UNIVERSITY OF BERN

Master's Thesis

Identifying the Response of Credit Aggregates to a Monetary Policy Shock, Based on the U.S. Data

Abstract

How do cov-lite leveraged loans and other credit aggregates, as well as credit to GDP ratios, respond to a contractionary monetary policy shock? In this paper I aim to provide answers to these questions using a structural VAR model, based on the several decades of monthly U.S. data. I demonstrate that various credit aggregates react differently. Some, as consumer and real estate loans, decrease on impact. Others, such as loans extended to businesses, on the contrary, expand. Together with the changing term structure, this growth may serve as an indicator of positive reaction of leveraged loans to a contractionary monetary policy shock. I also show that using monetary policy as an instrument to manipulate credit leverage of the economy is likely inefficient due to disproportionally low reaction of the indicator.

Programme	Master's in International and Monetary Economics
Submitted by	Vladimir Krasnogorskiy
E-mail	vladimir.krasnogorskiy@students.unibe.ch
	v.krasnogorskiy@gmail.com
Student number	16-118-226
Academic Advisor	Luca Benati
Submission date	10.9.2019

Contents

1 Introduction **3**

2 Background and related literature **4**
2.1 'The Age of Credit' 4
2.2 The decade of 'leveraged cov-lite loans'? 6
2.3 Monetary transmission mechanism and credit 8

3 Data **11**

4 Methodology **14**
4.1 The reduced-form VAR 14
4.2 Identification 14
4.3 Choosing combinations of variables 15

5 Results **15**
5.1 Response of credit aggregates and rates 15
5.2 Response of credit to GDP ratios 16
5.3 Response of cov-lite leveraged loans 16

6 Conclusions **18**

7 References **19**

A Appendix **22**
A.1 Summary of variables 22
A.2 IRFs and FEVs: reaction upon a monetary policy shock 23
A.3 Description of the algorithm 28
A.4 Matlab Code 32

B Statement of Authorship **49**

1 Introduction

"Cyclical fluctuations in credit quality, arising out of fluctuations in the standards used by lenders to assess risk and by borrowers to assess the prospects of ventures, may well play a part in the cyclical process."[1]

The years that pre-dated the financial crisis of 2007-08 were marked by loosening lending standards as creditors, due to general decline of returns on investments, were tempted to seek higher-yield deals even at the cost of their lower quality. The default risks were precipitated by market conditions that included the two following phenomena: first, the housing bubble was fostered by pervasive use of securitized mortgage obligations (that presumably veiled the actual state of the underlying mortgages); and secondly, business loans, extended for the purpose of leveraged buy-outs of the then highly profitable companies, gained significantly. Eventually, it was the real estate market crash that provided the impulse for the chain effect of non-payments that resulted in the evaporation of value in financial markets, the banking collapse, and the following prolonged erosion of the real activity. However, it is not as widely discussed that the failing leveraged loans market was affected immediately after housing during the unfolding of the Great Recession.

Recently, some of the major central banks and international financial institutions, including the Federal Reserve, the Bank of England and the Bank for International Settlements, have warned of the evolving risks in the leveraged covenant-light ('cov-lite') loans sector: their share in the total business loans has been estimated to be close to that of the subprime mortgages in the total real estate loans just before the break-out of the Great Recession (around 10-12 percent). Although the growth rates of the cov-lite loans have stabilized over the last three quarters (as of September 2019), their levels are still reported as worrisome. Even more importantly, the exposure of the underlying contracts in case of stress (for example, from a sudden decrease in the cash flow of debt holders) can hardly be predicted, given the overall high level of indebtedness and due to the less tight initial loan approval requirements. Also, the increasingly popular *collateralised loan obligations* - the instruments that resemble collateralised mortgage obligations not only name-wise but also in their economic nature (pooling of various-grade underlying contracts into one security), supposedly make the concomitant risks less transparent to the investors.

Using a structural VAR model and based on the monthly U.S. data from January 1964 to July 2007, I aim at achieving the following: (1) to *quantitatively* estimate of the response of various credit aggregates to a monetary policy shock; (2) to *quantitatively* estimate the response of the according credit aggregates to GDP ratios to a monetary

[1] Friedman and Schwartz (1963), p. 248.

policy shock; (3) to *qualitatively* assess the reaction of the cov-lite leveraged loans' levels to a monetary policy shock.

2 Background and related literature

2.1 'The Age of Credit'

"If it were asked how that wonderful people, the Romans, commencing with a petty village, gradually extended their Empire over so large a portion of the World, it would probably be said it was due to their hardihood and their discipline. But, probably, a cause which has been entirely overlooked, contributed in no slight degree to the result - and that is their wonderful and methodical habits of business. The Romans were, as far as we are aware, the creators of the great system of Credit in all its branches".

This excerpt is taken from one of the first systematic studies on the subject of credit: "The Theory of Credit" by Macleod (1889). Credit, as the passage suggests, has been central to economies for millennia, and it is sometimes considered to be the underlying principle of money itself[2]. However, only since the seminal studies by Jordà, Schularick, and Taylor (2015, 2017) (hereunder - JST), has the role of credit in the stability of economies become so starkly evident.

JST have compiled a dataset covering 17 developed economies and 140 years of yearly observations. Based on this data they have investigated the development of the interconnection between credit, monetary aggregates, asset prices and macroeconomic fluctuations. One of their key findings is that the world economy has been moving from the "Age of Money" towards the "Age of Credit". A "financial hockey stick" as they have called the shape of this development reflected a relatively stable credit to GDP ratio until roughly 1970s and its subsequent explosive increase. The data showed that until WWI the credit grew faster than money, between WWI and the 1950s the credit growth rates dropped significantly down-weighed by the Great Depression, while the money spiked, fuelled by WWII. Between 1950s and 1970s the total bank loans to GDP, and broad money (M2) to GDP ratios reached equality, but since then the credit leverage grew much faster. The crucial implication was that the central banks lost control over the credit expansion, which they had manipulated steering the M2 during the "Age of Money". The "Age of Credit" was marked by self-reference of the financial system that backed the new credit by the instruments created by itself; which also implied the tighter link between credit and macroeconomic fluctuations.

JST showed that the "financial hockey stick" was largely created by the expansion of credit to households, as opposed to loans extended to non-financial corporations. And

[2]Schumpeter (1954) in his fundamental "History of Economic Analysis" said that "there is no essential difference between those forms of 'paper credit' that are used for paying and lending".

the growth of credit to households, in its turn, was propelled by the rise in the real-estate mortgaged loans. The share of mortgages in the bank loans grew from around 30 percent in the beginning of the 20th century, to 60 percent nowadays, making the banks *de facto* mortgage institutions. The corporate debt also increased during the second half of the previous century, however not as fast as the household debt. The homeownership rates increased in almost every developed economy along with the housing prices. The households became wealthier but their indebtedness grew even faster, such that they became as levered as never before in history. As a result, the properties of macroeconomic fluctuations were affected.

First of all, the credit and GDP expansions and contractions have become more synchronized. Before the WWII the fraction of years the output and the credit have both decreased or increased comprised 61 percent, after the WWII this indicator has reached 79 percent. Secondly, since the WWII, not only the connection of credit and GDP has become tighter, but also the correlations of credit and real variables such investment and consumption have increased. The same has held true for credit and house prices. Thirdly, the correlations of money, as opposed to credit, and the mentioned variables have also increased but, uniformly, to a lesser extent. Finally, the correlation between credit and inflation rates has increased and is currently comparable to that of M2 and inflation. JST have demonstrated that the credit leverage is negatively, and strongly, correlated with the mean GDP growth and that higher leverage has strong negative correlation with skewness. In other words, it is related to deeper economic crises.

These findings may provide a statistical backdrop to the explanations of the severity of the Great Recession which happened at all-time high of the housing-bubble-fuelled credit leverage. However, the natural question that arises thereof is whether the central banks could have used their policy instruments to mitigate the blowing up of the bubble[3].

Benati (2016) gives a positive answer to this question. The study shows that the house prices react much more sensitively to an increase in the federal funds rate than both the unemployment and the output. Thus, it is argued that a *modest policy intervention "could have prevented the housing bubble which pre-dated the financial crisis at a comparatively small cost in terms of real activity"*. However, the author stresses that a lax monetary policy by no means was the major cause of the bubble and that this conclusion does not imply that monetary policy of 'leaning against the bubble' is the best way to tame asset prices[4]. The investigation provides solid empirical grounds against the argument that monetary policy is ineffective or too much of a 'massive' tool to be used against housing bubbles. The monetary policy shocks that the study identifies cause significant decrease in house prices, houses starts, hours worked in construction and real estate loans and

[3]A separate question would be whether the bubble may have been detected in the real time. Benati (2017) shows that, with high confidence, it would have been possible.

[4]Bernanke (2010) advocated monetary policy as a supplementary tool that may be used together with the more targeted regulatory approach.

a statistically significant temporary increase in the real rent, while the decrease in real activity turns out to be relatively small. Weak but systematic reaction of the FED would have prevented the housing bubble from developing during the period that pre-dated the Great Recession, the study shows.

2.2 The decade of 'leveraged cov-lite loans'?

The previously discussed studies focused on the issue of leverage in consumer real estate loans, the growing bubble in which pre-dated the Great Recession. Today the housing credit to GDP ratio still remains the highest among other types of bank loans in the U.S. However, looking at the plotted ratios of different credit aggregates to GDP (Figures 1 and 2), one may notice that over the last decade real estate loans to GDP ratio has decreased quite significantly, from 0.27 to 0.21, while other loan-types' ratios either returned to their pre-recession levels or increased. I am now drawing the readers' attention to the second highest to GDP ratio (0.11) - and that is of *commercial loans* aggregate[5].

Commercial and industrial (CI) loan is any loan given to a business or a company, rather than a person. Commercial and industrial loans may be used as a source of working capital or to finance purchases at any time in the life of a business. These loans are provided for short periods of time (usually up to two years) and, importantly, are backed by some collateral. Commercial loans rates are usually flexible and are connected to LIBOR or bank prime rate. To prove their financial standing borrowers would also file statements on an annual basis or more frequently, according to the level of their creditworthiness. Creditors would usually make a requirement on a proper maintenance of the underlying collaterals and fulfilment of some covenants such as debt to service ratios. The majority of the borrowers making use of commercial and industrial loans are small and medium size businesses as they would more often have difficulty generating enough cash flow to finance their on-going activities and also because they are less capable of accessing other means of financing such as issuing bonds or equity in an open market. However, interest on the CI loans may be high and the debt service would naturally take away from the creditor's working capital potentially putting additional pressure on the business processes.

