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Financial factors and the propagation of the *Great Depression*[☆]

Gustavo S. Cortes[a,*], Bryan Taylor[b], Marc D. Weidenmier[c]

[a] *Warrington College of Business, University of Florida, Gainesville, FL, United States*
[b] *Global Financial Data, Inc. San Juan Capistrano, CA, United States*
[c] *Argyros School of Business and Economics, Chapman University and National Bureau of Economic Research. Orange, CA, United States*

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ABSTRACT

We investigate the role of forward-looking financial factors in propagating the Great Depression. We find that a new hand-collected bank stock index is better at predicting the onset of the Great Depression than the aggregate stock market or failed bank deposits. The bank stock index explains almost one-third of the fluctuations in industrial production after five years. Analysis disaggregated at each Federal Reserve district shows that bank stocks capture forward-looking information about debt defaults and credit. Our results suggest that future studies of the credit channel during the Great Depression should incorporate bank stocks to better identify the impact of credit crunches on economic activity.

1. Introduction

Financial economists have argued that the collapse of the banking system played a crucial role in the duration and severity of the Great Depression (Friedman and Schwartz,1963; Calomiris, 1993; Calomiris and Mason, 1997, 2003a, 2003b; Anderson et al., 2018; Vossmeyer, 2019). In an influential paper, Bernanke (1983) argued that the 7000 bank failures between 1929 and 1933 were a central propagating mechanism of the severe economic downturn.[1] Firms were credit constrained and often could not undertake profitable investment opportunities because of many bank failures. The fall in bank credit led to an investment drop through the financial accelerator, which ultimately led to a large decline in GDP.[2]

In many academic studies, the banking sector's importance for business cycle fluctuations during the Great De-

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* Corresponding author.
E-mail address: gustavo.cortes@warrington.ufl.edu (G.S. Cortes).

[1] As Bernanke (1983, pp. 262-263) writes in his classic study, "I agree that money was an important factor in 1930-33, but (…) I doubt that it completely explains the financial sector-aggregate output connection. This motivates my study of a nonmonetary channel through which an additional impact of the financial crisis may have been felt."

[2] In a recent evaluation of the 2008–2010 crisis, Bernanke (2018) revisits the literature on the Depression (including his own work) and identifies the importance of financial factors as a remarkable similarity between the Great Depression and the Great Recession. Gordon (2018, pp. 338–339), discussing Bernanke's paper, argues that "the panic in the stock market (…) resulted in self-perpetuating downward movements in stock prices as investors lost confidence. The emergence of the panic in 1929 very much mirrored that in 2008."

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pression has been proxied by coincident economic indicators. These proxies include bank failures, bank balance sheet aggregates, and the stock of failed bank deposits (see, e.g., Bernanke, 1983; Calomiris, 1993; Anari et al., 2005; Breitenlechner et al., 2021). In this paper, we introduce a new monthly market-capitalized bank stock index for the period 1920–1939. We propose that this new index should be incorporated into standard credit-channel vector autoregressions (VARs) of the Great Depression. To the extent that stock markets are forward-looking, bank stocks gage the health of financial intermediaries (i.e., banks' idiosyncratic shocks) in real time and with more precision than coincident indicators (see, e.g., Chousakos et al., 2020). As such, stock market-based financial factors should help identify the impact of bank-specific shocks on economic activity in the Great Depression.

We begin our descriptive analysis by introducing a new bank stock database. We then examine financial intermediaries' stock market performance during 1920–1939 and uncover new stylized facts about bank stocks.[3] First, we document that the financial sector was the largest publicly traded sector on US financial markets before the Great Crash of 1929 with a market capitalization of $17 billion, representing almost one-fifth (19%) of all publicly traded stocks in the United States. Between 1920 and 1932, the financial sector represented 16% to 19% of total market capitalization in the United States and then fell to the 11–12% range between 1933 and 1939.

Next, we examine bank stocks' performance during the Great Bull and Bear markets of the 1920s and 1930s. First, we find that the Global Financial Data (GFD) bank stock index rose from 100 in January 1920 to a peak value of 709.73 in September 1929. We attribute the enormous rise in bank stock prices to financial innovation and economic growth that increased the profits of financial intermediaries (see, e.g., White, 1984; Field, 2012). The 609.73% increase in the bank stock index during the Great Bull market of the 1920s was subsequently followed by a steep decline that began a month before the 1929 Crash. The bank stock index fell more than 87% from September 1929 to an index value of 89.37 in May 1932. By the end of our sample in 1939, bank stocks remained well below their peak in 1929. It would be decades before the market capitalization of financial intermediaries surpassed their high point in 1929.

We then begin our empirical analysis at the national level. We estimate two VARs over the entire sample (1920–1939) using either the bank stock index or the S&P composite index as a forward-looking variable that might explain business cycle fluctuations during the interwar period. The first VAR shows that the forward-looking bank stock index explains about 30% of industrial production movements after 60 months. The stock of failed bank deposits can account for about 5% to 6% of the forecast error variance in industrial production. Replacing the bank stock index with the S&P composite index, we obtain quantitatively similar results with aggregate stock market conditions as the forward-looking business cycle variable.

The credit-channel VARs estimated separately suggest that the empirical results are quite similar whether we use the bank stock index or the S&P composite index. To provide some additional insight into this question, we estimate a VAR that contains both the bank stock index and the S&P index. Initially, we give the bank stock index the first ordering in the Cholesky decomposition. We find that the bank stock index can explain about one third (31%) of the movements in industrial production over 60 months vis-à-vis only about 15% for the S&P index. When we give the S&P index the first ordering in the VAR, we find that the forward-looking aggregate stock market index explains only about 16% of the economic activity movements over five years. In contrast, the bank stock index maintains virtually the same performance (29%). Interestingly, while the S&P index underperforms the bank stock index at longer leads (24, 36, 48, and 60 months) regardless of the variables' ordering, the aggregate market index generally outperforms the bank stock index in earlier leads (6 and 12 months).

In a historical decomposition, we show that innovations to the bank stock variable are influential in explaining the time-series variation of industrial production. The bank stock index does an excellent job forecasting real economic activity during 1929, including the Great Crash and the onset of the Great Depression. The S&P index, on the other hand, has considerably less predictive power than the forward-looking bank stock index at the start of the Depression, becoming a significant predictor of business cycles after the second half of 1930 (see also Romer, 1990).

Finally, inspired by Calomiris and Mason's (2003a, p. 938) view that "disaggregation is a promising means of identification," we investigate the mechanisms driving our national results by looking at more granular data (see also Wicker, 1980, 1996). We collect new data at the Federal Reserve district level to test three influential channels discussed in the literature: (i) the "default forecasting channel," (ii) the "new credit supply channel," and (iii) the "technological bust channel" (see, e.g., Calomiris and Wilson, 2004; Nicholas 2007, 2008). The empirical evidence demonstrates that the default forecasting channel and especially the new credit supply channel explain fluctuations in economic activity at the Federal Reserve district level. We find less support for the technological bust channel, perhaps because financial intermediaries generally did not fund tech firms in the 1920s and 1930s (see, e.g., Lamoreaux et al., 2011; Nanda and Nicholas, 2014; Babina et al., 2020).

Overall, our paper makes four contributions to the literature. First, bank stocks contain information that is better at forecasting economic activity than other stock prices.[4]

[3] Gandhi and Lustig (2015) were unable to study the relation between bank stocks and government guarantees before 1970 because very few bank stocks traded on the NYSE after delisting in the 1920s.

[4] There are a few notable exceptions in the literature that study bank stocks during the Great Depression and other crises. Calomiris and Mason (1997) discussed bank stock price changes as indicative of bank condition and failure risk. Calomiris and Wilson (2004) discussed bank stock returns, standard deviations, and their links to credit supply for New York City banks. Saunders and Wilson (2001) use market values of US banks to analyze how market values change over time to reflect business opportu-

Second, bank stock prices primarily explain economic activity in sectors of the economy that rely on bank credit (as opposed to sectors that banks do not fund). Third, bank stocks forecast borrower distress and credit change. Fourth, our results also suggest that credit supply shocks plausibly account for a significant portion of the credit change (as opposed to credit demand) given the findings of the earlier literature. This implies that the large decline in bank stock prices was a causal factor in the decrease in credit supply (e.g., Bernanke, 1983; Calomiris, 1993; Calomiris and Mason, 1997, 2003a, 2003b; Anderson et al., 2018).

The remainder of the paper proceeds as follows. We first provide a brief history of banking and banking crises during the 1920s and 1930s. Then we introduce the database of bank stocks from 1920 to 1939. We then follow up with an empirical analysis of bank stock returns and the relationship between bank stock returns and the broader equity market. Then, we estimate a series of national- and regional-level VARs to measure the impact of including forward-looking bank stocks in explaining movements in economic activity during the Great Depression and for the entire interwar period from 1920 to 1939. The last section concludes.

2. A brief history of banking crises, 1920–1939

The 1920s saw a transformation in the activities of banks in the United States. The Federal Reserve was established in 1913 to provide for a more elastic currency and play the role of a lender of last resort. The stimulus to increase funding for the government during World War I, electrification, and the development of large-scale industries created new profit opportunities for industry (White, 1990). Indeed, the US economy grew at a rate of 3.7% between 1920 and 1929. Banks, trusts, and related financial intermediaries dramatically increased their profits and stock prices during the 1920s as they found new ways to finance investment projects (White, 1990). National banks faced competition from trusts after WWI, which offered a broader range of financial services to their customers and enabled them to combine banking services with fiduciary powers. The expansion of fiduciary powers to national banks in 1918 allowed them to compete directly with trusts and expand their services.

New government regulations for financial intermediaries accompanied the expansion of banking across the United States. The McFadden Act of 1927, for example, dealt with three crucial banking issues. First, the legislation granted the 12 Federal Reserve Banks and national banks perpetual charters, replacing their 20-year charters. The action was taken, in part, because the US government failed to renew the 20-year charter of the Second Bank of the United States. The McFadden Act also expanded branch banking. It permitted national banks to have branches to the extent that it was allowed by state law. This permission meant that national banks did not have to operate in just one building as they did in many states (Rajan and Ramcharan, 2015). The coastal states on the east and west generally allowed branching, while interior states were more likely to have unit banking. The legislation encouraged banks to acquire other banks and expand their services to a larger geographic area.

The economic expansion ended in August 1929, which marked a turning point in economic activity as the US entered what appeared to be a “garden variety recession” (Friedman and Schwartz, 1963). Three months later, stock prices on the New York Stock Exchange (NYSE) fell more than 20% over two days. The New York Fed quickly responded to the Great Crash by adding liquidity to financial markets through open market operations. Friedman and Schwartz (1963) refer to the New York Fed’s action as a textbook case of a successful lender-of-last-resort policy. They argue that the New York Fed’s policy limited the effects of the financial shock from the Great Depression on real economic activity.[5]

The early stages of the Great Depression were relatively mild. Many government leaders and members of the business community were looking for a quick rebound in economic conditions in the fall of 1930. The economic decline accelerated over the next couple of years with four banking crises. Wicker (1996) studied the geographic incidence of the banking crises of the Depression. The first major crisis occurred in the St. Louis Federal Reserve district when Caldwell and Company collapsed in November 1930 (Wicker, 1980). The bank was a rapidly growing firm that was also the largest financial holding company in the South (Richardson, 2013). The firm’s large stock portfolio took a big hit with the Great Crash of 1929 and began to have financial difficulties with the meltdown in real estate and equity prices. The Bank of Tennessee, a subsidiary of Caldwell, closed its doors on November 7.

