the worsening in macroeconomic conditions that follow tighter regulation. The worse macroeconomic environment is visible in the IRFs of other variables, which we discuss in turn.

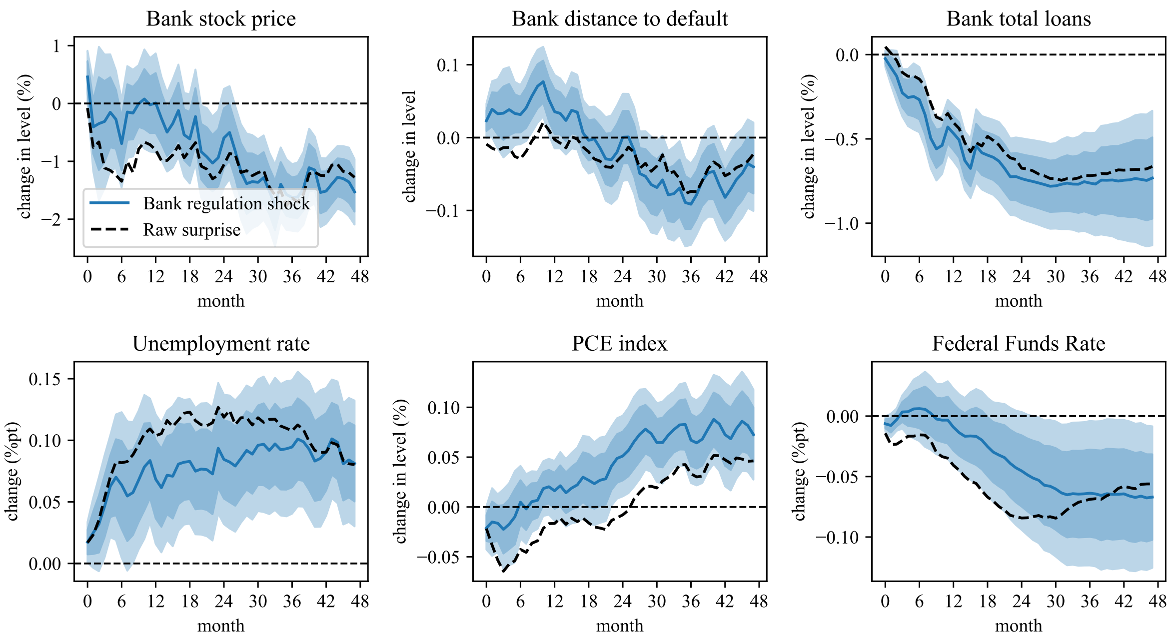
The bank regulation news shock gives rise to a persistent decline in bank lending. Here we measure bank lending as the volume of total loans in the US Financial Accounts. The 1% reduction in bank stock prices leads to a drop in the volume of bank loans in the US economy of between 0.5% and 1%. The contraction in lending activity is associated with a reduction in economic activity, as shown by the increase in unemployment. The unemployment rate rises with a small delay and reaches a level that is about 10 bp higher after two to three years. It remains elevated afterwards.

Tighter bank regulation news also gives rise to inflation. The 1% reduction in bank stock prices is associated with an increase in the level of the PCE price index

[13]The normalization is such that the bank stock price index declines by 1% at high frequency. The implied impact on the bank stock price IRFs at monthly frequency can differ from 1%.

[14]To estimate the IRFs in Figure 4 and subsequent figures, we excluded the years 2020-23 from the sample. As shown in the Online Appendix, we obtain similar results when including those years. However, due to the unusual behavior of unemployment in the COVID period, we estimate much larger unemployment effects, implying higher costs of regulation. Thus, to be conservative, we end the sample for the IRFs at the end of 2019.

Figure 4: IRFs to bank regulation news shocks



Notes: IRFs estimated with the local projection (2). The solid lines correspond to the bank regulation news shock identified by the sign restrictions in Table 2, Panel (a). The shocks are normalized to induce a 1% decline in bank stock prices at high frequency. Error bands represent 68% and 90% confidence interval, based on HAC standard errors. The dashed black lines superimpose, for comparison, the responses associated with a raw surprise (before imposing sign restrictions).

of close to 0.1% after several years. Converted into annual inflation rates, this is an economically relatively mild effect. Interestingly, there is a small decrease in prices on impact. The increase in the price level is slower than the response of real economic activity. This is in line, for example, with the slow and gradual price response to monetary policy shocks (Aruoba and Drechsel, 2024). The positive sign of both the unemployment and price level responses indicates that bank regulation news shocks act through an aggregate supply contraction. This finding is interesting in light of the question whether financial disruptions more broadly act as aggregate supply or aggregate demand shocks, see e.g. Benguria and Taylor (2020) and Mian et al. (2020).

In response to tighter than expected bank regulation, the Fed loosens monetary policy, as indicated by the reduction in the Federal Funds Rate. The Federal Funds Rate falls with a delay of almost two years after the news shock, likely reflecting a monetary policy easing in reaction to the uptick in unemployment and potentially leading to the mild rise in consumer prices, which the Fed appears to tolerate.

We further discuss the magnitudes of the estimated effects in separate section below, when we draw conclusions about quantitative trade-offs surrounding bank regulation. From a statistical point of view, all the results are highly significant. This observation echoes the insights of Jayawickrema and Swanson (2023) that the frequent occurrence of Fed speeches and increased sample sizes (relative to using only FOMC announcements) enhances the statistical power of the shocks constructed with high-frequency identification techniques.

The IRFs we estimate should be interpreted as symmetric. Tighter than expected bank regulation reduces bank lending, increases unemployment and prices, and temporarily mitigates bank risk, while looser than expected bank regulation increases lending, lowers unemployment and prices, and temporarily increases bank risk.

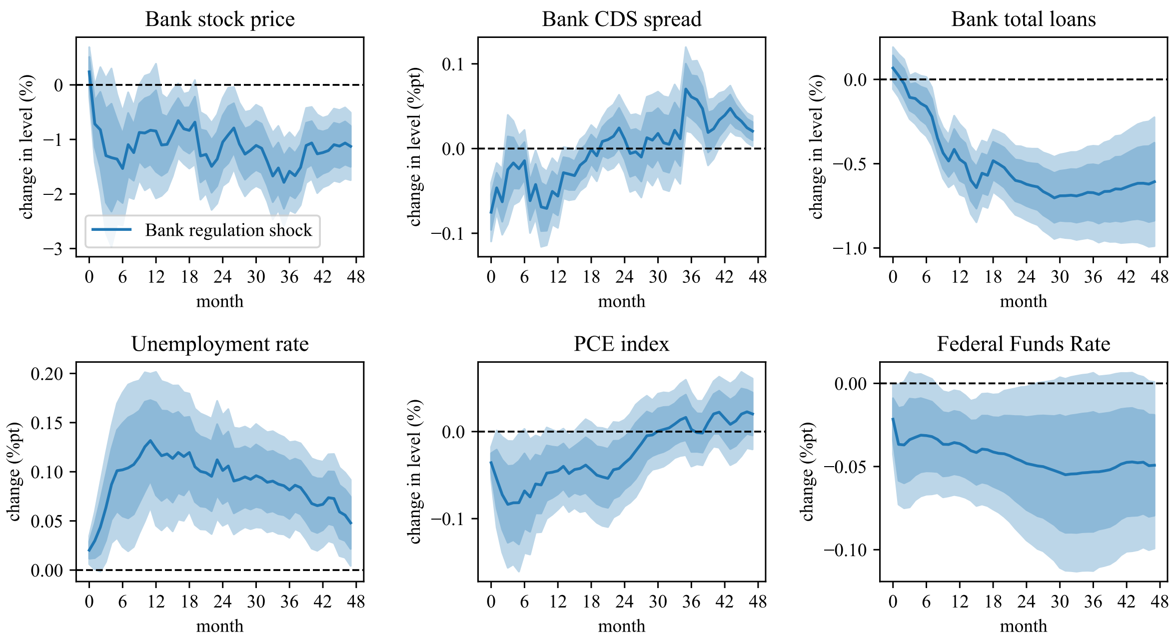
Results for raw surprises. A comparison with the macroeconomic dynamics associated with raw surprises, shown as the dashed black lines in Figure 4, provides additional insights on what our sign restriction procedure accomplishes. These responses likely reflect a convolution between bank regulation news shocks and bank health news shocks. The distance to default response to a raw surprise is relatively flat. While the bank stock price response and loan contraction are quantitatively similar, the raw surprise is associated with larger unemployment response, a sharper Fed easing and less of an inflationary response. This means, that without our refinement strategy, we would not be able to detect the effects of regulation on bank risk, and overestimate the negative activity effects of bank regulation.

5.2 Results with CDS premiums as alternative risk measure

We use CDS premiums as an alternative measure of risk, replacing distance to default in our sign restriction procedure. The resulting IRFs are presented in Figure 5. When comparing the CDS spread response with the distance to default response above, note that an increase in CDS premiums and a decrease in distance to default both imply an increase in bank risk. The figure shows that we find broadly similar results overall. The CDS premium response reveals a very similar profile of the risk dynamics as the results for distance to default, with a reversal from risk reduction to risk increase after two to three years. There is also a persistent and economically strong decline in bank loans. The resulting increase in unemployment is even stronger than for the specification with distance to default.

Interestingly, in the specification with CDS premiums, the initial decline in the PCE price index that we found above is now larger and more persistent. In fact, we do not see an increase in the price level after the first few years, although there is also a similar decrease in the Federal Funds Rate as in the results above. The comovement unemployment-inflation implied by these IRFs looks more like a contraction in aggregate demand than in aggregate supply. One explanation could be that the sample in which we have CDS data available only starts in 2002. This gives the GFC, a period with a strong aggregate demand contraction, a larger footprint in the results. We discuss the role of the GFC in our sample separately later in the paper.

