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ABSTRACT

We compile a new monthly database for each Federal Reserve district between 1923-33 to analyze the national and regional nature of the monetary transmission mechanism around the Great Depression. We employ sign-identified structural VARs and narrative sign restrictions informed by uncontroversial theory and the historical record. Our findings demonstrate that there was significant heterogeneity in regional monetary policy as well as its dynamic effects on real economic activity. Prices in the 12 Fed districts were generally more responsive to contractionary regional monetary policy shocks. The district reserve banks played a key role in the great contraction.

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Gustavo S. Cortes Warrington College of Business University of Florida 306 Stuzin Hall, PO Box 117168 Gainesville, FL 32611 gustavo.cortes@warrington.ufl.edu "Why was monetary policy so inept? (...) The monetary system collapsed, but it clearly need not have done so (...) pursuit of the policies outlined by the [Federal Reserve] System itself (...) would have prevented the catastrophe." — MILTON FRIEDMAN AND ANNA J. SCHWARTZ (1963)

"I would like to say to Milton and Anna: regarding the Great Depression. You're right, we did it. We're very sorry. But thanks to you, we won't do it again." — BEN S. BERNANKE (2002), GOVERNOR OF THE FEDERAL RESERVE SYSTEM

1 Introduction

The Great Depression is the most severe economic downturn in the last 100 years and one of the most studied events in the history of economics. Friedman and Schwartz (1963) argued in their seminal work, "A Monetary History of the United States," that the Federal Reserve did not respond to the one-third decline in the money supply. The Fed failed to play the role of a lender-of-last-resort and provide liquidity assistance to banks which led to bank failures and bank suspensions. The Fed's inadequate response turned a "garden variety recession" into a depression (Hamilton (1987)). Bernanke (1983) subsequently argued that the collapse of the banking system also contributed to the depth and duration of the Great Depression because firms had reduced access to credit and therefore could not undertake profitable investment opportunities. Financially solvent banks reduced lending because they were concerned about the possibility of a bank run (Calomiris (1993); Calomiris and Mason (1997, 2003a,b)).

Unlike today where monetary policy decision-making is centralized in Washington DC, the twelve regional Federal Reserve banks had the power to set their own discount rate until the mid-1930s. The decentralized nature of US monetary policy during this period raises an important question: To what extent was the economic contraction of the Great Depression driven by regional and national monetary shocks?¹ We address this question by studying a unique empirical setting where there were regional and national monetary policies that varied across the Federal Reserve System during the Great Depression.² Chandler (1971), for example, noted that the New York Fed had the most aggressive and expansionary monetary policy of all the Federal Reserve banks during the Great Depression. On the other hand, many of the Federal Reserve district banks adhered to the real bills doctrine and did not believe in aggressive countercyclical monetary policy.

¹The scope for fiscal policy in the US was very limited until Roosevelt's New Deal in March of 1933 (Romer (1992)). The relative absence of fiscal policy improves the identification of monetary policy shocks. On the other hand, Jacobson, Leeper, and Preston (2019) argue that fiscal policy was important for the economic recovery from the Great Depression.

²The identification-through-disaggregation approach was pioneered by Wicker (1980, 1996) and later inspired Calomiris and Mason (2003a). In recent work, Nakamura and Steinsson (2014) also exploit disaggregated data for US states and regions to improve upon the identification of fiscal policy shocks in the postwar period.

Our research is motivated, in part, by the work of Rockoff (2003), who argues that the United States did not become a full-fledged monetary union until the mid-1930s. A specific shock, for example, could cause a monetary contraction that exacerbated the original disturbance. The regional crisis often precipitated a discussion about the role of monetary and financial institutions which could further increase uncertainty and intensify the economic downturn.³ More recent research by Rajan and Ramcharan (2011, 2015, 2016a,b) has highlighted some of the frictions in the banking system during the 1920s, which is consistent with an imperfect monetary union during the interwar period. The authors find that areas that had higher credit availability suffered a greater decline in land prices and a larger increase in bank failures that persisted for decades. With respect to the Great Depression, Rajan and Ramcharan (2015) find that banking markets became more concentrated in areas that experienced a large banking collapse. Furthermore, they find that limits on branch banking after the Great Depression appear to have made the great contraction more persistent.

Given capital market frictions, we assess the real effects of quasi-independent monetary policy of the 12 Federal Reserve District banks during the Great Depression. We employ new methods in structural vector autoregressions (SVAR) developed by Antolín-Díaz and Rubio-Ramírez (2018) that marries traditional sign restrictions with narrative sign restrictions to better identify the real effects of monetary policy shocks during the 1920s and the Great Depression. Their methodology is ideal for studying the Depression given the rich economic history literature that informs the narrative sign restrictions. Bernanke (2002), for example, discusses four monetary policy "quasi-natural experiments" during the late 1920s and early 1930s that were identified by Friedman and Schwartz as unrelated to changes in US economic conditions.⁴

Our empirical analysis, based on sign restrictions and narrative sign restrictions from Friedman and Schwartz, demonstrates that there was significant regional heterogeneity in monetary policy. Region-specific vector autoregressions (VARs) show that monetary policy had a significant effect

³For the first 150 years, Rockoff (2003) suggests that the US may have been better off if each region had its own currency that could act as shock absorber for local economic shocks. He also argues that it was not until the establishment of institutions such as the Federal Deposit Insurance Corporation (FDIC) in 1933 as well as the ability of the federal government to distribute fiscal transfers throughout the country (i.e., unemployment insurance and social security) did the US have a well functioning monetary union (see also Cohen-Setton (2016, Ch. 2)).

⁴We describe each episode in greater detail in Section 4.2.3, but these episodes can be briefly summarized as follows: (i) the New York Fed raises the discount rate in 1928 to curb speculative behavior on the New York Stock Exchange; (ii) the New York Fed increases the discount rate following the UK's exit from the gold standard in 1931; (iii) succumbing to political pressure, the 1932 monetary expansion was the largest on record since the founding of the Fed in 1913; and (iv) the contractionary monetary policy shock in the first quarter of 1933, characterized by considerable uncertainty about the future of US economic policy since Roosevelt was elected in November 1932 but did not take office until March 1933.

on local retail sales, building permits, as well as short-term interest rates and prices. The median response of retail sales to a contractionary monetary policy shock on impact ranges from –9 percent in Atlanta to as low as –1 percent in San Francisco. With respect to building permits, New York and Boston display median responses to a contractionary shock on impact of around –5 percent, while we observe substantially stronger impacts in other districts. The differences across the Federal Reserve System generally hold true even accounting for estimation uncertainty. In terms of variance decompositions, a monetary policy shock explains between 7 and 22 percent of the forecast error variance of retail sales in the twelve Federal Reserve districts after five years. For building permits, a 25 basis point increase in the discount rate explains, at the mean, between 6 and 25 percent of the movements in building permits.

We follow-up the baseline empirical analysis by examining the systematic component of the regional monetary policies. To that end, we estimate the identified monetary policy reaction functions in the discount rate equations for each of the 12 Fed districts. Interestingly, we find that the New York Fed had the strongest response to retail sales and building permits in the Federal Reserve System. Richmond, however, had the biggest response to food prices, while New York had the second largest response. Nevertheless, the response coefficients of the discount rate by the New York Fed to retail sales, building permits, and food prices was less than one, which suggests little evidence of systematic monetary policy during the Great Depression. Discretion ruled the day.

We next investigate whether national- or regional-led monetary policy mattered more for real activity. To do so, we pool the twelve identified monetary policy shocks series—for each Federal Reserve district—and extract a common factor. We interpret the common factor of all identified monetary policy shocks as a proxy for the national component of monetary policy shocks. We then construct the orthogonal, regional components of monetary policy shocks by subtracting each district-specific shocks from the common factor. Using these shocks as instruments in proxy-VARs, we observe substantial differences in the extent of the exposure to both a contractionary *national* monetary policy shock, and a *Fed-district-specific* monetary policy shock across the different regions. In response to a tightening of national monetary policy, the impulse response functions for retail sales and building permits in the Boston and New York districts show less depth and persistence compared to the other Fed districts. Like the baseline regional VARs, our proxy-VARs also demonstrate substantial heterogeneity across the Federal Reserve System. While some regions do not have

a strong exposure to national-level shocks, they always display significant exposure to Fed-districtspecific monetary shocks—with the exception of Boston. Again, the analysis points to the heterogeneity and importance of regional monetary policy shocks as opposed to national monetary policy.

The tenor of our baseline results remains unchanged across various robustness checks in model specifications and identifying restrictions. We augment our baseline VAR model with the spread between each Federal Reserve district and the discount rate of the New York Federal Reserve. The interest-rate differential is a measure of the idiosyncratic component of monetary policy for a given district *vis-à-vis* the more influential New York Fed (Friedman and Schwartz (1963)). Our results are qualitatively unchanged. Then, we incorporate failed bank deposits into our baseline VARs (Calomiris and Mason (2003a); Anari, Kolari, and Mason (2005)). We find that the credit channel measure does not alter the baseline results. There remains considerable heterogeneity in the impact of a contractionary monetary policy shock across the twelve Federal Reserve districts. Again, the findings suggest that contractionary monetary policy shocks at the regional Federal Reserve banks had a larger negative impact on economic activity than national monetary policy shocks.

