The Credit Boom in Loans to Brokers and Stock Price Fluctuations in the 1920s

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Abstract

This paper investigates how the credit boom in brokers' loans interacted with fluctuations in stock prices and macroeconomic variables during the 1920s. I estimate demand, supply, monetary and financial shocks in a Bayesian VAR by using a combination of sign and variance decomposition restrictions. The results indicate that monetary policy contraction was not effective to stabilize credit growth and stock prices while implying a relevant output and price level trade-off. Besides, I find that financial factors played an important role in output growth. Further, I confirm the existence of an effect of credit supply shocks in the level of stock prices.

1 Introduction

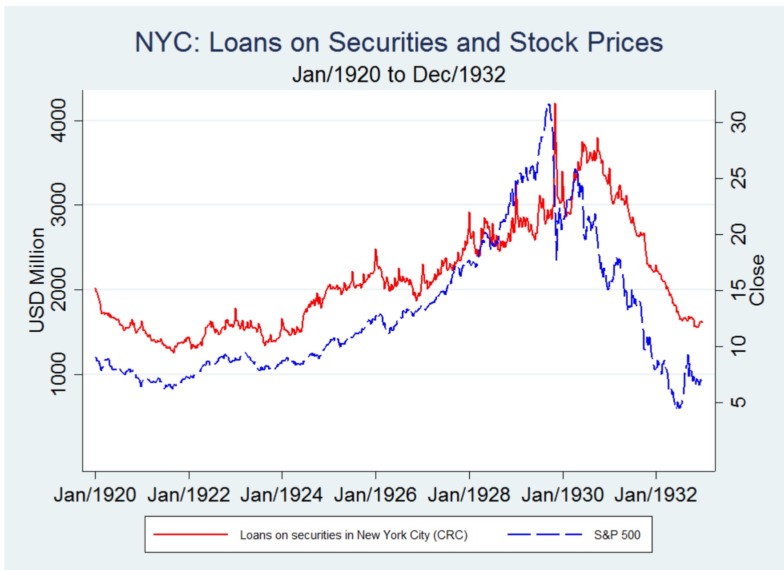
The dramatic expansion in stock market credit in the 1920s, in the form of brokers' loans, is considered one of the key factors that contributed to the boom in stock prices prior to the crash of October 1929 (Smiley & Keehn, 1988; White, 1990; Rappoport & White, 1993). Brokers' loans were important money market instruments at that time, and a reasonable share of banks' asset position, specially in New York City. The loans were used to buy stocks, and the acquired securities would enter as collateral in the transaction. Variable margin was required by the lender. Brokers' loans were very short-term, usually daily and renewable, but could be called by the bank at any time.

Figure 1[1] shows the amount of brokers' loans in New York City banks and the S&P index of stock prices from January 1920 to December 1932. The level of brokers' loans grew from roughly from \$1.5 Billion in the middle of the decade to \$3 Billion in late 1929. The rise in stock prices is obviously very correlated with the growth in brokers' loans, and they peak just at the crash of October 24th 1929. One year prior, on October 3rd 1928, the amount of brokers' loans extended by New York City member banks was \$2,416 million. In October 3rd 1929, just three weeks before the crash, this figure has grown to \$3,040 million, a 25.8% rise from previous year (Board of Governors of the Federal Reserve System, 1943).

[1] In some statistical sources loans to brokers are described as loans on securities, secured by stock. We use the names loans to brokers and loans on securities interchangeably.

From a wider perspective, the 1920s decade is characterized by overall economic growth and credit expansion. Total loans for the weekly reporting member banks accounted $11,349 million in January 1922, raising 50% in nominal terms to $17,041 in January 1930. Brokers' loans experimented an even more aggressive 109% growth rate going from $3,791 to $7,906 in the same time interval. As a consequence, we observe a growing share of brokers' loans as a percentage of the total portfolio of loans. For the weekly reporting banks, the share rises from 33% to 46% between January 1922 and 1930, and for New York City Banks the share is already more than 55% by the end of 1928.

Figure 1: Loans on securities in New York City banks and S&P 500 Stock Prices, from Jan/1920 to Dec/1932. Source: *Banking and Monetary Statistics* and *Global Financial Data*.



Excessive credit in loans to brokers was a relevant concern to policy makers at that time period (Wright, 1929; Warburg, 1930). Particularly influenced by the real bills doctrine, the founders of the Federal Reserve had hoped that the new central bank structure and activities would channel credit away from "speculative" uses towards what was considered "productive" activities (White, 1990). Paul Warburg, one of the founders of the Fed, writing in 1927 stated that one of the System's most serious shortcomings was its inability to create important discount markets outside of New York City, and consequently its failure to "lessen the congestion of the country's unemployed funds on the New York Stock Exchange (NYSE)" (Warburg, 1930). The author recognizes that the concentration of money in the stock exchange was more pronounced than ever before, an such condition carried dangers for the banking system, a well as for the NYSE itself.

The desire to end the "orgy of speculation" in stocks and to halt the "undue absorption" of the country's credit supply to speculative uses guided the Federal Reserve System's decision in January 1928 when it started contracting monetary policy (Warburg, 1930). The discount rate was raised from 3.5% to 5% in six months, as a consequence of fears about excessive flow of credit to the stock market. In the following months, even though there was still general agreement on the risks involved, the continuation of monetary contraction was subject to debate. Directors at the New York Fed argued that speculation could only be reduced by further raising the discount rate. However, members of the Board pushed for a "direct pressure" procedure, which would deny access to the discount window to member banks making loans on securities (White, 1990). The Board view prevailed and the discount rate stood still until August 1929, when it was raised only in New York.

Although the important role that brokers' loans played in the expansion of the stock price bubble is widely recognized, some critical research questions remain to be addressed. Fundamentally, it is not clear how much of the stock price rise can be attributed to the growth in the supply of brokers' loan credit. In other words, was the credit boom really affecting stock prices, or did the boom in credit just followed from higher demand to buy stocks? The question follows not only from historical interest, but it can also be framed as a fundamental question in macroeconomics and finance, as it relates to how credit supply shocks can impact asset prices and propagate to the rest of the economy. From the policy perspective, it is crucial to understand the link between credit supply and asset price fluctuations. Different propagation mechanisms imply different policy prescriptions for financial stability.

This paper, thus, aims to investigate the relationship between the credit boom in brokers' loans and fluctuations in stock prices and other macroeconomic aggregates during the 1920s cycle. My interest lies in three basic questions. First, I explore how effective was the policy tool, that is adjusting the discount rate, in stabilizing credit growth and stock prices. This assumption was at the heart of the motivation for the contractionary monetary cycle started in January 1928, but even if it is valid, it is interesting to understand what was the trade-off between output loss and credit stabilization at that time. Second, I assess how financial factors, like the easing of credit conditions and the valuation of stock prices guided by either fundamentals or optimism, contributed to aggregate macroeconomic growth, to fluctuations in prices and to the reaction of the policy rate. Third, and most importantly, I want to measure how credit supply in brokers' loans impacted stock prices. The answer should reveal important facts about the transmission of credit supply shocks to asset prices, as well as help our understanding of possible policy choices designed to address financial stability issues.

I address the research questions by estimating a Bayesian Vector Autoregression model on monthly US data, and applying different econometric procedures to identify structural shocks. I start with a simple recursive ordering identification approach. Although useful, this method requires strong assumptions about how the structural (unobserved) shocks impact observed macro variables on the first period. To circumvent this limitation, I adopt a sign restrictions identification strategy, which is a widely used method in contemporary empirical macroeconomic research (Canova & De Nicolo, 2002; Furlanetto, Ravazzolo, & Sarferaz, 2017), in combination with additional variance decomposition restrictions (Weale & Wieladek, 2016).