Figure 5: IRFs to bank regulation news shocks (CDS premiums instead of distance to default)



Notes: IRFs estimated with the local projection (2). The solid lines correspond to the bank regulation news shock identified by the sign restrictions in Table 2, Panel (b). The shocks are normalized to induce a 1% decline in bank stock prices at high frequency. Error bands represent 68% and 90% confidence interval, based on HAC standard errors.

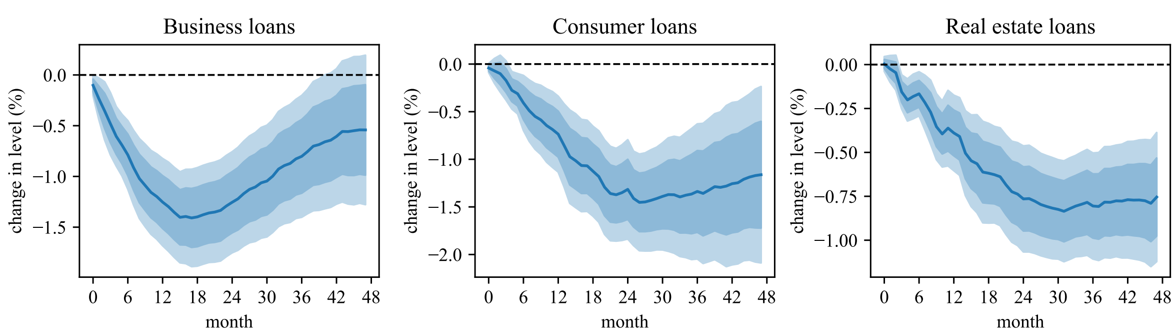
As data on CDS is available for a smaller time period than distance to default data, we report all subsequent results based on the specification with distance to default, represented by Table 2, Panel (a) and Figure 4. However, the advantage of using CDS premiums as a measure of risk is that their unit is interpretable in a more convenient way. We therefore come back to the results based on CDS premiums in more detail in Section 6, when we provide a more in-depth discussion on magnitudes.

5.3 Inspecting the economic mechanisms

Our shock triggers *news* about bank regulation. If agents in the economy learn that bank regulation tightens or loosens in the future, what kinds of reactions *today* lead to the results we uncover? What general equilibrium effects might be at play? To shed more light on the underlying mechanisms, we present IRFs of additional variables.

Types of bank lending. We analyze different types of bank lending after a regulation news shock. While Figure 4 plots the response of total bank loans, Figure 6 breaks down the response into different types. It makes clear that the reduction in lending activity is broad based. Business loans, consumer loans, and real estate loans all fall in volume. While there are differences in magnitude and persistence, news about tighter bank regulation leads to a bank lending reduction across the board. We study heterogeneity in the responses of individual banks further below.

Figure 6: Responses of additional variables: loan types

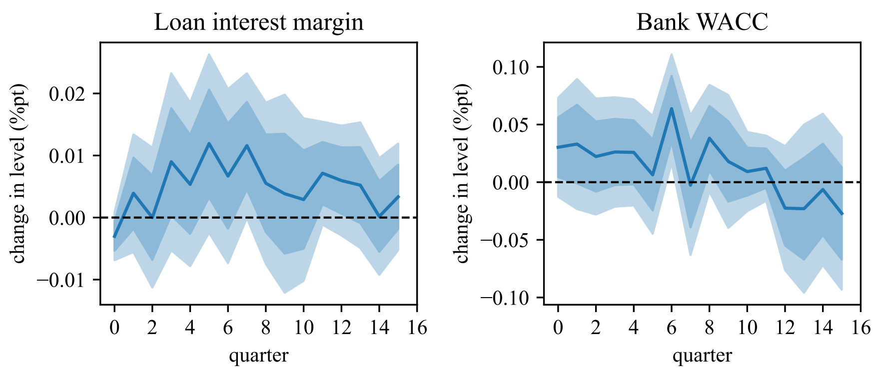


Notes: Breakdown of bank loan IRF into different loan types. Source: Federal Reserve US Financial Accounts.

Loan supply vs. loan demand. We test to what degree the decrease in bank loans following tighter regulation news comes from an active loan supply decision by banks. This is useful to know, given that the fall in loans can also come from lower loan demand by firms or households. As we are interested in identifying the full general equilibrium effects of bank regulation, the presence of loan demand forces is not a concern for our empirical strategy, but part of the mechanism. That said, we want to examine the degree to which a loan supply reduction is a significant part of the reason why loan volumes fall in Figures 4 and 5.

The first panel of Figure 7 supports a loan supply interpretation. Here, we study banks' loan interest margin as a measure of loan pricing. We can only compute the loan interest margin at quarterly frequency, so we aggregate our shocks to quarterly frequency to construct the IRF. We find that the loan interest margin increases in response to tighter than expected bank regulation after several quarters. The higher loan interest margin persists for several years, although the estimated effect is statistically somewhat weak. A fall in the quantity of loans and an increase in the price of loans is consistent with loan supply contraction following news about tighter than expected bank regulation.

Figure 7: Responses of additional variables: loan pricing and bank costs



Notes: The loan interest margin is calculated based on the FDIC Quarterly Banking Profile as (loan interest income / total loans) minus (total interest expense / total liabilities). Bank weighted average cost of capital (WACC) is calculated from Bloomberg for the banks in our CDS sample.

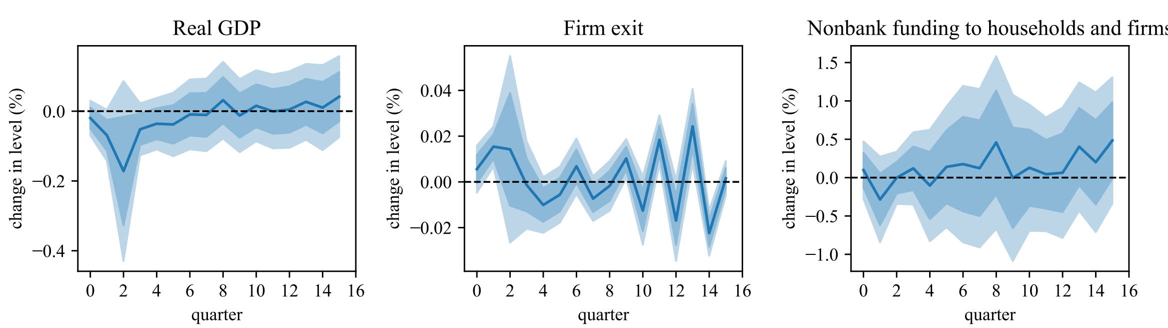
Given that we find an inward shift in credit supply, it is natural to compare the magnitude of our unemployment effects with studies on the labor market effects of credit supply shocks, such as Chodorow-Reich (2014) and Huber (2018). In Figure 4, we estimate a 10 bp increase in the unemployment rate after a 0.75% decline in the level of loans. Under a close mapping between employment losses and unemployment increases (labor force participation roughly fixed), this implies an employment–credit elasticity of around 0.14. While our effect is not purely about credit supply, it is roughly in line with the aforementioned studies. In the natural experiment around Commerzbank's lending cut in Huber (2018), high dependence on Commerzbank is associated with roughly 20.5% lower bank debt and roughly 5.3% lower employment. This implies an employment-credit elasticity of around 0.26. This number is not drastically different from our 0.14 elasticity, bearing in mind that this is a rough comparison, as our estimates contain general equilibrium effects.

Bank funding costs. An important channel through which regulatory news can already have effects today is through the immediate reaction of investors in banks and the associated changes in banks' funding costs. As tighter regulation in the future makes banks less profitable, banks' funding costs might rise. In turn, this alters banks' loan issuance behavior on impact, even when the actual regulation might not have taken place yet. The second panel of Figure 7 shows this is indeed the case. Following news about tighter regulation, the weighted average cost of capital (WACC) of US banks rises. The response is significant already on impact, indicating that bank funding is more difficult immediately after investors receive the news about tighter bank regulation.

This bank funding cost mechanism is at play in structural macroeconomic models of bank regulation. For example, in Elenev et al. (2021), tighter bank leverage regulation increases costly equity issuance for banks, thereby raising their WACC and leading to lower loan supply.

Additional real activity dynamics. We study GDP as opposed to unemployment as a measure of economic activity. GDP is quarterly. The first panel of Figure 8 shows this response is statistically noisy and that GDP does not fall as strongly as unemployment rises. However, its reduction is further evidence of a contraction in economic activity following news about tighter than expected bank regulation.

Figure 8: Responses of additional variables: GDP, firm exit and nonbank funding



Notes: Firm exit is the establishment death rates from the Business Employment Dynamics (BED). Nonbank funding to households and firms comes from the From-Whom-to-Whom Relationship data in the US Financial Accounts. Nonbanks are defined as money market funds, mutual funds, closed-end funds, exchange-traded funds, issuers of asset-backed securities, equity real estate investment trusts, mortgage real estate investment trusts, finance companies, security brokers and dealers, and other financial businesses.

Furthermore, we study firm exit, to better understand how bank regulation and the reduction in loan supply impact nonfinancial firms and whether this is consistent with the strong unemployment effects we uncovered. Firm exit rates come from the establishment data of the Business Employment Dynamics (BED). The second panel of Figure 8 shows that news about tighter bank regulation, and the associated reduction in credit supply, lead to a quick increase in firm exit, though the subsequent dynamics are less clear. The impact effects on firm exit are in line with the strong and relatively quick increase in unemployment we found above.

The role of nonbank financial institutions. Finally, we test whether there is increased lending activity by nonbank financial institutions when banks get more stringently regulated. This is an important theme in the existing literature on bank regulation, see e.g. Begenau and Landvoigt (2021) or Irani et al. (2020) for discussions. We calculate the amount of nonbank funding to households and firms using the From-Whom-to-Whom Relationship data in the US Financial Accounts. Interestingly, third panel of Figure 8 shows that nonbank lending is flat after the bank regulation news shock. This finding suggests at least tentatively that nonbank lenders do not "fill the gap" in lending created by regulation in the banking sector. As our results account for general equilibrium effects, this could come from the second-round effect of lower credit demand by firms in a weaker macroeconomic environment.