As mentioned, banks issuing CI loans normally require collaterals and fulfilment of covenants to prove the standing of borrowers. However, in case of the two types of loans described below, these requirements become much less strict.

Leveraged loan is a loan that is extended to companies or individuals that already have accumulated large volumes of debt and/or have poor credit history. Given that these loans obviously carry higher risk for lenders, they also cost more for borrowers. There is no standardized way to identify a loan as 'leveraged', however they might be tracked by higher spreads from LIBOR. If the margin exceeds some certain level, it may signal higher risks associated with lower quality of borrowers. Alternatively, if the credit

[5] Second highest, not considering total credit and total bank credit that include other aggregates.

ratings of the borrowers are below the 'investment' grade, loans given out to them may be considered leveraged.

Although a *covenant-light loan* resembles a leveraged loan in a sense that it carries higher risks for lenders and consequently costs more for borrowers, the reason of increased exposure is different. As the name suggests, this type of loan has looser protective covenants built into the contract, such as maintenance of lower debt-to-service ratios or less tight requirements on collaterals. Cov-lite loans originate from 'leveraged buyouts' (LBOs) that became especially popular during the pre-Great-Recession years. Private equity firms would borrow significant amounts to purchase companies that showed good performance at a relatively high price-to-equity ratios in an anticipation of favourable returns. As the economic conditions before the crisis were such that these investments paid off quickly, creditors were inclined to finance the deals at much lower covenant requirements than they normally would have. For instance, in 2006 private equity firms purchased over 650 U.S. companies for more than 370 billion dollars - that was 18 times more than the level of transactions in 2003 (Samuelson (2007)). Eventually, in the turmoil of 2007, the high-yield debt and leveraged finance markets were affected immediately after the mortgage market collapse triggered the 'chain reaction'.

Now, why turning attention to the leveraged and cov-lite loans should be relevant to the current stage in the business cycle? The reason is that over the recent years the 'subprime lending' in the business sector has grown to pre-crisis levels. In November 2018 Bank of England released its Financial Stability Report where it warned about the rising loss-risks in the leveraged loans market: *"The global and UK markets for leveraged loans (typically loans to non-investment grade firms that are highly indebted or are owned by a private equity sponsor) have grown rapidly in recent years. This reflects strong creditor risk appetite and a marked loosening of underwriting standards. This growth has contributed to a pickup in aggregate corporate indebtedness, particularly in the US. The rapid growth in leveraged lending has been driven by increased securitisation activity through collateralised loan obligations (CLOs) as well as demand from investment funds."*. CLO is a security that pools a number of credit contracts. It is similar to the collataralized mortgage obligation (a type of a mortgage-backed security), however, instead of having underlying mortgages as a collateral, it pools loans extended to businesses. According to BOE estimates, the total volume of leveraged loans (which, as reported, at the moment contain 60 percent of cov-lite loans) in 2018 constituted 2.2 trillion U.S. dollars which comprised 9 percent of total advanced-economies credit to non-financial corporations, compared to 1.1 trillion U.S. dollars of subprime mortgages that amounted to 13 percent of the total stock of the U.S. mortgages before the Great Recession. The annualized growth rates of leveraged loans market was around 15 percent in 2018 against 16 percent growth rate in the U.S. subprime mortgages in 2006.

BOE have not been alone in warning about the rising risks in the leveraged loans market. The Bank for International Settlements (BIS) reported 'a risky resurgence' in leveraged loans in their Quarterly Review in September 2018. According to their estimates, the U.S. market size was around 0.8 trillion U.S. dollars at that time. They also warned that the normalization of the *monetary policy* may worsen borrowers' debt coverage ratios via the floating feature of leveraged loans, communicating that the default rate on institutional leveraged loans increased from around 2 percent in mid-2017 to 2.5 percent in June 2018.

The FED's Chair Jerome H. Powell' speech at the 24th Annual Financial Markets Conference on May, 20th 2019 was devoted entirely to the business debt topic. His conclusions are twofold. On the one hand, business debt levels have been approaching historic maxima and the riskiest segments of commercial and industrial loans have been growing especially rapidly. As a result, in case of worsening economic conditions some companies may experience severe financial strain. On the other, this does not pose a threat to the overall stability of the financial system, Powell notes. First of all, because the overall credit to GDP ratio has been rising steadily with no signs of being fuelled by or fuelling an asset bubble; and secondly, because banks have accumulated significant stability buffers that should help avoid liquidity squeezes in case of stress.

The question of the influence of the monetary policy on the level of leveraged loans is a topic of high importance both, given the actual effect central banks' actions have on the dynamics of the credit in the economy, and for the public trust in the monetary policy institutions. After the breakout of the Great Recession, the central banks' decisions came under scrutiny as some analyses suggested that the monetary policy of the pre-crisis years was too lax to counter the growing bubble in the mortgage market, or even helped it develop. The similar voices begin to be heard now. Financial Times in June 2019 was prompt to declare that *"a decade of ultra-loose monetary policy has caused an extraordinary lending boom"*. The current level of the policy rate has presumably reached its local peak and, thus, it may be quite a relevant time to asses what effect it could have produced on the loan markets and specifically on the credits extended to businesses.

Therefore, the purpose of this study is to identify the reaction of credit aggregates to a monetary policy shock with particular attention paid to the business loans given that the situation in this sector is assumed to have potential to amplify the downturn in case of the next financial disruption.

2.3 Monetary transmission mechanism and credit

Before presenting and analysing the data I shall give an overview of the monetary transmission mechanism and the role of credit within it.

The ***traditional approach*** to monetary transmission in its *basic Keynesian ISLM form* is summarized by the following causal chain: $M \downarrow \Rightarrow i_r \uparrow \Rightarrow I \downarrow \Rightarrow Y \downarrow$, where M stands for money, i_r for real interest rate, I for investment, and Y for output. The upward and downward arrows denote rises and decreases in the corresponding variables.

Thus, we read: the unanticipated decrease in money supply depresses the real interest rate which subsequently drives the decrease in investment and declining output. Mishkin (1996) points out two features in this scheme. First, the original view by Keynes (that this channel operates through firms' decisions about investment) was augmented in the later literature by proposition that households' decisions on investing in housing and durables are also of relevance. Second, the short-term nominal interest rate that is controlled by a central bank translates into the real interest rates (both the long- and the short-term ones) through sticky prices frictions. Also, the expectations hypothesis of the term structure suggests that the long-term rate is an average of the expected future short-term rates, meaning that the rise in the short real rates inevitably leads to increasing long rates.

As an objection to the traditional ISLM view, *other asset prices channel* was suggested. The key idea behind is that, whereas the previous mechanism takes into account an asset price - the interest rate, it omits other important asset prices such as an exchange rate and equity prices. This can be represented as: $M \downarrow \Rightarrow i_r \uparrow \Rightarrow E \uparrow \Rightarrow NX \downarrow \Rightarrow Y \downarrow$, where E is the relative price of a dollar and NX are net exports. Thus, the appreciation of currency leads to the relative cost disadvantage of domestic production in the world market which drives the decline in output.

Equity channel (backed by Tobin (1969) q hypothesis, where q is the relation of a firms' equity prices to the replacement cost of capital) is represented by $M \downarrow \Rightarrow P_e \downarrow \Rightarrow q \downarrow \Rightarrow I \downarrow \Rightarrow Y \downarrow$, with P_e denoting equity prices. The link between money and pricing deserves attention as it is at the core of this mechanism. First of all, the monetarist view would suggest that the public notices the shortage of money on hands and would want to increase its holdings by spending less - the equities market being one of the tools. This explanation can be enhanced by adding that in case of rising rates, the stocks might be seen less preferable to bonds that would demonstrate increasing yields.

Lifetime resources model is based on Modigliani (1971). When the contractionary monetary policy shock hits the economy, the stock prices decline (as previously) decreasing the lifetime resources of the consumer (which are composed of human capital, real capital and financial wealth) and, therefore, her consumption. Schematically: $M \downarrow \Rightarrow P_e \downarrow \Rightarrow \textit{wealth} \downarrow \Rightarrow \textit{consumption} \downarrow \Rightarrow Y \downarrow$. The asset prices channel may also be directed through *housing and land prices*. Interestingly, both Tobin's q mechanism and Modigliani-explained wealth effect work here exactly analogously as with the equity prices. A decrease in relative real estate value against the replacement costs contracts construction while the decline of the lifetime resources of the public depresses consumption.

The above traditional approach mechanisms, however, did not have much success in explaining how the manipulation of a short-term rate affects long-lived investments. This led to investigation of the ***credit channel mechanisms*** which are based on the notion of asymmetric information in credit markets. The *bank lending channel* functioning is explained via a realistic assumption that certain borrowers are not able to access credit unless they do it through a bank. Thus, a bank acts as a financial intermediary in a situation when there is no perfect substitutability between bank deposits and other sources of funding. Contractionary monetary policy then propagates in the following way: $M \downarrow \Rightarrow \textit{bank deposits} \downarrow \Rightarrow \textit{bank loans} \downarrow \Rightarrow I \downarrow \Rightarrow Y \downarrow$. Importantly, credit channel works stronger for smaller firms and households that have no direct access to bond or equity markets to finance their investments.

Another important channel is a *balance-sheet channel*. The contractionary monetary shock affects balance sheets of borrowers both directly and indirectly. Firstly, if the borrowers have outstanding floating-rate debt then the rise in a rate will worsen their standing deteriorating access to loan markets, since banks usually place certain requirements on the financial position of the firms seeking credit. As well as they usually would require collateral against credit, and the price of this collateral would decrease on a monetary contraction. This mechanism may be captured by the two following schemes: $M \downarrow \Rightarrow P_{collateral} \uparrow \Rightarrow lending \downarrow \Rightarrow I \downarrow \Rightarrow Y \downarrow$ and $M \downarrow \Rightarrow i \downarrow \Rightarrow cash\ flow \downarrow \Rightarrow lending \downarrow \Rightarrow I \downarrow \Rightarrow Y \downarrow$. It is worth mentioning that in the latter case, it is the nominal interest rate that is at the core of the mechanism, and not the real one as in the asset prices channels. Also the interest rate that is of higher relevance here is a short-term rate since the firms cash flow typically depends more on payments on short debt than on the long debt.