Previous research have analyzed the US economy by the use similar methods, but either focused in different time periods or were interested in alternative reseach questions not related to credit. Calomiris and Hubbard (1989) estimate a structural VAR model using monthly data from the pre-World War I era and find that credit availability contribute substantially to explain output fluctuations. Canova (1991) investigates how the macroeconomic dynamics of the US changed by the creation of the Fed. He estimates a structural VAR model using monthly data from two separate samples: from 1891-1913 and 1924-1937. The focus is on how financial crisis were generated by a combination of internal seasonal movements and unexpected external shocks, but there is no specific role for credit in his model. Nason and Tallman (2015) also apply a VAR method, but cover a longer period at a lower, annual frequency from 1890 to 2010. They are interested in how the propagation of shocks differ in periods of financial crisis, and do not specifically address the 1920s credit cycle nor the role of asset price fluctuations. The work by Furlanetto et al. (2017) is methodologically the most similar to the research presented here. The authors specifically address the role of financial factors in macroeconomic fluctuations, but they cover the modern period of 1985 until 2013.

The research is related to a wide literature on macroeconomics and finance which investigates the relationship between credit expansions, fluctuations in asset prices and its consequences to the business cycle. Housing finance has been recognized as the primary form of debt to influence economic activity in modern economies, and the subject naturally attracted a great deal of attention after the Financial Crisis of 2007/08 (Mian, Sufi, & Verner, 2017a). Jordà, Schularick, and Taylor (2016) demonstrates that mortgage credit became an increasingly important factor for business cycle dynamics during the twentieth century for most advanced countries, as well as an important source of financial fragility. The financial stability concern is also brought by Schularick and Taylor (2012) who argue that credit booms concurrent with asset price booms are strong predictors for banking crisis. We claim that mechanisms similar to the housing finance channel may operate for other asset classes as well. So something can be learned by investigating how credit extended to buy stocks on margin might drive fluctuations in stock prices. The magnitude of the credit and asset price boom observed in the 1920s make this a great *locus* for research.

An additional contribution of the research is related to whether the central bank should react to asset price fluctuations, and what what are the consequences of each policy instrument. Even though the subject has been discussed for decades it remains an open question for policy making nowadays (Bernanke & Gertler, 2001; Schularick & Taylor, 2012). We hope to provide measures useful to understand how interventions in the financial system could be beneficial, if ever, in order to prevent extreme fluctuations in asset prices, and its negative effects in the real economy.

The paper is organized as follows. In section 2, I present the model along with the estimation method and data sources. Section 3 presents the results of several estimation and identification exercises. Finally, in the last session I discuss the relevance of the findings.

2 Model estimation

I adopt a Vector Autoregressive (VAR) model represented in reduced form as

$$Y_t = B_0 + B(l)Y_{t-1} + u_t$$

where vector Y_t of size $N \times 1$ holds all endogenous variables observed at t, (l) is the lag operator, p is the number of lags, and u_t is the vector of reduced form disturbances. The matrix B_0 of size $N \times 1$ contains the intercepts of each equation, to be estimated. The coefficients to be estimated for each lagged endogenous variable are held in matrix $B(l)$, of size $N \times N$.

The distributional assumption characterizes reduced form disturbances by a multivariate normal process, $u_t|(l)Y_{t-1} \sim N_N(0, \Sigma_{N\times N})$. This implies that reduced form shocks can be correlated between N variables for same period, but are independent over time.

2.1 Bayesian estimation

The reduced form model estimation will follow methods presented by Greenberg (2012) and Koop, Poirier, and Tobias (2007). We first represent the VAR system in SUR form (Zellner, 1962). The vector X_{it} is composed of lagged values for all endogenous variables for a chosen p number of lags. We add a constant 1 to the last position in order to estimate an intercept. To save on notation, we call each variable on Y_t as y_{it}, where $i = 1, ..., N$.

$$X_{it} = \begin{bmatrix} y_{1,t-1} & ... & y_{N,t-1} & & ... & y_{1,t-p} & ... & y_{N,t-p} & 1 \end{bmatrix}$$

We then build the matrix of regressors X_t, of size $N \times (pN+1)$, with X_{it} on the main diagonal and zeros on the rest. For ease of notation we will define $K = pN + 1$, which is the width of each line of regressors.

$$X_t = \begin{bmatrix} X_{it} & 0 & ... & 0 \\ 0 & X_{it} & ... & 0 \\ ... & 0 & ... & 0 \\ 0 & ... & ... & X_{it} \end{bmatrix}$$

The system in matrix form is

$$Y_t = X_t\beta + \varepsilon_t \tag{1}$$

The defining assumption of the SUR model is that $\varepsilon_t|X \sim N_N(0, \Omega)$, where $X = (X_1, ..., X_T)$ and $\Omega_{N\times N} = \omega_{ij}, i = 1, .., N, j = 1, ..., N$ (Greenberg, 2012). Thus, in our formulation this implies that the disturbances are allowed to be correlated between N variables for the same time period, but not correlated across time. This is the usual assumption of a reduced form VAR system.

Next, we specify a conditionally conjugate prior for the model, in order to proceed estimation with a standard Gibbs sampler (Greenberg, 2012; Koop et al., 2007). The regression coefficients are assumed to have a Gaussian prior, $\beta_{KN\times 1} \sim N_{KN}(\beta_0, B_0)$, while the covariance matrix of disturbances is assumed to follow an inverse Wishart distribution $\Omega \sim IW_N(\nu_0, R_0^{-1})$.

The parameters β_0 and B_0 are chosen by using a Minnesota Prior as suggested by Kilian and Lütkepohl (2017). I take the hyper parameters $\lambda = 0.2$ and $\theta = 0.6$. The authors originaly suggest $\theta = 0.3$ for analysis of quarterly macroeconomic time series, but I choose less shrinkage as our model is estimated on a monthly frequency. Note that the use of this procedure requires that we normalize all the variables before estimation so the coefficient magnitudes are comparable across all variables. Finally, regarding the covariance matrix of disturbances hyperparameters, I choose a low value for the degrees of freedom $\nu_0 = K + 1$, following Kilian and Lütkepohl (2017) , and a standard R_0^{-1} that equals to the frequentist estimate of the covariance matrix $\hat{\Omega}$.

2.2 Data sources

The observed variables to be used in the VARs are six: output, prices, the discount rate of the Federal Reserve Bank of New York, a measure of leverage of the financial system in New York, the spread on brokers' loans and stock price index for the New York Stock Exchange (NYSE). In this paper, I am primarily concerned with banks in New York City as the most representative of the financial system and where most of the market for brokers' loans operated. The observed variables will be represented in levels as widely adopted in empirical macroeconomic studies in order to avoid the loss of information (Furlanetto et al., 2017).

Data for output and prices are broad US measures. I use the Consumer Price Index and Industrial Production available from the FRED database at a monthly frequency. Data about discount rate come from *Banking and Monetary Statistics*(Board of Governors of the Federal Reserve System, 1943). The publication provides discount rates for the whole period and the specific day they were adjusted. I take the prevailing rate at the last day of the month set by the New York Fed.

The measure of leverage must be designed to consider only brokers' loans, as this is the specific type of credit we are interested in. The datasource is the *Weekly Reporting Member Banks in Leading Cities* (Federal Reserve Board, 1915-1935), which provides aggregated data on the main assets and liabilities of banks, classified by each of the twelve Federal Reserve Districts plus the Central Reserve City of New York. This dataset allow us to measure brokers' loans for the full 1920s decade, at a relatively high frequency [2], which can be then converted to monthly as needed. The variable *leverage* is defined as the ratio of brokers' loans to public deposits. Public deposits are calculated as the sum of net demand deposits and time deposits.