5.4 Additional results and validation exercises

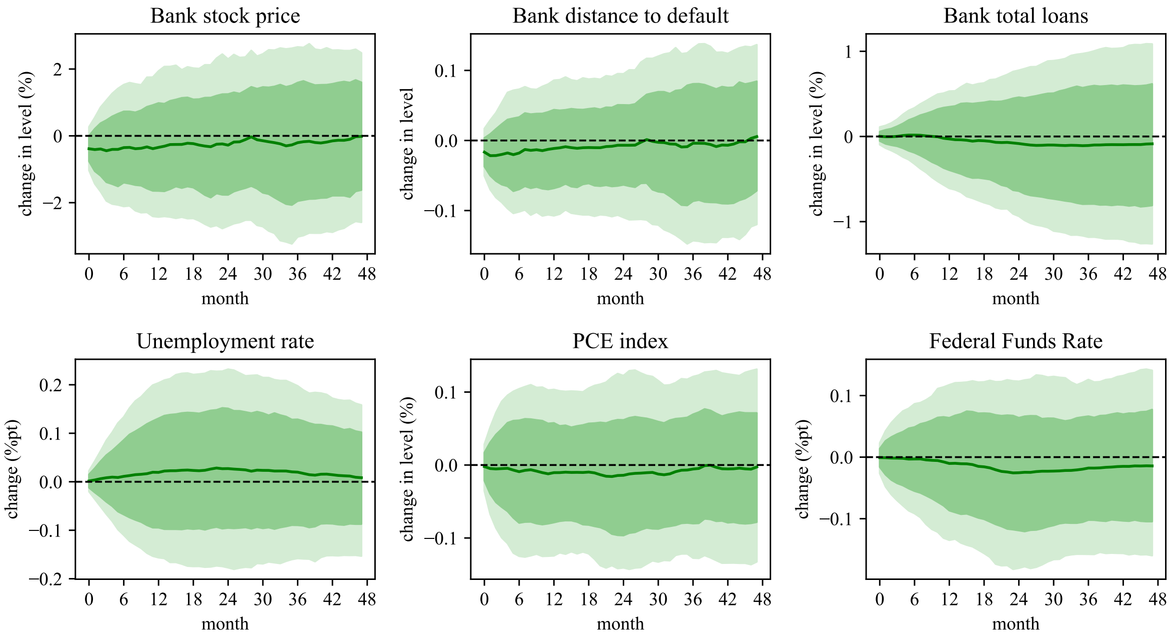
We provide a variety of additional results and validation exercises. These underline the robustness and broader implication of our findings.

5.4.1 Placebo tests

Do we really capture new information conveyed by speeches, or do the high-frequency surprises we construct merely reflect unrelated fluctuations in bank stock prices? In the latter case, the IRFs we estimate might mechanically pick up the macroeconomic dynamics following "some" innovation in the bank stock price index, instead of a regulation related surprise. To address this concern, we follow a "Placebo" strategy. We construct bank stock price surprises in randomly selected time windows, rather than around speeches. We choose the same window size and randomly draw the same number of points in time that we use to measure our raw surprises, and then construct the surprises and associated IRFs for those random points in time. This process is repeated 1,000 times.

Figure 9 presents the result of the Placebo study. The green shaded areas show percentiles of the IRFs across the 1,000 Placebo repetitions. Clearly, these shaded areas are well centered around zero and do not reveal any systematic response

Figure 9: Result for Placebo test using random bank stock price changes



Notes: We randomly select high-frequency intervals in the main analysis sample, then construct bank stock prices index surprises over these intervals and estimate associated IRFs. We repeat this process 1,000 times and show percentiles over the 1,000 draws in each panel as green shaded areas (dark area corresponds 68% percentiles, light area 90% percentiles).

of macroeconomic variables. This is in sharp contrast to our main IRFs. These results support the conclusion that our method for constructing surprises captures meaningful information conveyed by Fed speeches and does not just mechanically capture unrelated movements in bank stock prices.

5.4.2 Monetary policy surprises in bank-related speeches

Speeches by Fed officials might systematically reveal information about the course of monetary policy, even after selecting speeches that primarily discuss bank regulation. To examine this concern, we measure monetary policy surprises on days when bank-related speeches were given, using Federal Funds Rate futures. The Online Appendix documents that the correlation between bank-related surprises and monetary policy surprises around bank-related speeches is low. Thus, even if Fed speeches on bank regulation might reveal some information about monetary policy, the relationship does not appear to be systematic. When we control for these monetary policy surprises in the local projections, we obtain close to identical results.

5.4.3 Information about the state of the economy

A crucial concern addressed with our sign restriction procedure is that Fed speeches reveal information about the banking sector's health to the public. A related concern that our restrictions might not address is that the Fed could reveal new information about the economy's *overall* health. This mechanism is sometimes called information effect in the monetary policy surprise literature (Romer and Romer, 2000; Nakamura and Steinsson, 2018). Recent work by Bauer and Swanson (2023) casts doubt on the argument that Fed announcements give rise to such effects. Nevertheless, we want to verify that our bank regulation news shocks are not contaminated by such effects. We do so with two different exercises.

Correlation with other macro shocks. First, we verify if our bank regulation news shocks are convoluted by other macroeconomic shocks, which the public may learn about from Fed speeches. Reassuringly, Table 4 shows that our shocks are uncorrelated with monetary policy shocks, uncertainty shocks, oil supply news shocks and fiscal policy shocks estimated by the literature.

Table 4: Correlation with other shock measures from the literature

Shock type	Correlation	p-value	Sample
Monetary (Bauer and Swanson, 2023)	0.095	0.218	1998M1-2023M8
Uncertainty (Bloom, 2009)	-0.001	0.987	1998M1-2023M8
Oil supply news (Känzig, 2021)	0.080	0.301	1998M1-2023M8
Fiscal (Ramey and Zubairy, 2018)	0.086	0.580	1998Q1-2015Q4

Surprises around speeches about the state of the economy. As a second exercise, we construct high-frequency bank stock price surprises around speeches that are not related to bank regulation, but instead to the state of the economy itself. This is another type of "Placebo" exercise, where instead of selecting Topics 2 and 4 in Figure 1, we select Topic 5 and then repeat the remaining steps of our methodology. The speeches primarily related to that topic cover the general state of the economy. The resulting IRFs, presented in the Online Appendix, look very different from those triggered by surprises around bank related speeches. For example, we cannot detect significant bank loan, unemployment or Fed Funds Rate responses. Given that IRFs to news about the state of the economy are very different alleviates the concern that our bank regulations news shocks are contaminated by broader information effects.

5.4.4 The role of the sample

Our main analysis sample begins in the 1990s, when tick data for bank stock prices become available. This is a common constraint in the high-frequency literature. For example, the analysis of Swanson (2021) using tick data on Fed Funds futures begins in 1991. The short sample period raises the concern that a few shocks or specific periods dominate our result. Indeed, our shocks exhibit large movements during the GFC, as shown in Figure 3. We carry out two tests to better assess these concerns.

Leave-one-out test. We re-estimate our main IRFs 10 different times. Each time we leave one out of the ten largest shocks in absolute value. The idea of this test is to verify whether one specific shock drives our results. The findings of this leave-one-out test are presented in the Online Appendix. We obtain relatively similar IRFs across the 10 re-estimations.

Excluding the GFC. In the Online Appendix, we present IRFs for an alternative sample that entirely excludes the GFC period. In this more restrictive test, we indeed lose statistical power. While we do not find any results going significantly in the other way from our main results, several IRFs cannot be distinguished from zero at conventional levels. Reassuringly, several IRF are still significantly different from zero, such as the reduction in bank loans and the increase in distance to default. We also still estimate an increase in inflation. To further alleviate the concern about a small sample with a big footprint of the GFC, the next section estimates a daily version of our high-frequency surprises for a longer sample.

5.4.5 Daily version of surprises starting in 1970s

To consider a longer time period, we use daily data. Specifically, we retrieve the NASDAQ Bank Index from Bloomberg from 1971 to 2023.[15] The long sample has two distinct advantages. First, it contains many additional regulatory changes. For example, the 1980s saw a wave of financial deregulation. Second, we can consider almost 3,000 speeches, including speeches by the FDIC and not only the Fed (see Table 1). We cannot consider FDIC speeches in our high-frequency baseline as we do not have precise time stamps for them.

[15]This index covers companies listed on the NASDAQ exchange that are classified as banks according to the Industry Classification Benchmark. The Bloomberg ticker is 'INDEXNASDAQ: BANK'. After 1998, it is highly correlated with the index we construct in our main 1998-2023 sample.

Using daily data has the disadvantage that high-frequency identification is less credible. Even on days with speeches, daily price changes in bank stocks may capture other shocks occurring during the day. Therefore, we instead employ identification via heteroskedasticity (Rigobon and Sack, 2004). The idea of this approach is that the variance of the structural shock of interest increases on event days. If other shock variances remain unchanged, one can difference out nuisance variation. In our case, on days with speeches about bank regulation we assume that the variance of bank surprises increases. Both Ottonello and Song (2025) and Känzig (2023) complement high-frequency identification with heteroskedasticity-based identification.[16]

The results based on this approach are presented in the Online Appendix. We confirm that at daily frequency bank related speeches contain surprises that have statistically significant impacts on our outcome variables of interest. We find that a shock lowering bank stock prices reduces bank loans, increases the unemployment rate, raises the PCE index and lowers the Fed Funds rate. All of these responses are in line with our baseline findings. We do not find that the heteroskedasticity identified shock moves distance to default in a meaningful way. Note, however, that our heteroskedasticity-based approach does not impose a sign restriction on distance to default. All IRFs considered, the longer time period and alternative approach are not in contradiction to our main analysis. This at least somewhat alleviates the concern around the GFC period being important for our main results.