The third balance-sheet channel to be considered is connected with an *unanticipated general price level decrease*. Suppose a contractionary monetary policy shock hits an economy and consider a firm that produces traded commodities. Within some short period of time the firm's revenues decrease in accordance with the asset pricing mechanism discussed above, however its constant expenses would remain intact for some time due to price stickiness, thus the net worth position of the firm would decline which, finally, would worsen its access to credit. Schematically, this may be represented as follows: $M \downarrow \Rightarrow P_{general} \downarrow \Rightarrow lending \downarrow \Rightarrow I \downarrow \Rightarrow Y \downarrow$.

To summarize I shall refer to Bernanke and Gertler (1995) who stressed that - although there was some agreement among the economists that, at least in the short run, monetary policy may significantly affect the track of the economy - there was no common perception of how exactly its effects propagated into the real activity. They pointed out that the traditional view that had been prevailing in the literature, that the monetary policymakers exercise their leverage over the short-term interest rates to influence the cost of capital, which affects the spending on durables and thus the level of production, had been incomplete. The problem was with the empirical difficulties to identify any significant cost-of-capital effects in spending. And if these effects were actually present they had largely been determined by such non-neoclassical factors as lagged output, sales and cash-flow. The other part of the puzzle was in the observed strong effect of monetary policy on purchase of long-lived assets. This type of spending should intuitively depend on the long-term rates, whereas central banks have the closest control only over the short-term ones (e.g. the federal funds rate is an overnight rate). They concluded that the introduction of the credit channel potentially helps resolve the above-mentioned problems. They argued that the immediate effects of the monetary policy are amplified by what is called an external finance premium - the difference in cost of issuing equity or debt and retaining earnings. They also stressed the fact that using a cumulative credit aggregate in the analysis - that is summing up all the loans in one variable - is largely uninformative since some of the credit types, for example *commercial credits, may actually increase after monetary tightening*, since firms often attempt to finance inventory build-up after short-term rate increase.

3 Data

My dataset comprises 20 variables, including real GDP, non-borrowed reserves of depository institutions, M2 money stock, CPI, nominal effective exchange rate, federal funds rate, 10-year treasury constant maturity rate, 3-month treasury bill rate, 10-year treasury minus 3-month bill rate and 11 credit aggregates. The credit aggregates consist of two major parts: bank credit aggregates and total credit aggregates. The first ones include consumer loans, real estate loans, commercial and industrial loans, loans and leases in bank credit, other loans and leases, securities in bank credit and total bank credit. The total credit aggregates consist of credit to non-financial corporations, credit to general government credit to households and non-profit institutions serving households and the total credit to non-financial sector. The summary of variables is contained in Appendix A.1. The variables are of monthly frequency covering the period from January 1964 to July 2007. The major sources of information are the databases of the Federal Reserve Bank of St. Louis (FRED) and the Bank for International Settlements (BIS). The real monthly GDP data is taken from Mark Watson's web-page. I present the variables graphically in 5 figures. I plot credit aggregates as ratios to GDP (nominal values divided by nominal value) in Figures 1 and 2 and I use Figures 3, 4 and 5 to plot data as they are used in the models, that is all the values, except the rates, are in logs. I am commenting on some data that are of particular importance for the research topic of this paper below.

Total credit is the largest of the aggregates and it is composed of three parts: credit to the general government, credit to households and non-profit institutions that are serving households (churches, religious societies, sports and other clubs, trade unions and political parties) and credit to non-financial corporations. This aggregate includes credit from all sources, including domestic banks, other domestic financial corporations, non-financial corporations and non-residents. Total credit to GDP ratio is plotted in Figure 1 - the leverage stayed at the level of roughly 1.2 from 1950s to 1980s and then started increasing drastically reaching around 2 before the Great Recession; during the last decade it has grown to slightly below 2.5.

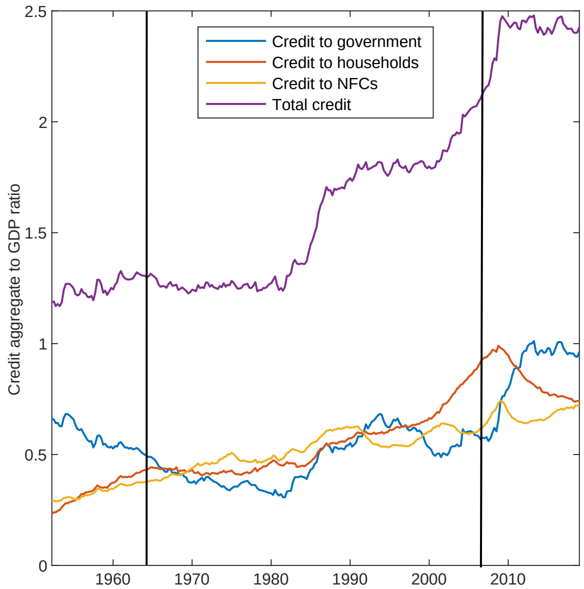


Figure 1: Credit to GDP ratios, 1952-2018
Vertical lines denote initial and last observations in the model

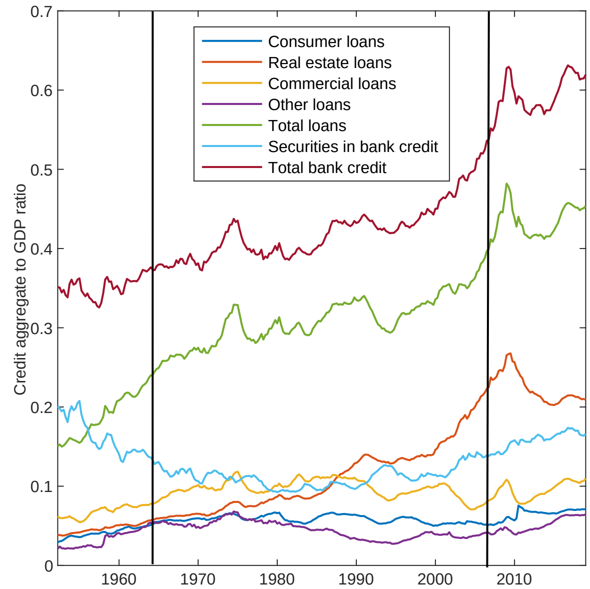


Figure 2: Bank credit to GDP ratios, 1952-2018
Vertical lines denote initial and last observations in the model

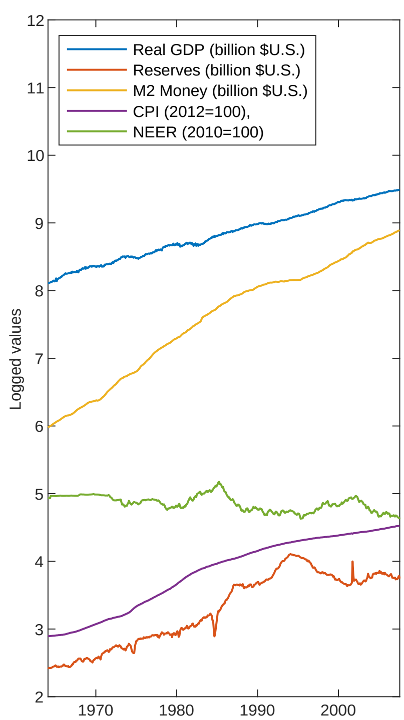


Figure 3: Macro-indicators

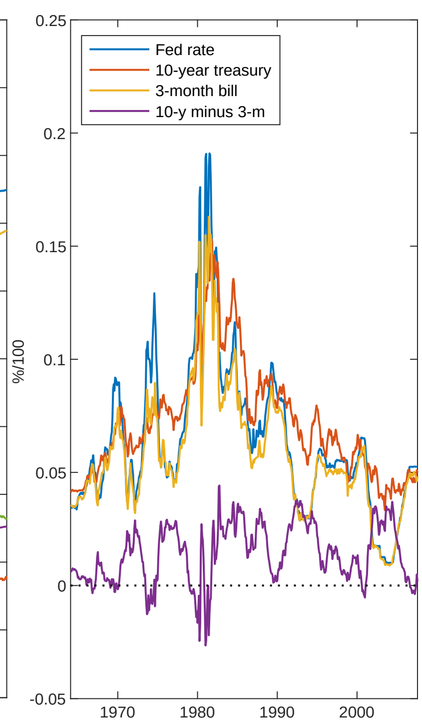


Figure 4: Rates

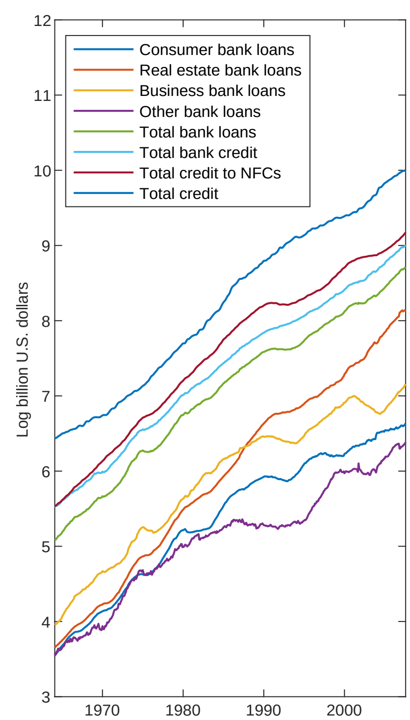


Figure 5: Credit aggregates

Credit to non-financial corporations (NFCs) includes loans and debt securities. It is one of the components of the total credit aggregate and amounts to 30 percent of it. Over the last 65 years the ratio of credit extended to NFCs to GDP has increased 2.5 times - approximately from 0.3 to 0.75. It is more than the total credit leverage has grown (around 2 times) but less than the credit to households leverage has (over 3 times). However, if we consider the last decade - the commercial credit increased by roughly 10 percent, while the credit to households (which includes real estate loans) decreased by more than 20 percent[6].

Total bank credit is the aggregate that pools loans and leases, and securities in bank credit. The latter consist of treasury and agencies securities including mortgage-backed securities. Total bank credit leverage has grown by 80 percent over the last 65 years: from 0.35 to 0.6. The largest growth in its components' to GDP ratio is observed in real estate loans - 5.5 times.