Data for the price index for NYSE is taken from *Global Financial Data*. I use the S&P 500 series as representative of the market. Data for the spread on brokers' loans is calculated as the difference between the average rate on call loans in NYC and the discount rate in the same district. I collect the monthly average rate on Stock Exchange new call loans in New York City from *Banking and Monetary Statistics*(Board of Governors of the Federal Reserve System, 1943).

My sample of interest starts in December 1919 and goes until the end of the credit boom in September 1929. The sample is restricted to end just before the stock market crash of October 1929 on purpose. The reason is clear, as the research interest is to investigate the dynamics of the credit cycle during the boom period, and how monetary policy shocks were potentially affecting credit growth and stock prices. Besides that, the magnitude of the shock resulted in a huge revision of expectations and possibly altered the relationship of macro variables. The semi-structural model adopted here would not be able to address this issues.

[2] In comparison to the Weekly Reporting, the quarterly Call reports dataset only collects specific statistics for broker's loans after October 1928.

3 Results

This section describes the results of estimating different specifications of the structural VAR model. I begin with a simple baseline model with three equations and no financial shocks. Then, I proceed to analyze the main model with two financial factors, namely a credit supply and a stock preference shock. Finally, in the last part I run a series of robustness checks in a simpler model with only one financial factor, credit supply.

All variables are normalized to mean zero and standard deviation before estimation. The Markov-Chain Monte Carlo simulation was run for 10,000 draws in each estimation. I considered the first 1,000 draws as burn-in time.

3.1 Preliminary exercise: three equation monetary VAR

As a baseline exercise, I estimate a standard monetary VAR with only three variables, output, prices and interest rate. The objective is to enable comparison of the baseline model with richer models including financial variables. I will analyze the model using two different identification strategies, first a standard recursive ordering strategy, and later a sign-restriction identification method similar to Weale and Wieladek (2016).

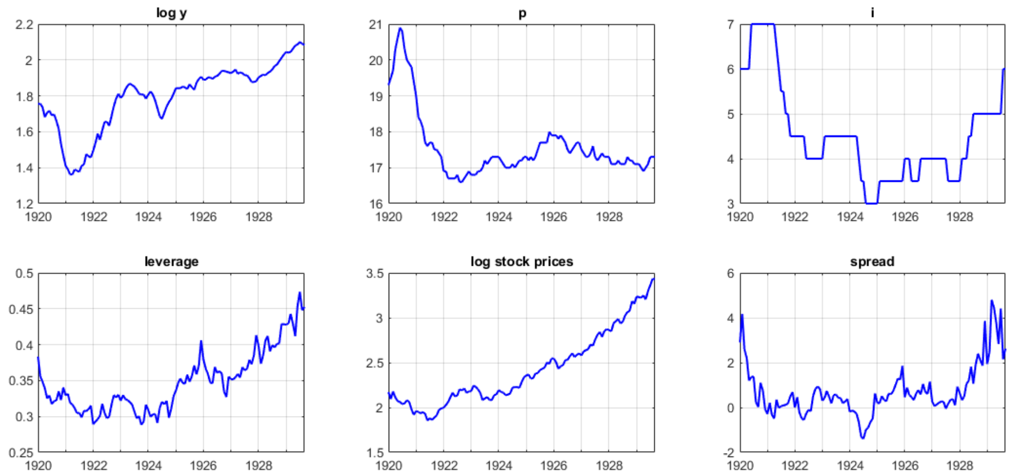
The observed data series at this moment are, respectively, US industrial production in logs, US Consumer Price Index in levels, and the nominal discount rate in New York Fed in levels. The vector of endogenous variables is thus $Y_t = [y_t, p_t, i_t]'$, where y represents output, p stands for prices, and i for the discount rate. I will use a sample of monthly observations, from Dec/1919 to Sept/1929, totaling 117 observations. The number of lags is arbitrarily set to $p = 2$. I have previously run frequentist estimations of the model, and the specification with 1 lag was suggested by Schwarz's Bayesian information criterion. I decided for one additional lag in order to better capture the dynamics of the system. Figure 2 shows a plot of all observed series, including financial variables which are going to be addressed in later sections.

3.1.1 Recursive ordering identification

The identification of structural shocks in the first exercise will be done by standard recursive ordering. This strategy is widely adopted in this type of small VAR (Kilian & Lütkepohl, 2017). The underlying assumption is that output and inflation respond with lags to changes in discount rate, while the central bank use information about the current month to set the rate. Moreover, we assume that output has a slower adjustment than prices.

The impulse response functions are plotted in Figure 3 in the Appendix. First, we observe the usual effect of a restrictive monetary policy shock, that is an increase in the discount rate, in reducing the price level. The effect in prices is relatively strong and persistent. On the other hand, the effect of monetetary shocks in output is less distinguishable. The wide uncertainty bands do not allow us to identify a negative output response. Second, shocks to the price level lead to output reduction, as expected, combined with a positive response of the discount rate for at least two years. Finally, shocks to output lead to an increase in price levels for approximately two years, while inducting a positive response of the discount rate. In general, the responses are well in line with expected results.

Figure 2: Observed variables: log output, prices, discount rate, leverage, log stock prices, spread. Sample from Dec/1919 to Sept/1929.



3.1.2 Identification by sign-restrictions

In the second exercise, I follow a sign-restriction scheme to identify demand, supply and monetary shocks. The assumptions are as follows. A positive demand shock should affect output, prices and the discount rate positively. A supply shock must drive output and prices in opposite directions. A monetary contraction shock must increase the discount rate, and drive down both output and prices. The restrictions are summarized in Table 1. Note that the system is fully identified even though I leave the reaction of the discount rate to supply shocks unrestricted. This scheme is equivalent to a subset of restrictions in Weale and Wieladek (2016) or Furlanetto et al. (2017).

Table 1: Restrictions in the baseline three equation model.

Observed Variable	Demand	Supply	Monetary
Output	+	+	−
Prices	+	−	−
Discount rate	+	NA	+

The estimation of impulse response functions (IRFs) for the model identified with sign restrictions involves drawing M parameters from the posterior distribution, and then calculating a set of rotation matrices Q for each draw, which must not violate the sign-restrictions (Kilian & Lütkepohl, 2017). We obtain a distribution of IRFs, which we summarize by taking the median at each point in time. The procedure accounts for uncertainty about both parameters and identification, and is described below.

First, I draw β^i and Ω^i from the posterior distribution and compute an initial Cholesky decomposition P^i. Next, I consider a random rotation matrix Q, and compute the implied impulse response function $\Theta^i|\beta^i, \Omega^i, P, Q$. Third, if Θ^i satisfies the sign restrictions, I store the value in a sequence $\{\Theta^i\}_{i=1,..,M_\Theta}$. Otherwise, Θ^i is discarded. The steps are repeated in order to sample a fixed number M_Q of IRFs for each value of the posterior. In this exercise, I have fixed $M_Q = 100$, resulting in $M_\Theta = 90,000$ given the posteriors are of size 9,000.

Figure 4 shows the median impulse response functions and credibility intervals for all three shocks. The general findings are well in line with expected, and similar to those obtained in the last section. I highlight the fact that this identification scheme allow us to observe a clearer effect of monetary policy on output. An increase in the rate drops output for about 14 months, and the credibility interval is now negative for the first four months.

Table 2 reports the contribution of each of the three identified structural shocks to the forecast error variance of each observed variable. The variance decompositions are calculated based on the median impulse response function for each shock, as described by Kilian and Lütkepohl (2017). Some results are worth noticing. First, supply shocks account for the largest share of output fluctuation, as well as considerable share of price variability. Second, demand shocks explain the largest share of fluctuations in the discount rate, which may reflect the fact that policy was responding aggressively in an intent to stabilize output. This was specially the case during the recession 1921-1922, when the discount rate fell from 7% to 4%. Finally, monetary shocks appear to have important effects on price fluctuations as was already observed in the IRFs.