Several days later, other financial intermediaries associated with Caldwell suspended operations (Richardson, 2013). A financial crisis ensued as depositors rushed to take their funds out of insolvent banks. The crisis was mostly regional and did not impact the New York money market (Wicker, 1996). It deepened as the Bank of United States closed its doors on December 11, following a failed attempt to merge with another New York bank. Again, fearful depositors withdrew their funds from the troubled financial institution and other banks with financial difficulties (Richardson, 2013).

The second banking crisis of the Great Depression, from April to August of 1931, was centered in the Chicago and Cleveland Federal Reserve districts (Wicker, 1996). Chicago experienced numerous bank failures, especially in unit banks that financed Chicago suburbs’ rapid growth in the 1920s. With the onset of the Great Depression, many unit banks failed as real estate prices plummeted. The third banking crisis of the Great Depression began on September 21, 1931, when the Bank of England announced that it would leave the gold standard. The action led investors to sell dollar assets for gold in anticipation that the US might also abandon the gold standard. The gold

nities and risks banks take. Finally, Baron, Verner, and Xiong (2021) also study bank equity returns, banking panics, and banking crises from an international perspective.

[5] Recently, Amir-Ahmadi, Cortes, and Weidenmier (2020) revisit Friedman and Schwartz’s claims and find strong empirical evidence that the New York Fed’s actions had positive effects on real economic activity.

drain reduced the US gold supply, and depositors withdrew funds from their banks. The internal and external drain reduced the money supply, which created deflation and exacerbated the downturn (Engemann, 2013). However, Wicker (1996) finds that the effects of Britain's abandonment of the gold standard were confined mainly to three large cities: Chicago, Pittsburgh, and Philadelphia.

The fourth banking panic of the Great Depression started at the end of 1932 and lasted until March of 1933. In early 1933, some states declared bank holidays, meaning that banks did not have to redeem demand deposits. Over 5190 banks closed their doors over the year (Grossman, 2008). People rushed to withdraw their deposits before state regulators closed their banks. National banks accounted for 1475 of the financial intermediaries that suspended operations. President Roosevelt declared a national bank holiday a day after his inauguration on March 4, 1933, and Secretary of the Treasury Henry Morgenthau began granting licenses to banks to reopen beginning on March 13, 1933 (Grossman, 2008).

The Great Depression's banking crises led to some of the most important and well-known banking legislation in American history (Flannery, 1985). The Glass–Steagall Act of 1933, for example, created the Federal Deposit Insurance Corporation (FDIC), which insured demand deposits starting January 1, 1934. The Banking Act of 1935 made the FDIC a permanent institution. All Federal Reserve member banks were required to join the FDIC. By mid-1934, federal deposit insurance covered over 15,000 banks, representing 97% of bank deposits.

3. Data and descriptive statistics

We begin our empirical analysis describing the data sources and construction of variables used in our estimations. We then provide summary statistics, focusing on documenting how bank stocks performed in the bull and bear markets of the interwar period.

3.1. Data sources and construction of variables

3.1.1. Aggregate time series data

Macroeconomic time series are from the Federal Reserve Bank of St. Louis's FRED database unless otherwise noted. In constructing the S&P composite index, we combine the post-1926 data from the Center for Research in Securities Prices (CRSP) with pre-1926 stock-level data for NYSE stocks collected by Goetzmann et al. (2001), available at Yale University's Center for International Finance. Like many empirical studies of the Great Depression and the interwar period, our sample starts in the early 1920s (1920:M1) and ends in 1939:M12 to avoid World War II's effects on the US economy.

3.1.2. Bank stock price data

Data on bank stock prices are from the United States Stock Database, maintained by GFD and constructed from hand-collected data of contemporary newspapers and magazines. Information on the price of bank stocks was obtained by GFD primarily from the Commercial and Financial Chronicle (CFC). Data on non-financial firms used to create the 17 Fama–French sector indices are also from GFD.[6] Price data are from the CFC's Monthly Supplements (1920–1928) and from the Bank and Quotation Record (1928–1939). The monthly supplement to the CFC provided the closing price for each stock listed on the NYSE and the bid and ask for stocks listed over the counter. The Bank and Quotation Record provided the monthly closing value for stocks from the New York Stock Exchange, a dozen regional exchanges, and the bid and ask for over-the-counter stocks. GFD obtained data on the dividends paid by each company and the shares outstanding from the Moody's Manual of Investments.

These sources provide information on about 2000 securities each month listed on the NYSE, regional exchanges, and stocks traded over the counter. GFD assigned SIC codes to companies and used the 17 Fama–French sectors to determine the largest companies by market capitalization in January of each year from 1920 to 1939 to calculate 17 sector indices from 1920 to 1939.[7] Our bank stock index is based on each year's 15 largest banks (as measured by market capitalization) whose stocks traded on US financial markets from 1920 to 1939. The index is updated every January to adjust for changes in the composition of the largest banks in the United States.[8]

As shown in Appendix Fig. A.1, the financial intermediaries in the national bank index have more capital, greater profits, and more deposits than other banks. Furthermore, Appendix Table A.1 shows the city distribution of banks for the entire sample period, 1920–1939. Table A.1 reports that 54% of the banks in the sample were in New York City. Boston, Los Angeles, and San Francisco each account for 8.1% of the sample (24.3% together). If we only count banks that enter the index calculation for at least ten years (half the sample size), then New York City represents 80% of the sample. The data show that New York City banks dominate the national index. To a lesser extent, financial intermediaries in Boston, Los Angeles, and San Francisco also show some importance.[9]

3.1.3. Regional time series data

We use data disaggregated at the Federal Reserve district level to improve our national-level analysis and test three transmission channels. To construct variables disaggregated at each Fed district for our regional VARs, we use Park and Richardson's (2012) series of retail sales—a Fed-district-specific measure of economic activity. We construct the M1 series for each Fed district using data from

[6] GFD collected these data from the CFC and the publications described in Appendix A.2.

[7] For the Fama–French 17 sector indices, GFD was only able to include the top 10 firms based on market capitalization to ensure all sectors have the minimum number of stocks each year.

[8] Choosing the top 15 banks helps to mitigate concerns of stale prices and includes more banks from outside New York City. In unreported results available by request, we test and reject the stale price hypothesis for bank stocks included in our index.

[9] As expected, this restrictive list of banks includes the most important banking groups of the past and present, such as JP Morgan & Co. Inc. (Guaranty Trust), Chase National Bank of the City of New York, CitiCorp Inc. (National City Bank), Wells Fargo (Northwest Bancorporation), and BankBoston (First National Bank of Boston).

Table 1
Dating of bull and bear market stock returns for 17 Fama–French Sectors.
This table presents dates that define the bull and bear markets for each one of the 17 Fama–French sectors. It also presents the stock market index and the average returns for the boom and bust phases of the cycle of each sector.

Sector	Peak sector index value (Jan 1920=100)	Date of sector peak value	% Change (Jan 1920-peak)	Trough index value	Date of trough index value	% Change (Peak to trough)	End of sample index value (Dec 1939)	% Change (Trough to end of sample)
Utilities	1487.64	Jun 1929	1387.64%	219.10	May 1932	−85.27%	335.05	52.92%
Machinery	784.93	Aug 1929	684.93%	89.91	May 1932	−88.5%	398.61	343.34%
Banks	709.73	Sep 1929	609.73%	89.37	May 1932	−87.41%	156.8	75.45%
Retail	692.14	Aug 1929	592.14%	119.50	May 1932	−82.73%	330.52	176.59%
Other	607.3	Aug 1929	507.3%	141.99	Jun 1932	−76.62%	318.76	124.49%
Automobiles	556.50	Feb 1929	456.50%	46.95	Jun 1932	−91.56%	316.63	574.40%
Construction	473.69	Aug 1929	373.69%	78.64	May 1932	−83.40%	316.16	302.03%
Chemicals	465.66	Feb 1929	365.66%	53.97	Jun 1932	−88.41%	353.43	554.86%
Consumer	387.28	Aug 1929	287.28%	152.04	May 1932	−60.74%	356.88	134.73%
Food	372.16	Aug 1929	272.16%	94.75	Aug 1929	−74.54%	241.08	154.44%
Steel	347.76	Aug 1929	247.76%	22.95	Jun 1932	−93.4%	133.49	481.66%
Oil	321.35	Aug 1929	221.35%	58.92	May 1932	−81.66%	134.98	129.09%
Mining	319.34	Apr 1929	219.34%	52.038	May 1932	−84.01%	194.37	280.83%
Transportation	262.77	Aug 1929	162.77%	27.04	Jun 1932	−89.71%	83.92	210.36%
Durable	225.50	Sep 1929	125.50%	21.83	Jun 1932	−90.32%	83.72	283.56%
Clothes	208.92	May 1928	108.92%	64.84	Jul 1932	−68.96%	64.84	160.21%
Fabricated products	186.51	Sep 1929	86.51%	30.53	Jun 1932	−83.63%	118.96	289.65%

Table 2
Average stock market returns and volatility: bull and bear markets for 17 Fama–French sectors.
This table shows the average stock returns for 17 Fama–French sectors. We calculate arithmetic means and standard deviations of stock returns for the entire sample period (1920 to 1939) and in subperiods that characterized the bull market of the 1920s (i.e., from 1920 to each sector's peak before the 1929 Great Crash) and the bear market of the 1930s (from each sector's peak to its trough). The peaks and trough dates are shown in Table 1.

Sector	Average returns 1920–1939	Standard deviation 1920–1939	Average return bull market (1920-sector peak)	Standard deviation bull market (1920-sector peak)	Average return bear market (Sector peak-sector trough)	Standard deviation bear market (Sector peak- sector trough)	Average return (Sector trough-Dec 1939)	Standard deviation (Sector trough-Dec 1939)
Utilities	0.90%	8.85%	2.58%	5.73%	−3.93%	12.15%	0.64%	10.36%
Machinery	0.97%	8.89%	1.91%	4.53%	−5.10%	12.36%	1.84%	10.94%
Banks	0.47%	7.50%	1.82%	4.90%	−5.23%	10.68%	0.66%	8.38%
Retail	0.83%	8.15%	1.87%	6.00%	−4.27%	10.31%	1.19%	9.37%
Other	0.67%	6.11%	1.60%	3.67%	−3.12%	9.26%	0.99%	6.72%
Automobiles	1.23%	12.62%	1.98%	9.08%	−4.99%	12.34%	3.02%	15.31%
Construction	0.83%	8.50%	1.44%	3.89%	−4.41%	10.08%	1.81%	11.36%
Chemicals	0.97%	9.40%	1.61%	6.13%	−4.22%	12.75%	2.49%	10.10%
Consumer	0.75%	6.65%	1.35%	5.71%	−1.67%	7.40%	0.94%	7.30%
Food	0.57%	6.39%	1.21%	3.60%	−3.29%	8.76%	1.24%	7.51%
Steel	0.80%	12.41%	1.22%	5.14%	−6.43%	11.76%	3.08%	17.29%
Oil	0.47%	8.37%	1.16%	5.41%	−3.91%	11.28%	1.22%	9.73%
Mining	0.52%	7.16%	1.16%	4.70%	−4.44%	6.93%	1.84%	8.73%
Transportation	0.35%	9.39%	0.89%	3.25%	−5.51%	9.71%	2.00%	12.99%
Durable	0.39%	9.78%	0.83%	5.09%	−6.02%	9.63%	2.16%	12.95%
Clothes	0.40%	6.17%	0.81%	3.95%	−2.15%	4.45%	1.21%	8.46%
Fabricated products	0.48%	8.80%	0.82%	7.03%	−4.71%	9.43%	1.89%	9.87%

several issues of the Federal Reserve Bulletin. To construct bank stock indices for each Fed district, we gather stock price data on the top ten banks in each Fed district, following the same methodology and sources used in our national bank index construction.[10]

To test for the default forecasting channel, we collect data on the dollar value of failed business liabilities from the Federal Reserve Bulletins. To test for the new credit supply channel, we use data on aggregate bank balance sheets (total bank loans and bank assets) of member banks in each Fed district. The data are also taken from the Federal Reserve Bulletin. Finally, we use firm-level patent data from 1920 to 1939 hand-collected by Nicholas (2007, 2008) to test for the technological bust channel. Then we aggregate the patent data by Federal Reserve district using the location of the headquarters for each firm reported in the Moody's Manuals as in Cortes and Weidenmier (2019).[11]

[10] The Kansas City Fed district has data limitations that require its index to include only nine banks. Due to these limitations, all other regional bank indices use only the top ten bank stocks.