Finally, we discuss the robustness of our conclusions by comparing the baseline responses with prior-robust identified sets. Specifically addressing the critique of sign-identified SVARs and following the transparent reporting standards detailed in Baumeister and Hamilton (2015, 2020), Schorfheide (2017), and Watson (2019), we report our baseline results along with their respective identified sets (i.e. the point-wise maximum and minimum estimates reported as bounds).⁵ Again, we find remarkably similar dynamic responses driven by evidence in the data. The similarity of results using both methods suggest our conclusions on the substantial heterogeneity of monetary policy across Fed districts are robust.

The remainder of the paper proceeds as follows. Section 2 discusses the institutional evolution of the Fed from its inception in 1913 until the centralization of monetary policy in the mid-1930s. Section 3 describes our data for each Fed district. Section 4 presents our empirical strategy. Section 5 shows the results. We first report the findings for the baseline VAR model, followed by our examination of the impact of regional and national monetary policy on economic activity in the twelve Federal Reserve districts. Section 6 provides robustness tests of the baseline results.

⁵In recent work, Baumeister and Hamilton (2020) discuss various useful tools and strategies for reporting results and drawing conclusions in set-identified SVARs.

2 The Federal Reserve before the Centralization of Monetary Policy

President Woodrow Wilson signed the Federal Reserve Act on December 23, 1913. The legislation established a central bank in the United States following a series of financial crises—often characterized by bank runs and bank suspensions—during the classical gold standard period. A central bank could provide a more elastic currency and play the role of a lender of last resort during a financial panic to assist illiquid banks (Miron (1986); Bernstein, Hughson, and Weidenmier (2010)).

The Federal Reserve Act created a public-private partnership where the Federal Reserve Board in Washington, DC provided oversight of the twelve Federal Reserve banks. Regional banks were established in large cities within each district.⁶ Each Federal Reserve bank had the power to set their own discount rate and cover ratio to maintain the gold standard. The head of each Federal Reserve bank was given the title of *governor*, which signified that the district banks exercised considerable control over monetary policy in each region.

The regional Fed banks formed the Open Market Investment Committee (OMIC) to discuss monetary policy. The group regularly met beginning in 1923 and sometimes coordinated monetary policy among the Federal Reserve district banks. The Fed system learned that the buying and selling of government bonds influenced short-term interest rates. Open market purchases helped stimulate economic activity in 1924 and 1927. The actions of the OMIC were not binding, however, and reserve bank governors could implement their own monetary policy if they did not agree with the recommendations of the OMIC. As Figure 1 shows, there was substantial heterogeneity in the discount rates across Federal Reserve banks. One episode that exemplifies such disagreement was the Great Crash of 1929, when regional Federal Reserve banks differed in their response to the stock market crash. The New York Fed stepped in and provided liquidity to financial markets, a lender-of-resort action praised by Friedman and Schwartz (1963). Many of the regional Federal Reserve banks did not change their discount rate and provide liquidity to their local regional stock exchange. Rather, the dissenting governors believed that central banks should not respond to large changes in asset prices.

The New York Fed continued to reduce discount rates after the Great Crash. By the end of 1929, its discount rate was 4.5 percent. Following six more rate cuts, the discount rate of the New York Fed

⁶Boston (1st District), New York (2nd), Philadelphia (3rd), Cleveland (4th), Richmond (5th), Atlanta (6th), Chicago (7th), St. Louis (8th), Minneapolis (9th), Dallas (10th), Kansas City (11th), and San Francisco (12th).



Figure 1. Discount Rate set by each Federal Reserve district. Each panel plots the discount rates of the 12 Federal Reserve banks. The black thick line represents the data for the respective Fed District indicated in the title of the panel, and the data for the remaining Fed districts are depicted in grey for comparison purposes. To highlight the New York Fed District, we depict its time series in red in its respective panel.

bottomed out at 1 percent. In contrast, six other Federal Reserve banks lowered their discount rate from 5 to 3.5 percent and four Federal Reserve banks cut their discount rate from 5 to 2.5 percent. The exception was the Boston Fed which lowered its discount rate from 5 to 2 percent. Chandler (1971) concluded that the New York Fed was by far the most aggressive Federal Reserve bank in reducing its discount rate in the early years after the onset of the Great Depression.

As shown by Chandler (1971), many of the regional Federal Reserve banks did not believe in expansionary and interventionist monetary policy. Fed officials were often proponents of the real bills doctrine, that called for a *reduction* in lending during economic downturns. A letter by William McChesney Martin, Governor of the St. Louis Federal Reserve Bank, outlines the governor's reasoning for supporting non-interventionist monetary policy during the banking panic of 1930 (Chandler (1971, p.142)):

"I cannot see how the situation can be benefited by putting 50 millions of dollars, or, in fact, any other amount, into the general market at this time... The reason that more money is not being used is because it is not needed, and when there is already money to meet the expressed needs, seems to me unwise to artificially add to the amount already sufficient in order to encourage a use which because based on a redundancy of money rather than actual needs may be hazardous."

Several other Federal Reserve banks held the same position on monetary interventions as the St. Louis Fed. Chandler (1971) points out that the Dallas and Richmond Federal Reserve banks also embraced the real bills doctrine and did not support activist monetary policy. A notable exception was the Atlanta Federal Reserve Bank which, as noted above, aggressively lent funds to member and non-member banks during the Great Depression.

As pointed out by Bernanke (2002) and Friedman and Schwartz (1963), Federal Reserve leadership was another important factor in the coordination of monetary policy in the early years of the central bank. Benjamin Strong, the President of the New York Fed, was an influential leader in the Federal Reserve System. He helped coordinate monetary policy among the 12 Federal Reserve districts on many occasions even though he frequently disagreed with policy recommendations from the Federal Reserve Board in Washington, DC. Friedman and Schwartz (1963) argued that he understood the importance of the lender-of-last-resort function for central banks. Notably, they believed that the Great Depression would have been less severe if Strong did not die in 1928. Without his guidance, there was a leadership vacuum at the Fed.

The Banking Acts of 1933 and 1935 introduced new banking regulation and largely transformed the Federal Reserve System into its current makeup. Known as the Glass–Steagall Act, the 1933 legislation created deposit insurance and called for the separation of commercial and investment banking. The law also included Regulation Q, which prohibited the payment of interest on checking accounts. In addition, the Banking Act of 1933 created the Federal Open Market Committee (FOMC), but did not provide the Federal Reserve Board with voting rights. The Banking Act of 1935 subsequently reorganized the structure of the Federal Reserve (Richardson, Komai, and Gou (2013)). The Board of Governors of the Federal Reserve System—which replaced the Federal Reserve Board—became more independent from the executive branch of government. The Secretary of the Treasury and the Comptroller of the Currency were no longer members of the Federal Reserve Board. The regional Federal Reserve banks lost much of their control over monetary policy. The head of the regional Federal Reserve banks were no longer called governors. Instead, they were given the new title of "president," which symbolized a reduction in the power of the regional banks to implement their own monetary policy. The regional Federal Reserve banks could no longer conduct open market operations in their respective districts. Rather, the newly created Federal Reserve Open Market Committee (FOMC) determined the size and scope of open market operations, with centralized monetary policy decision-making in the nation's capital.

3 Data: Fed District-Level Monthly Macroeconomic Database

We now detail the construction of our macroeconomic and financial database at the Federal Reserve district level used in the empirical analysis. For time series plots of all variables as well as technical details about the data, we refer the reader to Internet Appendix A.

Real Economic Activity: Retail Sales. Our first measure of real economic activity is monthly retail sales which proxies for aggregate consumption. As discussed by Park and Richardson (2012), the Federal Reserve established a nationwide network for collecting data and information about economic conditions shortly after beginning operations. In 1919, the Fed began tabulating retail sales data. For the next 10 years, the Federal Reserve published retail sales data each month by Federal Reserve district. Beginning in 1929, the Fed compiled monthly data on retail sales by Fed district, but did not report the consumption measure in the Fed Bulletins or through press releases. Park and Richardson (2012) subsequently assembled the in-house reports from the archives of the Board of Governors and constructed a consistent series on retail trade at the district level and made it available to researchers.

Real Economic Activity: Building Permits. The second measure of economic activity is building permits which proxies for aggregate investment. The real estate variable is measured as the total value of building permits in commercial and residential construction. The monthly building permit data are from Cortes and Weidenmier (2019), who hand-collected the original time series for 215 cities across the United States from several issues of *Dun & Bradstreet's*, a well-known monthly business publication in the 1920s and the 1930s. The real-time data are assembled from building

inspector reports collected by the *F. W. Dodge Division*, a *McGraw-Hill Information Systems* company. The value of building permits is based on the estimated cost of new commercial and residential buildings provided by building inspectors. We construct a measure of total building permits at the Fed district level by aggregating Cortes and Weidenmier's (2019) city-level data by summing up the values relative to all cities in a Fed district.