Table 2: Median forecast error variance decompositions for the three equation model with sign identification.

	Horizon	Demand	Supply	Monetary policy
Output	1	0.24	0.54	0.22
	12	0.12	0.74	0.14
	24	0.17	0.72	0.11
Prices	1	0.24	0.53	0.23
	12	0.16	0.39	0.45
	24	0.12	0.32	0.56
Discount rate	1	0.58	0.00	0.41
	12	0.84	0.00	0.16
	24	0.84	0.02	0.15

3.2 Financial factors

In this section, I adopt a larger model with financial factors to capture the dynamics of credit and stock markets. The three observed variables added to the VAR model are *leverage*, *stock* and *spread*. The first variable represents the relative leverage of the financial system in the New York City district considering loans to brokers. It is calculated as the ratio of brokers' loans to public deposits, in levels. The second variable, *stock*, is the stock price index from NYSE in logs. The last variable, *spread*, is the difference between the observed rate on loans to brokers in the New York City district and the NY Fed discount rate.

The VAR model with financial factors holds 6 endogenous variables:

$$Y_t = [y_t, \pi_t, i_t, leverage_t, stock_t, spread_t]' \quad (2)$$

I am going to use a combination of sign restrictions and variance decomposition restrictions to identify two different financial shocks, a stock preference and a credit supply shock, in combination with the previous demand, supply and monetary policy shocks.

The stock preference shock is simply defined as a structural shock which increases the demand for stocks. So, given this shock, we should expect stock prices to increase along with the spread for brokers' loans. Note that the stock preference shock can be motivated by economic fundamentals, such as an increase in payed dividends as well as a revision of expectations about future dividends or cash flows. It also can be motivated by market sentiment, or factors not related to fundamentals, such as exogenous changes in expectations of future price growth, behavioral factors such as herd behaviour, etc. At this time, I adopt an ample definition of the stock preference shock.

On the other hand, the credit supply shock in brokers' loans is a structural shock which increases leverage and stock prices while decreasing the spread for brokers' loans. This shock captures banker's and other investors' willingness to lend in the form of brokers' loans. Note that leverage can also increase due to a stock preference shock, so the observed variable which allow us to differentiate between the two structural shocks is the spread. Table 3 provides a list of the sign restrictions adopted for identification.

Table 3: Sign restrictions in the model with two financial factors.

Observable	Demand	Supply	Monetary	Financial (Credit)	Financial (Stock pref.)
Output	+	+	−	+	+
Prices	+	−	−	NA	NA
Discount rate	+	NA	+	+	+
Leverage	NA	NA	NA	+	+
Stock prices	NA	NA	NA	+	+
Spread	NA	NA	NA	−	+

So far, the use of sign restrictions is not sufficient to uniquely identify financial shocks from each of the other structural innovations. I am avoiding any assumptions about the effect of financial shocks on prices, so they are not distinguishable from supply shocks. Besides, demand shocks are assumed to have positive effect on output and the discount rate so they are not distinct, at this point, to any financial shock. The strategy I adopt is to use additional variance decomposition restrictions as in Weale and Wieladek (2016) to fully identify the model. The technique rests on the assumption is that a shock that is variable-specific should explain the largest fraction of the variance of that variable, at least upon impact and for the first few time periods. In our particular model, this gives rise to the following assumptions: (i) financial shocks, either credit or stock preference, must explain a larger fraction of the variation in leverage and stock prices than supply or demand shocks; (ii) supply shocks must explain a larger fraction of the variation in prices than financial shocks. This set of assumptions are summarized in Table 4, and they now allow me to fully identify the five shocks of interest in the model. As the VAR has six observed variables, there is still one structural residual shock which will not be of our interest.

The procedure to identify the model calculating the set of admissible IRFs is similar to the one used previously, when we generated sequences of decomposition matrices Q, and rejected the ones which violated the conditions (Kilian & Lütkepohl, 2017). Specifically, I assumed the variance restrictions should hold upon impact and for the first three time periods, following Weale and Wieladek (2016). Given the size of the model, the simulation is now repeated by sampling $M = 200$ random draws of parameters (β^i, Ω^i) from the posterior distribution and accepting $M_Q = 25$ rotation matrices for each draw, resulting in $M_\Theta = 5,000$ impulse response functions.

Table 4: Variance decomposition restrictions in the model with two financial factors.

Shock	Restriction
Demand	$Var_{leverage}(shockDemand) < Var_{leverage}(shockCredit)$
	$Var_{stock}(shockDemand) < Var_{stock}(shockStock)$
Supply	$Var_{leverage}(shockSupply) < Var_{leverage}(shockCredit)$
	$Var_{stock}(shockSupply) < Var_{stock}(shockStock)$
Financial (Credit)	$Var_{price}(shockCredit) < Var_{price}(shockSupply)$
Financial (Stock preference)	$Var_{price}(shockStock) < Var_{price}(shockSupply)$

Figure 5 shows all the impulse response functions identified in the model with financial factors. The first important finding is that a monetary policy shock is apparently not effective to contain either stock price growth or leverage during the period. In principle, we would expect that a higher discount rate would discourage lending to brokers by the banking system, and lead to lower leverage. Avoiding further expansion of the amount of brokers' loans was, in fact, one important reason behind the Federal Reserve decision when pursuing monetary policy tightening between January and September of 1929, as previously discussed. At the same time, the rise in the discount rate should reprice stocks downwards in a standard forward-looking asset pricing model. Once the risk free rate is adjusted, the present value of future dividends must fall.

Contrary to this logic, the results obtained in estimation for this period do not imply a negative reaction of stock prices to an unexpected increase in the discount rate. The IRFs show a response very close to zero and not conclusive credibility intervals. The point estimate is even positive, which would imply the opposite result. Regarding the effect on leverage, we observe very small negative response and also non conclusive credibility intervals. Additionally, the forecast error variance decomposition estimated at the median IRF, see Table 5, confirms very little contribution of monetary policy shocks to the variability of financial variables. One possible interpretation is that the stock price bubble was an autonomous stochastic process, that was independent of the interest rate.

We should note, however, that this finding is observed for the period previously to the stock market Crash of October 1929. A common view in the literature is that monetary policy contraction conducted in the later part of the decade contributed to initiating an economic downturn. Some authors point that the evidence of an oncoming recession, beginning in July 1929, consequently caused an aggressive reversal of expectations about economic growth, leading to the Crash (White, 1990). From this interpretation, and considering a larger time frame, then raising the discount rate was, ironically, an extremely successful policy to lower the level of brokers' loans and stock prices, but which carried disastrous side effects. The estimation results show that policy was not effective to attain the original objective of policy makers, that is to moderately contain the credit boom or stock prices, but it was effective in causing real output loss.

The second important finding is evidence that financial factors have relevant real effects during the economic cycle of the 1920s. A positive stock preference shock of one standard deviation, resulting in an increase of 2.48% in stock prices, leads industrial production to increase 0.76% after four months and carries positive effect in the long run. Credibility intervals for this impulse response include positive effect for ten months. Likewise, a one standard deviation credit supply shock, which increases leverage in the banking sector by 0.73 percentage point, leads to output increasing by 0.36% in the short run. In this case, the effect is positive in the long run, 0.51% after two years, but uncertainty is higher and credibility interval includes negative responses. The variance decomposition in Table 5 confirms that financial factors have a contribution of about 15% the variability of output.