[11] Due to the high geographical concentration of corporate innovation—a fact widely recognized in the innovation literature—we can construct

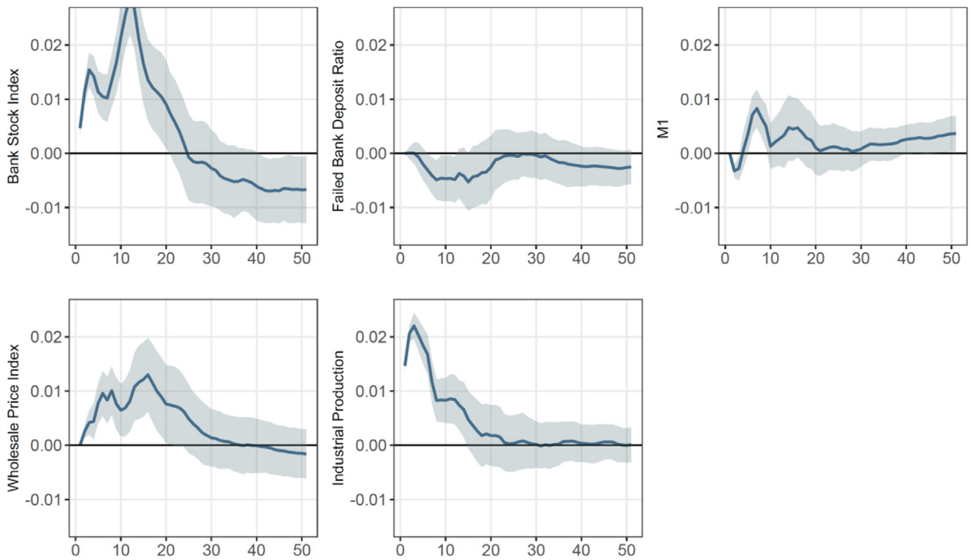

Fig. 1. Impulse responses for industrial production: bank stock index as financial factor.
This figure presents IRFs using the following ordering: (1) the log of the bank stock index (*LBankStock*); (2) log of industrial production (*LIP*); (3) the log of the wholesale price index (*LWPI*); (4) the log of the money supply, measured by the monetary aggregate (*LM1*); and (5) the ratio of failed banks' deposits to total deposits (*FailedStock*). In each panel, the thick lines are point estimates, and the shaded areas are 68% (i.e., one standard deviation) confidence bands. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Following the work of Nicholas (2008), our patent-based indices combine patent counts with future patent citations to identify impactful innovations.

3.2. Summary statistics: banks in the bull and bear markets of the interwar period

Table 1 reports summary statistics for the banking sector from 1920 to 1939, breaking down the interwar sample period into the 1920s and post-Great Crash period. From January 1920 until September 1929, the bank stock index increased from 100 to 706.9, an increase of 609.73%. The dramatic rise in bank stock prices even led several of the presidents of New York banks to publicly state that the share prices of New York banks were overvalued (Calomiris and Oh, 2019). Many New York banks subsequently delisted from the NYSE and traded over the counter in an attempt to curb excessive speculation in the stock. Following the Great Crash, the bank stock index fell from 709.73 to a low of 89.37 in May 1932. The large decline represents more than an 87% decrease in the bank stock index. Banks gradually recovered for the remainder of the sample period. The bank stock index value rose 75%, from 89.37 in May 1932 to 156.8 in December 1939.[12]

A similar story emerges if we look at average monthly stock returns for the banking sector. Table 2 shows that the bank stock index increased an average of 0.47% per month over the sample period. For the Great Bull market period that ended in September 1929, the bank stock index rose 1.82% per month. Following the Great Crash, bank stocks lost 5.2% per month and bottomed out at an index value of 89.37 in May 1932, below its value in 1920. For the remainder of the sample period, the bank stock index increased an average of 0.66%.

We also look at the standard deviation of stock returns for the bank index to gain insight into their risk profile. The stock volatility for financial intermediaries averaged 7.5% per month for the period 1920–1939. The monthly standard deviation of bank stock returns was 4.9% for the bull market run-up of the 1920s and then increased to 10.7% during the bear market decline. Stock volatility then fell to 8.4% per month from the sector trough in May 1932 until the end of the sample in December 1939.

To put the banking sector in a broader perspective, we compare the bank stock index's baseline performance with the other Fama–French sectors. Table 1 reports the sector performance of the bull market during the 1920s. The data show that the banking sector had the third-largest run-up during the 1920s among the 17 Fama–French sectors. Utilities had the most significant rise with a 1387% increase, followed by the machinery stock index that rose almost 695%. On the other hand, durable goods, transportation, mines, and the oil sector increased less than 200% during the bull market. The large disparity in sector performance is consistent with previous research that found wide varia-

Fed-district-level innovation indices for only 7 of the 12 districts. The districts are Boston, New York, Philadelphia, Cleveland, Richmond, Chicago, and San Francisco.

[12] For an analysis of bank charter value, see Saunders and Wilson (2001).

Table 3
Forecast error variance decomposition for industrial production. This table shows the forecast error variance decomposition of movements in industrial production (IP) estimated in four specifications. Panel A shows the results for the VAR with only the bank stock index as a financial factor variable. Panel B shows the results for the VAR with only the S&P composite index as a financial factor variable. Panel C presents the baseline specification, which includes both the bank stock index (ordered first in the VAR Cholesky ordering) and the S&P index (ordered second). Panel D presents the alternative specification, which reverses each financial factor's order; i.e., it includes the bank stock index ordered second in the VAR Cholesky ordering and the S&P composite index ordered first.

A. Including bank stock index only

Months	Bank stock	IP	WPI	M1	Failed stock
6	26.35%	91.49%	5.54%	2.36%	0.58%
12	47.77%	37.38%	8.20%	3.55%	3.10%
24	54.49%	20.46%	17.52%	4.31%	3.21%
36	53.27%	19.21%	20.04%	4.43%	3.04%
48	53.22%	18.87%	19.91%	4.72%	3.29%
60	54.05%	17.89%	18.80%	5.31%	3.95%

B. Including S&P index only

Months	S&P	IP	WPI	M1	Failed stock
6	47.12%	47.71%	3.26%	1.45%	0.46%
12	56.99%	29.48%	5.25%	3.83%	4.46%
24	52.11%	24.64%	13.28%	3.63%	6.35%
36	48.29%	23.56%	17.18%	4.43%	6.55%
48	48.27%	22.29%	17.26%	5.69%	6.49%
60	49.90%	20.59%	15.99%	7.24%	6.27%

C. Baseline ordering: Including both Bank stock index (ordered first) and S&P index (ordered second)

Months	**Bank stock**	**S&P**	**IP**	**WPI**	**M1**	**Failed stock**
6	11.73%	18.29%	56.58%	6.02%	5.61%	1.78%
12	28.53%	9.96%	37.50%	9.17%	8.84%	6.00%
24	31.45%	12.02%	25.40%	16.77%	8.58%	5.78%
36	30.27%	14.41%	22.89%	17.33%	9.81%	5.30%
48	29.60%	13.96%	22.41%	17.14%	10.64%	6.25%
60	30.65%	14.78%	21.20%	16.21%	10.39%	6.78%

D. Alternative ordering: Including both bank stock index (ordered second) and S&P index (ordered first)

Months	**Bank Stock**	**S&P**	**IP**	**WPI**	**M1**	**Failed Stock**
6	1.31%	28.70%	56.58%	6.02%	5.61%	1.78%
12	5.90%	32.59%	37.50%	9.17%	8.84%	6.00%
24	23.43%	20.04%	25.40%	16.77%	8.58%	5.78%
36	27.57%	17.11%	22.89%	17.33%	9.81%	5.30%
48	26.89%	16.68%	22.41%	17.14%	10.64%	6.25%
60	29.47%	15.96%	21.20%	16.21%	10.39%	6.78%

tion in stock returns across different industries during the 1920s (Means, 1931; White, 1990).

For the bear market, Table 1 shows that the banking sector had the seventh-largest decline with a peak-to-trough fall of more than 87%. The steel (−93.4%), automobile (−91.56%), transportation (−89.71%), durable (−90.32%), machinery (−88.5%), and chemical (−88.41%) sectors all had larger declines. Finally, the banking sector had the second smallest recovery of all the 17 Fama–French sectors with a 75.45% rise from May 1932 until December 1939. Only the utility sector had a smaller increase, which measured about 75%.

4. Aggregate analysis

In this section, we focus on aggregate, time series evidence. We begin by describing our VAR methodology and then present results in the form of impulse-response functions, forecast error variance decompositions, and historical decompositions.

4.1. National-level VARs

We estimate VARs to analyze the dynamic effects of forward-looking stock market indicators and failed bank deposits on economic growth. Formally, we estimate the following specification:

$$Y_t = \mathbf{A}_0 + \mathbf{A}_1 Y_{t-1} + (\dots) + \mathbf{A}_P Y_{t-P} + \varepsilon_t, \varepsilon_t \sim N(0, \Sigma), \quad (1)$$

where Y_t is a vector of macroeconomic variables described below, $\mathbf{A}_0$ is a matrix of intercept coefficients, and $\mathbf{A}_1$ through $\mathbf{A}_P$ are matrices of coefficients relative to each lag of Y, ranging from 1 to P. To obtain causal relations between the variables of the VAR, we estimate Eq. (1) and map the reduced-form shocks ε_t into structural shocks applying a Cholesky decomposition of the variance-covariance matrix Σ. This procedure—known as recursive identification—is introduced by Sims (1980) and implies that the variables' ordering matters for determining the dynamic relations between the VAR variables. To