Price Indices. We use food prices for 50 cities from several issues of the Bulletin of the US Bureau of Labor Statistics to construct equally-weighted food price indices for each Fed district.

Monetary Aggregates. The monetary aggregate, M1, is constructed from data on total currency in circulation and total demand deposits of member banks for each Federal Reserve district. Both components of the monetary aggregate are hand-collected from various issues of the Federal Reserve Bulletin and then added together by each month and Fed district.

Commercial Paper Rates. Following the macroeconomics literature of the interwar period, we use commercial paper rates as our measure of the short-term, market-based interest rate. The time series are hand-collected from various issues of the Federal Reserve Bulletin.

Federal Reserve Discount Rates. We collect the monthly Federal Reserve discount rate of each regional Fed bank from various issues of the Federal Reserve Bulletin. The time series are shown in Figure 1 above.

Data Limitations and Sample Period. While most time series are available for a longer period (i.e., 1920:*M*01 to 1939:*M*12), the food price indices cover only 1923:*M*01–1936:*M*12. Additionally, the interest rate for commercial paper ends in 1933:*M*02, when the Federal Reserve Bulletin stopped reporting detailed data on the regional Federal Reserve banks. As a result, our sample period covers 1923:*M*01–1933:*M*02. Despite these limitations, our complete data set covers most of the 1920s and the entire NBER-defined Great Depression period—except for March 1933, the last month of the downturn.

9

4 Empirical Strategy

4.1 Region-Specific VARs

For our baseline specification, we estimate a Bayesian VAR for each regional Federal Reserve district with data on retail sales (rs_t), building permits (bp_t), food prices (p_t), M1 (m_t), commercial paper rates (cpr_t), and the respective Federal Reserve district discount rates (r_t). We model the regional dynamics of the following vector of observables:

$$\mathbf{y}_{\mathbf{t}} = \left(\begin{array}{ccc} rs_t, & bp_t, & p_t, & m_t, & cpr_t, & r_t \end{array} \right)'. \tag{1}$$

All variables for each region enter the VAR in log levels multiplied by 100, except for commercial paper rates and discount rates, which enter in percent levels. We consider a Gaussian VAR in the $n \times 1$ vector of observables **y**_t. The VAR is given by

$$\mathbf{y}_{t}'\mathbf{A}_{0} = \sum_{p=1}^{P} \mathbf{y}_{t-p}'\mathbf{A}_{p} + \mathbf{c} + \epsilon'_{t},$$
(2)

with $\epsilon_t \sim \mathcal{N}(0, \mathbf{I_n})$, for $1 \leq t \leq T$, where **c** is the constant term, ϵ_t is an $n \times 1$ vector of orthogonal structural shocks that have an economic interpretation, $\mathbf{A_p}$ is an $n \times n$ matrix of structural parameters for $0 \leq p \leq P$ with $\mathbf{A_0}$ invertible, *P* is the lag length, and *T* is the sample size. The SVAR described in equation (2) can be written as

$$\mathbf{y}_{t}'\mathbf{A}_{0} = \mathbf{x}_{t}'\mathbf{A}_{+} + \boldsymbol{\varepsilon}_{t'}' \tag{3}$$

where $\mathbf{A}_{+}' = \begin{bmatrix} \mathbf{A}_{1}' \cdots \mathbf{A}_{p}' & \mathbf{c}' \end{bmatrix}$ and $\mathbf{x}_{t}' = \begin{bmatrix} \mathbf{y}_{t-1}' \cdots \mathbf{y}_{t-p'} & 1 \end{bmatrix}$. The dimension of \mathbf{A}_{+}' is $m \times n$, where m = nP + 1. We refer to \mathbf{A}_{0} and \mathbf{A}_{+} as the structural parameters. The reduced-form vector autoregression (VAR) implied by equation (3) is

$$\mathbf{y}_t' = \mathbf{x}_t' \mathbf{B} + \mathbf{u}_t',\tag{4}$$

where the reduced form coefficient matrix is $\mathbf{B} = \mathbf{A}_{+}\mathbf{A}_{0}^{-1}$, the innovation vector is $\mathbf{u}'_{t} = \epsilon'_{t}\mathbf{A}_{0}^{-1}$, and the innovation covariance matrix can be factored as $\mathbb{E}[\mathbf{u}_{t}\mathbf{u}'_{t}] = \Sigma = \mathbf{A}_{0}\mathbf{A}_{0}^{-1}$. Let $\mathbf{\Theta} = (\mathbf{A}_{0}, \mathbf{A}_{+})$ collect the value of the structural parameters.

4.1.1 The Systematic Component of Monetary Policy

The identification of monetary policy shocks either directly specifies or implies the systematic component of policy, which characterizes the systematic endogenous monetary policy reaction to economic conditions (see Leeper, Sims, and Zha (1996), Leeper and Zha (2003), and Sims and Zha (2006)). Without loss of generality, we follow Arias, Rubio-Ramírez, and Waggoner (2018) and let the first shock be the monetary policy shock. Thus, the first equation of the SVAR,

$$\mathbf{y}_{\mathbf{t}}'\mathbf{a}_{0,1} = \sum_{p=1}^{p} \mathbf{y}_{\mathbf{t}-\mathbf{p}}'\mathbf{a}_{p,1} + \epsilon_{1t},$$
(5)

is the monetary policy equation, where ϵ_{1t} denotes the first entry of ϵ_t , $\mathbf{a}_{p,1}$ denotes the first column of \mathbf{A}_p for $0 \le p \le P$, and $a_{p,ij}$ denotes the (i, j) entry of \mathbf{A}_p , which describes the systematic component of monetary policy. In order to represent the systematic interest rate monetary policy equation, we can rewrite equation (5), abstracting from lag variables, as

$$r_t = \alpha_{rs} rs_t + \alpha_{bp} bp_t + \alpha_p p_t + \alpha_m m_t + \alpha_{cpr} cpr_t + \epsilon_{rt}, \tag{6}$$

where $\alpha_{rs} = -a_{0,61}^{-1}a_{0,11}$, $\alpha_{bp} = -a_{0,61}^{-1}a_{0,21}$, $\alpha_{p} = -a_{0,61}^{-1}a_{0,31}$, $\alpha_{m} = -a_{0,61}^{-1}a_{0,41}$ and $\alpha_{cpr} = -a_{0,61}^{-1}a_{0,51}$. Note the the position of the elements in $a_{0,ij}$ refer to the ordering of the variables detailed in equation (2).

4.1.2 Impulse Response Functions

Given a value Θ of the structural parameters, one can compute the impulse response functions (IRFs). The response of the *i*th variable to the *j*th structural shock at horizon *k* corresponds to the element in row *i* and column *j* of the matrix $\mathbf{L}_{\mathbf{k}}(\Theta)$ which is defined recursively by

$$\begin{split} \mathbf{L}_{\mathbf{0}}\left(\mathbf{\Theta}\right) &= \left(A_{0}^{-1}\right)' \\ \mathbf{L}_{\mathbf{k}}\left(\mathbf{\Theta}\right) &= \sum_{p=1}^{k} \left(A_{p} A_{0}^{-1}\right)' \mathbf{L}_{\mathbf{k}-\mathbf{p}}\left(\mathbf{\Theta}\right), & \text{for } 1 \leq k \leq P, \\ \mathbf{L}_{\mathbf{k}}\left(\mathbf{\Theta}\right) &= \sum_{p=1}^{P} \left(A_{p} A_{0}^{-1}\right)' \mathbf{L}_{\mathbf{k}-\mathbf{p}}\left(\mathbf{\Theta}\right), & \text{for } P \leq k \leq \infty, \end{split}$$

4.1.3 Structural Shocks and Historical Decomposition

Given a value Θ of the structural parameters and the data, the structural shocks at time *t* are:

$$\epsilon'_t(\Theta) = \mathbf{y}_t' \mathbf{A}_0 - \mathbf{x}_t' \mathbf{A}_+. \tag{7}$$

The historical decomposition calculates the cumulative contribution of each shock to the observed unexpected change in the variables between two periods. Formally, the contribution of the *j*th shock to the observed unexpected change in the *i*th variable between periods t and t + h is

$$\mathbf{H}_{i,j,t,t+h}\left(\boldsymbol{\Theta},\boldsymbol{\epsilon}_{t},\ldots,\boldsymbol{\epsilon}_{t+h}\right) = \sum_{p=0}^{h} \mathbf{e}_{i,n}^{\prime} \mathbf{L}_{\mathbf{p}}^{\prime}\left(\boldsymbol{\Theta}\right) \mathbf{e}_{j,n} \mathbf{e}_{j,n}^{\prime} \boldsymbol{\epsilon}_{t+h-p}, \tag{8}$$

where $\mathbf{e}_{j,n}$ the *j*th column of \mathbf{I}_n , for $1 \leq i, j \leq n$ and for $h \geq 0$.