The *commercial and industrial loans* aggregate to GDP ratio increased 1.8 times over the same period. However, if we consider the last decade, real estate loans leverage has decreased by 10 percent, while the same indicator for the commercial loans has grown by 20 percent.

The *long-short interest rate spread*, measured as difference between the 10-year treasury rate and the 3-month treasury rate is an indicator that shows how economy values long-term credit compared to short-term credit. Over the last decades it has been observed that the decreasing spread is associated with deteriorating economic conditions.[7] Before each of the recessions of at least last 5 decades this indicator approached zero or descended into the negative territory (may be noted in Figure 4), which reflected the fact that the market players valued short credit equally to or more than the long credit[8].

Thus, a combination of increasing credit leverage in the economy and thinning long-short rate spreads may either serve as an indicator of deteriorating economic conditions, or, if these developments are caused exogenously, for example as a result of a monetary policy shock, they may signify an appetite for shorter-term and riskier investments that are associated with the rise in the leveraged and the covenant-light loans.

[6] The leader in this respect is the government debt as it has grown by 70 percent (reaching almost 1), but this type of debt is different in the sense that the obligations of the state in case of stress may be fulfilled through a wider variety of instruments.

[7] Investors' demand for yields switches to shorter-cycle revenues (signifying relatively lower attractiveness of the real sector projects, that usually have longer term pay-off horizons and that are at the core of sustainable economic development), and debtors experience cash-flow problems to service their existing long-term credit obligations and begin to resort to shorter-term refinancing, pushing the short rates up.

[8] As of September 2019 this indicator is below zero.

4 Methodology

4.1 The reduced-form VAR

I closely follow Arias, Caldara, and Rubio-Ramirez (2018) in methodological approach and I shall in most cases use their notation to avoid confusion.

Let us consider the following structural VAR:

$$y_t' A_0 = \sum_{l=1}^{L} y_{t-l}' A_l + c + \varepsilon_t' \qquad \text{for } 1 \leq t \leq T, \tag{1}$$

where y_t is a $1 \times N$ vector containing endogenous variables, ε_t is a $1 \times N$ vector of structural shocks, A_l is a $N \times N$ matrix of structural parameters with $0 \leq l \leq L$ (A_0 being invertible), c is a $1 \times N$ vector of parameters, L is the lag length, T is the sample size.

This can be rewritten as

$$y_t' A_0 = x_t' A_+ + \varepsilon_t' \qquad \text{for } 1 \leq t \leq T, \tag{2}$$

where $A_+' = [A_1' \ \ \ldots \ \ A_L' \ \ c']$ and $x_t' = [y_{t-1}' \ \ \ldots \ \ y_{t-L}' \ \ 1]$ for $1 \leq t \leq T$. A_+ is of dimension $m \times N$, where $m = NL + 1$. A_0 and A_+ are called structural parameters.

The reduced form VAR is denoted by the following equation:

$$y_t' = x_t' B + u_t' \qquad \text{for } 1 \leq t \leq T, \tag{3}$$

with $B = A_+ A_0^{-1}$, $u_t' = \varepsilon_t' A_0^{-1}$, $\mathbb{E}[u_t u_t'] = \Sigma = (A_0 A_0')^{-1}$.

Since the structural parameters are not identified, some identification restrictions are needed to recover the structural shocks. In the current framework I only restrict the monetary policy equation such that only the monetary policy shock is identified. Since less than $n-1$ zero restrictions are imposed the SVAR is set identified no matter how many sign restrictions are imposed, as shown in Rubio-Ramirez, Waggoner, and Zha (2010).

4.2 Identification

The restrictions that I impose in order to identify the monetary policy shock take Leeper, Sims, Zha, Hall, and Bernanke (1996), Leeper and Zha (2003), Sims and Zha (2006) as a theoretical backdrop to distinguish the systematic component of the monetary policy. I consider the FED Funds rate to react contemporaneously only to real GDP and the price level, the rationale for which is that the FED's mandate is to stabilize prices and real activity.

I also impose sign restrictions on several variables, namely a contractionary monetary policy shock (an increase in a FED funds rate) negatively affects non-borrowed reserves and M2 money.

4.3 Choosing combinations of variables

I am estimating the reaction of the total of 19 variables and, given the state of available technology, I am unable to evaluate all of them simultaneously. Having done a number of tests, I choose a baseline set-up of 7 variables, comprising real GDP, non-borrowed reserves, M2 money, CPI, NEER, Fed rate and the total credit aggregate, and then run the model a number of times to compute the reactions of the rest of the credit aggregates and the interest rates - adding one to the baseline setting: thus, estimating 8 variables each time[9].

5 Results

My results comprise 14 sets of impulse response functions and fractions of error variances which are presented in Appendix A.2. Overall, the reaction of 19 variables is estimated. The results are grouped in 3 parts each of which gives an answer to one the questions of this paper. The description of the reaction of the variables of the baseline setting is given in the footnote[10]. The reaction of federal funds rate is standardised to 0.25 percent: a common step for FED rate target range.

5.1 Response of credit aggregates and rates

The highlights of the outcomes are compiled in Figure 6. Upon a contractionary monetary policy shock that induces a standardised to 0.25 percent federal funds rate hike *total credit* rises to the maximum of 0.1 percent[11] above the steady state 5 years after the shock. *Total bank credit* decreases insignificantly reaching -0.07 percent in 3 years. *Total bank loans* rise on impact about 0.1 percent, and then decrease to -0.15 percent below the steady state 4 years after the shock. *Total credit to non-financial corporations* rises to 0.05 percent above the steady state and then steadily decreases, breaking below zero 6 years after the shock. *Commercial and industrial loans* rise to 0.3 percent above the steady state and return to zero 4 years after the shock; *real estate loans* decrease to -0.2 percent in 3 years; *consumer loans* decrease to -0.35 percent below the steady state in 3 years; *other loans aggregate* rises on impact to 0.2 percent but then quickly decreases and slides below zero 2 years after the shock.

[9] Although technically I was able to compute responses of 10 variables simultaneously, the CPU time required for that rose non-proportionally, while the reactions varied only mildly.

[10] Upon a contractionary monetary policy shock the federal funds rate rises immediately to standardized 0.25 percent (this value being a usual step for federal funds target range) above the steady state which is assumed to be zero (*below, all the figures I am giving, refer to mean reaction*). The rate reaches maximum at 0.35 percent and then returns to the steady state around 3 years after the shock. Real reserves, M2 money and the exchange rate rise on impact; the real GDP decreases to -0.15 percent below the steady state approximately 2 years after the shock has occurred; the general price level stays close to zero for about 3 years and then decreases steadily to -0.1 percent below the steady state.

[11] All the figures I am giving in this section, refer to mean reaction.

3-month rate increases to 0.18 percent above the steady state on impact, spikes at 0.25 percent twomonths later and then returns steadily to zero, normalizing about 4 years after the impact. *10-year treasury* rises to around 0.05 percent above the steady state and then decreases slowly together with the FED rate. *The long-short spread* drops to -0.15 percent on impact returning to zero in about 2 years.

5.2 Response of credit to GDP ratios

Figure 7 shows percentiles difference between credit aggregates' impulse response functions and gross domestic impulse response functions. The resulting graphs correspond to the reaction of the credit aggregates to GDP ratios, or leverage, upon a contractionary monetary policy shock. *Total bank credit* and *total bank loans* to GDP ratios react positively, although to a very limited extent[12]. The reaction of the *real estate loans* 'leverage' is essentially zero, same holds true for the *other loans aggregate*; *consumer loans* to GDP ratio slightly decreases; *credit to non-financial corporations* and bank *commercial and industrial loans* to GDP ratios slightly increase. The only substantial growth is observed in the*credit to general government* leverage, the mean reaction of which reaches almost 0.3 percent above the steady state.

A monetary policy shock has practically no impact upon the *total credit* 'leverage' in the economy as well as on other credit aggregates to GDP ratios, except for the credit to the general government. Thus, with substantial degree of confidence, it is infeasible to use monetary policy as a tool for manipulating credit aggregates to GDP ratios due to their disproportionately low response compared the reaction of the federal funds rate[13].

5.3 Response of cov-lite leveraged loans

Federal funds rate hikes may deflate some particular credit aggregates, such as consumer loans and real estate loans. However, for the other types, for example commercial and industrial loans (that contain leveraged, cov-lite loans), contractionary monetary policy shock induces levels growth. Furthermore, the fact that the shock results in a stronger increase in the short rates than in the long rates means that the market conditions switch to an expansion in the riskier, and higher-yield credit deals - exactly the ones that are characteristic of the leveraged cov-lite sector. Although there is no possibility to separate the cov-lite leveraged loans out of the commercial and industrial loans aggregate (due to absence of classification and lack of statistics) and therefore quantify their exact reaction, it is plausible to conclude that a contractionary monetary policy shock leads to an increase in the levels of leveraged, cov-lite loans.

[12]For example, the mean of leverage in total credit, which pools all credit to the non-financial sector from all sources, increases to 0.003 percent above the steady state upon a 0.25 percent increase in the federal funds rate.

[13]With the only exception of the credit to government to GDP ratio that reacts strongly positively upon a contractionary monetary policy shock within 4 years from impact.