5.4.6 The effects of bank health news shocks

In the Online Appendix, we study the IRFs following a bank health news shock, a by-product of our procedure. By construction, a negative bank health news shock reduces stock prices and lowers distance to default on impact (see Table 2). Over time, the distance to default IRF remains negative and does not flip sign as it does for the regulation news shocks. Bad bank health news reduces bank lending activity and contracts the economy. The increase in unemployment is larger than for a regulation news shock normalized to the same stock price change. It is accompanied by a fall in the price level. The Federal Funds Rate falls, suggesting that the Fed eases policy in response to bad bank health news.

[16]While in Rigobon and Sack (2004), daily heteroskedasticity identifies daily-frequency effects, we extend the approach to lower frequency (monthly) outcomes. This requires allowing for multiple event days within a month and events and control days coexisting within a month. The Online Appendix explains the details, including a consistency proof for our procedure.

5.4.7 Heterogeneity across individual banks

Our main empirical strategy uses an aggregated index of US bank stocks. Given that we have access to the underlying data for 18 individual US banks, we can construct IRFs of stock prices and distance to default for any of these banks separately. The Online Appendix presents these IRFs for selected banks. We find that there is indeed some interesting heterogeneity. In response to news about tighter bank regulation, the stock price of Citigroup falls relatively quickly and quite strongly in magnitude. The stock price of Goldman Sachs actually rises on impact, but declines strongly and persistently after about two years. A similar rise-and-fall pattern can be observed for Morgan Stanley. The decline in the Wells Fargo stock price is smaller than that of other banks. The response of distance to default looks remarkably similar across banks, suggesting a strong common risk component. For all banks, news about tighter bank regulation triggers an initial increase in distance to default, followed by a subsequent decline after roughly two years.

6 Quantifying the stability-activity trade-off

Our results suggest that financial regulation involves a trade-off between risk mitigation and economic activity. To quantify this trade-off, we use simple calculations that draw on our empirical estimates. We then put these calculations in the context of existing estimates in the literature and discuss important caveats.

6.1 Back-of-the-envelope comparisons

To quantify the stability-activity trade-off with "back-of-the-envelope" calculations, we first compare the IRFs of bank CDS premiums as a measure of risk and the unemployment rate as a measure of economic activity. The magnitudes of CDS premium responses can conveniently be converted into numerical default risk, making their economic significance easy to interpret. Further below, we also approximate the probability of a financial crisis using our distance to default IRF. We focus on the unemployment rate as a key macroeconomic variable, but we also consider the impact on real GDP in our comparison with the literature.

For simplicity, we compare the *peaks* of the IRFs of these variables with each other. This comparison is crude, as it does not account for persistence. We emphasize that this comparison likely overstates the reduction in risk and understates the slowdown in economic activity. The reason is that the risk related IRFs are less persistent and even revert sign, while the unemployment effect is quite persistent. In that sense, our quantification is generous toward the benefits of regulation.

Based on the results in Figure 5, we calculate that a roughly 10 bp peak reduction in bank CDS premiums is accompanied by a roughly 15 bp peak increase in the unemployment rate. A CDS premium can be interpreted as the product of the loss-given-default and the probability of default. The loss-given-default is calculated by subtracting the recovery rate from 1. This procedure yields a risk-neutral probability of default (Huang et al., 2009). Assuming a recovery rate of 0.4, a 10 bp reduction is equivalent to an 16.67 bp lower annual probability of default.[17] The average annual probability of default priced in the CDS market in our sample is 1.5%, with a standard deviation of 1.2%. When we exclude the Great Recession from the calculations, the average is 1.2% and the standard deviation is 0.36%.

Based on these numbers, we conclude that 16.67 bp is a meaningful fraction of the annual probability of default of major US banks. Reducing default risk by that order of magnitude is therefore an economically significant change in the financial system and a significant (*gross*) benefit of regulation. However, a 15 bp increase in the unemployment rate is also a significant reduction in macroeconomic activity and thus constitutes a meaningful (*gross*) cost of tighter regulation.

Whether or not the *net* benefit of regulation is positive is more difficult to determine. One reason is that it will of course ultimately depend on social preferences. Another reason is that one needs to convert benefit and cost into the same unit. It is unclear from our estimates how much unemployment gets avoided when bank default risk falls by 16.67 bp, so it is unclear how large the benefit is in "unemployment units." We return to these and other caveats in more detail after we compare the magnitudes of estimates to the previous literature.

6.2 Comparison with the literature

One way to compare our estimates to the existing literature is by focusing on selected (cross-)elasticities. In the previous section, we already verified that the responses of bank loan supply and unemployment are broadly in line with studies on the labor market impact credit supply shocks, e.g. Huber (2018), Chodorow-Reich

[17]The calculation is $10bp/(1-0.4) \approx 16.67bp$. A recovery rate of 0.4 is common in financial practice when calculating loss-given-default. See Hull (2021) (Chapter 24) for a textbook treatment.

(2014). The comparison we focus on in this section about the broader stability-activity trade-off. Although that is more complex, we find that our estimate of the economic costs of bank regulation is sizable in the context of the existing literature.

We consider a meta study conducted by the Bank for International Settlements (BIS) (Birn et al., 2020). It summarizes nine studies that examine the reduction in the probability of a crisis and the downward impact on GDP after an increase in the bank capital ratio by 1 percentage point (pp). When comparing our estimates with the meta study, it is important to keep two aspects of our results in mind. First, our GDP estimates are much weaker than the ones for unemployment, so a focus on GDP understates the negative activity impact implied by our findings. Second, the meta study focuses on bank capital requirements specifically, while our results capture regulation news based on a variety of instruments (see Section 4.2).

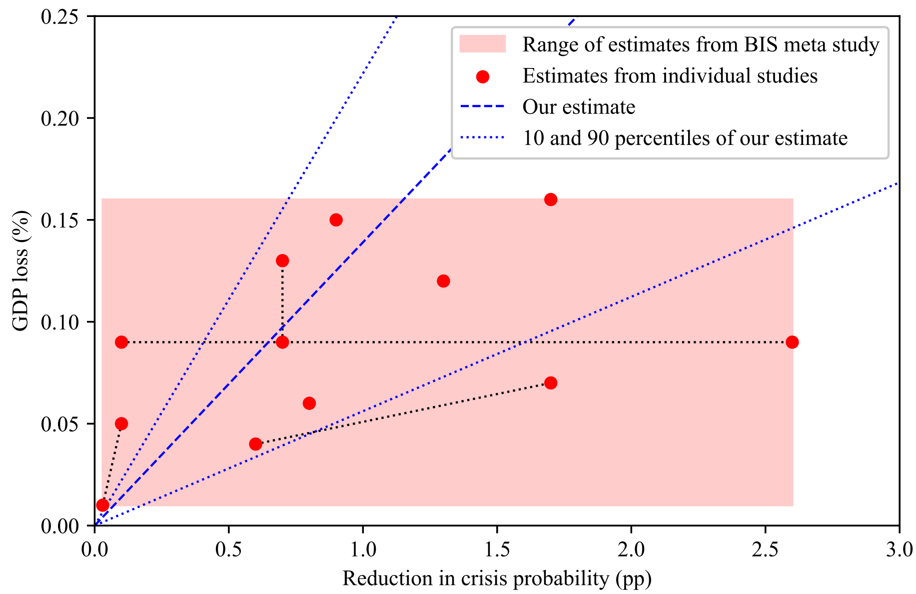
Figure 10 plots the range of estimates reported in Birn et al. (2020) as the shaded rectangular area. According to their survey, the reduction in the crisis probability ranges from 0.03 to 2.6 pp, while the associated GDP decline ranges from 0.02% to 0.16%. Each dot presents a study that is included in their survey. Some studies report ranges of estimates, which we represent as dotted lines. Successful regulation with small economic costs should ideally lead to coordinates that are located to the bottom right of the figure (a lot of crisis reduction, little GDP loss).

To convert our estimates into the space of reduction in crisis probability, we proceed as follows. Based on our IRFs, we linearly approximate the implied crisis probability based on how much distance to default moves in the GFC. Specifically, we normalize the probability of a crisis to 100% for the GFC and then compute the probability of a crisis for Figure 4 by dividing the peak distance to default response in that figure by the distance to default change during the GFC in the data. For the GDP loss, we use our peak GDP response in Figure 8. Finally, dividing the crisis probability by the GDP loss gives us a ratio, which is represented by the dashed blue line in Figure 10. We approximate uncertainty around this ratio by plotting its 10th and 90th percentile based on the Delta method.[18]

We find that our estimates and associated uncertainty bands fall into the range of estimates that the literature has reported. Indeed, most of the estimates in Birn et al. (2020) are located inside our 10th and 90th percentiles. Comparing the dashed line

[18]Suppose the $A =$ (peak change in distance to default from our IRF / distance to default change in the GFC) $*100$, and $B =$ peak change in GDP from our IRF. We plot A/B and compute $SE(B/A) = sqrt((SE(B)/A)^2 + (B * SE(A)/A^2)^2$. For simplicity, we assume $Cov(A, B) = 0$.

Figure 10: Tradeoff between crisis prevention and activity loss: our estimates vs. the literature



Notes: Comparison between the tradeoff implied by our estimates (peak IRFs) and a meta study conducted by the Bank for International Settlements (BIS) (Birn et al., 2020).

implied by our point estimates with the full shaded area that spans the estimates in the meta study, it appears that our estimated is tilted towards the top left of the graph, which is exactly not the direction that successful regulation with little economic costs should be in. Bear in mind that we generally find much stronger effects on unemployment than on GDP. Therefore, a similar picture with unemployment effects would likely represent a pattern even less favorable in terms of the macroeconomic costs of regulation. Taken together, the costs of regulation implied by our estimates appear to be quite pronounced when compared to the literature.