4.1.4 Estimation and Identification

As it is well-known, structural VARs require additional identifying restrictions to map the reducedform innovations (u_t) to structural shocks (ϵ_t). For set-identified SVAR models, this typically involves factoring Σ by a Cholesky decomposition with a lower-triangular factor denoted by $\tilde{\mathbf{A}}^{-1}$ and a rotation matrix \mathbf{Q} . A typical prior choice for \mathbf{Q} is the Haar prior, which is a uniform prior over the orthogonal rotation matrices $\mathbf{Q} \in \mathcal{O}(n)$, i.e. the set of all orthogonal $n \times n$ matrices (see, e.g., Uhlig (2005), Rubio-Ramírez, Waggoner, and Zha (2010), and Arias, Rubio-Ramírez, and Waggoner (2018)). For the reduced form representation, this can be summarized as:

$$u'_t = \epsilon'_t \tilde{\mathbf{A}}^{-1} \mathbf{Q}, \qquad \Sigma = \tilde{\mathbf{A}}^{-1} \mathbf{Q} \left(\tilde{\mathbf{A}}^{-1} \mathbf{Q} \right)', \qquad \mathbf{Q} \mathbf{Q}' = I_n.$$
 (9)

In set-identified SVARs, the key identifying restrictions in the mapping of innovations to structural shocks formally constrains the domain of the rotation matrix \mathbf{Q} such that the qualitative sign restriction on the resulting impulse response functions are satisfied. We can write our full model as:

$$p(\mathbf{y}^{\mathrm{T}}, \mathbf{B}, \boldsymbol{\Sigma}, \mathbf{Q}) = \ell(\mathbf{B}, \boldsymbol{\Sigma} | \mathbf{y}^{\mathrm{T}}) \pi_0(\mathbf{B}, \boldsymbol{\Sigma}) \pi_{\mathbf{Q}}(\mathbf{Q} | \mathbf{B}, \boldsymbol{\Sigma}),$$
(10)

where \mathbf{y}^{T} collects the history of observables, $\ell(\cdot)$ is the likelihood function, $\pi_{0}(\cdot)$ denotes the prior over the identifiable reduced-form parameters, and $\pi_{\mathbf{Q}}(\cdot)$ denotes the prior over \mathbf{Q} that incorporates restrictions on impulse responses.

Model, **prior**, **and estimation specification**. For the estimation of the model, we use a uniformnormal-inverse-Wishart distribution for the priors over the orthogonal reduced-form parameterization. In our empirical implementation, we use a standard Minnesota-type prior over (**B**, Σ) and otherwise specifically follow Antolín-Díaz and Rubio-Ramírez (2018) to do causal inference for the orthogonal reduced-form parameterization implementing Algorithm 1. In our benchmark we set the lag length to 6 and include a constant⁷. Following the notation of Del Negro and Schorfheide (2011), we choose an overall tightness parameter of $\lambda_1 = .2$, a decay parameter of $\lambda_2 = 2$, prior for the covariance matrix of error terms $\lambda_3 = 1$, sums-of-coefficients prior with $\lambda_4 = 1$ and copersistence prior with $\lambda_5 = 1.^8$ We base all our results on 5000 admissible draws that satisfy our respective combination of identifying restrictions for each model.⁹

4.2 Identification of Monetary Policy Shocks

4.2.1 Sign Restrictions

Since the seminal papers by Faust (1998), Canova and De Nicolò (2002) and, most prominently Uhlig (2005), sign-restricted SVARs have become an increasingly popular tool for estimating dynamic causal effects in macroeconomics. Many researchers use Uhlig's (2005) algorithm or its variants to impose theory-based or uncontroversial restrictions on the sign of impulse response functions to identify a shock of interest. As these types of identifying constraints restrict the resulting identified responses to a bounded set, these models are known as set-identified. Over the past few years, a growing literature has proposed important methodological refinements and advances (e.g., Rubio-Ramírez, Waggoner, and Zha (2010); Baumeister and Hamilton (2015); Antolín-Díaz and Rubio-Ramírez (2018); Arias, Rubio-Ramírez, and Waggoner (2018); Arias, Caldara, and Rubio-Ramírez (2019); Granziera, Moon, and Schorfheide (2018); Giacomini and Kitagawa (2021)).

The main advantages of the approach are that the identifying sign constraints are theoretically well motivated, avoids zero-type restrictions, and uncontroversial. Its limitations are that the identifying sign constraints typically offer *weak* identification, i.e., usually restricting only the direction by means of the sign of a few IRFs for a few periods. In many applications, this yields notably

⁷Experimenting with a model specification excluding the constant term does not change our results.

⁸A thorough discussion of the hyperparameters and its choices for Bayesian VARs can be found in Giannone, Lenza, and Primiceri (2015) and Del Negro and Schorfheide (2011).

⁹The estimation was programmed in Matlab and run on an iMac with a 4 GHz Intel Core i7 and 32 GB 1867 MHz DDR3 of RAM. The estimated runtime varies substantially depending on Fed district, model specification and combination of identifying restriction. For the benchmark model, the fastest estimated runtime was 2.5 hours for the Federal Reserve district of Boston while the slowest took as long as 27 hours for the Federal Reserve district of Dallas. The estimated runtime for our benchmark specification with a loop over all Federal Reserve districts is about a week.

large error bands or wide identified sets that are either insignificant or inconclusive. Therefore, it is difficult and rare to find robust evidence and clear conclusions among competing hypotheses on the sources of business cycle fluctuations when employing these methods.¹⁰

Among the many important advances, the approach proposed by Antolín-Díaz and Rubio-Ramírez (2018) is particularly promising in our setting due to rich, existing historical narratives of monetary policy interventions during the Depression. They show that combining the standard approach with simple *narrative* sign restrictions (NSR) on the structural shocks and/or the historical decomposition tend to be highly informative. This approach imposes the sign of the identified shock series at specified points in time to agree with the established narrative account of these episodes.

A common problem in monetary VARs with sign restrictions is that output can respond positively to a contractionary shock unless it is explicitly restricted, as highlighted in Uhlig (2005). A recent important contribution by Wolf (2020) provides a rigorous analysis of the underlying problem, sources and its resolution. Wolf (2020) argues that some *masquerade* of linear combination of positive supply and demand shocks can generate monetary policy sign-consistent response while leading to increases in output which is an artifact. Wolf (2020) further argues that this puzzling outcome can be resolved with sign restrictions on the Taylor rule adopting the approach proposed by Arias, Caldara, and Rubio-Ramírez (2019). They propose to sharpen inference and avoid ambiguous results by imposing sign restrictions directly on the monetary policy reaction function in equation (6). They illustrate its usefulness for the analysis of post-World War II US data. While uncontroversial for that specific time period, there is clearly less consensus as to what was the systematic monetary policy reaction function at the time of the Great Depression—and even less at each Fed district, if there was a Taylor-rule-type policy in place at all. We therefore do not adopt this type of constraints and rather opt for directly sign-constraining output to achieve the same goal of addressing the identification problem of expansionary effects of a contractionary shock.¹¹

¹⁰Uhlig (2005) argues that this is precisely why sign restrictions are useful, as they provide a transparent assessment of what one can robustly conclude from the data while imposing only what macroeconomists believe they know.

¹¹We substantiate this choice replicating and extending the simulation exercise of Wolf (2020) adding the case with output restricted impulse response functions and show how that approach as as an alternative recovers the the true dynamics in a very similar degree of precision as does the alternative with sign restrictions on the Taylor rule. In our application, it furthermore happens to be computationally more efficient to directly add a sign restriction on output rather than adding restrictions on the policy reaction function.

Table 1. Benchmark Identification: Traditional sign restrictions on selected impulse response functions and narrative sign restrictions on all four major monetary policy episodes. This table details the sign restrictions imposed on the variables included in the VAR. Positive sign restrictions are denoted by "+", negative sign restrictions are denoted by "-", and variables left without sign restrictions are denoted by "x". The variables included in the VARs are the following: retail sales (rs_t), building permits (bp_t), food prices (p_t), money aggregate M1 (m_t), commercial paper rate (cpr_t), and Federal Reserve discount rate (r_t).

	rs _t	bp_t	p_t	m_t	cprt	r _t	
SR	_	_	_	_	x	+	
SR-Horizon	month 0, , 6						
Narrative Sign Restriction	Brief description of narrative					Date	
$\mathcal{NSR1}:(-)$	Ant	1928:M04					
$\mathcal{NSR2}:(-)$	Con	1931:M10					
$\mathcal{NSR3}:(+)$	Exp	1932:M04					
$\mathcal{NSR4}:(-)$	Con	1933:M01					

4.2.2 Baseline Identification

Our basic identification restrictions for a contractionary monetary policy shock essentially follows the combination of Uhlig (2005) and Antolín-Díaz and Rubio-Ramírez (2018) , imposing the impulse response functions of retail sales (rs_t) , building permits (bp_t) , food prices (p_t) , and money aggregate M1 (m_t) to be negative following the shock for 6 months, while the impulse response functions of the Federal Reserve discount rate (r_t) is constrained to be positive for that period and the commercial paper rate is left unconstrained. Beyond its transparent nature to impose only what macroeconomic theory established as facts, in our case we do not have to take a stance on a specific policy instrument or rule in place. Our baseline sign restrictions are summarized in Table 1. We further add rich narrative sign restrictions to our baseline specification, as detailed in the next section. We present robustness checks that include variations of our standard sign restrictions, narrative sign restrictions, specifications, and data in Section 6.