Figure 6: Reaction of variables upon a monetary policy shock. *Note that the first 7 sets of IRFs and FEVs were computed simultaneously in a 7-variable model. The other 10 variables' sets of IRFs and FEVs were computed one at a time, in 8-variable models together with the first 7 variables. Please refer to Appendix for complete sets. The reaction of the first 7 variables in each of the 11 runs varies only mildly.*

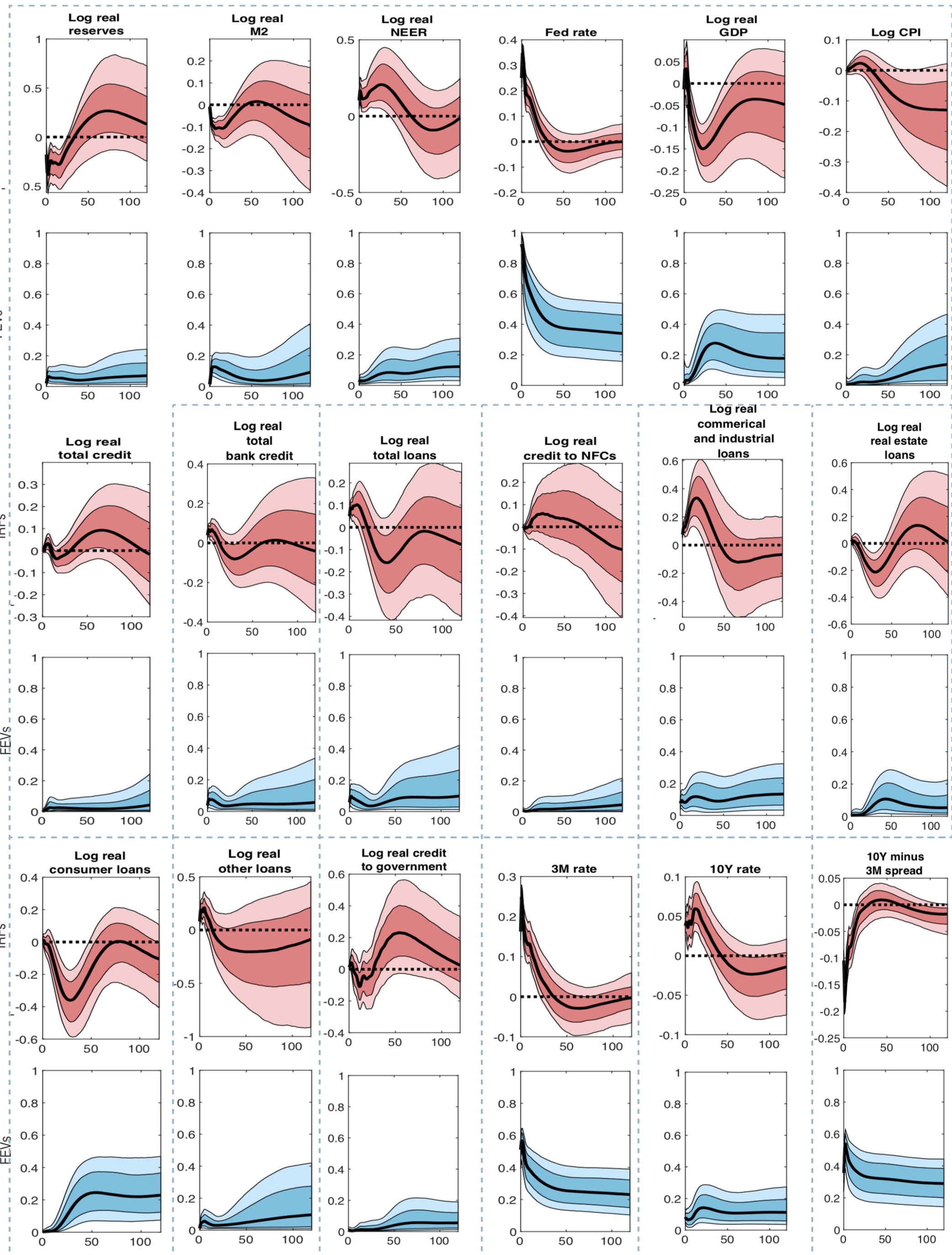
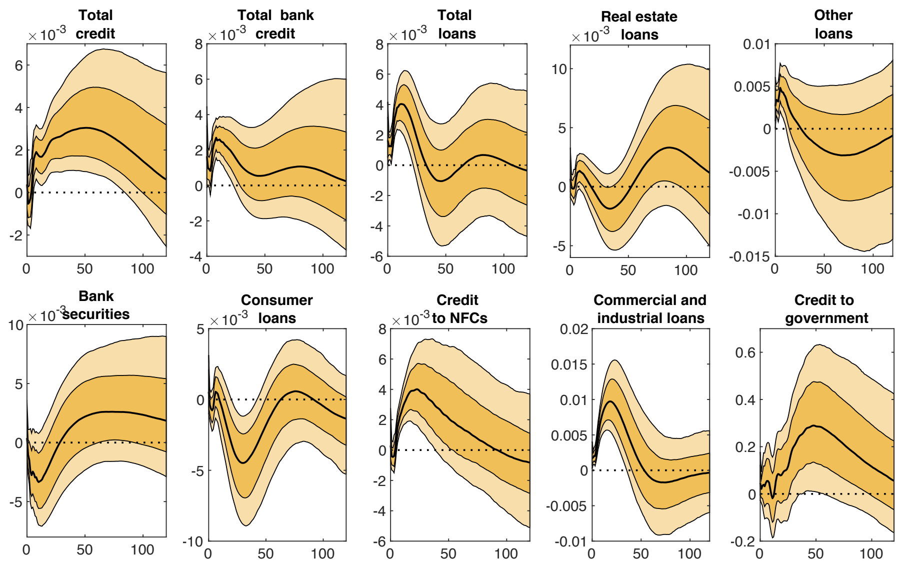


Figure 7: Percentiles difference between credit aggregates IRFs and GDP IRFs. *The resulting graphs correspond to the reaction of the credit aggregates to GDP ratios upon a contractionaty monetary policy shock.*



6 Conclusions

In this paper I have estimated the response of the credit aggregates to a monetary policy shock via a structural VAR model based on the U.S. data (from January 1946 to July 2007). The results I have obtained show that, *first*, the magnitude and the signs of the reactions vary across different aggregates. In particular, consumer and real estate loans decrease upon a contractionary monetary policy shock while business loans and credit to the general government increase. *Second*, the reactions of the credit aggregate ratios to GDP, including the total credit leverage, are close to zero, although the ratio of the credit to government to GDP reacts strongly positively upon a contractionary monetary policy shock. *Third*, the short-term interest rates and the long-term interest rates react in the same direction as the federal funds rate, but as the response of the short rates is more pronounced, the long minus short interest rates spread decreases. Together with the growing commercial and industrial loans aggregate it reflects the move of the investors towards riskier high-yield contracts that are characteristic of the leveraged cov-lite loans. Thus, a contractionary monetary policy shock may lead to an increase in cov-lite leveraged loans. This may provide an additional research question to the use of monetary policy as an instrument for taming unwanted growth rates in various markets as the reactions may be ambivalent.

7 References

Arias, J. E., Caldara, D., & Rubio-Ramirez, J. F. (2018). The systematic component of monetary policy in SVARs: an agnostic identification procedure. *Journal of Monetary Economics*.

Benati, L. (2016). *Would a 'Modest Policy Intervention' Have Prevented the U.S. Housing Bubble?* (Diskussionsschriften No. dp1609). Universitaet Bern, Departement Volkswirtschaft. Retrieved from `https://edit.cms.unibe.ch/unibe/portal/fak_wiso/b_dep_vwl/a_inst_vwl/content/e195818/e195991/e556277/e677987/dp1609_ger.pdf?preview=preview`

Benati, L. (2017, May). *Could the Bubble in U.S. House Prices Have Been Detected in Real Time?* (Diskussionsschriften No. dp1705). Universitaet Bern, Departement Volkswirtschaft. Retrieved from `https://ideas.repec.org/p/ube/dpvwib/dp1705.html`

Bernanke, B. (2010). *Monetary policy and the housing bubble: speech at the annual meeting of the american economic association, atlanta, georgia.*

Bernanke, B., & Gertler, M. (1995). Inside the black box: the credit channel of monetary policy transmission. *Journal of Economic perspectives*, *9*(4), 27–48.

Friedman, M., & Schwartz, A. J. (1963). *A monetary history of the united states, 1867-1960.* Princeton University Press.

Jordà, Ò., Schularick, M., & Taylor, A. M. (2015). Leveraged bubbles. *Journal of Monetary Economics*, *76*, S1–S20.

Jordà, Ò., Schularick, M., & Taylor, A. M. (2017). Macrofinancial history and the new business cycle facts. *NBER macroeconomics annual*, *31*(1), 213–263.

Leeper, E. M., Sims, C. A., Zha, T., Hall, R. E., & Bernanke, B. S. (1996). What does monetary policy do? *Brookings papers on economic activity*, *1996*(2), 1–78.

Leeper, E. M., & Zha, T. (2003). Modest policy interventions. *Journal of Monetary Economics*, *50*(8), 1673–1700.

Lütkepohl, H. (2005). *New introduction to multiple time series analysis.* Springer Science & Business Media.

Macleod, H. D. (1889). *The theory of credit. in 2 vols.* Longmans Green XII.

Mishkin, F. S. (1996). *The channels of monetary transmission: lessons for monetary policy* (Tech. Rep.). National Bureau of Economic Research.

Modigliani, F. (1971). Monetary policy and consumption. *Consumer spending and monetary policy: the linkages*, 9–84.

Primiceri, G. E. (2005). Time varying structural vector autoregressions and monetary policy. *The Review of Economic Studies*, *72*(3), 821–852.

Rubio-Ramirez, J. F., Waggoner, D. F., & Zha, T. (2010). Structural vector autoregressions: Theory of identification and algorithms for inference. *The Review of Economic Studies*, *77*(2), 665–696.

Samuelson, R. (2007). *The private equity boom.* Retrieved 2007-03-15, from http://www.washingtonpost.com/wp-dyn/content/article/2007/03/14/AR2007031402177.html?noredirect=on

Schumpeter, J. A. (1954). *History of economic analysis.* Allen and Unwin (Publishers) Ltd.

Sims, C. A., & Zha, T. (2006). Does monetary policy generate recessions? *Macroeconomic Dynamics*, *10*(2), 231–272.

Tobin, J. (1969). A general equilibrium approach to monetary theory. *Journal of money, credit and banking*, *1*(1), 15–29.