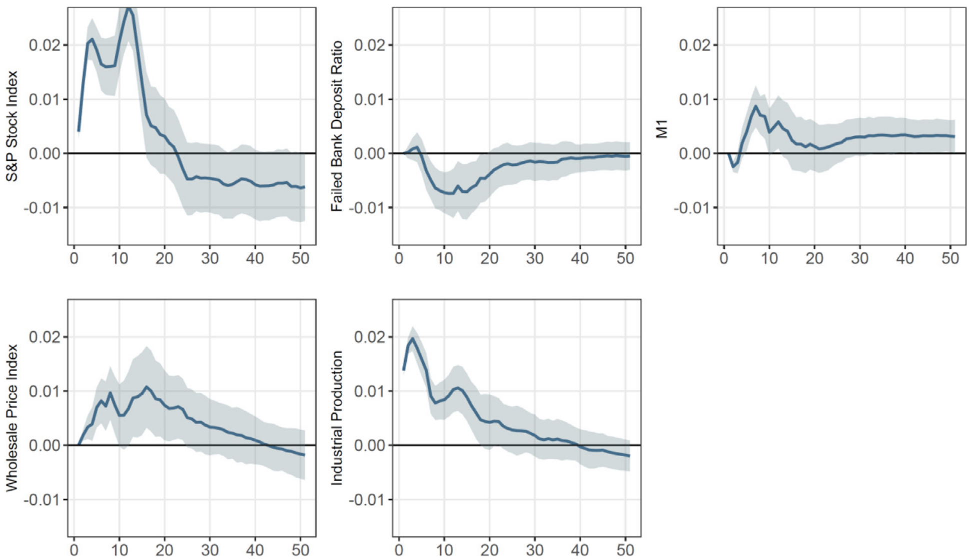

Fig. 2. Impulse responses for industrial production: S&P composite index as financial factor.
This figure presents IRFs using the following ordering: (1) the log of the S&P composite stock index (*LSP*); (2) log of industrial production (*LIP*); (3) the log of the wholesale price index (*LWPI*); (4) the log of the money supply, measured by the monetary aggregate (*LM1*); and (5) the ratio of failed banks' deposits to total deposits (*FailedStock*). In each panel, the thick lines are point estimates, and the shaded areas are 68% (i.e., one standard deviation) confidence bands. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

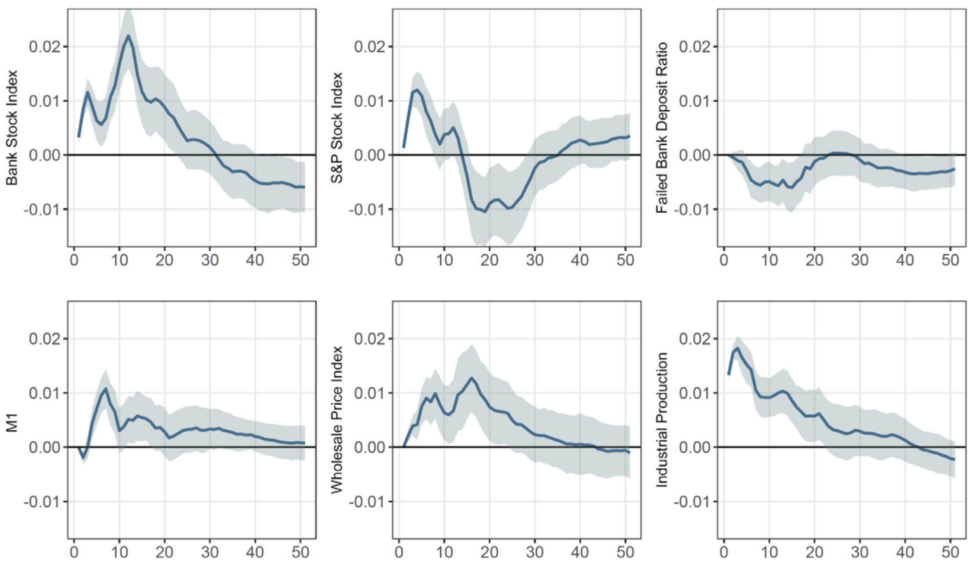

Fig. 3. Impulse responses for industrial production: baseline ordering, including both bank stock index and S&P composite index as financial factors.
This figure presents IRFs using the following ordering: (1) the log of the bank stock index (*LBankStock*); (2) the log of the S&P composite stock index (*LSP*); (3) log of industrial production (*LIP*); (4) the log of the wholesale price index (*LWPI*); (5) the log of the money supply, measured by the monetary aggregate (*LM1*); and (6) the ratio of failed banks' deposits to total deposits (*FailedStock*). In each panel, the thick lines are point estimates, and the shaded areas are 68% (i.e., one standard deviation) confidence bands. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

avoid making ad hoc choices, we closely follow the literature on the Great Depression and present results for different orderings to test our results' robustness. As usual, we focus on impulse-response functions and forecast error variance decompositions, which are transformations of the VAR coefficients. Finally, we choose a lag order of $P = 12$ to include one year of variation in the data.

4.2. National-level results

We begin our analysis by estimating separate VARs, including one stock market variable at a time. Following Anari et al. (2005), we include the following variables: (1) the log of the forward-looking bank stock index (*LBankStock*), (2) log of industrial production (*LIP*), (3) the log

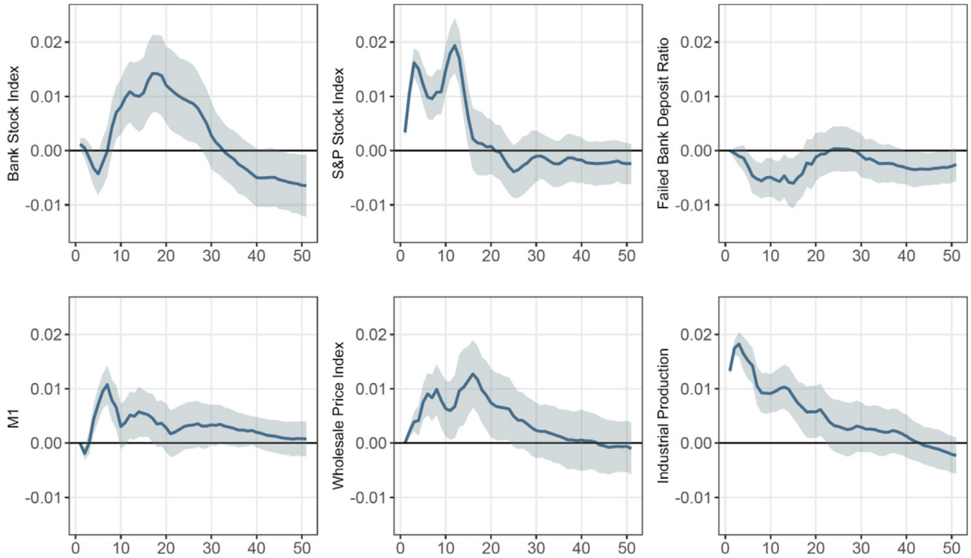

Fig. 4. Impulse responses for industrial production: alternative ordering, including both bank stock index and S&P composite index as financial factors. This figure presents IRFs using the following ordering: (1) the log of the S&P composite stock index (*LSP*); (2) the log of the bank stock index (*LBankStock*); (3) log of industrial production (*LIP*); (4) the log of the wholesale price index (*LWPI*); (5) the log of the money supply, measured by the monetary aggregate (*LM1*); and (6) the ratio of failed banks' deposits to total deposits (*FailedStock*). In each panel, the thick lines are point estimates, and the shaded areas are 68% (i.e., one standard deviation) confidence bands. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

of the wholesale price index (*LWPI*), (4) the log of the monetary aggregate M1 (*LM1*), and (5) the ratio of failed banks' deposits to total deposits (*FailedStock*).[13] Our choice of Cholesky ordering also follows the previous literature on credit-channel VARs (see, e.g., Anari et al., 2005). Placing the forward-looking bank stock index first follows a widely accepted convention that stock markets move faster than virtually any other macroeconomic variable commonly included in VARs. Given the structure imposed by recursive identification to the impulse-response functions, it is realistic to order the bank stock index first.

Fig. 1 shows the impulse-response functions for industrial production using the bank stock index as the forward-looking variable. A positive shock to the bank stock index raises industrial production for over two years. A one standard deviation shock to wholesale prices or the money supply also increases economic activity, while a shock to failed bank deposits reduces industrial production.

Panel A in Table 3 presents the forecast error variance decompositions for 6, 12, 24, 36, 48, and 60 months. Results in Panel A show that the bank stock index explains 54.05% of the unforecastable movements in industrial production after 60 months. The stock of failed bank deposits can only explain as much as 5% of the forecast error variance in industrial production over a five-year forecast horizon.

Next, we estimate a VAR using the S&P composite index as the forward-looking variable instead of the bank stock index—keeping the same ordering of the other variables—to see if it captures the same information as the bank stock index. Fig. 2 reports the impulse responses for industrial production. A positive shock to the aggregate stock market index increases industrial production. A one standard deviation increase in wholesale prices and the money supply also leads to a rise in economic activity, and a shock to failed bank deposits lowers industrial production. For the forecast error variance decompositions, Panel B of Table 3 shows that the aggregate stock market index explains 49.90% of industrial production fluctuations after 60 months. The stock of failed bank deposits accounts for less than 7% of the changes in economic activity. Overall, the empirical results for the S&P index are very similar to those using the bank stock index, suggesting the importance of forward-looking financial factors in explaining the dynamics of the real economy.

Given the similar results obtained using the bank stock index and the aggregate stock market, we estimate a credit-channel VAR that uses both variables. We first run the baseline specification—giving the bank stock index the first ordering in the Cholesky decomposition since the variable was slightly more important for explaining business cycle fluctuations at a 60-month forecast horizon in our initial analysis. Fig. 3 shows the impulse responses incorporating both the bank stock variable and the aggregate stock market into the credit-channel VAR. A positive shock to the bank stock index raises industrial production unambiguously throughout the entire five-year horizon. A one standard deviation increase in the S&P initially raises industrial production, temporarily reverting to a negative impact on economic activity for horizons between 12 and 24 months. As before, a shock to wholesale prices and the money supply increases industrial production.

Panel C of Table 3 shows that the bank stock index explains 30.65% of the forecast error variance in industrial

[13] The time-series graphs of all variables used in our VAR are in Appendix Fig. A.2.