Finally, the model identification allow us to disentangle the relationship between the two financial factors, stock preferences and credit to brokers. Theoretically there should be a positive feedback between both factors. The first channel can be understood as the "asset prices to credit" effect. An exogenous increase in demand for stocks should raise the demand for credit as well, raising the spread charged for brokers' loans, provided the supply of credit remains constant. The complementary channel is the "credit to asset prices" effect. An exogenous increase in credit supply should lower the spread for brokers' loans, decreasing the cost of investing in stocks and encouraging investors to buy more of the asset, thus raising stock prices.

In our model, we estimate that a typical stock preference shock, of 2.48% raise in stock prices, leads to persistent higher leverage in brokers' loans by 0.31 percentage points in the same month, and 0.22 after one year. The credibility interval remains positive for 24 months. The relevance the "asset price to credit" channel is confirmed by the variance decomposition, which suggests that stock preference shocks are the second most important factor driving the variability of leverage.

More importantly, the estimation confirms the existence of a "credit to asset prices" channel. The typical credit supply shock raises leverage in the banking sector by 0.73 percentage point, and leads to an increase in stock prices of 0.98% on impact. The credibility interval is positive for the first two months. After that, the point estimate is persistently positive and implies an increase in stock price level of 1.25% after two years, but this estimate is subject to higher uncertainty. The variance decomposition confirms that credit supply shocks can explain a reasonable variability of stock prices in the short run.

3.3 Robustness checks

In this section, I present different identification exercises in a simplified model with only one financial factor. My interest is to check the findings for robustness, regarding the effect of monetary policy on credit to brokers, and also how financial shocks interacted with economic activity. The VAR model adopted includes the basic three variables, output, prices and the interest rate, plus leverage.

Table 5: Median forecast error variance decompositions for model with two financial factors.

	Horizon	Demand	Supply	Monetary policy	Credit	Stock preference
Output	1	0.30	0.27	0.29	0.06	0.09
	12	0.19	0.27	0.31	0.04	0.19
	24	0.34	0.26	0.25	0.05	0.10
Prices	1	0.19	0.66	0.14	0.00	0.01
	12	0.09	0.31	0.40	0.20	0.00
	24	0.07	0.23	0.43	0.25	0.02
Discount rate	1	0.38	0.00	0.44	0.10	0.08
	12	0.39	0.09	0.14	0.06	0.33
	24	0.29	0.11	0.18	0.04	0.38
Leverage	1	0.12	0.03	0.01	0.71	0.13
	12	0.16	0.02	0.02	0.58	0.22
	24	0.24	0.02	0.02	0.46	0.25
Stock prices	1	0.12	0.01	0.01	0.12	0.75
	12	0.27	0.00	0.01	0.05	0.67
	24	0.35	0.01	0.06	0.06	0.52

3.3.1 Did monetary policy affect leverage prior to the Crash of 1929?

In order to further investigate this question, I first revisit the recursive ordering strategy in a model with one financial factor. The ordering for the observables is $(y_t, p_t, leverage_t, i_t)$. The additional assumption, from the baseline three equation model, is that banks respond to changes in the discount rate by adjusting their leverage with a delay of one month. I keep the initial assumption that the Fed sets its discount rate using all available information. I also assume that changes in output and prices are slower than changes in leverage.

The resulting impulse response functions can be seen in Figure 6, and we find that leverage does not appear to react substantially to changes in the discount rate, at least in the period estimated which starts in December 1919 and goes until September 1929. In quantitative terms, the point estimate for the response of leverage to an increase in the nominal discount rate is negative for the first 30 months. A one-standard deviation increase in the rate, representing 0.19 percentage points, implies a negative effect of approximately -0.001 percentage points in leverage, after 17 months when the response is on its lower bound. Not only is this effect very small, but also the calculated one standard-deviation credibility interval includes positive effects. Besides, the negative effect is transitory, as leverage returns to the original level after less than three years.

Next, I re-estimate the model by changing the ordering of the variables. The objective is to explore whether the recursive approach chosen initially may be driving the findings. By placing *leverage* after i we are assuming that policy reacts only with a one month delay to changes in leverage, and that banks react within the month to changes in the policy rate[3].

[3] Note that assumptions for output and prices, as well as its impulse response functions remain the same

The ordering, thus, become $(y_t, p_t, i_t, leverage_t)$. As can be seen in Figure 7, the effect in leverage given a shock in interest rates is slightly higher (in absolute value) than before, but still relatively small. A one-standard deviation non-expected increase in the discount rate results in -0.0013 percentage points in leverage, after 12 months. Importantly, the effects continue to be transitory and the one standard-deviation credibility interval is all over the positive and negative ranges.

My second robustness exercise to check the effect of monetary policy on leverage is to apply an "agnostic" identification procedure similar to Uhlig (2005) . The method consists of imposing restrictions on the response of some variables, while leaving the response of the main variable of interest unrestricted. The only assumption I make is that a contractionary monetary policy shock leads to a raise on the discount rate, as well as a decrease in output and prices. The objective is to be as concise as possible with the set of restrictions, so I purposefully do not identify any other structural shock.

Figure 8 displays the responses of each variable to an unexpected monetary policy contraction. Output drops during the first 14 months, while the negative effect on prices is much more persistent and spans 40 months. These results are very much in line with the previous three equation model exercise with sign restriction identification. The relevant finding of the "agnostic" procedure is that the response of leverage appears not distinguishable from zero. Even if the median of the IRF is negative for the first 18 months, the absolute value of the response is relatively very small and the credibility intervals are wide, including both positive and negative responses. Again, monetary policy contraction appears to be ineffective as a tool to restrain credit to brokers.

My last robustness test in this section is to apply a full identification scheme on the model with one financial factor. I take the sign restrictions adopted in the three equation model and further assume that a positive financial shock should impact leverage, output and the interest rate positively. In this case, the financial shock can be interpreted either as increase in credit supply to brokers' loans or a stock preference shock, which would cause leverage to increase too. The set of assumptions is similar to Furlanetto et al. (2017), except that I am avoiding any restrictions about the effect of financial factors on prices.

Table 6 summarizes the sign-restrictions. I will have to adopt additional variance decomposition restrictions (Weale & Wieladek, 2016) to distinguish the financial shock from innovations in demand or supply. At this time, financial shocks are assumed to explain the largest fraction of the variation in leverage upon impact and with a three period delay.

The impulse response functions in Figure 9 show the response of all variables to the four identified shocks in this model. Again we confirm the findings that an unexpected monetary policy shock does not seem to affect credit supply. The response is very small and our confidence includes both positive and negative values. The variance decomposition shown in Table 7 confirms very little contribution of monetary policy shocks to the variability of leverage.

Moreover, we also observe the usual effect of tightening monetary policy on prices, that is a decrease for long period, and temporary output contraction. A 0.12 percentage points increase in discount rate impacts industrial production by 1% after 4 months, and effects

as their order has not changed from the previous specification. The block y, p is always before the block $i, leverage$.

Table 6: Sign and variance decomposition restrictions in the model with leverage.

Observed Variable	Demand	Supply	Monetary	Credit
Output	+	+	−	+
Prices	+	−	−	NA
Discount rate	+	NA	+	+
Leverage	NA	NA	NA	+
Variance decomp. restrictions	$Var_l(shock_i) < MAX(Var_l)$	$Var_l(shock_i) < MAX(Var_l)$	NA	$Var_l(shock_i) = MAX(Var_l)$

are neutralized after 17 months. I highlight the fact that we find relevant variability of the discount rate due to demand and financial shocks in the variance decomposition. This finding may be related to the fact that Fed was reacting to stabilize demand during the recession period of the early 1920s, as well as acting in an attempt to limit credit expansion, as it was clearly stated by policy makers.

Table 7: Median forecast error variance decompositions for model with leverage and identification by sign and variance decomposition restrictions.