6.3 Caveats and broader discussion

There are important qualifications to our analysis of the stability-activity trade-off. First, a lower annual probability of default of banks reduces the tail risk of a severe financial crisis, which itself would likely lead to a large increase in unemployment. In other words, to properly compare the 16.67 bp default probability reduction with the 15 bp unemployment rate increase, we want to put both in "unemployment units." If we consider the GFC as a case in point, the US unemployment rate rose by around 5.5 pp. During the same period, the probability of default of US banks increased by roughly 500 bp. Combining these two numbers with the 16.67 bp lower probability of default we estimate, we can roughly extrapolate that a 16.67 / 500 * 5.5 = 0.183 pp "crisis unemployment" gets avoided due to tighter regulation. In comparison with the 0.15 pp unemployment rate increase we estimate following a regulatory tightening, this implies positive *net* benefits of regulation (as $0.183 > 0.15$).

Second, while our IRFs capture average effects across the sample, the effects of bank regulation could be state-dependent and/or nonlinear. For example, Mendicino et al. (2018) show theoretically that higher capital requirements are beneficial at low levels of regulation, while the benefits decline or revert at higher levels. Accounting for state-dependence and nonlinearities is possible with empirical techniques and we think that extending our analysis in this direction could be promising.

Finally, an argument for tighter regulation is that a stable economic environment supports economic growth in the long run, despite negative effects in the short run. Mendicino et al. (2020) who show that higher bank capital requirement make banks safer in the long run, while reducing credit supply and economic activity in the short run. Even though our IRFs are estimated to be persistent, the transitory nature of our high-frequency shocks might fail to capture some of these long-run benefits. A similar discussion arises for high-frequency approaches to other policy changes that likely have long-term effects, such as climate policy (Känzig, 2023).

We believe that for assessing longer term effects of regulation, structural models are arguably the better tool. Indeed, we are confident our estimates can be useful to discipline the short run dynamics of structural models that can speak to longer-term economic effects. For these models to be credible, they need to be consistent with evidence of short-run impacts of regulation and regulation news.

7 Conclusion

This paper contributes new empirical findings on the delicate balance between bank regulation and economic activity. Studying this balance is challenging because financial regulation and economic outcomes are simultaneously determined. Using a high-frequency approach that measures the impact of speeches by regulators on bank stock prices, we examine how news about banking regulation affects the economy. News about tighter than expected bank regulation reduces measures of bank risk, indicating improved financial stability in the banking sector. However, this comes at the cost of lower economic activity, reflected in reduced bank lending and higher unemployment. We assess this trade-off quantitatively and conclude that our estimates imply a relatively high macroeconomic cost of regulation, at least in the short run. The implications of our findings are relevant for policymakers tasked with designing financial regulations, who need to consider the shorter-run contractionary consequences that accompany the longer-term benefits of bank regulation.

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ONLINE APPENDIX TO

The macroeconomic effects of bank regulation: New evidence from a high-frequency approach

by Thomas Drechsel and Ko Miura

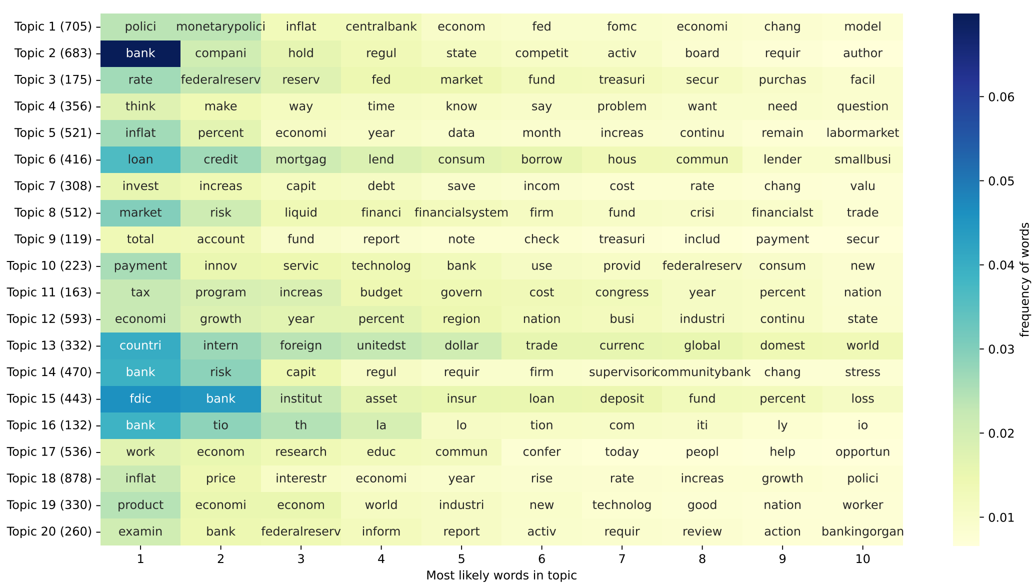
Contents

A Alternative number of topics in NLP step

Figure A.1: Topics and associated words in Fed speeches – alternative number of topics

(a) Number of topics is $K = 10$

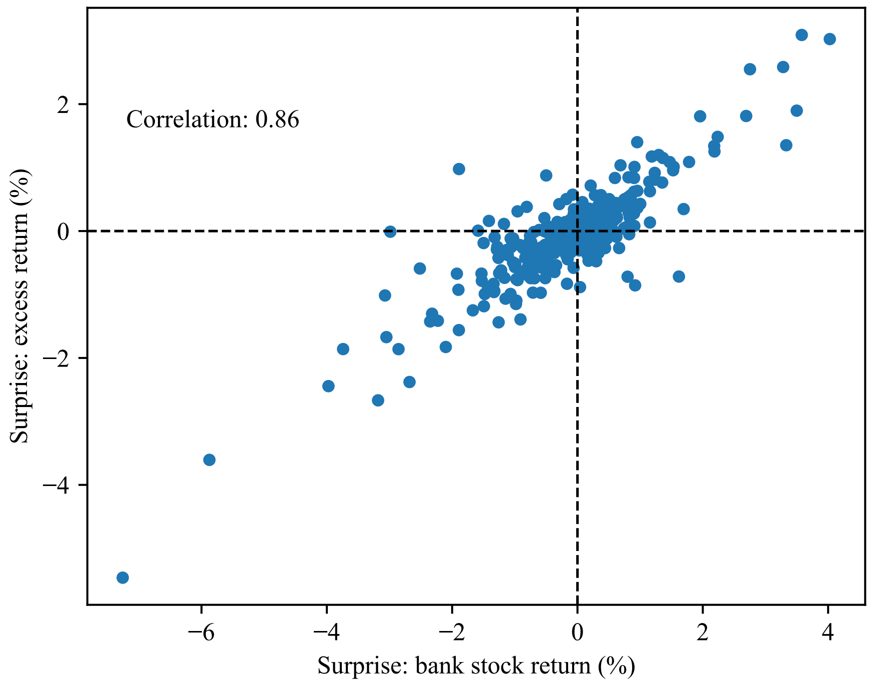
(b) Number of topics is $K = 20$



Notes: The two panels of this figure repeat Figure 1 from the main text, for alternative choices of the number of topics in the LDS algorithm of Hansen, McMahon, and Prat (2018).

B Relation of return vs. excess return surprises

Figure B.1: High-frequency surprises in bank stock returns vs. in excess returns of bank stocks

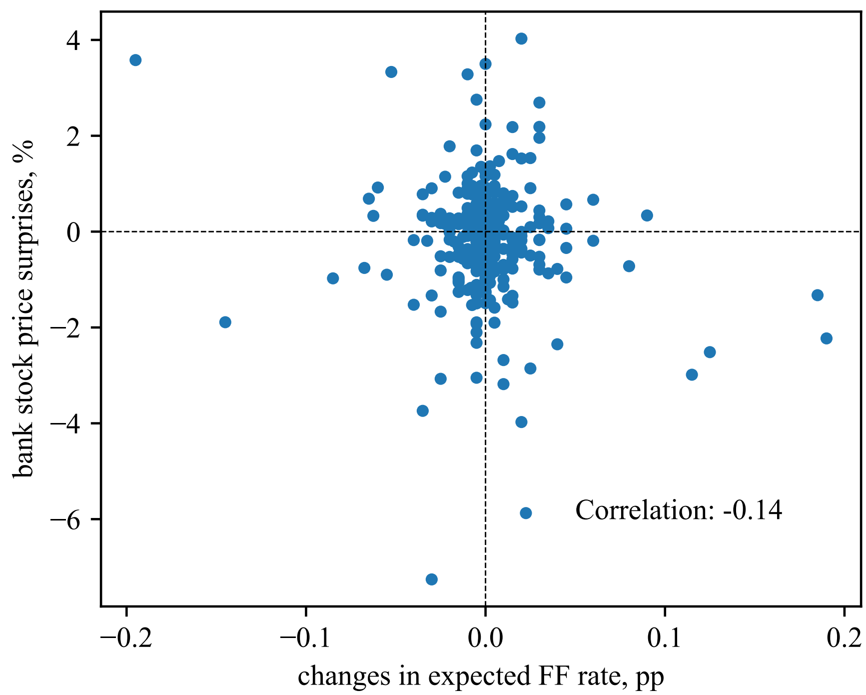


Notes: Comparison between raw high-frequency surprises computed as the return on the bank stock price index and the excess return of that index over the S&P 500.