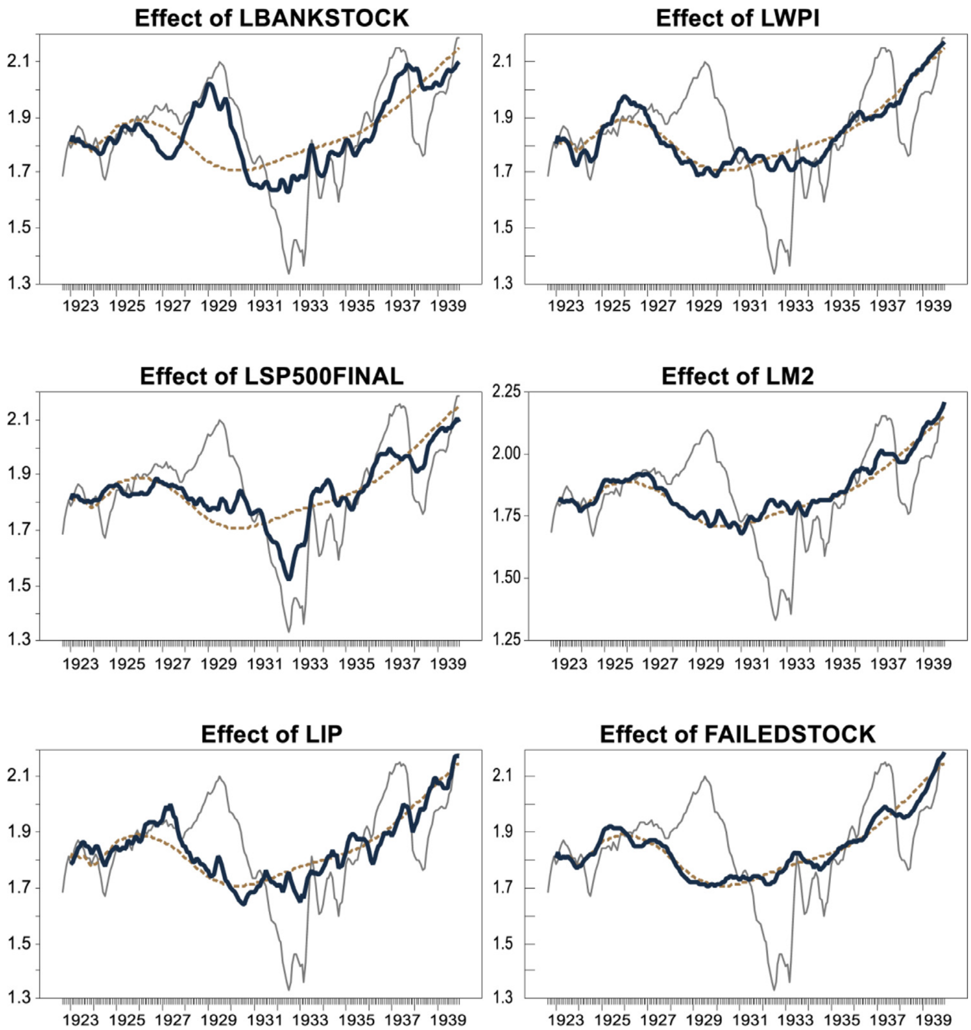

Fig. 5. Historical decomposition of industrial production.
This figure depicts the historical decomposition of each variable included in the vector autoregressions. It shows whether movements in industrial production were likely the result of past innovations in other variables of the VAR. In all panels, the continuous thin gray line shows the actual time series of industrial production, and the dashed gold line represents a one-step-ahead forecast of industrial production at $t + 1$ using data up to period t. The thick black line represents how much of the time-series variation of industrial production is attributed to shocks in each variable of the VAR. For example, in the top-left panel, the thick line shows the effect of the bank stock index on industrial production. The narrow gap between the continuous thick black and continuous thin gray lines indicate that the past innovations of the bank stock variable are influential drivers of the movements in the time series of industrial production.

production after 60 months—reaching maximum explanatory power of 32.24% after 15 months. The S&P composite index, on the other hand, accounts for 14.78% of the movements in industrial production over 60 months. The stock of failed bank deposits explains 6.78% of the fluctuations in economic activity.

We next reorder the forward-looking variables and place the S&P index first in the Cholesky decomposition. The impulse-response analysis for industrial production appears in Fig. 4, which shows that a positive shock to the S&P index and the bank stock index persistently raises industrial production. As before, positive shocks in wholesale prices and money supply increase economic activity, and an increase in the share of failed bank deposits lower industrial production.

As for the variance decomposition, Panel D of Table 3 shows that the aggregate stock market can explain approximately 16% of the forecast error variance in industrial production at a five-year forecast horizon (maximum of 33.32% after 13 months). Bank stocks account for 29.47% of the economic activity movements after 60 months (maximum of 29.47% after 60 months). The coincident economic indicator of failed bank deposits explains less than 7% of industrial production movements at all forecast horizons.

Interestingly, the bank stock index can still account for almost 30% of the movements in industrial production in the Cholesky decomposition—approximately twice the amount of the S&P index—even when it is not ordered first in the VAR. Given that bank stocks explain a large percentage of the aggregate economic activity's movements re-

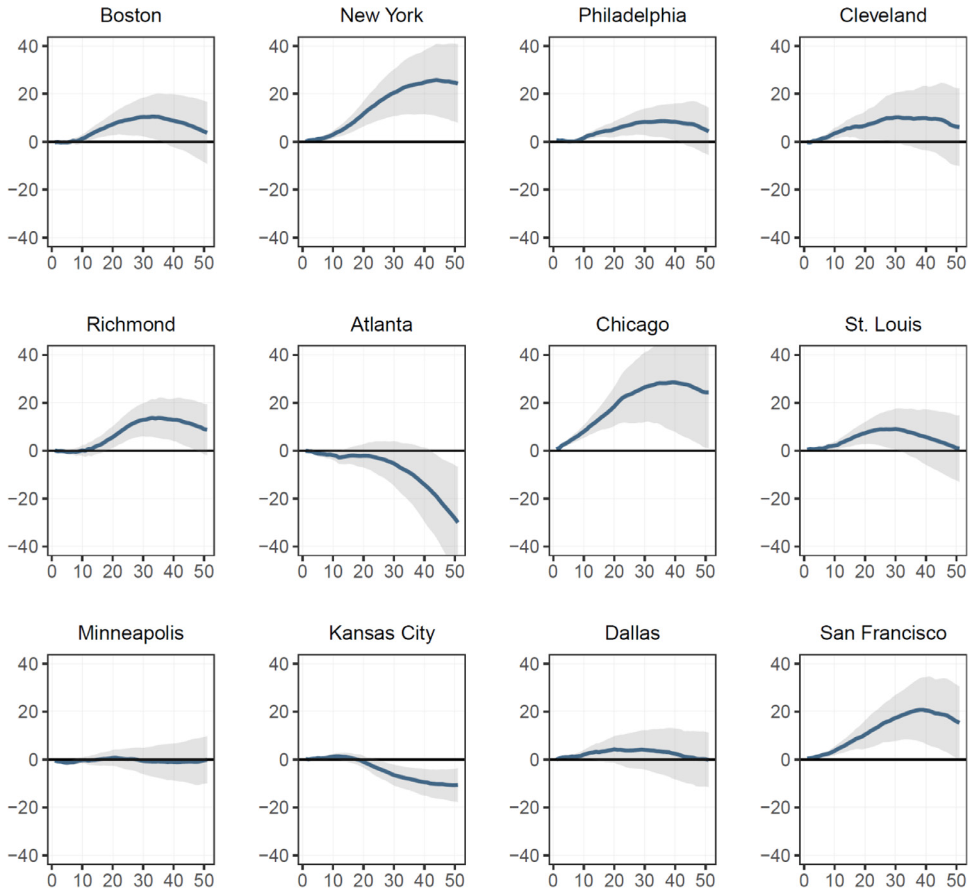

Fig. 6. Regional VARs: impulse responses for retail sales, baseline ordering, with both bank stock index and S&P composite index as financial factors. This figure presents IRFs using the following ordering: (1) the log of the bank stock index (*LBankStock*); (2) the log of the S&P composite stock index (*LSP*); (3) log of retail sales (*LRS*); (4) the log of the wholesale price index (*LWPI*); (5) the log of the money supply, measured by the monetary aggregate (*LM1*); and (6) the ratio of failed banks' deposits to total deposits (*FailedStock*). Thick lines are point estimates, and shaded areas are 68% (i.e., one standard deviation) confidence bands. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

gardless of the ordering in the Cholesky decomposition, we conclude that the bank stock index has valuable idiosyncratic information about business cycle fluctuations that is not in the S&P composite index. One possible explanation for this finding is that aggregate stock market indices from this period contained very few bank stocks since financial intermediaries often traded over the counter.[14]

Finally, we estimate a historical decomposition using the baseline empirical model to examine the importance of innovations in each variable on economic fluctuations throughout the 1920s and 1930s. In all panels of Fig. 5, the thin continuous gray line shows the actual time series of industrial production, and the dashed gold line represents a one-step-ahead forecast of industrial production implied by the VAR estimates. More importantly, the thick continuous black line represents how much of the time-series variation of industrial production is attributed to shocks from each VAR variable. Simply put, the narrower the gap between the thick black and thin gray lines, the more indication that innovations to a variable are influential in explaining variation in industrial production. The top-left panel of Fig. 5 shows that the bank stock index does an excellent job forecasting real economic activity in the period surrounding the Great Crash of 1929 and the onset of the Great Depression. The narrow gap between the continuous lines indicates that the bank stock variable's past innovations have high explanatory power of the movements in industrial production. The S&P index, on the other hand, has considerably less predictive power than the forward-looking bank stock index at the onset of the Depression, becoming a significant explanatory variable of business cycles only after the second half of 1930.

5. Regional analysis and transmission channels

As a follow-up, we investigate the effect of bank stocks on economic activity at the Federal Reserve dis-

[14] In unreported results, we also estimated VARs using aggregate bank credit and the bank stock index. Even if we order the credit aggregate first in the VAR, it can only explain 4.6% of the movements in industrial production after 60 months. On the other hand, the bank stock index explains 62% of the forecast error variance in industrial production if the variable is given the second ordering in the Cholesky decomposition. These results are available upon request.

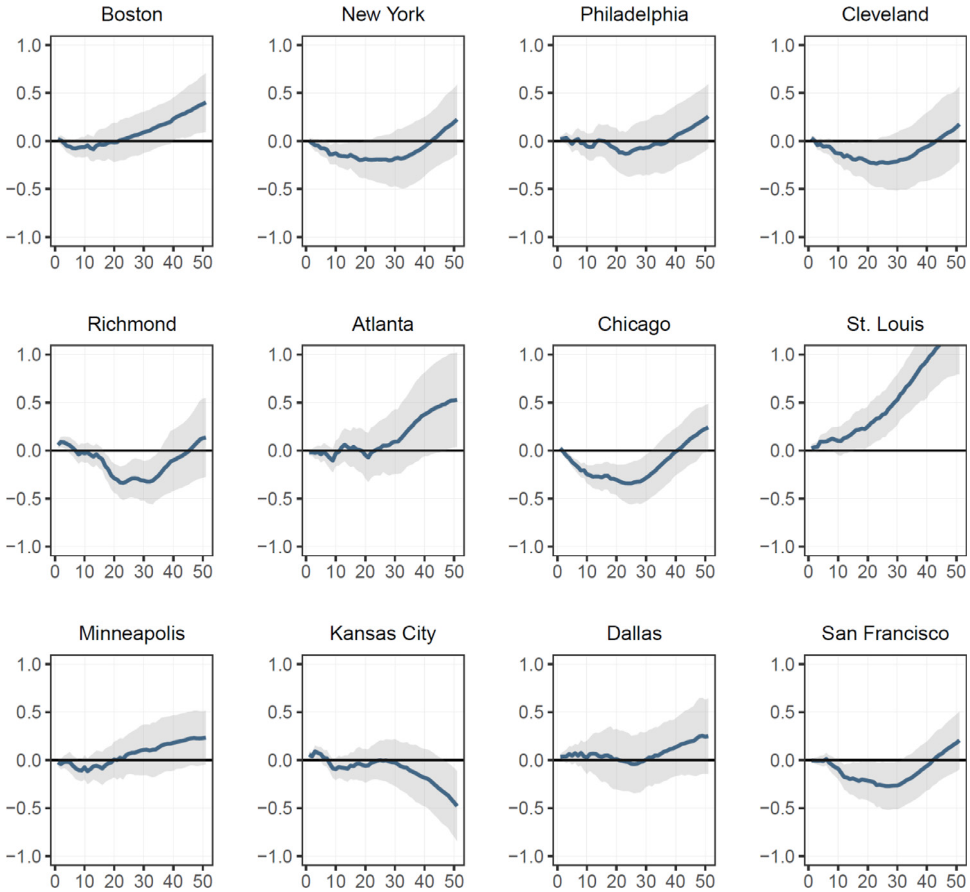

Fig. 7. Channel 1: the default forecasting channel, regional VARs: impulse responses for retail sales.
This figure presents the response of failed business liabilities (log) to a shock in the bank stock index (log). The VAR specification is the same as the regional VAR described in Section 5.1, except that it is augmented with the channel-specific variable (i.e., the log of the dollar value of failed business liabilities). In each panel, the thick lines are point estimates, and the shaded areas are 68% (i.e., one standard deviation) confidence bands.

trict level. We first explain how we adapt our national-level model to estimate VARs specific to each Federal Reserve district. We then present results of the regional analysis.