	Horizon	Demand	Supply	Monetary policy	Financial (Credit)
Output	1	0.22	0.43	0.23	0.12
	12	0.17	0.28	0.18	0.36
	24	0.36	0.25	0.10	0.29
Prices	1	0.26	0.49	0.24	0.01
	12	0.26	0.28	0.41	0.05
	24	0.21	0.21	0.50	0.08
Discount rate	1	0.48	0.00	0.43	0.09
	12	0.41	0.06	0.16	0.38
	24	0.26	0.06	0.15	0.53
Leverage	1	0.15	0.05	0.03	0.77
	12	0.16	0.02	0.03	0.78
	24	0.20	0.02	0.03	0.76

3.3.2 Does financial factors drive output fluctuations?

This robustness test verifies how financial factors impact output under different identification schemes. As the model now has only four observables, it is not possible to distinguish the source of financial shock as it is done in the full VAR model with six variables. The assumption taken is that a positive financial shock increases leverage on impact, and that this increase is orthogonal to other structural demand, supply and monetary shocks. The source of the financial shock could either be coming from innovations in stock preferences, from the supply of credit or from something else.

The results from the initial recursive ordering identification $(y, p, leverage, i)$, seen in Figure 6, confirms that positive financial shocks drive permanent output gains. The estimate is that industrial production increases by 0.5% in the long run due to a structural financial shock that increases 1.26 percentage points in leverage. This is a rather sizable effect quantitatively. In the short run, industrial production increases by 1.54% at the peak, after one year. We still find that prices respond negatively to financial shocks, while the discount rate reacts positively after a few months.

Under the full identification method, using sign and variance decomposition restrictions and shown in Figure 9, we again confirm that financial factors have real effects. A typical financial shock, that results in higher leverage by 1 percentage point on impact, increases industrial production by 1.3% after 9 months and by 0.6% in long run. The credibility intervals are on the positive sign for almost twenty months. The structural innovation also leads to a reaction of interest rate, which increases 0.12 percentage points after one year. In this case, there is nothing we can say about the effect on prices. The variance decomposition presented in Table 7 confirms that financial shocks explain a relatively large share of output variability, of about 30% after one and two years. The share is comparable to demand and supply shocks.

4 Conclusion

I propose a Bayesian VAR model to analyze the dynamics of the 1920s credit cycle, stock prices and macroeconomic fluctuations. The model was estimated with monthly data from December 1919 until September 1929, and I applied a combination of sign and variance decomposition restrictions to identify several structural shocks of interest. The contributions of this research can be summarized in three parts as follows.

First, I find that monetary policy was a blunt instrument to respond to the boom in credit and stock prices during the 1920s expansion. The Federal Reserve policy makers were concerned about excessive credit for speculation, but the financial system did not react to their tight money policy as expected until the Crash of 1929. The estimation demonstrated that the effect of unexpected changes in the discount rate on credit to brokers is either very small or not different from zero, and transitory in any case. The use of different model identification methods, like recursive ordering, "agnostic procedure" or a full sign-restrictions identification scheme does not alter the results qualitatively, and very little in quantitative terms. At the same time, contractionary monetary policy implied short-term output loss and persistent decline in the price level. We stress that this finding is observed for the period from December 1919 until September 1929, that is, prior to the Crash of 1929 which substantially depressed stock prices and, as a consequence, reduced lending to brokers.

Second, financial factors played an important role for output fluctuations during the 1920s expansion. The estimation demonstrated that output reacted positively and permanently to financial shocks, and suggested that financial factors may have accounted for between 15% to 30% of the variability in output, as measured by industrial activity. This result was also tested for robustness by the use of different model identification strategies. The finding is related to modern research on financial factors as drivers of fluctuations in output and investment, such as Furlanetto et al. (2017). The authors use a similar model, a Bayesian

VAR with sign restrictions identification, and find that financial factors explain around 24-30% of fluctuations in GDP for the period 1985 to 2013. Our contribution is to test and confirm the hypothesis for an earlier business cycle era. Furthermore, a particular result stressed by the Furlanetto et al. (2017) is the limited response of prices to financial shocks, which they sustain "has not been discussed in the previous literature". In our calculated IRFs, financial shocks generally imply a negative response of prices, so we are able to confirm this fact too.

Third, the main contribution of this research is to confirm and quantify the relevance of the "credit to asset prices" channel for the case of stocks. The estimation have found that stock prices are expected to increase by almost 1% on impact, due to a structural credit supply shock of typical size, in the form of brokers' loans. To the best of my knowledge, this is the first research to demonstrate this relationship empirically for the 1920s credit boom. While the credit to asset prices channel has been intensively debated by previous historical research on the subject (Kindleberger, 1978; White, 1990), it was never quantified econometrically. Moreover, this research finding in a way revisits the hypothesis of Eichengreen and Mitchener (2004) who characterize the Great Depression as a credit boom gone wrong. Although the authors take into account the general credit expansion, I focus on the particular form of credit that experienced the largest relative boom in the period, which is brokers' loans. Brokers' loans were directly related to the asset price bubble. The method proposed in this paper is able to quantify the impact of credit expansion on further inflating asset prices.

This research finding is related to recent work on credit supply shocks, economic activity and asset prices (Mian, Sufi, & Verner, 2017b; Gilchrist, Siemer, & Zakrajsek, 2018). Most of this line of investigation focus on the housing market and the mortgage channel, specially during the 2000s expansion. In turn, I was able to demonstrate that stocks are also assets that can be subject to the dynamics of the credit cycle, by measuring how much the price of stocks were influenced by credit conditions during the 1920s expansion.

Finally, the fact that credit to buy stocks on leverage can be potentially fueling an asset price bubble, and playing a role in economic booms and busts has policy implications. Eichengreen and Mitchener (2004) suggest that policy makers should act to prevent the development of unsustainable credit booms, that may have serious negative macroeconomic and financial consequences when they turn to bust. After the Financial Crisis of 2007/08, the need for specific policy regarding credit expansion became widely recognized. Policy makers have adopted a set of macroprudential financial regulation tools, such as the Basel III recommendations, but the interactions of monetary policy and financial stability measures are still actively debated. My contribution is to empirically demonstrate the relevance of an additional channel that occurs between the intensity of credit supplied on margin and stock price fluctuations. Hopefully, the findings can provide useful elements to the analysis of macroprudential policies designed to smooth the credit cycle and consequently prevent negative macroeconomic outcomes of credit busts.

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A Figures

Figure 3: Impulse Response Functions in three equation model with recursive identification. Ordering is (y, p, i). Red line is median IRF, blue dotted lines are one standard deviation credibility intervals. Sample is Dec/1919 to Sept/1929. Size of shock is one standard deviation.