C Bank regulation and monetary policy surprises

Figure C.1 plots the raw surprises in bank stock prices against changes in Federal Funds futures (3-month Eurodollar futures) on days of bank-related speeches. The correlation coefficient -0.14. The low correlation suggests that even if Fed speeches on bank regulation might reveal some information about monetary policy, the relationship does not seem to be systematic. These results are also in line with the lack of correlation between our shock and measures of other types of macroeconomic shocks studied in the literature (as shown in Table 4 in the main text).

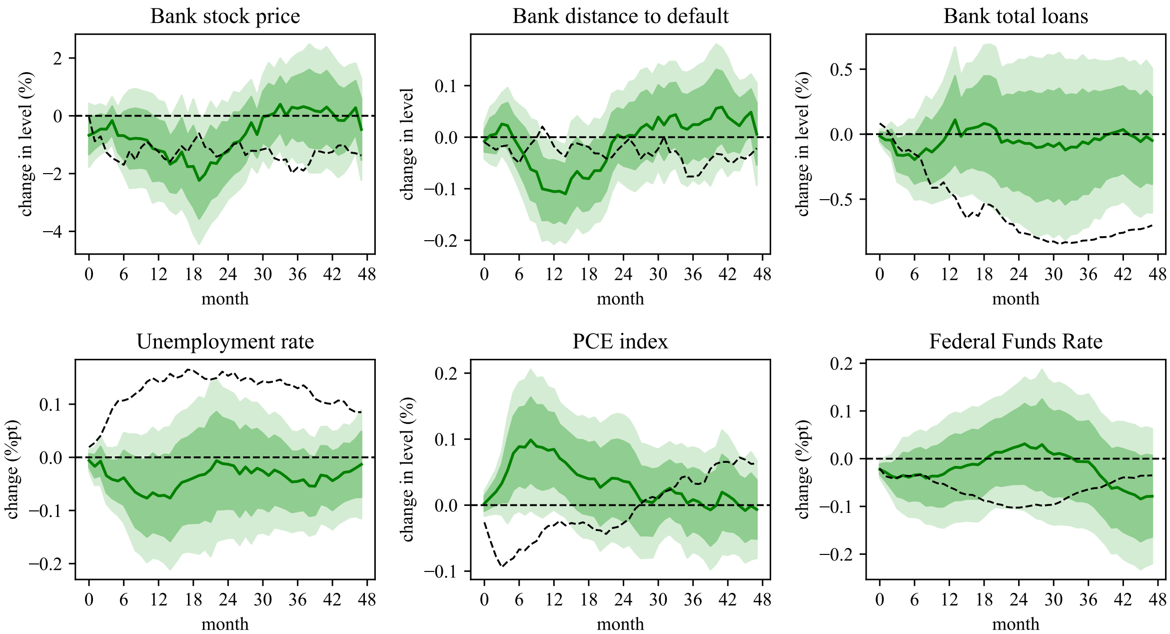
Figure C.1: Bank regulation surprises and monetary policy surprises



Notes: This figure plots the raw surprises in bank stock prices against changes in Federal Funds futures (3-month Eurodollar futures) on days of bank-related speeches.

D Surprises around other speeches

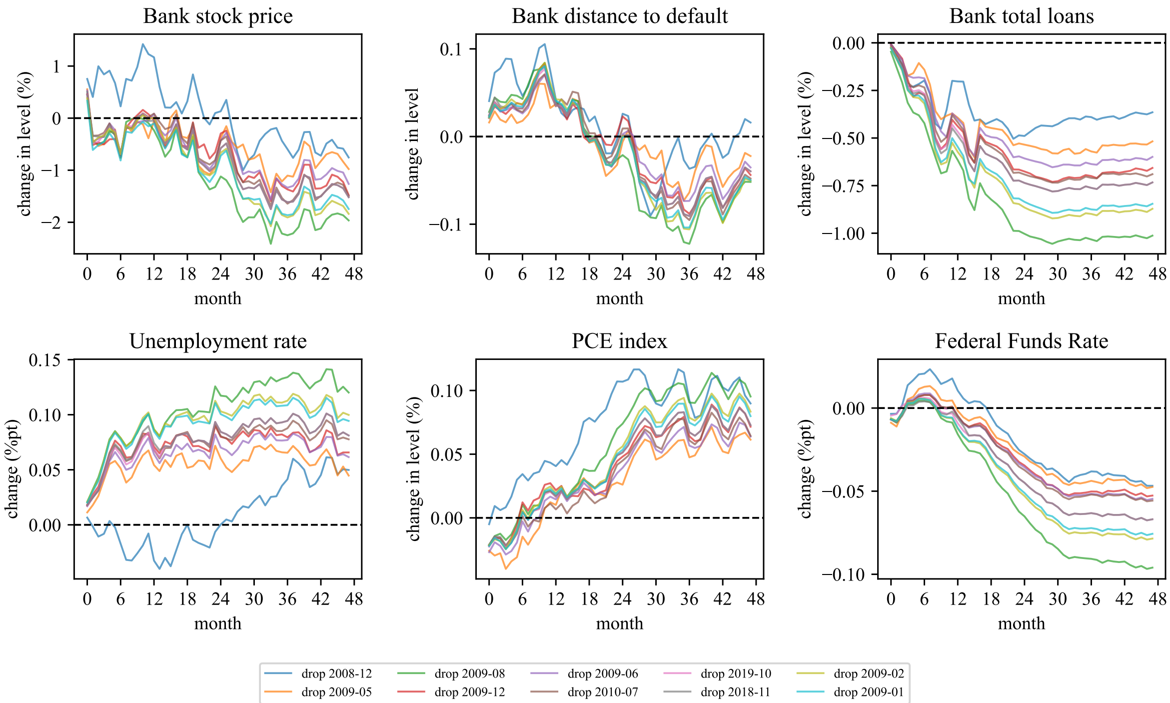
Figure D.1: IRFs to surprises coming from speeches about the state of the economy



Notes: This figure constructs IRFs to the raw surprises around speeches that are not about bank regulation but about the general state of the US economy, see Topic 5 in Figure 1. The dashed black line shows the IRFs to our baseline raw surprises around bank related speeches (see Topics 2 and 4 in Figure 1).

E Leave-one-out test

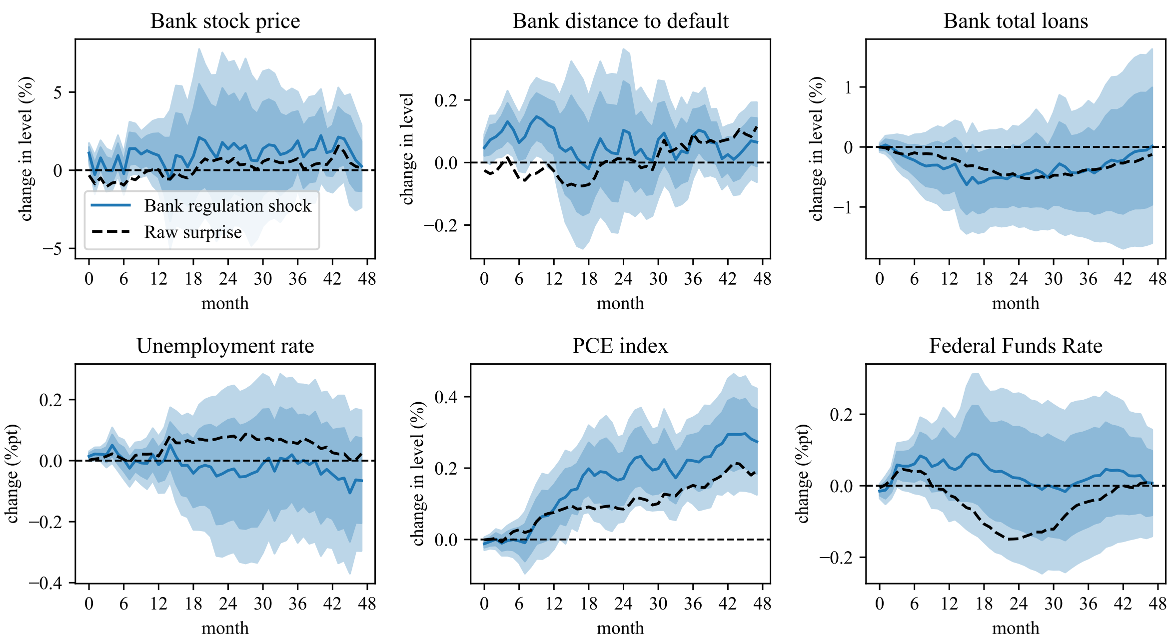
Figure E.1: IRFs to bank regulation news shock excluding one of the ten largest shocks



Notes: This figure presents 10 different point estimates of IRFs to bank regulation news shocks. In each case, one of the 10 largest shocks in absolute value is excluded when the local projections are estimated.