4.2.3 Narrative Sign Restrictions: Monetary Policy and the Great Depression

We now describe four monetary policy events during the Great Depression that Friedman and Schwartz (1963) considered to be exogenous to define narrative sign restrictions as in Antolín-Díaz and Rubio-Ramírez (2018).¹² For convenience, all narrative sign restrictions along with the traditional sign restrictions are also briefly described in Section C of our internet appendix.

The first episode is a monetary contraction. In the words of Bernanke (2002), it was "a deliberate tightening of monetary policy that began in the Spring of 1928 and continued until the stock market

¹²This section borrows the rich narrative description from Friedman and Schwartz (1963) and Bernanke (2002).

crash of October 1929. Why did the Federal Reserve tighten in early 1928? A principal reason was the Board's ongoing concern about speculation on Wall Street." Friedman and Schwartz (1963) point out that by July 1928 the discount rate of the New York Fed had been raised to 5 percent, its highest level since 1921. The holdings of government securities by the Federal Reserve System also fell from \$600 million at the end of 1927 to \$210 million by August 1928. They concluded that this period represented a tightening in monetary policy not related to economic conditions. This leads us to define our first narrative sign restriction:

Narrative Sign Restriction 1 (*Monetary Policy Contraction in April 1928*). Beyond standard sign restrictions on the impulse response functions, the sign of the monetary policy shock must be positive in April 1928 to represent an identified monetary policy shock.

The second episode is also a monetary contraction. The Federal Reserve raised the discount rate from 1 to 2 percent on October 9, 1931. The increase was then followed by another rise in the discount rate to 3 percent on October 16, 1931. The policy was a response to the speculative attacks on the pound sterling that led the UK to abandon the gold standard. Again, the interest rate increase is exogenous to US economic conditions since the policy was directly aimed at preventing a run on the dollar. Friedman and Schwartz (1963) argued that the 200 basis point increase in the discount rate increased bank failures and bank runs, with 522 commercial banks closing their doors in October alone. The policy tightening contributed to the decline in the money supply as well as economic activity. We therefore define our second narrative sign restriction as:

Narrative Sign Restriction 2 (*Monetary Policy Contraction in October* 1931). Beyond standard sign restrictions on the impulse response functions, the sign of the monetary policy shock must be positive in October 1931 to represent an identified monetary policy shock.

The third episode we study is an expansionary intervention. Friedman and Schwartz (1963), Hsieh and Romer (2006), and Bordo and Sinha (2016) argue that the monetary expansion of April 1932 was one of the most important monetary policy shocks in US history. In fact, the open market expansion was the largest in the history of the Federal Reserve at the time of its implementation. All 12 Federal Reserve banks participated in the monetary expansion that was largely undertaken because of political pressure from Congress. The Board of Governors eventually acquiesed to moral suasion and conducted large-scale open market operations between April and June of 1932. The



Figure 2. The 1932 Monetary Policy Expansion. This figure depicts the time series of US government bond holdings of the twelve Federal Reserve districts around the 1932 monetary policy expansion episode. The data are from the Federal Reserve Bulletins and are in million USD.

large quantitative easing program appears to have temporarily increased economic activity before fizzling out following the removal of the monetary stimulus in the late summer of 1932.

Figure 2, Panel A shows the holdings of US government securities for the 12 regional Federal Reserve banks. The New York Fed stands out as it accounts for about 40 percent of the total government securities in the system. The size of the Federal Reserve banks' portfolio of government securities varies considerably across the 12 Federal Reserve districts, but its expansionary stance is unambiguous across districts. Figure 2, Panel B highlights that the 1932 expansion did not take place only at the New York Fed. Instead, the intervention had impressive magnitude and reach, involving all Fed districts. This leads us to define our third narrative sign restriction:

Narrative Sign Restriction 3 (*Monetary Policy Expansion in April 1932*). Beyond standard sign restrictions on the impulse response functions, the sign of the monetary policy shock must be negative in April 1932 to represent an identified monetary policy shock.

The fourth and last episode studied by Friedman and Schwartz (1963) was a contractionary shock from January 1933 to the banking holiday in March 1933. There was considerable economic uncertainty during this period given that President Roosevelt was elected in November 1932 but did not take office until March of 1933. Market participants were unclear about the future direction of US economic policy, although many speculated that Roosevelt might devalue the

dollar or leave the gold standard altogether. Some people converted their cash into gold which pressured the banking system and the gold reserves of the Federal Reserve (Bernanke (2002)). Between September 1932 and March 1933, the United States experienced its largest decline in economic activity during the Great Depression.

Narrative Sign Restriction 4 (*Monetary Policy Contraction in January* 1933). Beyond standard sign restrictions on the impulse response functions, the sign of the monetary policy shock must be positive in January 1933 to represent an identified monetary policy shock.

Finally, as a variation expressing stronger beliefs, we focus on the least controversial narrative restriction, the monetary stimulus of April 1932. Given its expansionary effects, we consider an additional narrative sign restriction that imposes a *magnitude* restriction on the importance of monetary shocks in April 1932. Specifically, the narrative sign restriction requires the monetary policy shock to be the most important contributor to the Federal Reserve discount rate shock in April 1932. This is formalized by defining a "strong expansion" on our fifth and last narrative sign restriction:¹³

Narrative Sign Restriction 5 (*Strong Monetary Policy Expansion in April 1932*). Let Narrative Sign Restriction 3 be dominant for r_t , i.e., for the periods specified by Narrative Sign Restriction 3, monetary policy shocks are the most important and dominant contributor to the movements in the Fed discount rate, r_t .

4.3 Decomposing Monetary Policy Shocks into a National and Regional Component

Instruments. To decompose monetary policy's dynamic effects into national and Fed-district-level components, we pool the estimated region-specific monetary policy shocks together and extract the first principal component. Since VAR innovations are typically serially uncorrelated and orthogonal to past information, a static factor model facilitates this decomposition.¹⁴ We refer to the common component as a measure or proxy for the national monetary policy shock. Similarly, we refer to the idiosyncratic component as a measure or proxy for the respective Fed-district-level monetary policy shock. We then use the common and idiosyncratic components of monetary policy to obtain impulse response functions in a Proxy-SVAR setting.

¹³Our "strong expansion" narrative sign restriction is a "Type A" restriction in the language of Antolín-Díaz and Rubio-Ramírez (2018). A "Type A" narrative sign restriction means that the absolute value of the contribution of monetary policy shocks is larger than the absolute value of the contribution of any other structural shock.

¹⁴A static factor model suffices since this decomposition requires no lag structure.

Proxy-SVAR Identification. Following the approach of Stock and Watson (2012) and Mertens and Ravn (2013), let \mathbf{m}_t be a $k \times 1$ vector of proxy variables that are correlated with k structural shocks of interest but orthogonal to other shocks in the system. We set k = 1 since our application focuses on identifying a single shock ("*target shock*") with a single proxy variable at a time. Without loss of generality, we assume that \mathbf{m}_t is linked to the first shock in ϵ_t and uncorrelated with the remaining structural shocks. Hence, the shock of interest is $\epsilon_{1,t}$ and the proxies provide structural identification as long as the instrument and the shocks satisfy the following conditions:

$$\boldsymbol{E}\left[\boldsymbol{\epsilon}_{1,t}\mathbf{m}_{\mathbf{t}}\right] = \boldsymbol{\phi} \neq \mathbf{0} \tag{11}$$

$$\boldsymbol{E}\left[\boldsymbol{\epsilon}_{j,t}\mathbf{m}_{\mathbf{t}}\right] = 0 \quad \text{for } j = 2, \dots, n. \tag{exogeneity} \tag{12}$$

As usual, the first condition states that the proxy variables are correlated with the shocks of interest while the second condition requires that the proxy variables are uncorrelated with all other shocks.

Proxy-VAR Estimation and Inference. As in Mertens and Ravn (2013), consider the following partitioning $\mathbf{A}_0^{-1} = [\mathbf{a}_1 \quad \mathbf{a}_2]$, where $\mathbf{a}_1 = [\mathbf{a}_{11}' \quad \mathbf{a}_{21}']$, $\mathbf{a}_2 = [\mathbf{a}_{12}' \quad \mathbf{a}_{22}']$ with nonsingular \mathbf{a}_{11} and \mathbf{a}_{22} . The conditions (11) and (12) along with $\mathbf{u}_t' = \epsilon_t' \mathbf{A}_0^{-1}$ then imply,

$$\phi \mathbf{a}_1' = \Omega_{mu'},\tag{13}$$

where the notation $\Omega_{mu'} \equiv E[m_t u'_t]$. Partitioning $\Omega_{mu'} = \begin{bmatrix} \Omega_{mu'_1} & \Omega_{mu'_2} \end{bmatrix}$, where $\Omega_{mu'_1}$ is $k \times k$ and $\Omega_{mu'_2}$ is k(n-k) and using (13), these restrictions can be expressed as

$$\mathbf{a}_{21} = \left(\Omega_{mu_1'}^{-1}\Omega_{mu_2'}\right)\mathbf{a}_{11}.$$
(14)

Estimation can proceed in three stages:

- 1. First Stage: Estimate the reduced form VAR by least squares.
- 2. Second Stage: Estimate $\Omega_{mu_1'}^{-1}\Omega_{mu_2'}$ from regressions of the VAR residuals on \mathbf{m}_t .
- 3. Final Stage: Impose the restrictions in (14) and estimate the objects of interest.