5.1. Fed district-level VARs

We construct a bank stock index for each Fed district following the same methodology in our national bank stock index, which vastly expands our indices' scope to 180 bank stocks per year (i.e., 12 Federal Reserve districts × top 10 banks in year t). We also create an M1 proxy at the regional level using disaggregated information for each Fed district. Following Calomiris and Mason (2003a), we replace the log of industrial production (a national-level time series) with the log of retail sales (a Fed-district-specific measure of economic activity) using data collected by Park and Richardson (2012). However, national-level variables like the S&P composite index and the wholesale price index cannot be disaggregated at the Fed Reserve district level. Finally, we use the same Cholesky orderings from our national-level VARs in the regional analysis.

5.2. Fed district-level results

Using data specific to each Fed district, we compute the impulse-response functions (IRFs) for each regional VAR model using the same methodology and variable orderings of our national VAR. Fig. 6 shows that the same positive relationship between bank stocks and real economic activity in the national analysis is also present in the regional VARs.

Interestingly, this relation is stronger and more significant in Fed districts where banks are bigger and more relevant (i.e., New York, Chicago, and San Francisco), and thus bank stocks are more likely to capture forward-looking information about economic fundamentals. As shown in Fig. A.3 in the Appendix, the results hold even when we order the bank stock index after the S&P composite index.

5.3. Transmission channels

Next, inspired by the evidence from our national- and regional-level VARs and earlier studies, we consider three channels through which forward-looking bank stocks might improve upon the forecast of real economic activ-

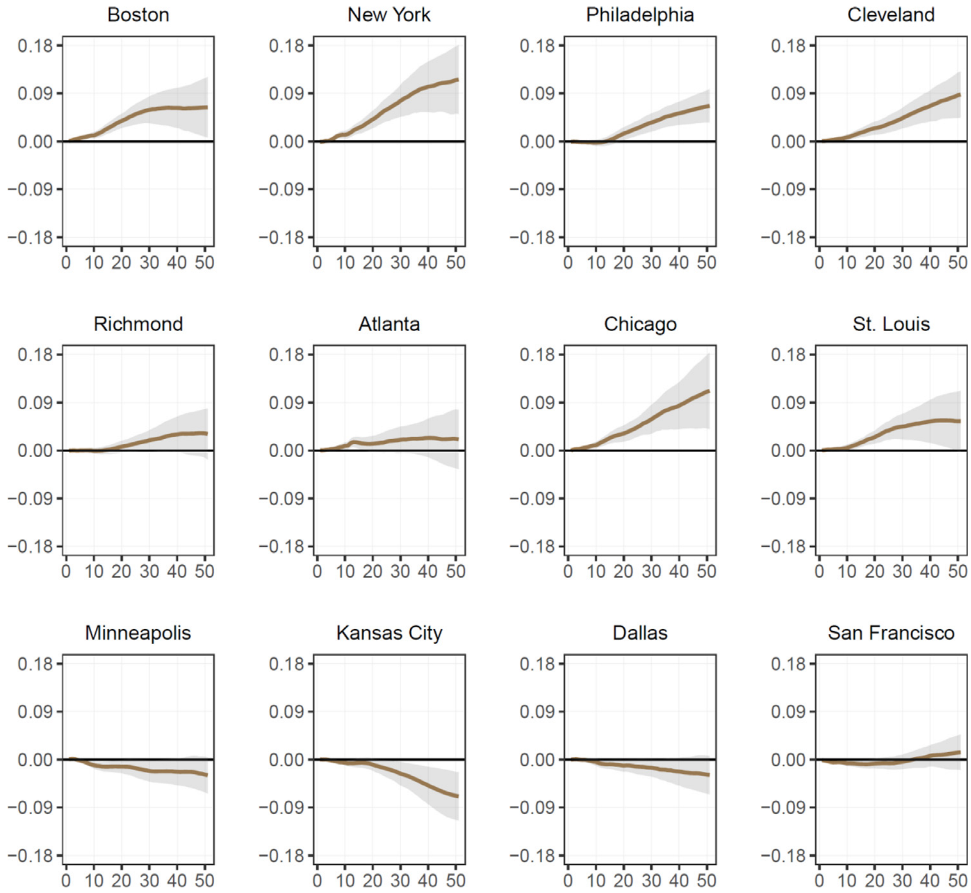

Fig. 8. Channel 2: the new credit supply channel, regional VARs: impulse responses for retail sales.
This figure presents the response of bank credit (scaled by total assets) to a shock in the bank stock index (log). The VAR specification is the same as the regional VAR described in Section 5.1, except that it is augmented with the channel-specific variable (i.e., bank credit). In each panel, the thick lines are point estimates, and the shaded areas are 68% (i.e., one standard deviation) confidence bands. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

ity. To formally test these channels, we augment each of our baseline regional VARs with a variable specific to the respective channel and then compute the usual impulse-response functions and forecast error variance decompositions for each regional VAR specification. If a channel matters for a particular Fed district, we should expect to see a significant relation between bank stocks and the channel-specific variable.

5.3.1. The default forecasting channel

First, we consider the hypothesis that bank stock values contain unique information about the real economy because they are a forward-looking assessment of how expected changes in real activity will matter for debt defaults, given that banks' assets are composed of debts. To test the "default forecasting channel," we run a VAR for each Federal Reserve district *d*, including the same variables of our regional VARs plus the log of failed business liabilities in district *d* at year-month *t*.

Fig. 7 presents the response of failed business liabilities in each Fed district to a shock in the bank stock index. The IRFs from the default-augmented regional VARs suggest that this channel matters in some important districts, such as Chicago, San Francisco, and Richmond. Interestingly, districts like Boston, New York, Philadelphia, Cleveland, and St. Louis do not show supportive evidence for the default forecasting channel, suggesting that other channels might be more important to understanding the results in these localities, as we discuss below.

5.3.2. The new credit supply channel

We then estimate VARs for the "new credit supply channel." Our hypothesis is that changes in bank stock values might affect the ability of banks to supply credit in the future. Indeed, Calomiris and Wilson (2004) show that this is true for New York City banks.[15] We use total bank credit scaled by total assets as our additional variable of the new credit supply channel. Adding this variable to our regional VARs, we show impulse responses in Fig. 8.

The IRFs suggest that the credit supply channel is highly relevant for explaining variations in New York,

[15] Consistent with Calomiris and Wilson (2004), there is a large literature on how depositors' risk aversion combined with the cost of raising new equity imply that bank equity losses translate into bank credit supply reductions (see, e.g., Calomiris and Mason, 2003a).

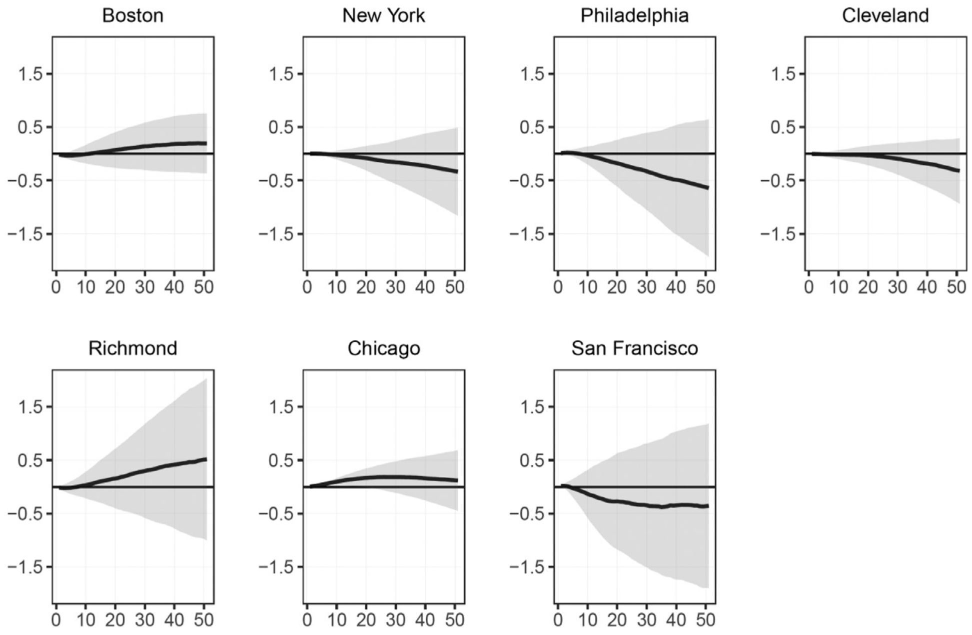

Fig. 9. Channel 3: the technological bust channel, regional VARs: impulse responses for the patent-based innovation index.
This figure presents the response of the patent-based innovation index to a shock in the bank stock index (log). The VAR specification is the same as the regional VAR described in Section 5.1, except that it is augmented with the channel-specific variable (i.e., the patent-based innovation index). In each panel, the thick lines are point estimates, and the shaded areas are 68% (i.e., one standard deviation) confidence bands.

Boston, Philadelphia, Cleveland, and St. Louis, implying that banks tend to cut lending in response to declines in bank equity value during the Depression.

5.3.3. *The technological bust channel*

To test whether bank stocks are related to the technological boom and bust of the 1920s, we construct a novel data set of firm-based innovation at the Fed district level. The hypothesis we test is that movements in forward-looking bank stocks are associated with movements in technological innovation.[16]

As shown by the IRFs in Fig. 9, the "technological bust channel" finds less support in the data, perhaps because banks typically did not finance the technology sector during the interwar period (see, e.g., Lamoreaux et al., 2011; Nanda and Nicholas, 2014; Babina et al., 2020).

5.3.4. *Transmission channels: summary*

We now conclude our investigation of the channels through which bank stocks help predict real activity in our national and regional VARs. Fig. 10 shows forecast error variance decompositions to summarize each channel's relative importance for the 12 Federal Reserve Districts at the 6-, 12-, 24-, 36-, 48-, and 60-month horizons. Specifically, each bar chart reports the percentage of movements that innovations to the bank stock index explain in the channel-specific variable.[17]

The empirical evidence demonstrates that the default forecasting and new credit supply channel variables have a significant amount of their fluctuations explained by bank stocks during the Great Depression. The default forecasting channel (channel 1) is particularly relevant in the Chicago, San Francisco, and Richmond Federal Reserve Districts. Bank stock prices are notably better for forecasting economic activity in the three Fed districts than the aggregate stock market. The new credit supply channel (channel 2) appears to matter the most in the Boston, New York, Philadelphia, Cleveland, and St. Louis Federal Reserve districts. Indeed, previous studies have found that credit supply shocks played a crucial role in propagating the Great Depression (Bernanke, 1983; Calomiris, 1993). Our findings, along with the previous literature, suggest that the decline in bank equity during the Great Depression may have had a causal impact on credit supply, lowering economic output. As mentioned above, the technological bust channel (channel 3) has less explanatory power because banks generally did not lend to this sector.

To summarize, one interpretation of our findings is that bank stocks are useful for at least two reasons. First, bank stocks help forecast credit distress in the private sector.

[16] Some changes are necessary to estimate our VAR specifications for this channel due to data limitations. First, because Nicolas's (2007, 2008) patent data are available only at the annual frequency, we interpolate the patent indices at the monthly frequency. Due to the lack of monthly variation, our VARs are estimated with a lag order $P = 1$. Second, as mentioned, many Fed districts display very few patents over the two decades as a result of the high concentration of corporate innovation, which limits our analysis to only seven Fed districts.