F Excluding the GFC

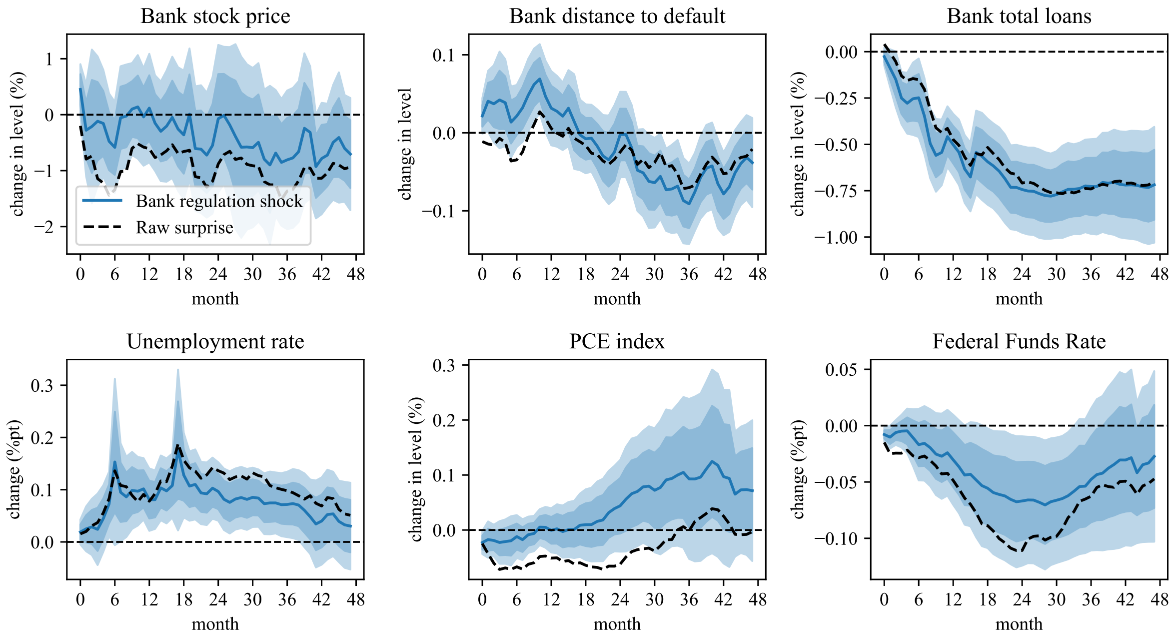
Figure F.1: IRFs to bank regulation news shock identified with sign restrictions, excluding GFC



Notes: This figure constructs the IRFs shown in Figure 4 for an alternative sample where shocks during the GFC (all months of 2008-2009) are set to zero.

G Including the COVID period

Figure G.1: IRFs to bank regulation news shock identified with sign restrictions, including 2020-23



Notes: This figure constructs the IRFs shown in Figure 4 for an alternative sample where 2020-2023 are included.

H Daily version for longer sample

H.1 Identification via heteroskedasticity

This appendix develops a local projection estimator that exploits daily-frequency heteroskedasticity to identify monthly impulse response functions. We first present the estimator under a general setup and subsequently specialize it to the bank surprise identification.

H.1.1 Setup

For horizon h and month t, consider the local projection:

$$y_{t+h} = \mu_h + \psi_h \, \varepsilon_t + \beta_h' x_{t-1} + \xi_{t,h},$$

where ε_t is the shock of interest in month t, x_{t-1} is a vector of controls, and ψ_h is the parameter of interest, representing the impulse response function (IRF) at horizon h. Define the Frisch–Waugh–Lovell residual:

$$y_{t+h}^{\perp} \;\equiv\; y_{t+h} - \hat{\mu}_h - \hat{\beta}_h' x_{t-1} \;=\; \psi_h \, \varepsilon_t + \xi_{t,h}.$$

On day d in month t, the observed asset price change is:

$$\Delta f_{t,d} = \phi \, \varepsilon_{t,d} + \eta_{t,d},$$

where $\varepsilon_{t,d}$ is the shock of interest on day d in month t, and $\eta_{t,d}$ is a nuisance term capturing all other influences. The nuisance term may be correlated with $\xi_{t,h}$, which is the source of potential bias. The monthly shock is the sum of daily shocks:

$$\varepsilon_t = \sum_{d=1}^{D_t} \varepsilon_{t,d}.$$

H.1.2 Estimator

For each month t, let $\mathcal{E}_t$ denote the set of event days and $\mathcal{C}_t$ the set of control days. A naive approach would use the average daily price change on event days, $|\mathcal{E}_t|^{-1} \sum_{d \in \mathcal{E}_t} \Delta f_{t,d}$, as a proxy for the monthly shock. However, the resulting regression would be biased due to the correlation between $\eta_{t,d}$ and $\xi_{t,h}$.

Instead, we use the following estimator:

$$\hat{\psi}_h = \frac{\frac{1}{T}\sum_{t=1}^{T}\Big(\frac{1}{|\mathcal{E}_t|}\sum_{d\in\mathcal{E}_t}\Delta f_{t,d} - \frac{1}{|\mathcal{C}_t|}\sum_{d\in\mathcal{C}_t}\Delta f_{t,d}\Big)\, y^{\perp}_{t+h}}{\frac{1}{T}\sum_{t=1}^{T}\Big(\frac{1}{|\mathcal{E}_t|}\sum_{d\in\mathcal{E}_t}(\Delta f_{t,d})^2 - \frac{1}{|\mathcal{C}_t|}\sum_{d\in\mathcal{C}_t}(\Delta f_{t,d})^2\Big)}.$$

This estimator is consistent for ψ_h under the assumptions stated below.

H.1.3 Proof of Consistency

We show that the estimator $\hat{\psi}_h$ is consistent for the true parameter ψ_h. To simplify the notation, define the following averaged expectations over event and control days:

$$\mathbb{E}_{\mathcal{E}}[g_{t,d}] \;\equiv\; \frac{1}{T}\sum_{t=1}^{T}\frac{1}{|\mathcal{E}_t|}\sum_{d\in\mathcal{E}_t}\mathbb{E}[g_{t,d}],$$

$$\mathbb{E}_{\mathcal{C}}[g_{t,d}] \;\equiv\; \frac{1}{T}\sum_{t=1}^{T}\frac{1}{|\mathcal{C}_t|}\sum_{d\in\mathcal{C}_t}\mathbb{E}[g_{t,d}].$$

Assumptions.

(A1) Variance shift in the target shock: $\Delta_\varepsilon \;\equiv\; \mathbb{E}_{\mathcal{E}}[\varepsilon^2_{t,d}] - \mathbb{E}_{\mathcal{C}}[\varepsilon^2_{t,d}] \;>\; 0.$

(A2) Daily orthogonality of the target shock: $\mathbb{E}[\varepsilon_{t,d}\,\varepsilon_{t,d'}] = 0 \quad$ for all $d \neq d'$.

(A3) Target shock $\perp$ LP error: $\mathbb{E}[\varepsilon_{t,d}\,\xi_{t,h}] = 0 \quad$ for all d, t, h.

(A4) Target shock $\perp$ nuisance term: $\mathbb{E}[\varepsilon_{t,d}\,\eta_{t,d}] = 0 \quad$ for all d, t.

(A5) Invariance of nuisance second moment: $\Delta_\eta \;\equiv\; \mathbb{E}_{\mathcal{E}}[\eta^2_{t,d}] - \mathbb{E}_{\mathcal{C}}[\eta^2_{t,d}] = 0.$

(A6) Invariance of nuisance covariance: $\Delta_{\eta y,h} \;\equiv\; \mathbb{E}_{\mathcal{E}}[\eta_{t,d}\, y^{\perp}_{t+h}] - \mathbb{E}_{\mathcal{C}}[\eta_{t,d}\, y^{\perp}_{t+h}] = 0.$

Proof.

Numerator. Expanding the representative term inside the summation in the numerator of the estimator:

$$\mathbb{E}[\Delta f_{t,d}\, y^{\perp}_{t+h}] = \phi\psi_h\, \mathbb{E}\Big[\varepsilon_{t,d}\sum_{d'}\varepsilon_{t,d'}\Big] + \phi\, \underbrace{\mathbb{E}[\varepsilon_{t,d}\,\xi_{t,h}]}_{=0 \text{ by (A3)}} + \mathbb{E}[\eta_{t,d}\, y^{\perp}_{t+h}].$$

By assumption (A2), $\mathbb{E}\big[\varepsilon_{t,d}\sum_{d'}\varepsilon_{t,d'}\big] = \mathbb{E}[\varepsilon_{t,d}^2]$, so that:

$$\mathbb{E}[\Delta f_{t,d}\, y_{t+h}^{\perp}] = \phi\psi_h\, \mathbb{E}[\varepsilon_{t,d}^2] + \mathbb{E}[\eta_{t,d}\, y_{t+h}^{\perp}].$$

Taking the difference between the averaged expectations over event and control days and applying assumption (A6):

$$\mathbb{E}_{\mathcal{E}}[\Delta f_{t,d}\, y_{t+h}^{\perp}] - \mathbb{E}_{\mathcal{C}}[\Delta f_{t,d}\, y_{t+h}^{\perp}] = \phi\psi_h\, \Delta_\varepsilon. \tag{3}$$

Denominator. Expanding the squared daily price change:

$$\mathbb{E}[(\Delta f_{t,d})^2] = \phi^2\, \mathbb{E}[\varepsilon_{t,d}^2] + 2\phi\, \underbrace{\mathbb{E}[\varepsilon_{t,d}\, \eta_{t,d}]}_{=0 \text{ by (A4)}} + \mathbb{E}[\eta_{t,d}^2] = \phi^2\, \mathbb{E}[\varepsilon_{t,d}^2] + \mathbb{E}[\eta_{t,d}^2].$$

Taking the event–control difference and applying assumption (A5):

$$\mathbb{E}_{\mathcal{E}}[(\Delta f_{t,d})^2] - \mathbb{E}_{\mathcal{C}}[(\Delta f_{t,d})^2] = \phi^2\, \Delta_\varepsilon. \tag{4}$$

Consistency. Combining (3) and (4), and noting that $\Delta_\varepsilon > 0$ by assumption (A1):

$$\hat{\psi}_h \xrightarrow{p} \frac{\phi\psi_h\, \Delta_\varepsilon}{\phi^2\, \Delta_\varepsilon} = \frac{\psi_h}{\phi}.$$