Mertens and Ravn (2019) discuss in greater detail a range of asymptotically valid inference methods to construct confidence intervals for structural impulse response functions. Our reported confidence intervals for the estimation of our Proxy VAR in Section 5.3 and Section 5.4 are based on a parametric bootstrap developed in Montiel Olea, Stock, and Watson (2020)¹⁵.

Scale Normalization. The scales of the shock and the respective impulse response functions are not separately identified because $\mathbf{u}'_t = \epsilon'_t \mathbf{A}_0^{-1}$. Following Stock and Watson (2016), we normalize the scale of the target shock $\epsilon_{1,t}$ so that it is interpretable in terms of the observed data \mathbf{y}_t . Specifically, we use the "*unit effect*" normalization, and then divide all impulse response functions by 4 to have a median 25 basis-point contemporaneous effect on the discount rate r_t .

5 Results

We start by presenting results for the baseline regional VARs in the next subsection. Then, we decompose our identified monetary policy shocks into national and Fed district-specific components. We then show the results for our national and regional-specific monetary Proxy-SVAR. We conclude by showing results that revisit key episodes of monetary policy during the Great Depression within our empirical framework.

5.1 Regional VARs

The impulse response function (IRF) analysis for the baseline vector autoregressions appears in Figures 3 through 6. For comparison purposes and a reference of scales, all panels include (in grey) the IRF of the New York Fed. The monetary policy shock for all graphs have been normalized to have a median impact of a 25 basis point increase in the discount rate for each of the 12 regional Federal Reserve banks. The impulse responses show the posterior median and 68% error bands. A 25-basis-point shock is employed for the impulse response analysis since it is the median rate increase over the sample period. Figure 3 shows that a shock to the discount rate significantly reduces retail sales for all Federal Reserve Districts. The findings for the New York District are particularly interesting because a contractionary monetary policy shock has less of an impact on retail sales than the other Federal Reserve districts. There is also some evidence that an increase in the discount rate by the Boston Federal Reserve has a smaller impact on retail sales than the

¹⁵We also estimated an alternative approach to construct valid confidence intervals based on the Delta method proposed by Montiel Olea, Stock, and Watson (2020). Results are very similar and robust to this alternative.



Figure 3. VAR Impulse Response Functions for Retail Sales. This figure depicts the response of retail sales in the twelve Federal Reserve districts to a 25-basis-point contractionary monetary policy shock. For comparison purposes, all panels include (in grey) the IRF of the New York Federal Reserve District. The sign-restriction of the monetary policy shock is binding for 6 months and is detailed in Table 1.

other regional Federal Reserve District banks. The remaining Fed districts generally experienced not only a bigger decline in retail sales, but also more persistent negative effects relative to New York. Noteworthy cases include Philadelphia, Atlanta, and Richmond.

The forecast error variance decompositions (FEVD)—shown in Table B.1 of the Internet Appendix—portray a similar story. Panel A shows that a shock to the New York Fed discount rate can only explain at the median about 14 percent of the movements in retail sales after 60 months. For Boston, we find that a discount rate shock explains about 12 percent of the forecast error variance after 5 years. In contrast, a contractionary monetary policy shock accounts for about 20 percent or more of the fluctuations in retail sales for Atlanta and Philadelphia Federal Reserve District. With respect to building permits, we find that a contractionary monetary policy shock



Figure 4. VAR Impulse Response Functions for Building Permits. This figure depicts the response of building permits in the twelve Federal Reserve districts to a 25-basis-point contractionary monetary policy shock. For comparison purposes, all panels include (in grey) the IRF of the New York Federal Reserve District. The sign-restriction of the monetary policy shock is binding for 6 months and is detailed in Table 1.

accounts at the median for 22–25 percent of the fluctuations in the Atlanta, Philadelphia, St. Louis, Richmond, Kansas City, Minneapolis, and San Francisco Federal Reserve districts.

Panel B in Table B.1 shows the maximum median FEVD for each series and the respective horizon for which this maximum is achieved across all Fed districts. The maximum median FEVD for building permits surpasses 20 percent in almost all districts, peaking at 44 percent in the Minneapolis Federal Reserve District. The horizons for which the maximum median FEVD is reached for building permits is typically within the first year with the notable exception of Philadelphia where the peak median was reached after 3 years.

In Figure 4, we find qualitatively similar responses for building permits, a forward-looking economic indicator that is sensitive to interest rates. A shock to the discount rate for the New York Fed has a much smaller impact on building permits than in the other Federal Reserve districts.



Figure 5. VAR Impulse Response Functions for M1. This figure depicts the response of the monetary aggregate M1 in the twelve Federal Reserve districts to a 25-basis-point contractionary monetary policy shock. For comparison purposes, all panels include (in grey) the IRF of the New York Federal Reserve district. The sign-restriction of the monetary policy shock is binding for 6 months and is detailed in Table 1.

The forecast error variance decompositions in Table B.1 show that the New York Fed discount rate can explain about 19 percent of the movements in the construction variable after five years. The IRF for the Boston Fed shows a similar pattern. A 25 basis point increase in the discount rate of the Boston Fed has a significant but small impact on building permits. A much different story emerges if we look at most of the remaining Federal Reserve banks, however. The FEVD shows that a one-standard deviation shock to the discount rate can explain between 22 and 25 percent of the movements in the real estate variable.

The regional Federal Reserve money supply estimates also display significant variation across the districts. Figure 5 shows that an increase in the discount rate significantly reduces M1 in all twelve Federal Reserve bank districts. Notably, the responses of the New York and Boston Federal Reserve districts show much less persistence in the decrease of the money supply in response to a



Figure 6. VAR Impulse Response Functions for Food Prices. This figure depicts the response of food prices in the twelve Federal Reserve districts to a 25-basis-point contractionary monetary policy shock. For comparison purposes, all panels include (in grey) the IRF of the New York Federal Reserve District. The sign-restriction of the monetary policy shock is binding for 6 months.

discount rate increase. The findings align with our baseline results. Specifically, the decline in M1 in response to a contractionary monetary policy shock becomes insignificant in less than a year in Boston and New York. M1 declines for up to five years in the other Federal Reserve districts. The FEVDs in Table B.1, Panel B indicate that monetary policy shocks account for about 6–18 percent of the movements of the money supply across the twelve Federal Reserve districts.

Finally, Figure 6 reports the IRFs for food prices in each Fed district. A contractionary monetary policy shock consistently reduces the price level in all twelve Federal Reserve districts. As before, the responses of prices to contractionary monetary policy shocks display heterogeneity in persistence and magnitude across Fed districts. The IRFs for the remaining variables of the baseline VAR—shown in Section B.1 of the Internet Appendix—are statistically significant and conform to economic

theory. For example, we find that a 25 basis point increase in the discount rate accounts for 8 to 46 percent of the movements of commercial paper rates.

5.2 Characterization of Regional Feds' Systematic Monetary Policy Rules

In Table 2, we report the posterior estimates of the contemporaneous coefficients characterizing the identified monetary policy reaction function in the discount rate equations for each Fed district. As a reference, the results for the New York Fed district are highlighted in grey.

Systematic monetary policy at the New York district exhibits a positive output elasticity in both measures of output, a positive price elasticity, and a positive money elasticity. Overall, the systematic response of the New York Fed's discount rate to output—both retail sales and building permits—and prices is the strongest among all 12 districts by a large margin. The only exception is the Richmond district's price elasticity, which has the strongest policy response with a median estimate α_{FP} of 0.52. This parameter is also estimated with relatively high precision, having a clearly positive lower bound.

Under our baseline identification, the posterior medians of α_{BP} , α_{RS} , and α_{FP} are 0.066, 0.035, and 0.387, respectively. That is, while the New York Fed district exhibits the strongest contemporaneous discount rate policy responses compared to the other districts, it does not react more than one-to-one to contemporaneous movements in output and prices. Only the upper bound estimate (84th percentile) of α_{FP} exceeds one. Hence, there is little evidence to argue in favor of strong systematic monetary policy rules during the US interwar period across all districts. Our estimated coefficients of the systematic component of monetary policy thus differ, e.g., from conventional post-World War II or post-Volcker estimates in typical empirical Taylor rule estimates or in the DSGE literature. The support 68% equally-tailed posterior probability intervals are wide in some cases, most notably for the contemporaneous responses to commercial paper rates α_{CPR} . This is common in set-identified VARs (see, e.g., the estimates of the systematic monetary policy rule in Arias, Caldara, and Rubio-Ramírez (2019)) and not surprising as we only use sign restrictions. We establish the robustness of these conclusions in a number of robustness checks, model, and identification variations in section B.3–B.10 of the internet appendix.