A Appendix

A.1 Summary of variables

No.	Variable	Source	Code	Frequency	Seas. Adj	Value
1	Interpolated Real GDP	Mark Watson	-	Monthly	Yes	Billions of Dollars
2	Non-Borrowed Reserves of Depository Institutions	FRED	BOGNONBR	Monthly	Yes	Billions of Dollars
3	M2 Money Stock	FRED	M2SL	Monthly	Yes	Billions of Dollars
4	Personal Consumption Expenditures Excluding Food and Energy	FRED	PCEPILFE	Monthly	Yes	Index 2012=10
5	Effective Exchange Rate for United States, Index	FRED	NNUSBIS	Monthly	No	Index 2010=10
6	Effective Federal Funds Rate	FRED	FEDFUNDS	Monthly	No	Percent
7	10-Year Treasury Constant Maturity Rate, Percent, Monthly, Not Seasonally Adjusted	FRED	GS10	Monthly	No	Percent
8	3-Month Treasury Bill: Secondary Market Rate	FRED	TB3MS	Monthly	No	Percent
9	10-Year Minus 3-Month Spread	Comupted as GS10 minus TB3MS	-	Monthly	No	Percent
10	Consumer Loans at All Commercial Banks	FRED	CONSUMER	Monthly	Yes	Billions of Dollars
11	Real Estate Loans All Commercial Banks	FRED	REALLN	Monthly	Yes	Billions of Dollars
12	Commercial and Industrial Loans All Commercial Banks	FRED	BUSLOANS	Monthly	Yes	Billions of Dollars
13	Loans and Leases in Bank Credit, All Commercial Banks	FRED	LOANS	Monthly	Yes	Billions of Dollars
14	Other loans and leases: All other loans and leases, all commercial banks	Computed as LOANS minus the sum of CONSUMER, REALLN and BUSLOANS	-	Monthly	Yes	Billions of Dollars
15	Bank Credit, All Commercial Banks		LOANINV	Monthly	Yes	Billions of Dollars
16	Total Credit to non-financial sector	BIS	Q:US:C:A:M:XDC:A	Monthly, interpolated	Quartetly data adj. for breaks	Billions of Dollars
17	Credit to Non financial corporations from All sectors at Market value, quarterly	BIS	Q:US:N:A:M:USD:A	Monthly, interpolated	Quartetly data adj. for breaks	Billions of Dollars
18	Credit to General government from All sectors at Market value, quarterly	BIS	Q:US:G:A:M:USD:A	Monthly, interpolated	Quartetly data adj. for breaks	Billions of Dollars
19	Credit to Households and Non-profit institutions serving households from All sectors at Market value, quarterly	BIS	Q:US:H:A:M:USD:A	Monthly, interpolated	Quartetly data adj. for breaks	Billions of Dollars
20	Securities in Bank Credit, All Commercial Banks	FRED	INVEST	Monthly	Yes	Billions of Dollars

A.2 IRFs and FEVs: reaction upon a monetary policy shock

Figure 8: Without credit aggregates

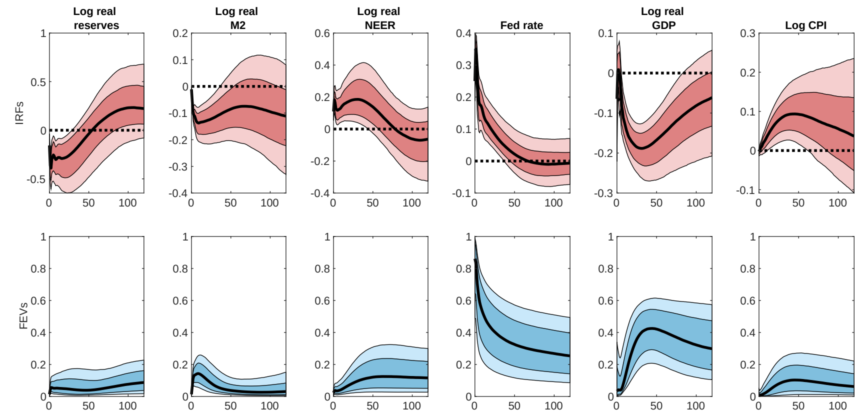


Figure 9: Baseline: seven variables including total credit aggregate

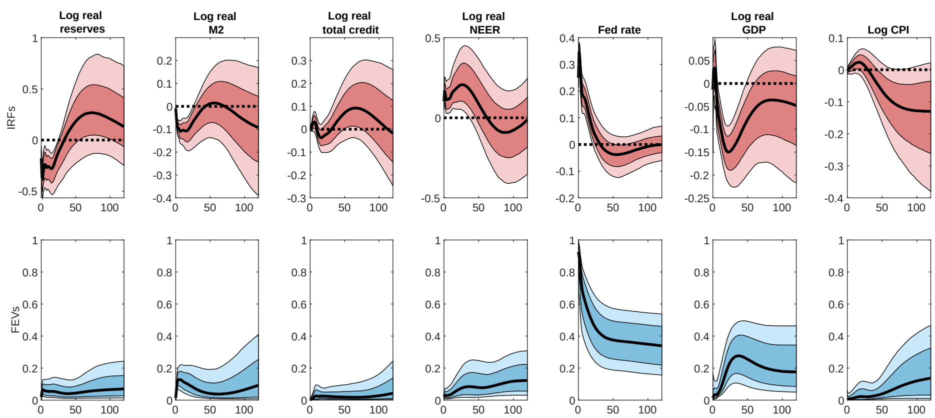


Figure 10: Total bank credit *(from here on, I name only variables that are added to the baseline setting)*