Choosing the unit of the shock such that $\phi = 1$ identifies ψ_h directly. ■

H.2 Results

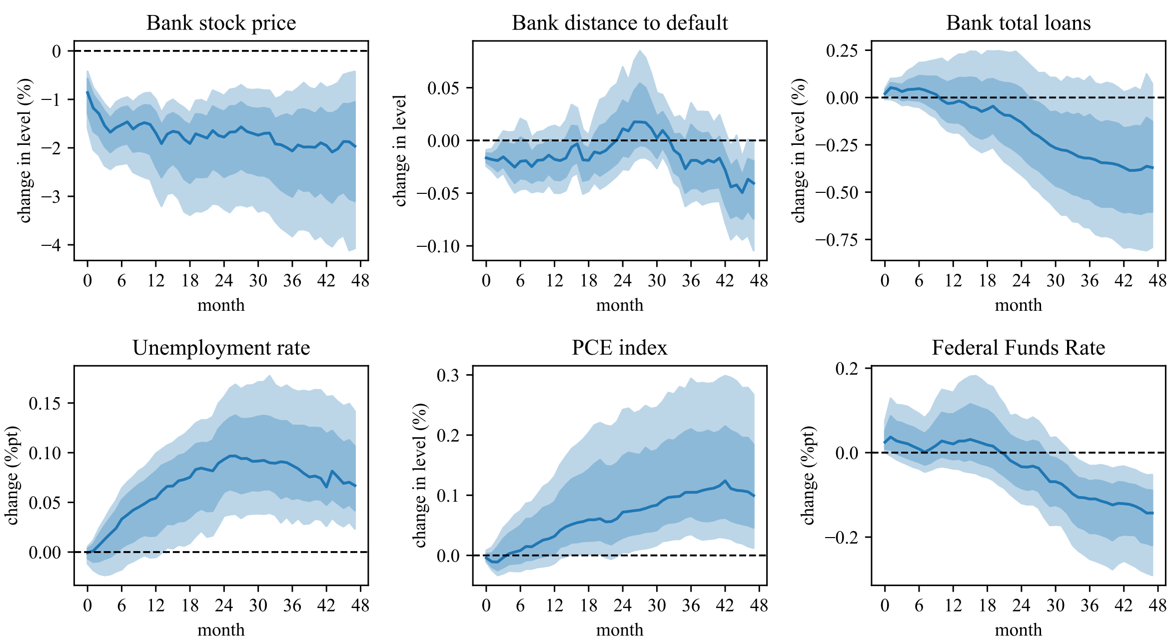
We apply this estimator to identify bank surprises from daily stock price changes. In this application, event days are defined as days on which Fed bank speeches occur, and control days are the trading days immediately preceding the speech days, following the approach of Rigobon and Sack (2004). The local projection takes the form:

$$y_{t+h} = \mu_h + \psi_h \, \varepsilon_t + \beta_h \, y_{t-1} + \xi_{t,h},$$

and standard errors are computed via a block bootstrap (5,000 samples).

Figure H.1 reports the estimated impulse response functions $\hat{\psi}_h$. Under the formal heteroskedasticity-based identification, bank speeches are found to contain surprises that have statistically significant impacts on the outcome variables.

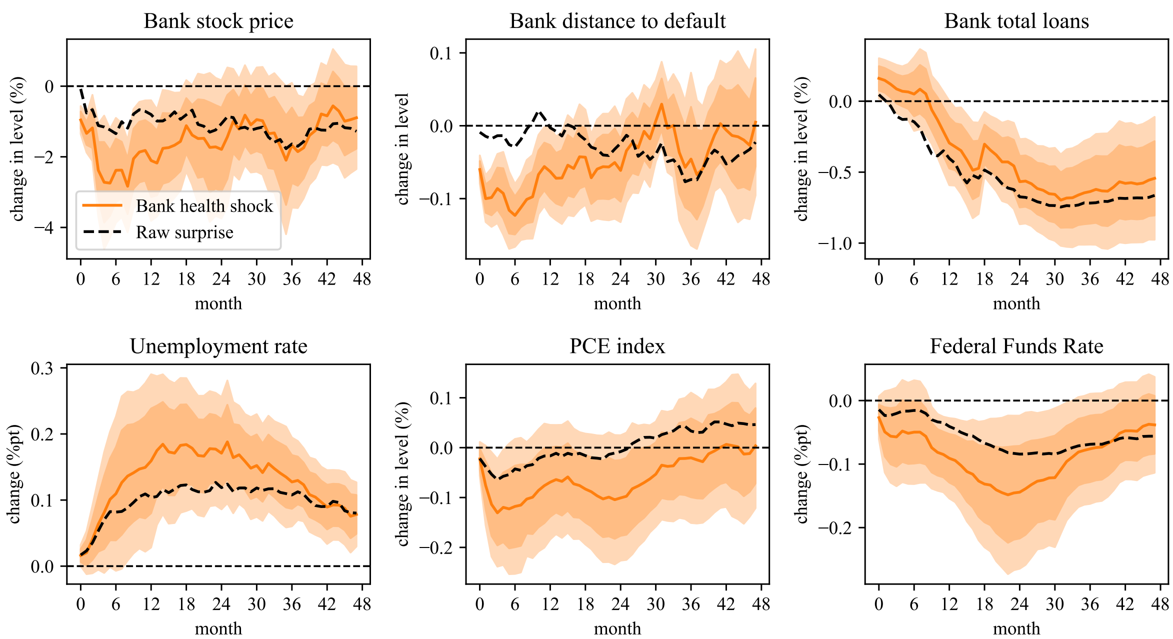
Figure H.1: IRFs to shock based on identification via heteroskedasticity



Notes: IRFs estimated with the heteroskedasticity-based estimator. The shocks are normalized as 1% decline in bank stock prices. Error bands represent 68% and 90% confidence interval, estiamted with block bootstrap (5,000 samples).

I Analysis of bank health shocks

Figure I.1: IRFs to bank health (instead of bank regulation) news shock



Notes: IRFs estimated with the local projection (2). The solid lines correspond to the bank health news shock (instead of the bank regulation news shock shown in the main text), identified by the sign restrictions in Table 2. The shocks are normalized as 1% decline in bank stock prices at high frequency (which can differ from the monthly impact). Error bands represent 68% and 90% confidence interval, based on HAC standard errors. The dashed black lines superimpose, for comparison, the responses associated with a raw surprise.

J Responses of selected individual banks

Figure J.1: Impulse response functions for selected individual banks (stock prices)

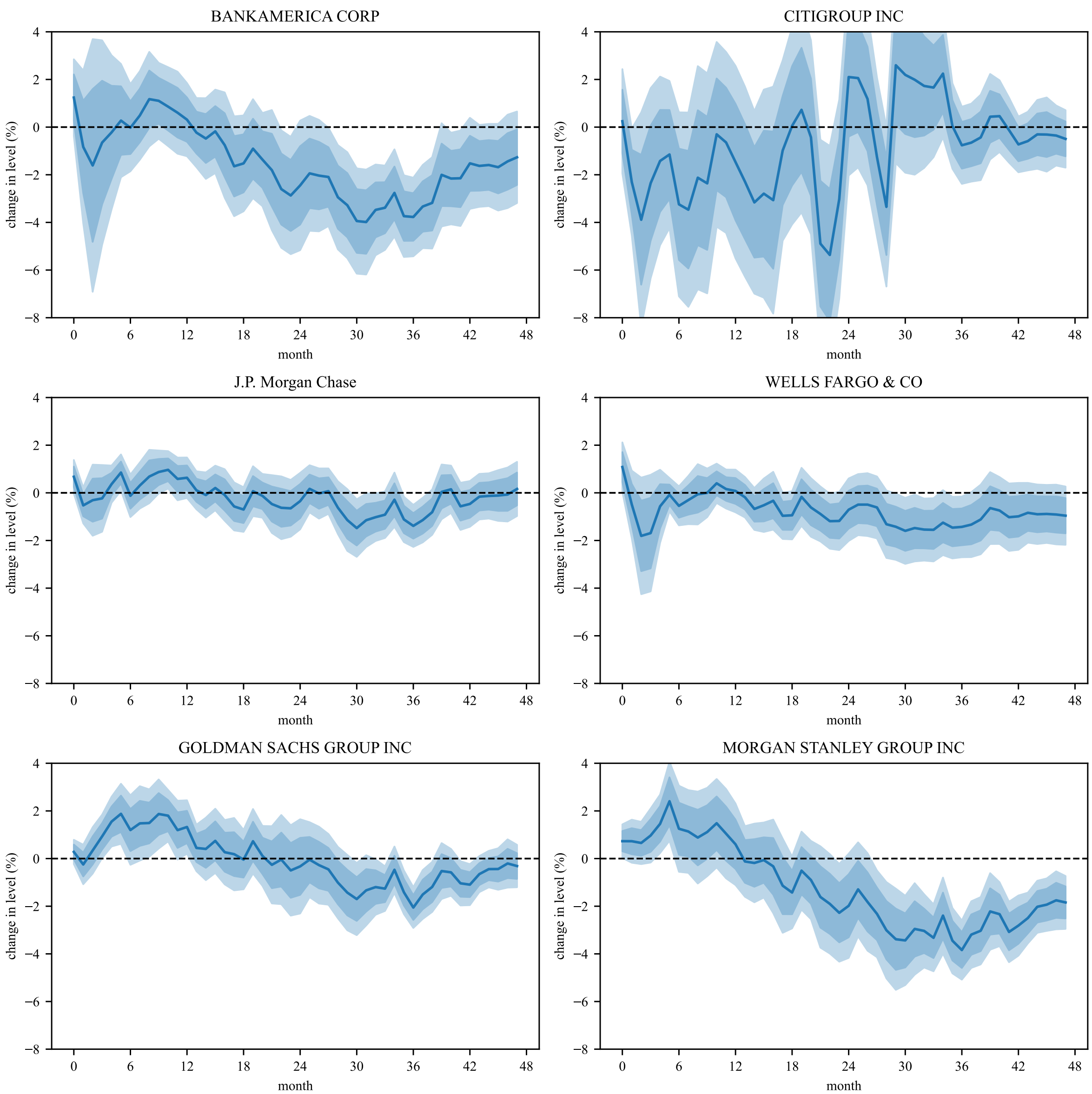


Figure J.2: Impulse response functions for selected individual banks (distance to default)