[17] In the default forecasting channel, we gauge how innovations in bank stocks help to explain movements in the failed business liabilities (given by a percentage of the total). In the new credit supply channel, the bar indicates the percentage of movements in bank credit (scaled by total assets) explained by innovations in bank stocks. Finally, in the technological bust channel, the bar indicates the percentage of movements in the citation-weighted patent index explained by innovations in the bank stock index.

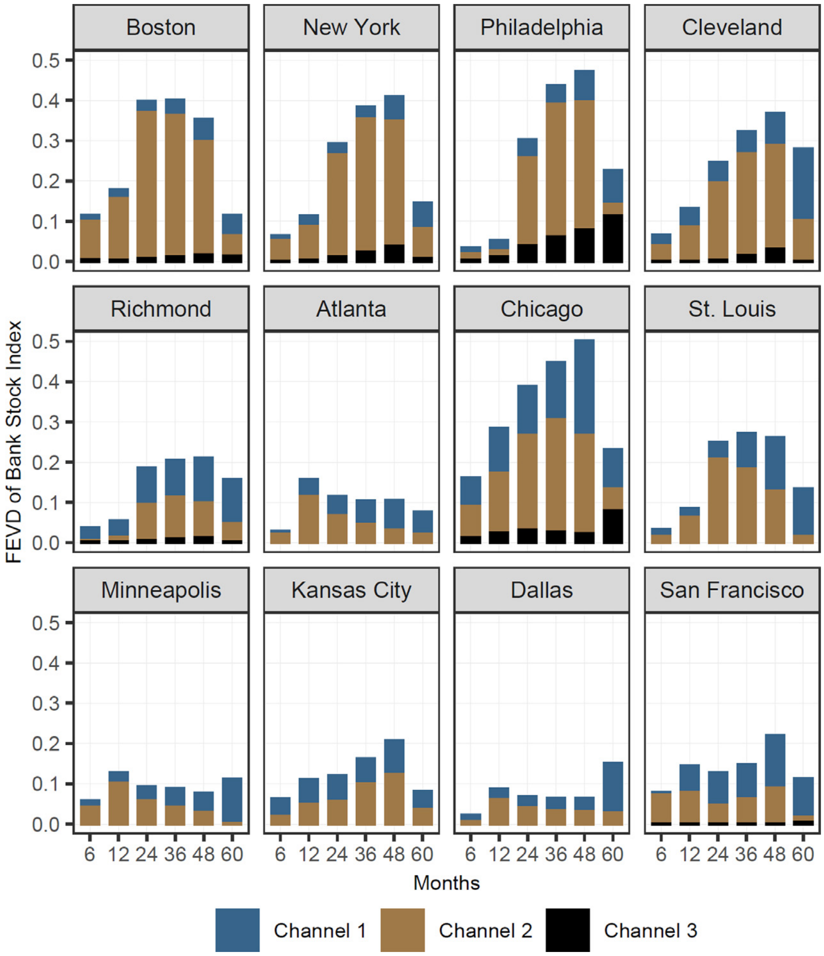

Fig. 10. Regional VARs: forecast error variance decompositions for all channels.
This figure presents forecast error variance decompositions (FEVDs) relative to regional VARs separately estimated and augmented with a channel-specific variable. In the default forecasting channel (channel 1), the bars indicate how innovations in bank stocks help explain movements in the failed business liabilities (given by a percentage of the total). In the new credit supply channel (channel 2), the bars indicate the share of movements in bank credit (scaled by total assets) explained by innovations in bank stocks. Finally, in the technological bust channel (channel 3), the bar indicates the share of movements in the citation-weighted patent index explained by innovations in the bank stock index. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Bank stocks are also useful because credit distress was a propagating mechanism of the great contraction. In addition, loan defaults reduce bank capital, which lowers the capacity of banks to supply funds to firms.[18] Naturally, the evidence presented here does not unequivocally prove that credit supply was the major driver of credit change. Nevertheless, given the well-developed and existing literature on bank lending during the Great Depression, it is reasonable to interpret our evidence as suggestive that bank stock returns forecasted—and perhaps even caused—a decline in credit supply.

[18] Therefore, this channel reflects both a pure forecasting channel (forecasting macro-relevant financial distress of firms unrelated to credit supply) and a bank credit supply channel. This credit supply channel captures the extent to which bank stock returns forecast future credit supply change because declines in bank equity actually cause (i.e., not just forecast) declines in credit supply.

6. Conclusion

We examine a new bank stock index's ability to better identify the credit channel and its impact on economic activity during the Great Depression and the interwar period. We introduce a new bank stock database from GFD constructed using hand-collected data from the Commercial and Financial Chronicle, one of the leading financial data sources during this period. We document that bank stocks had one of the most extensive bull market runs of any sector during the 1920s. Once the 1929 crash came, the bank stock indices lost nearly 90% of their value. We then examined the impact of the forward-looking bank stock index on economic activity. The bank stock index does an outstanding job at forecasting the onset of the Great Depression compared to the stock of failed bank deposits and the aggregate stock market. For the entire sample period, we find strong and robust evidence that shocks to bank stocks explain about 30% of the movements in industrial production at a 60-month forecast horizon even when the empirical specification includes the S&P index. We follow up the aggregate analysis with a study of bank stock prices at the Federal Reserve district level. The regional findings extend and support the baseline results from the national-level analysis.

Overall, this paper makes four contributions to the literature. First, bank stock prices were better at forecasting macroeconomic conditions than other stock prices. Second, financial intermediaries are better at explaining economic conditions in sectors where they loan funds. Third, the new bank stock indices forecast borrowers in distress as well as a change in credit conditions. Fourth, our empirical analysis indicates that credit supply shocks probably played an important role in credit change during the Great Depression, shown by previous studies (Bernanke, 1983; Calomiris, 1993). The significant decline in bank equity prices at both the Fed district and national level may have had a causal effect on reducing credit supply, leading to lower economic output.

Appendix A. Data details, additional empirical results, and primary sources

A.1. Data details and additional empirical results

Fig. A.1 presents the distribution of balance sheet characteristics for banks that are included and for banks not included in the construction of the national-level bank stock index. Fig. A.2 presents the time-series plots of all variables included in the national-level VARs. The shaded area represents the Great Depression as defined by the NBER recession dates. Fig. A.3 presents the regional VAR's impulse-response functions using retail sales as the economic activity variable under the alternative Cholesky ordering. Finally, Table A.1 shows the city distribution of banks included in constructing our national-level bank stock index.

A.2. Primary sources

For each bank, the CFC provided information on the bank's capital, surplus and profits, gross deposits, stock par value, and market bid and ask prices. The monthly supplement was followed by The Bank and Quotation Record, which began publishing in 1928 and continued publication until 1972. The number of banks covered by the CFC fluctuated as the total number of banks rose and fell throughout our sample period. The CFC covered 1186 banks in 1920, increasing to 1627 banks in 1925. Coverage then declined to 557 banks in 1933 and rose to 709 banks in 1940.

GFD used the Manual of Statistics to obtain extensive data on banks from 1900 until 1922**.** The Manual of Statistics was published annually and provided information on when each bank was established, bank capital, bank surplus and undivided profits, par value of the stock, five years of dividends, and the range of prices for each bank during the previous year. GFD also used Moody's and Poor's large volumes that provided even more extensive information on the banks that were publicly traded.[19]

The Moody's Manual of Investments introduced a volume in 1928 that focused on banks, insurance companies, investment trusts, real estate, finance, and credit. Each bank received a description of any changes in its corporate history, balance sheet and income data, dividends payments since 1909, changes in the bank's capital from its inception until the date of publication, and information on the officers, directors, and other individuals associated with the bank. By combining the information from the Manual of Statistics and the Moody's Manual of Investments, GFD was able to obtain data on dividends and shares outstanding for each bank listed in the CFC .

Global Financial Data uses a wide set of publications to collect individual bank-level data to construct consistent indices of stock prices. We list these publications below.

- Bank and Quotation Record, various issues, 1928 to 1939. New York: National News Service.
- Commercial and Financial Chronicle, various issues, 1920–1939. New York: National News Service.

[19] Poor's expanded their annual railroad publication in 1926 to include information on banks and insurance companies which provided data on hundreds of banks and insurance companies. The volume was retitled Poor's Railroad and Bank Section. Unfortunately, Poor's discontinued the inclusion of banks and insurance companies in 1930.

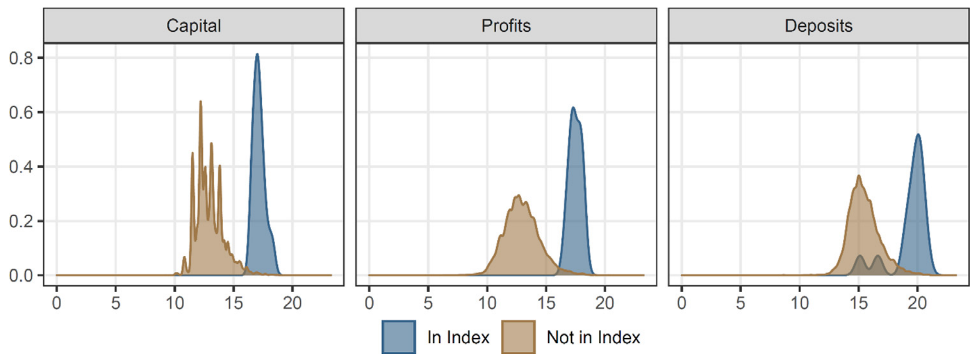

Fig. A.1. Balance sheet characteristics for index vs. non-index banks before the Great Crash.
This figure presents the kernel density distribution of balance sheet characteristics (in logs) relative to the year before the Great Crash (1928) for banks included in the index (i.e., banks with top 15 market capitalization in 1928:M12) versus banks not included in the index (i.e., all banks reported in the Commercial and Financial Chronicle in 1928:M12).

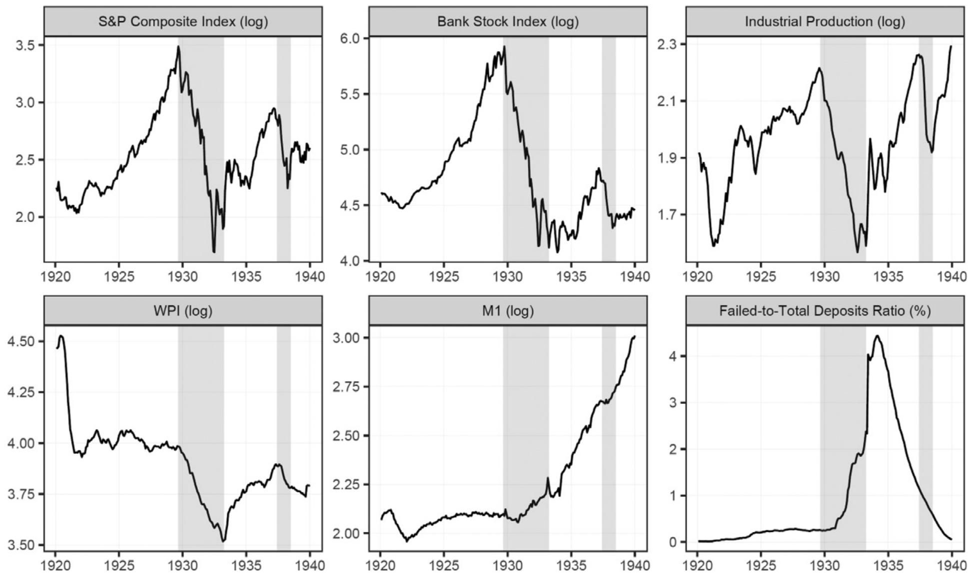

Fig. A.2. Time series of variables included in the national-level VARs.
This figure plots the time series of all variables included in the national-level VARs. The shaded areas represent the Great Depression and the 1937–1938 Recession as defined by the NBER recession dates.