The closest match in terms of estimated monetary policy responses to both measures of output is the Boston district. Interestingly, it is also the district whose output impulse responses to an

Fed District	α_{BP}	α_{RS}	α_{FP}	α_M	α_{CPR}
Boston	0.030	0.023	0 192	0.074	0.316
Doston	[0.009, 0.077]	[0.006, 0.064]	[-0.008, 0.603]	[0.013, 0.220]	[-0.514, 1.178]
New York	0.066	0.035	0.387	0.037	0.026
	[0.016 , 0.203]	[-0.002, 0.126]	[-0.011 , 1.130]	[-0.027, 0.168]	[-3.319 , 2.199]
Philadelphia	0.029	0.012	0.303	0.049	-1.213
	[0.006 , 0.092]	[0.000 , 0.043]	[-0.005, 1.029]	[0.010 , 0.163]	[-4.379, -0.217]
Cleveland	0.011	0.018	0.238	0.086	0.183
	[-0.006, 0.043]	[-0.000, 0.065]	[-0.033, 0.818]	[-0.018, 0.408]	[-1.528, 1.592]
Richmond	0.007	0.007	0.518	0.048	-0.003
	[-0.006, 0.026]	[-0.001, 0.024]	[0.242 , 1.127]	[0.015 , 0.122]	[-1.094, 0.903]
Atlanta	0.023	0.012	0.180	0.040	0.096
	[0.006 , 0.066]	[-0.007, 0.050]	[0.040 , 0.491]	[-0.002, 0.138]	[-0.904, 1.070]
Chicago	0.013	0.027	0.235	0.029	0.034
	[-0.000, 0.042]	[0.012 , 0.060]	[0.069 , 0.547]	[-0.011, 0.075]	[-0.711, 0.672]
St. Louis	0.009	0.018	0.364	0.022	0.043
	[-0.005, 0.038]	[-0.001, 0.056]	[0.176 , 0.777]	[0.001 , 0.060]	[-1.121, 0.928]
Minneapolis	0.003	0.026	0.174	0.013	0.321
	[-0.008, 0.023]	[-0.002, 0.099]	[-0.012, 0.569]	[-0.014, 0.076]	[-0.892, 1.464]
Kansas City	0.020	0.021	0.181	0.027	-0.443
	[0.002 , 0.057]	[-0.001, 0.056]	[-0.059, 0.569]	[-0.013, 0.113]	[-1.836, 0.312]
Dallas	-0.000	0.006	0.166	0.044	0.268
	[-0.016, 0.014]	[-0.001, 0.020]	[-0.005, 0.447]	[0.015 , 0.111]	[-0.314, 0.823]
San Francisco	0.000	0.016	0.370	0.018	0.102
	[-0.014, 0.013]	[-0.001, 0.049]	[0.156 , 0.723]	[-0.010, 0.075]	[-0.580, 0.682]

Table 2. Contemporaneous Coefficients in the Monetary Policy Equations. The entries in the table denote the posterior median estimates of the contemporaneous coefficients in the monetary policy equation under our benchmark identification. Each row refers estimated systematic monetary policy equation for the respective Fed district denoted in the first column. The 68% equal-tailed posterior probability intervals are reported in brackets. See the main text for details.

identified monetary policy shock deviate the least from New York (see Figures 3 and 4). Boston and New York exhibit the least adverse and volatile responses compared to the other districts. A stark contrast would be the output impulse responses of the Dallas district, that also produce the smallest estimates for α_{BP} and α_{RS} , coinciding with the most adverse impulse response functions.

5.3 National Monetary Policy Results

We now turn to the national analysis and show the impact of a 25-basis-points contractionary monetary policy shock on building permits for each of the 12 Federal Reserve districts. The IRFs for building permits are reported in Figure 7. The heterogeneity in the exposure to a contractionary national monetary policy shock is similar to the baseline regional VAR analysis. The impulse response for the Boston district compares favorably in depth and persistence to the New York district. Atlanta and Minneapolis, conversely, display much stronger and greater persistence in their impulse responses following a tightening of national monetary policy. Philadelphia, Cleveland, Richmond,



Figure 7. National Monetary Policy Proxy-VAR Impulse Response Functions for Building Permits. This figure depicts the response of building permits in the twelve Federal Reserve districts scaled to a 25-basis-point contractionary **national monetary policy shock**. For comparison purposes, all panels include (in grey) the IRF of the New York Federal Reserve District. The estimation is based on the Proxy-VAR detailed in Section 4.3. Bootstrapped intervals are 68 percentile intervals based on 5000 replications.

Kansas City, and Dallas represent a group of Fed districts with impulse responses that show size and persistence that is greater than the New York district, but less than Atlanta and Minneapolis.

Furthermore, we observe significant variation in the impulse responses to a national monetary policy shock across the Fed system if we replace building permits with retail sales as our measure of economic activity as shown in Figure 8. The heterogeneity also holds for other variables such as commercial paper and food prices across the 12 Fed districts. Overall, these results underscore a significant heterogeneity across the Federal Reserve system in response to a contractionary national monetary policy shock.¹⁶

¹⁶See section **B.1** of the internet appendix for additional results.



Figure 8. National Monetary Policy Proxy-VAR Impulse Response Functions for Retail Sales. This figure depicts the response of retail sales in the twelve Federal Reserve districts to a 25-basis-point contractionary **national monetary policy shock**. For comparison purposes, all panels include (in grey) the IRF of the New York Federal Reserve District. The estimation is based on the Proxy-VAR detailed in Section 4.3. Bootstrapped intervals are 68 percentile intervals based on 5000 replications.

5.4 Fed District-Specific Monetary Policy Results

We next discuss the effects of a contractionary monetary policy shock by each of the 12 Federal Reserve District banks on building permits. The impulse responses are reported in Figure 9. Boston continues to show very similar IRFs to New York. Virtually all other Fed districts exhibit a much stronger response to a contractionary regional monetary policy shock than a national monetary policy shock. The only exception is the estimates for Dallas which are imprecisely estimated with large error bands. The heterogeneity of impulse responses also carries over to retail sales, as shown by Figure 10. Finally, the heterogeneity in shape, depth, and duration of responses carries over to the other variables (see section B.2 of the internet appendix for additional results). For example,



Figure 9. Regional Monetary Policy Proxy-VAR Impulse Response Functions for Building Permits. This figure depicts the response of building permits in the twelve Federal Reserve districts to a 25-basis-point contractionary **regional monetary policy shock**. For comparison purposes, all panels include (in grey) the IRF of the New York Federal Reserve District. The estimation is based on the Proxy-VAR detailed in Section 4.3. Bootstrapped intervals are 68 percentile intervals based on 5000 replications.

food prices exhibit greater persistence and depth in response to a contractionary regional monetary policy shocks compared to a tightening of national monetary policy. Overall, the empirical analysis at the Fed-district level demonstrates a significant heterogeneity in the effects of regional-level contractionary monetary policy shocks on economic activity, prices, and short-term interest rates.

6 Robustness Checks

We now turn to robustness checks and variations of our model. As before, we focus our discussion on the responses of real-side variables (retail sales and building permits) to monetary policy



Figure 10. Regional Monetary Policy Proxy-VAR Impulse Response Functions for Retail Sales. This figure depicts the response of retail sales in the twelve Federal Reserve districts to a 25-basis-point contractionary **regional monetary policy shock**. For comparison purposes, all panels include (in grey) the IRF of the New York Federal Reserve District. The estimation is based on the Proxy-VAR detailed in Section 4.3. Bootstrapped intervals are 68 percentile intervals based on 5000 replications.

shocks. The findings for all variables in the robustness models are quite similar to our baseline results and are available from the authors upon request.

6.1 Deviations from New York Federal Reserve Policy

The baseline empirical results do not control for the impact of the New York Fed, which conducted a large share of the country's open market operations. New York was also the center of the US financial system. As a result, we augment our baseline, regional VAR with the spread between each Federal Reserve district and the discount rate of the New York Federal Reserve. As Figure 1 shows, the discount rate of the New York Fed can be interpreted as an approximation of national monetary policy. The interest-rate differential is a measure of the idiosyncratic component of monetary policy for a given Fed district. We then estimate a VAR for each Federal Reserve district using the idiosyncratic deviation of monetary policy for a given district from the discount rate of the New York Fed (see Internet Appendix Section C.2). In Section B.3 of the Internet Appendix we report our estimated IRFs. The results of the New York Fed spread specification are similar to our benchmark specification. The pattern of regional heterogeneity in estimated IRFs are in line with our baseline IRFs. Compared with the benchmark, the overall estimation precision of IRFs in the model including the New York Discount rate spread is higher. Our main conclusions remain and the heterogeneity across Federal Reserve districts are in some cases more pronounced.

6.2 Incorporating Failed Bank Deposits

Following Anari, Kolari, and Mason (2005), we augment our baseline, regional VAR with failed bank deposits. Section **B.4** of the Internet Appendix presents impulse responses of real activity variables for all Fed districts using the bank-failure augmented model. The impulse responses for the failed bank deposit-augmented model are again quite similar to the baseline responses confirming very similar response profiles and regional heterogeneity patters.