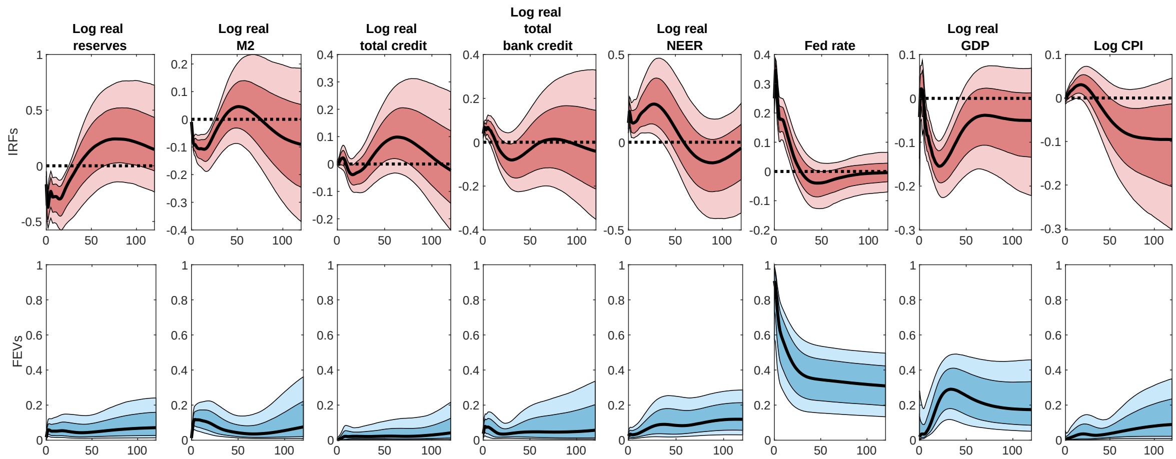


Figure 11: Total bank loans

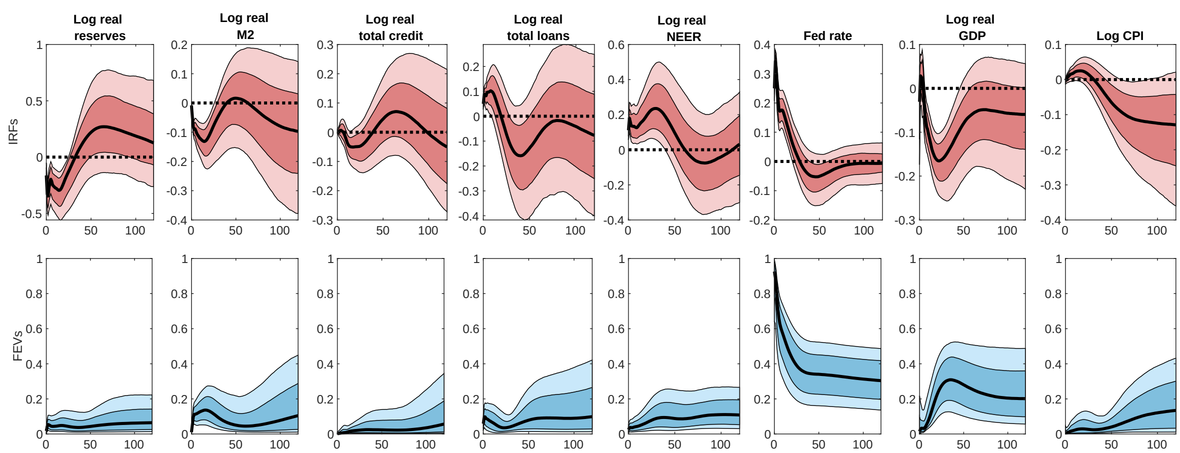


Figure 12: Commercial and industrial loans

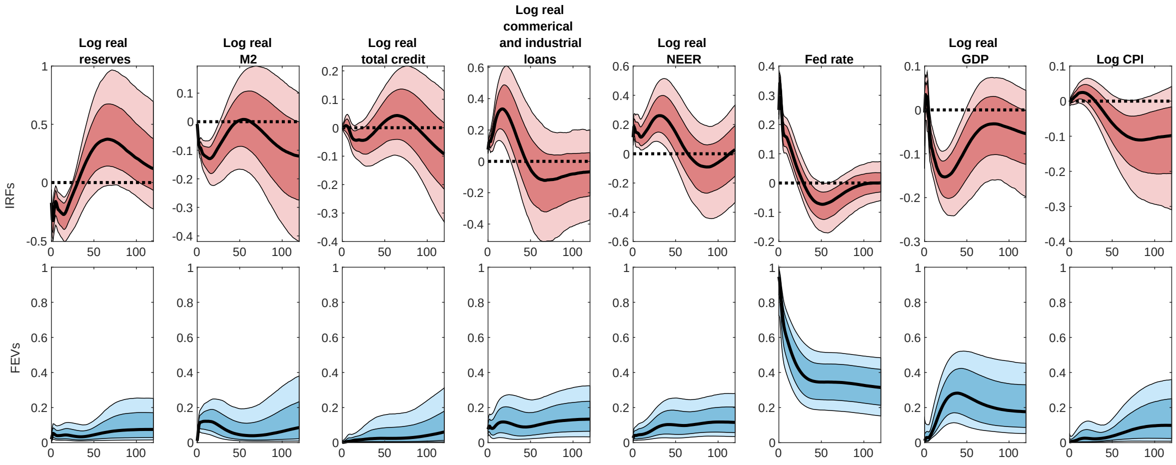


Figure 13: Real estate loans

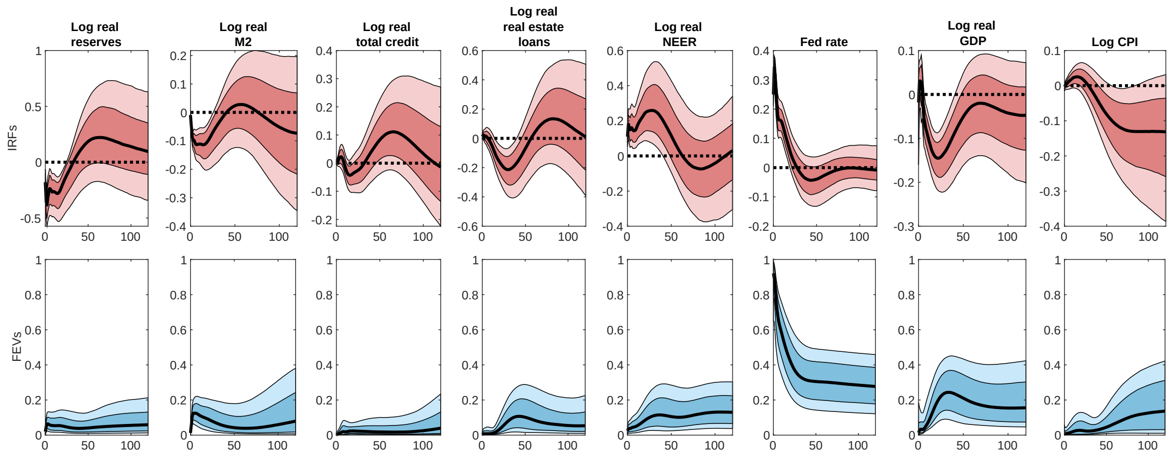


Figure 14: Consumer loans

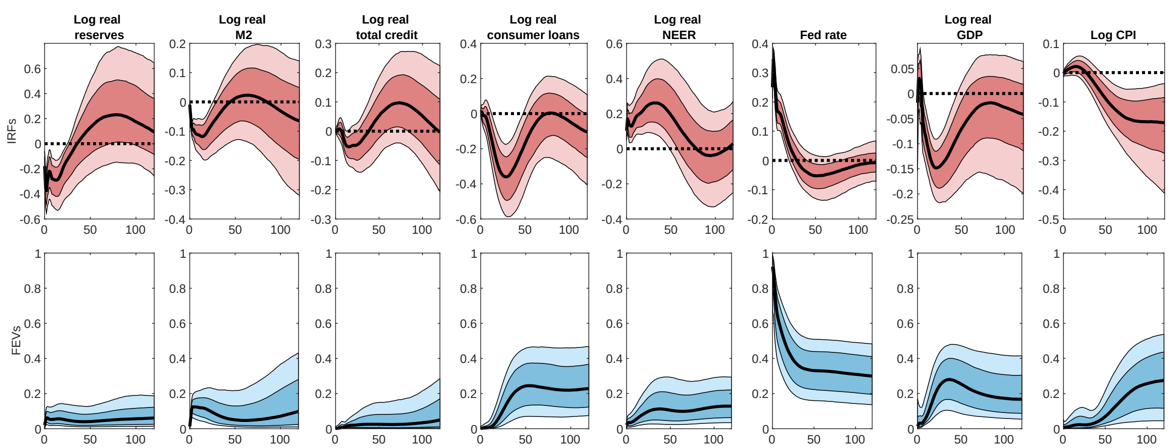


Figure 15: Other bank loans

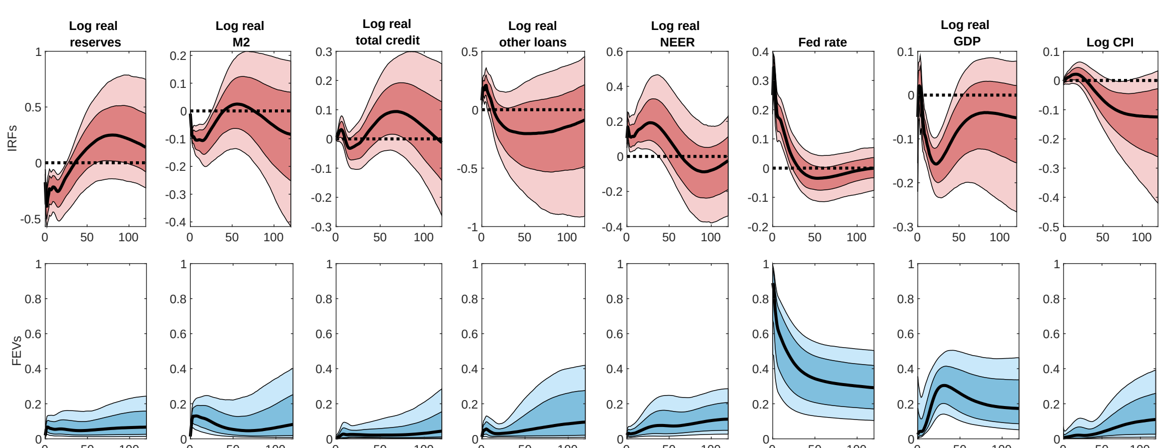


Figure 16: Total credit to non-financial corporations

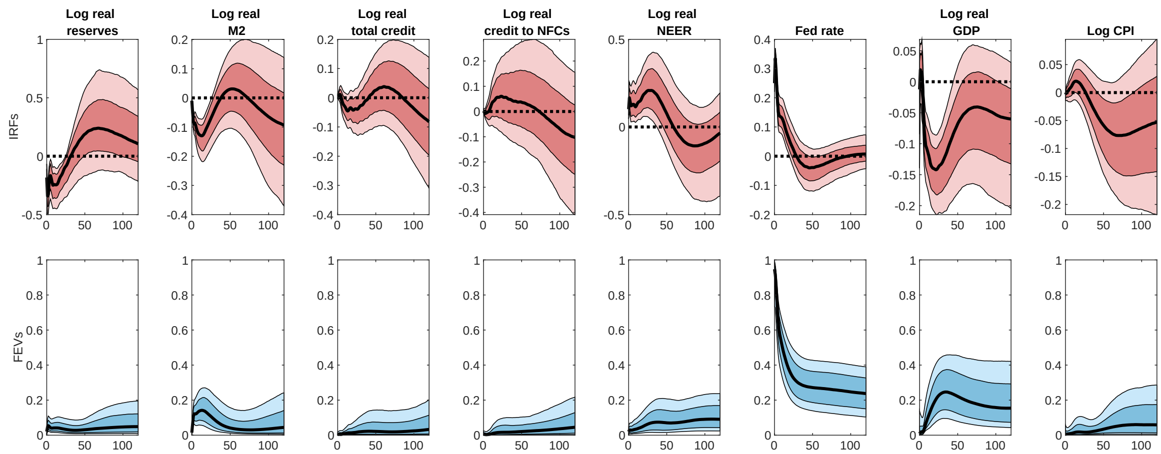


Figure 17: Credit to government

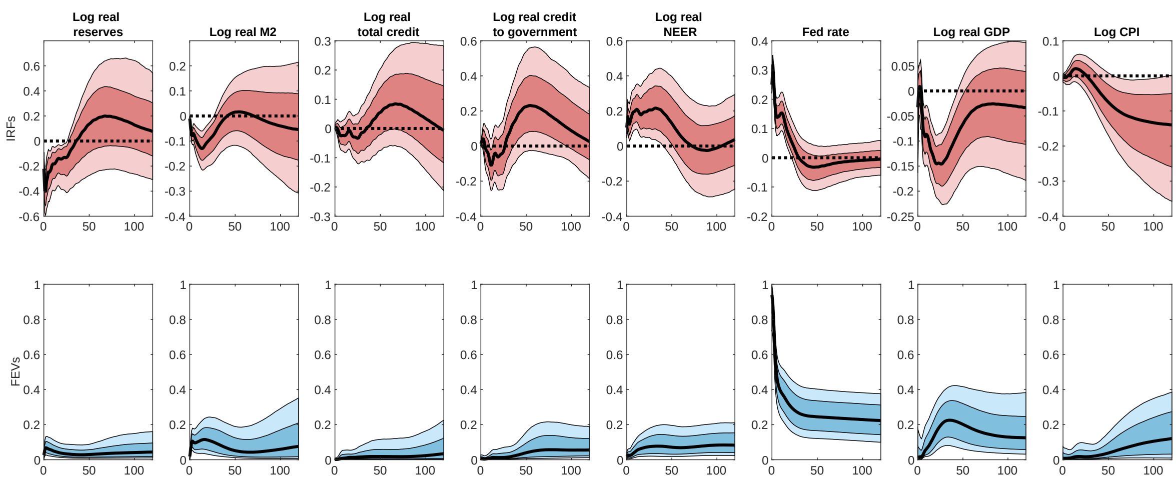


Figure 18: Securities in bank credit

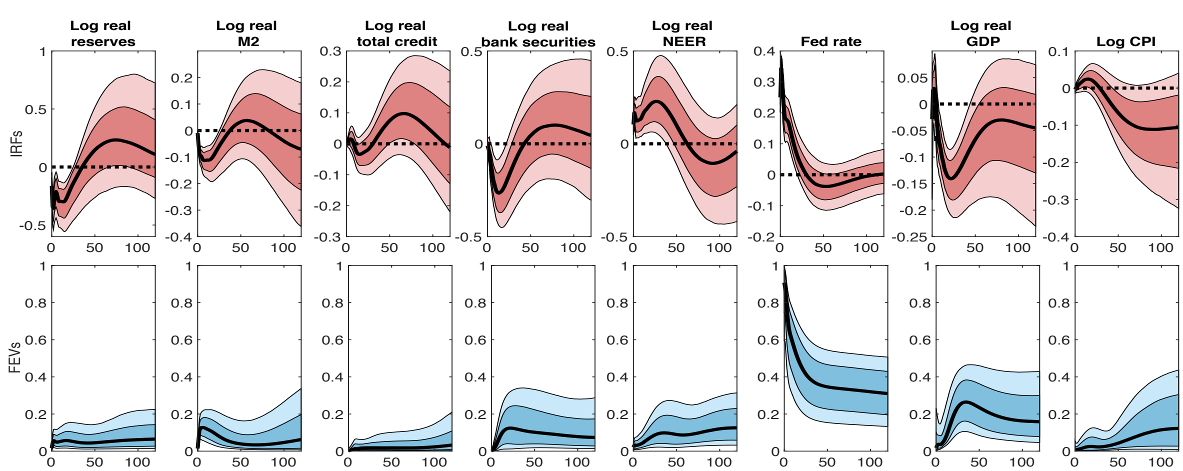


Figure 19: 3-month treasury bill

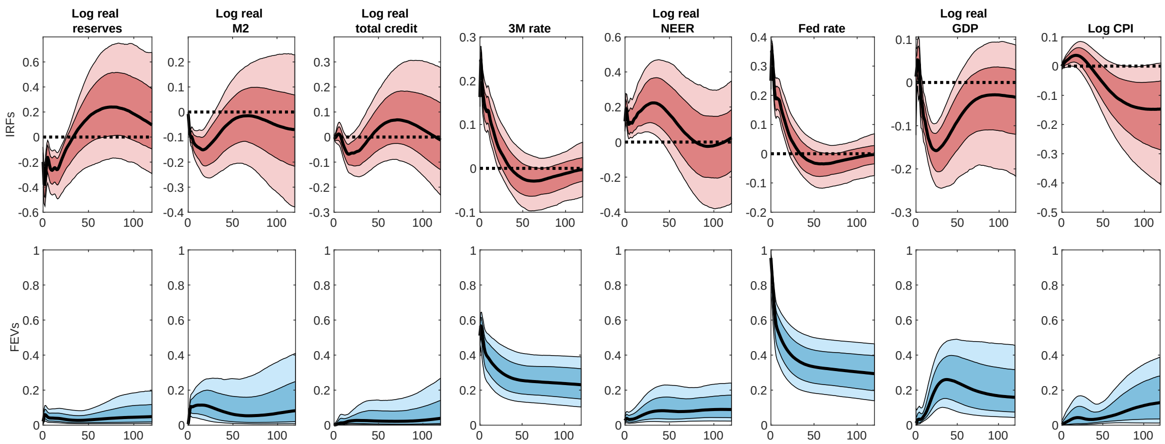


Figure 20: 10-year treasury bill

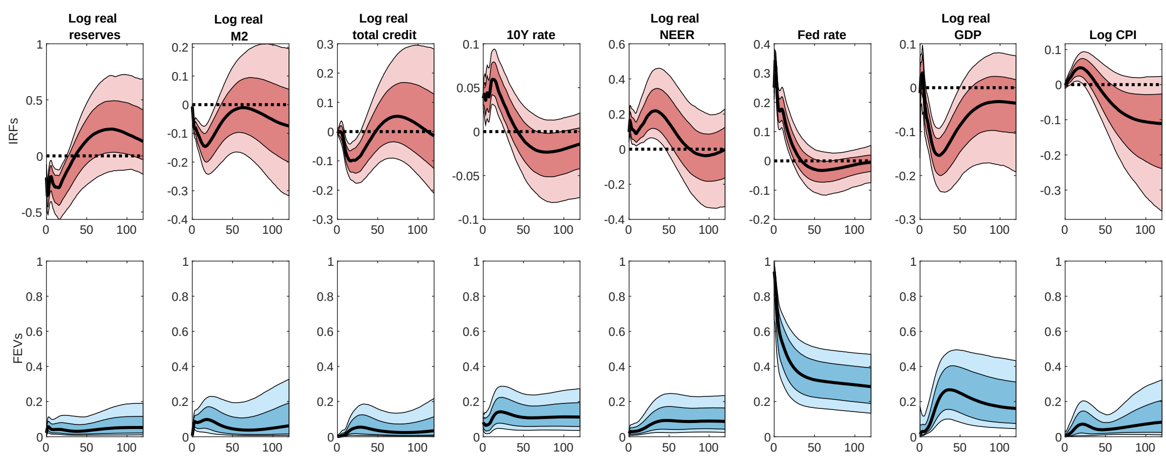
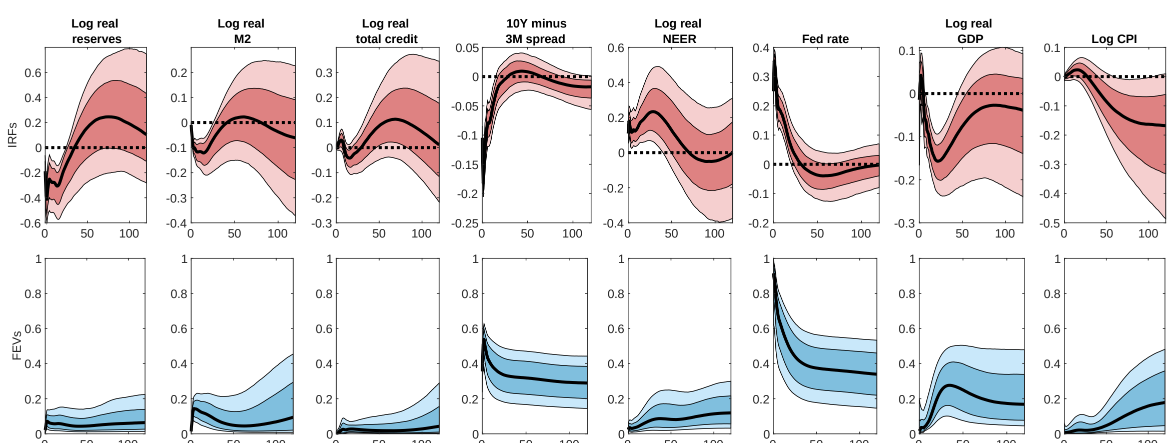


Figure 21: 10-year minus 3-month(treasury bill) rate



A.3 Description of the algorithm

Hereunder I will give a step-by-step description of the algorithm I am using to obtain the results. The estimation is done in a Mathworks Matlab, version R2018a. The code is provided in Appendix A.4.

Step 1: Setting priors

Following Primiceri (2005) we choose the prior for the VAR states to be normal with mean equal to the ordinary least square estimates of the time-invariant VAR over the first several years of data. The variance is chosen to be $N+1$ times the variance of the $\hat{B}_{OLS}$ variance-covariance estimation.

Step 2: Gibbs sampling burn-in

I use a Gibbs sampling which is a particular design of a Markov chain Monte Carlo (MCMC) method which implies drawing the lower dimensional conditional posteriors rather than the high dimensional joint posterior of the complete set of parameters.

I initialize the Gibbs arrays as zero matrices of the following dimensions:

- draws of the state vector ($\bar{\mathbf{B}}$): $N*(1+N*L) \times NG$, where NG is the number of draws from Gibbs sampler per data file;
- covariance matrices ($\bar{\mathbf{V}}$): $N \times N \times NG$;
- reduced-form VAR residuals ($\bar{\mathbf{U}}$): $T \times N \times NG$.

And then draw the initial VAR coefficients.

The burn-in procedure is used to reach the starting point of the MCMC run that will be close to the mean of the equilibrium distribution such that the algorithm runs efficiently. If the posterior covariance draw satisfies the restriction we impose on the roots for the companion form of a VAR(p) (such that their absolute difference from 1 is less than some parameter δ, that in my case I set to 0.005), then the algorithm stacks the coefficients vector in $\bar{\mathbf{B}}$; computes the recursive residuals for an unrestricted VAR, that are inserted in $\bar{\mathbf{V}}$; and finally executes the second stage of the Gibbs sampler generating random draws for the covariance matrix using the inverse-Wishart density (which are stacked into $\bar{\mathbf{V}}$).