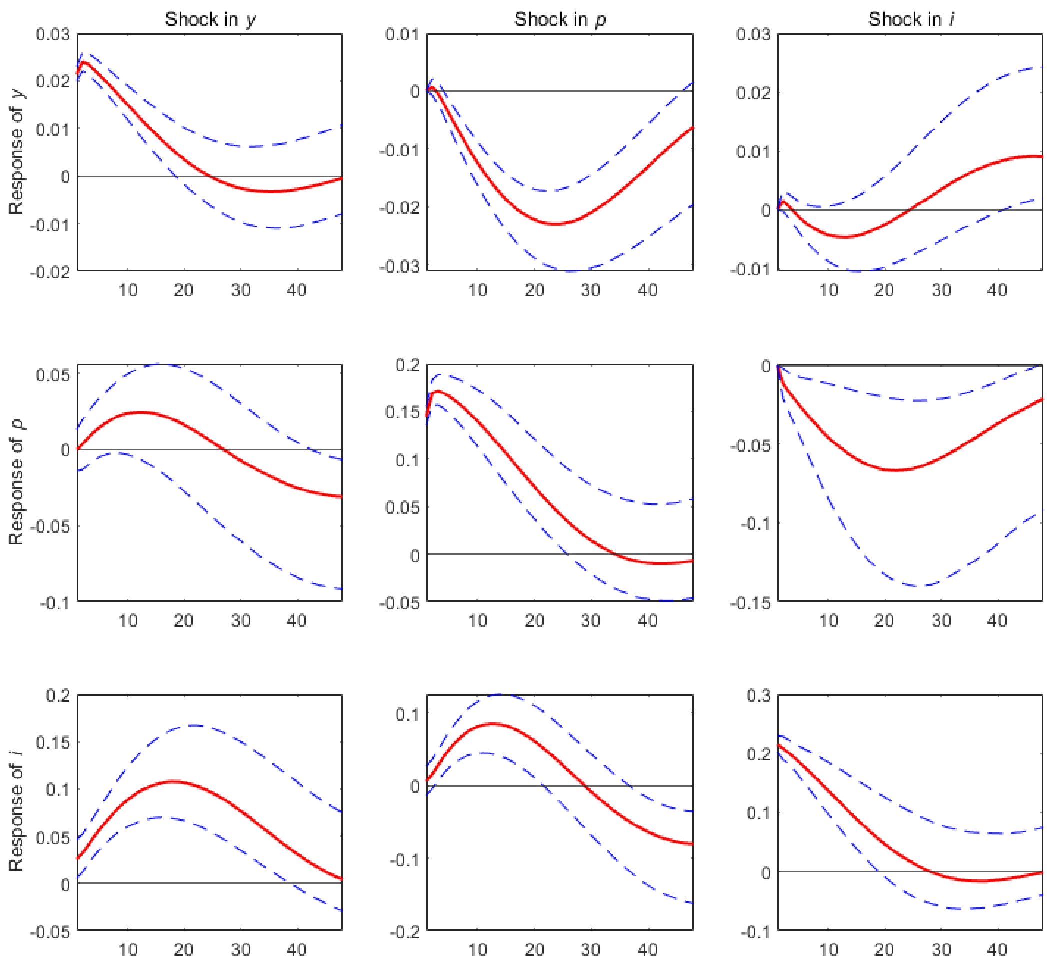

Figure 4: Impulse Response Functions in three equation model with identification by sign restrictions. Red line is median IRF, blue dotted lines are one standard deviation credibility intervals. Sample is Dec/1919 to Sept/1929. Size of shock is one standard deviation.

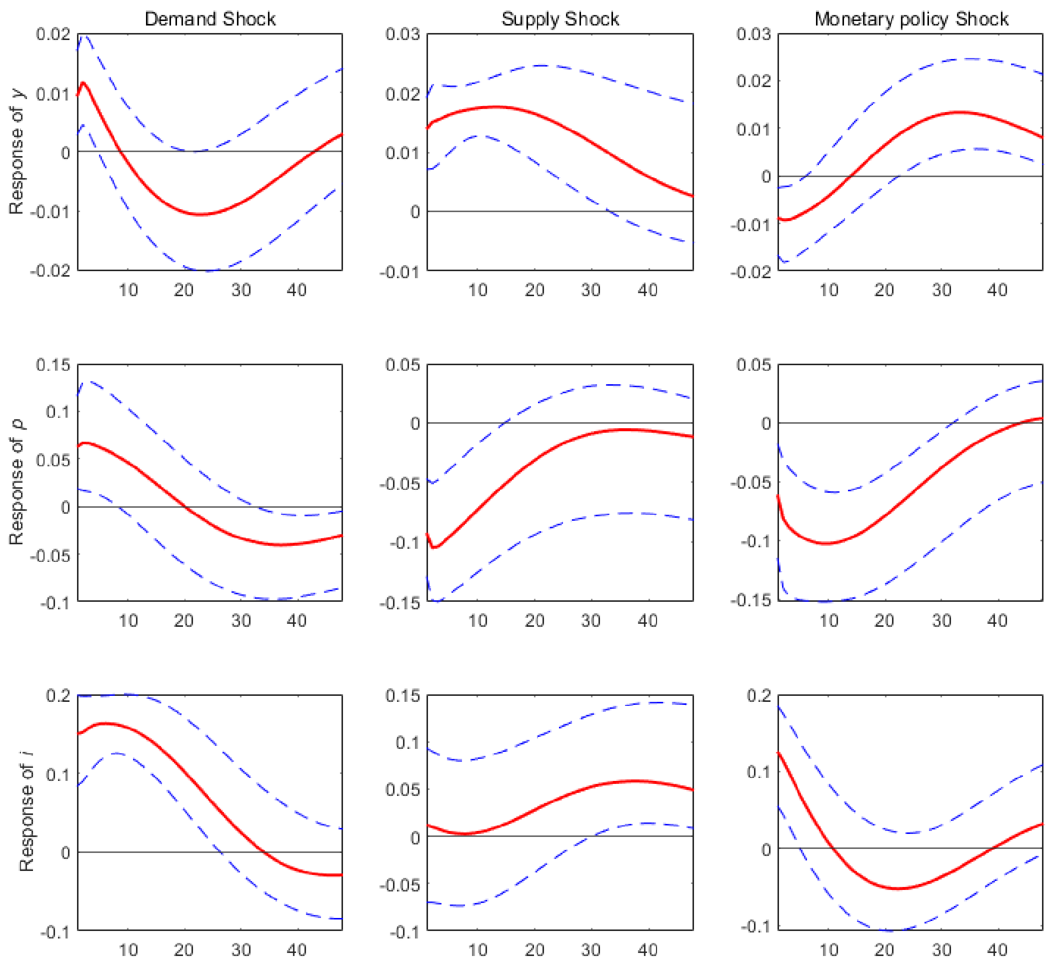

Figure 5: Impulse Response Functions in financial factors model with six variables. Shocks in columns are, respectively: demand, supply, monetary policy contraction, credit supply and stock preference. Red line is median IRF, blue dotted lines are one standard deviation credibility intervals. Sample is Dec/1919 to Sept/1929. Size of shock is one standard deviation.