6.3 Variations in Horizon for Binding Sign Restrictions

Our baseline results rely on sign restrictions that bind for 6 months following the shock period. In Section B.5 of the Internet Appendix, we report IRFs using shorter binding horizons for sign restrictions of 3 month following the shock period as described in Table 1 and in section B.6 we report results with restrictions on impact only.¹⁷ We can see that the results and conclusions to a large extent remain unchanged and echo our baseline IRFs. That holds true even for restrictions on impact only. There are surprisingly few cases where the precision of the posterior IRFs increases in substantive ways. One such example would be the responses of Fed District Chicago exhibiting wider equal-tailed posterior probability intervals.

6.4 Minimal Narrative Sign Restrictions

In our benchmark specification, we used all four narrative sign restrictions detailed in Section 4.2.3. Out of those, Narrative Sign Restriction 3 is the least controversial one. As a variation, we analyze

¹⁷We only report IRFs to be parsimonious in the number of tables and figures. Forecast error variance decomposition for these alternative variations are available from the authors upon request.

our IRFs imposing the narrative sign restriction only on the 1932 monetary intervention which was the largest open market purchase undertaken by the Fed since its founding in 1913 in combination with the traditional sign restrictions on IRFs. Specifically, we now impose only Narrative Sign Restriction 5, requiring the 1932 open market operations pursued by the Fed to be an expansionary and dominant force of monetary policy shocks in 1932:M04 as described in Internet Appendix Section C.5. Section B.9 of the Internet Appendix presents impulse responses of this variation. The impulse responses are broadly similar to our baseline results.

6.5 Incorporating Commodity Price Index

To capture the response of the policy maker to anticipated inflation, Sims (1992) proposed adding an index of sensitive commodity prices into the structural VAR systems. Since then it has become common practice to add the commodity price index to avoid anomalies such as the price puzzle including set-identified VARs with varying degrees of success. The commodity price index is only available at the national level. As a robustness check, we augment our baseline regional VAR with the commodity price index and report our results in section **B.5** of the Internet Appendix. The estimated IRFs are similar to our benchmark specification. The commodity price VAR analysis provides further evidence of regional heterogeneity in the estimated IRFs that are similar to our baseline results. Compared with the benchmark, we also find less precision in the estimation of the IRFs for building permits in the Cleveland and Chicago Fed districts. With the exception of the two Fed districts, our main conclusions hold and the empirical analysis continues to show significant heterogeneity across the Federal Reserve System. Details of the identifying restrictions are summarized in Internet Appendix Section **C.6**.

6.6 Characterizing the Prior-Robust Identified Bounds

To address Baumeister and Hamilton's (2015) critique of prior influence of rotations in set-identified SVARs, we follow their advice detailed in Baumeister and Hamilton (2020) and check the robustness of our results for all model variations by estimating the identified set¹⁸. Our estimates of the

¹⁸The identified set of impulse response functions can be informally defined by the upper bound (the supremum) and lower bound (the infimum) of all admissible rotations for some given set of reduced form parameters whose mapping from reduced form innovations to structural shocks satisfies a given set of identifying sign and narrative sign restrictions. Our reported approximations are based on an admissible set of 1000 accepted rotations \mathbf{Q} at the posterior median of reduced form VAR parameters. By acceptance or admissibility we mean that the resulting impulse response functions

identified sets are evaluated at the posterior median of the reduced form parameters and reported along with the respective 68% equal-tailed point-wise posterior probability bands. This allows us to check how robust our conclusions are and what role can be assigned to the prior over the rotations (see, e.g., Schorfheide (2017), Watson (2019), and Baumeister and Hamilton (2020) for a detailed discussion). In section B.10 of the Internet Appendix, we report the comparison for the benchmark model augmented with commodity price index. We present the bounds of the identified set as solid lines and the respective posterior impulse responses in shaded areas. Focusing on the IRFs of retail sales and building permits, we find the bounds of our reported posterior IRFs and the identified sets to be close. As expected, there is a tendency of posterior IRFs to lie within the bounds of the identified set. We do not find a pathological strong concentration of our reported posteriors within the identified set contradicting our finding or conclusions. Our reported identified sets confirm the robustness of the heterogeneity, echoing our results for the posterior IRFs. The upper bounds are more centered in levels, show less depth in the reaction but exhibit variation in their dynamic shapes and persistence following a contractionary monetary policy shock.

6.7 Model Variation Excluding Output Restrictions

How important are the sign restrictions on output measures for the resulting IRFs? Not surprisingly, these are important as detailed earlier in subsection Section 4.2.1. Specifically, if we do not have reliable knowledge and confidence about the different policy rules in place, then we should avoid making strong assumptions. As a result, we address the output puzzle by restricting output directly given that monetary policy was based on discretion rather than rules. While we are very sympathetic to the proposed solutions in the literature to avoid the output puzzle, this is not a viable option for the analysis of regional monetary policy during the Great Depression¹⁹.

We report results when output restrictions are excluded from the benchmark identification. Details of the identifying restrictions are summarized in Internet Appendix Section C.7. Surprisingly,

satisfy our definition of a monetary policy shock leading to impulse response functions and shock series satisfying the imposed sign pattern.

¹⁹In our internet appendix We further substantiate the choice of restricting output directly by replicating the simulation exercise Wolf (2020) and adding as an additional comparison the alternative case of restricting output instead of a Taylor rule restriction. The direct comparison shows that the identified set of the output restricted version Wolf (2020) is successful in recovering the true IRFs generated from a standard Smets and Wouters model. It performs very similar to the Taylor rule version. The identified set for output is actually slightly sharper round the the true output responses, i.e. the width of the identified set is smaller.

despite the weak identifying restrictions, we find that a third of the Federal Reserve districts still exhibit a contraction in economic activity. The IRFs of retail sales for Boston, New York, Cleveland and Atlanta show a clear decline in consumer spending. For the IRFs of building permits, we find a contraction in the construction sector in Atlanta, Chicago, Minneapolis and Dallas. The output related responses across the other districts, are ambiguous and potentially contain the confounding effects discussed in Uhlig (2005) and Wolf (2020) for post-World War II US data.

7 Concluding Remarks

What role did national and regional monetary policy play in the dramatic decline of the national money supply and the Great Depression? We address this question using new methods in structural vector autoregressions that combines traditional and narrative sign restrictions to better identify the real effects of monetary policy shocks. The methodology is well suited for studying the Great Depression given that the rich economic history literature can inform the narrative sign restrictions. Indeed, we use four "quasi-natural experiments" during the late 1920s and the Great Depression identified by Friedman and Schwartz (1963) and discussed by Bernanke (2002) for our narrative sign restrictions.

The empirical analysis demonstrates that there was significant heterogeneity across the Federal Reserve System in response to a contractionary monetary policy shock. Region-specific VARs show that regional monetary policy shocks had a significant effect on retail sales, building permits, short-term interest rates, and prices. Boston and New York generally have muted responses to a tightening of regional monetary policy compared to the other Fed districts that exhibit greater persistence and depth in their IRFs. Furthermore, we also examine the estimates of the contemporaneous coefficients of the monetary policy reaction functions in the discount rate equations for the 12 Federal Reserve banks. The analysis shows little evidence that any of the 12 Federal Reserve banks followed a monetary policy rule during the 1920s and the Great Depression period. For example, the response coefficients of the New York Fed discount rate was less than one for retail sales, building permits, and food prices. Discretion ruled the day.

Then we examine whether national or regional monetary policy mattered more real activity. To test this hypothesis, we extract a common factor from the monetary policy shocks of the 12 Federal Reserve banks. We interpret the common factor as a proxy for national monetary policy shocks. For regional monetary policy shocks, we subtract district-specific shocks from the proxy for national monetary policy shocks. Then, we use the two monetary policy measures as instruments in a proxy VAR. We find that Boston and New York have less depth and persistence in retail sales and building permits than the other Fed districts in response to a contractionary national monetary policy. Another important result from the proxy VARs is that some Fed districts do not have a strong exposure to national monetary policy shocks. This is not the case with respect to regional monetary policy shocks, however. All Fed banks display significant exposure to Fed-district specific monetary policy shocks except for Boston. This is especially true for food prices, which experienced greater persistence and depth in response to a contractionary regional monetary policy shock compared to a tightening of national monetary policy.

We conclude the empirical analysis with a series of robustness checks. We augment the baseline VAR with the spread between the discount rate for each Federal Reserve district and the discount rate of the New York. The basic tenor of the results remains unchanged. Next, we incorporate failed bank deposits into our baseline model. Again, the basic results are qualitatively similar. Finally, we document the robustness of the results by comparing the baseline responses with the prior-robust identified sets. Again, we find similar dynamic responses. Overall, the empirical analysis demonstrates that regional monetary policy shocks were more important than national monetary policy shocks during the 1920s and the Great Depression. Contractionary monetary policy shocks at the regional level played an important role in the dramatic decline the US money supply in the 1930s as well as the depth and duration of the Great Contraction.

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