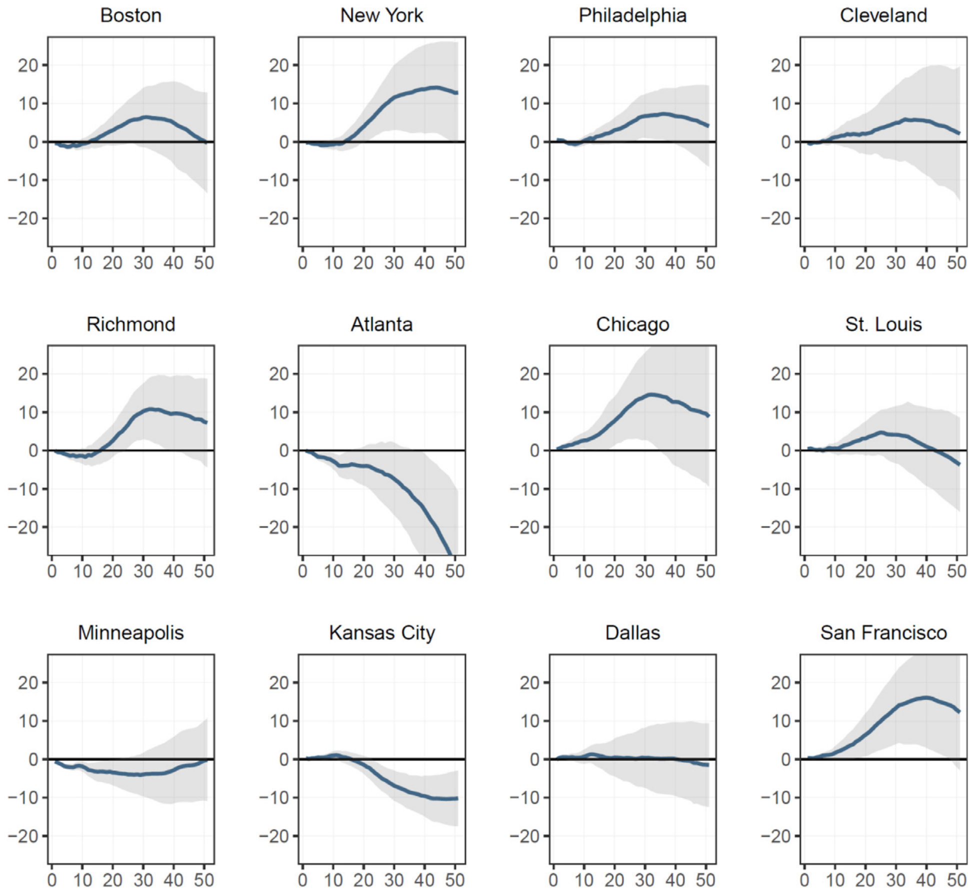

Fig. A.3. Regional VARs: impulse responses for retail sales, alternative ordering, with both bank stock index and S&P composite index as financial factors.
This figure presents IRFs using the following ordering: (1) the log of the S&P composite stock index (*LSP*); (2) the log of the bank stock index (*LBankStock*); (3) log of industrial production (*LIP*); (4) the log of the wholesale price index (*LWPI*); (5) the log of the money supply, measured by the monetary aggregate (*LM1*); and (6) the ratio of failed banks' deposits to total deposits (*FailedStock*). In each panel, the thick lines are point estimates, and the shaded areas are 68% (i.e., one standard deviation) confidence bands.

Table A.1
City distribution of banks included in the national-level bank stock index, 1920:M1–1939:M12.
This table presents the city and state distribution of banks included in the bank stock index (i.e., banks with top 15 market capitalization at the beginning of each year in the 1920–39 period). The "Full Sample" column refers to all bank stocks that enter the construction of our national bank stock index in at least one year. The full sample is made of 37 bank stocks. The "Restrictive Sample" column shows the city distribution for banks included in the index at least ten years of the sample (i.e., half of the entire sample period).

City	State	Full Sample	Restrictive sample
		All stocks (1920–39)	Stocks included in at least 10 years (half the sample period)
New York	NY	20 (54%)	12 (80%)
Boston	MA	3 (8.1%)	1 (6.6%)
San Francisco	CA	3 (8.1%)	–
Los Angeles	CA	3 (8.1%)	–
Chicago	IL	2 (5.4%)	2 (13.3%)
Philadelphia	PA	2 (5.4%)	–
Buffalo	NY	2 (5.4%)	–
Portland	ME	1 (2.7%)	–
St. Louis	MO	1 (2.7%)	–

- Poor's Manual, Railroad, and Bank Section, various issues, 1926–1931. New York: Poor's Publishing Co.
- The Manual of Statistics, various issues, 1900 to 1922. New York: Financial News Association.
- Standard Statistics. Dividend Record, various issues, 1929 to 1939. New York: Standard Statistics Corp.
- Moody's Corp. Moody's Manual of Bank & Finance Securities, various issues, 1928 to 1939. New York: Moody's Corp.

References

Amir-Ahmadi, P., Cortes, G.S., Weidenmier, M.D., 2020. Regional monetary policies and the Great Depression. Natl. Bureau Econ. Res. Unpublished Working Paper.
Anari, A., Kolari, J., Mason, J.R., 2005. Bank asset liquidation and the propagation of the US great depression. J. Money Credit Bank 37, 753–773.
Anderson, H., Calomiris, C.W., Jaremski, M., Richardson, G., 2018. Liquidity risk, bank networks, and the value of joining the federal reserve system. J. Money Credit Bank 50, 173–201.
Babina, T., Bernstein, A., Mezzanotti, F., 2020. Crisis innovation. Natl. Bureau Econ. Res. Unpublished Working Paper.
Baron, M., Verner, E., Xiong, W., 2021. Banking crises without panics. Q. J. Econ. 136, 51–113.
Bernanke, B.S., 1983. Nonmonetary effects of the financial crisis in the propagation of the great depression. Am. Econ. Rev. 73, 257–276.
Bernanke, B.S., 2018. The real effects of disrupted credit: evidence from the global financial Crisis. Brookings Pap. Econ. Act. 2, 251–342.
Breitenlechner, M., Mathy, G.P., Scharler, J., 2021. Decomposing the US great depression: how important were loan supply shocks? Explor. Econ. History 79, 101379.
Calomiris, C.W., 1993. Financial factors in the great depression. J. Econ. Perspect. 7, 61–85.
Calomiris, C.W., Mason, J.R., 1997. Contagion and bank failures during the great depression: the Chicago banking crisis of June 1932. Am. Econ. Rev. 87, 863–884.
Calomiris, C.W., Mason, J.R., 2003a. Consequences of bank distress during the great depression. Am. Econ. Rev. 93, 937–947.
Calomiris, C.W., Mason, J.R., 2003b. Fundamentals, panics and bank distress during the Depression. Am. Econ. Rev. 93, 1615–1647.
Calomiris, C.W., Oh, E., 2019. Who owned Citibank? Familiarity bias and business network influences on stock purchases, 1925-1929. Natl. Bureau Econ. Res. Unpublished Working Paper.
Calomiris, C.W., Wilson, B., 2004. Bank capital and portfolio management: the 1930s "Capital Crunch" and the scramble to shed risk. J. Bus. 77, 421–456.
Chousakos, K.T., Gorton, G.B., Ordoñez, G., 2020. The macroprudential role of stock markets. Natl. Bureau Econ. Res. Unpublished Working Paper.
Cortes, G.S., Weidenmier, M.D., 2019. Stock volatility and the Great Depression. Rev. Financial Studies 32, 3544–3570.
Engemann, K., 2013. Banking panics of 1931-33. Federal Reserve History.
Field, A.J., 2012. A Great Leap Forward: 1930s Depression and US Economic Growth. Yale University Press, New Haven, CT.
Flannery, M.J., 1985. An economic evaluation of bank securities activities before 1933. In: Walter, I. (Ed.), Deregulating Investment Banking. John Wiley & Sons, New York, pp. 67–87.
Friedman, M., Schwartz, A.J., 1963. A Monetary History of the United States. Princeton University Press, Princeton, NJ.
Gandhi, P., Lustig, H., 2015. Size anomalies in US bank stock returns. J. Finance 70, 733–768.
Goetzmann, W.N., Ibbotson, R.G., Peng, L., 2001. A new historical database for the NYSE 1815 to 1925: performance and predictability. J. Financial Markets 4, 1–32.
Gordon, Robert J., 2018. General discussion of "the real effects of disrupted credit: evidence from the global financial crisis. Brookings Pap. Econ. Act 2, 338–342.
Grossman, R.S., 2008. US banking history, Civil War to World War II. In: Whaples, R. (Ed.), The Economic History Association's EH.Net Encyclopedia.
Lamoreaux, N.R., Sokoloff, K.L., Sutthiphisal, D., 2011. The reorganization of inventive activity in the United States during the early twentieth century. In: Costa, D.L., Lamoreaux, N.R. (Eds.), Understanding Long-Run Economic Growth: Geography, Institutions, and the Knowledge Economy. University of Chicago Press, Chicago, IL, pp. 235–274.
Means, G., 1931. The separation of ownership and control in American industry. Q. J. Econ. 46, 68–100.
Nanda, R., Nicholas, T., 2014. Did bank distress stifle innovation during the great depression? J. Financ. Econ. 114, 273–292.
Nicholas, T., 2007. Stock market swings and the value of innovation, 1908-1928. In: Lamoreaux, N.R., Sokoloff, K.L. (Eds.), Financing Innovation in the United States. MIT Press, Cambridge, MA, pp. 217–246.
Nicholas, T., 2008. Does innovation cause stock market runups? Evidence from the great crash. Am. Econ. Rev. 98, 1370–1396.
Park, H., Richardson, G., 2012. Retail trade by federal reserve district, 1919 to 1939: a statistical history. Res. Econ. Hist. 28, 151–231.
Rajan, R.G., Ramcharan, R., 2015. Constituencies and legislation: the fight over the McFadden Act of 1927. Manage. Sci. 62, 1843–1859.
Richardson, G., 2013. Banking panics, 1930-31. Federal Reserve History.
Romer, C.D., 1990. The Great Crash and the onset of the Great Depression. Q. J. Econ. 105, 597–624.
Saunders, A., Wilson, B., 2001. An analysis of bank charter value and its risk-constraining incentives. J. Financ. Services Res. 19, 185–195.
Sims, C.A., 1980. Macroeconomics and reality. Econometrica 48, 1–48.
Vossmeyer, A., 2019. Analysis of stigma and bank credit provision. J. Money, Credit Banking 51, 163–194.
White, E., 1984. Banking innovation in the 1920s: the growth of national banks' financial services. Bus. Econ. History 13, 92–104.
White, E., 1990. The stock market boom and the Crash of 1929 revisited. J. Econ. Perspect. 4, 67–83.
Wicker, E., 1980. A reconsideration of the causes of the banking panic of 1930. J. Econ. History 40, 571–583.
Wicker, E., 1996. The Banking Panics of the Great Depression. Cambridge University Press, Cambridge, UK.