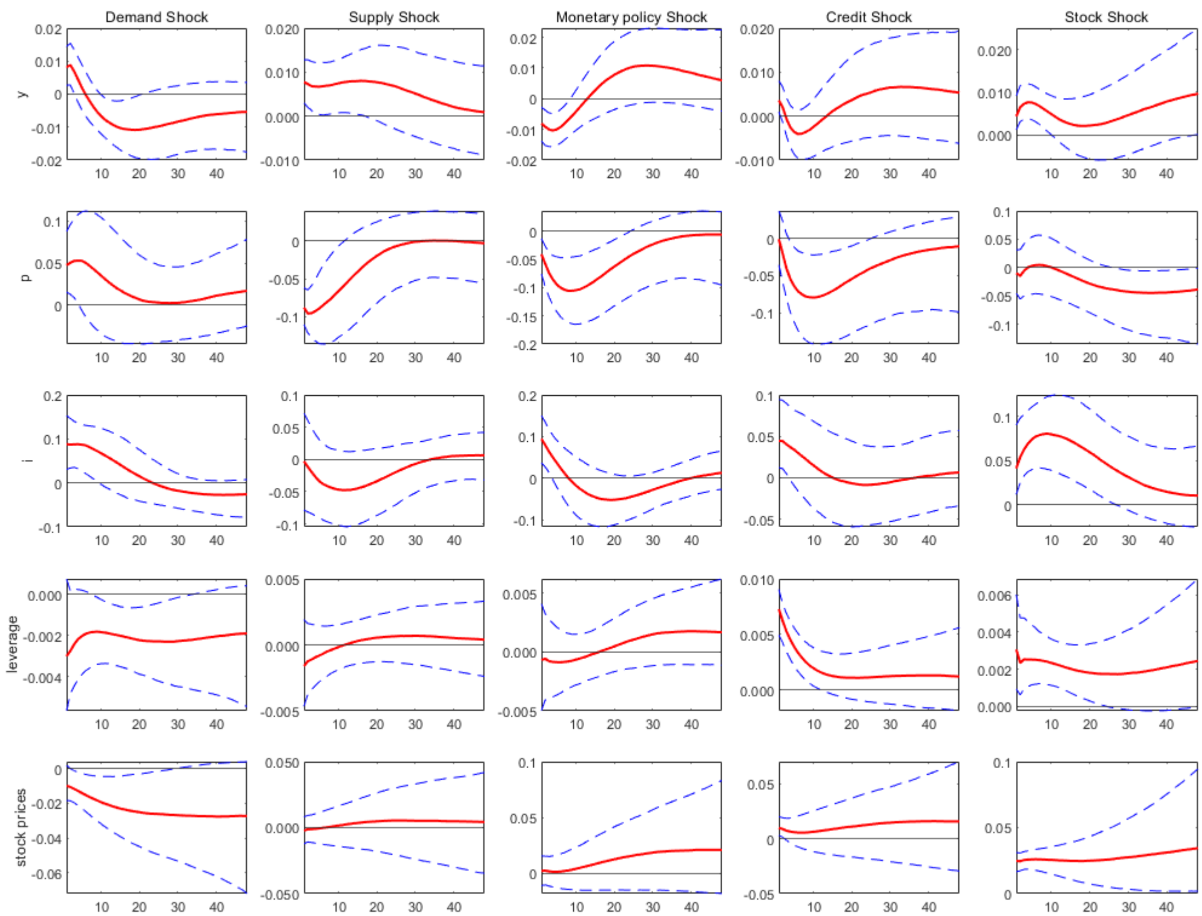

Figure 6: Impulse Response Functions in four variable model, with recursive identification. Ordering is (y, p, $leverage$, i). Red line is median IRF, blue dotted lines are one standard deviation credibility intervals. Sample is Dec/1919 to Sept/1929. Size of shock is one standard deviation.

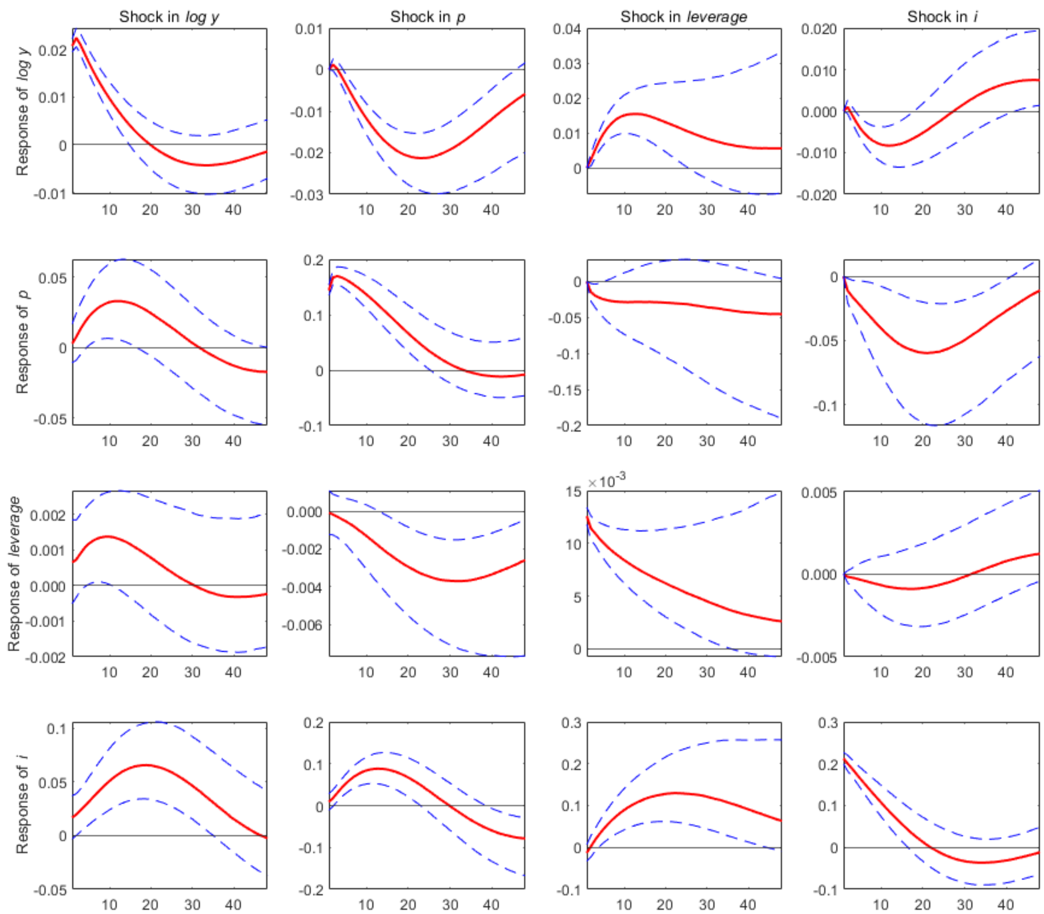

Figure 7: Impulse Response Functions in four variable model with recursive identification. Ordering is (y, p, i, $leverage$). Red line is median IRF, blue dotted lines are one standard deviation credibility intervals. Sample is Dec/1919 to Sept/1929. Size of shock is one standard deviation.

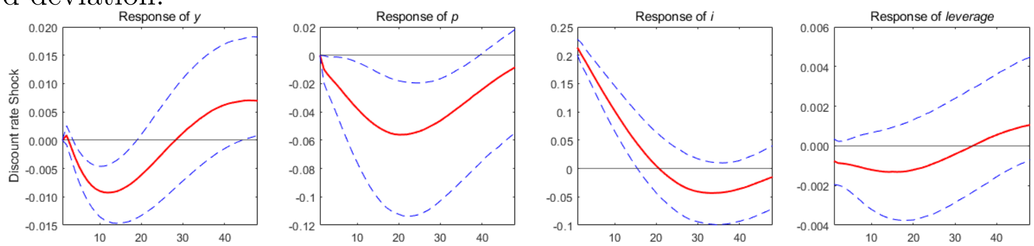

Figure 8: Impulse Response Functions to monetary policy tightening shock in four variable model, using agnostic identification procedure. Columns are respectively responses of $y, p, leverage, i$. Red line is median IRF, blue dotted lines are one standard deviation credibility intervals. Sample is Dec/1919 to Sept/1929. Size of shock is one standard deviation.

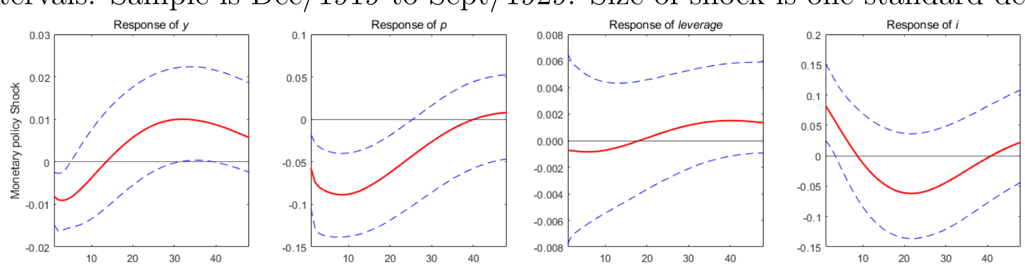

Figure 9: Impulse Response Functions in four variable model, using sign and variance decomposition restrictions identification. Red line is median IRF, blue dotted lines are one standard deviation credibility intervals. Sample is Dec/1919 to Sept/1929. Size of shock is one standard deviation.