Step 3: Reaching ergodic distribution via Gibbs sampling

Part 1. Obtaining initial structural impact matrix A_0^*.

After the initial iterations of Gibbs sampler are "burnt" I continue with the algorithm aimed at obtaining structural impact matrices A_0.

Table 1: Inputs of the Gibbs-sampling algorithm

No.	General notation	Matlab notation	Size	Description
1.	$\hat{\boldsymbol{\beta}}_0$	PriorMU	$K(1+Kp)\times 1$	Prior state of the estimates of the slope coefficients for the SVAR (vectorized)
2.	$\hat{\Sigma}_{\beta_0}$	PriorCovarianceMU	$(1+Kp)\times(1+Kp)$	Prior state of the variance-covariance matrix of the vectorized slope coefficients for the SVAR
3.	$\hat{\Sigma}_{u_0}$	COV0	$K\times K$	Prior covariance matrix of residuals U
4.	$Y_{(T)}$	YS	$K\times T$	Data matrix for the posterior sample (length T)
5.	$Z_{(T)}$	XS1$'$	$(1+Kp)\times T$	p-lags data matrix for the posterior sample arranged in a traditional concise matrix notation structure as in Lütkepohl (2005), equation (3.2.1)
6.	$\mathbf{Z_{(T)}}$	XS	$(1+Kp)\times K\times T$	$Z_{(T)}$ matrix, vectorized and arranged in a structure as in Table **??**.

The following steps are given for one successful iteration of Gibbs sampler. The description of inputs is given in the table below. Also, as previously the prior degrees of freedom are equal to $K+1$, and the posterior degrees of freedom are $T-\tau+K$.

1. First I compute posterior mean for the SVAR coefficients ($\bar{B}_T$) and the posterior covariance matrix ($\bar{\Sigma}_{B_T}$).
2. Then a diagonal matrix D of eigenvalues and a full matrix V whose columns are the corresponding eigenvectors, of posterior covariance matrix $\bar{\Sigma}_{B_T}$, is produced.
3. Then the state vectors $\bar{\mathbf{B}}$ are drawn.
4. If the roots' of the companion form of a VAR(p) absolute difference from 1, is smaller than δ, the first T column vectors of $\bar{\mathbf{B}}$ are input into a matrix of time-varying coefficients Θ (of size $K(1+Kp)\times T$), denoted "SA" in the Matlab code.
5. The matrix of posterior residuals $\bar{\mathbf{U}}$ of size $T\times K\times KG$ is composed.
6. The posterior covariance matrices are estimated via:

$$\bar{\mathbf{V}} = (N+1)\Sigma_B + \bar{U}'\bar{U}. \tag{4}$$

7. Finally, the initial structural impact matrix is computed as

$$A_0^* = VD^{1/2}, \tag{5}$$

where D is diagonal matrix of eigenvalues and V is the matrix of the corresponding eigenvectors, of the current draw of $\bar{\mathbf{V}}$.

Part 2. Obtaining A_0 matrices

(1) I define the positions and signs of monetary policy rule - that is how a Central Bank reacts to different variables under consideration. The federal funds rate responds in the same direction to changes inflation and output.

(2) Then I set sign restrictions on the reaction of the variables to a shock. This is implemented through imposing signs on the IRFs. The non-borrowed reserves and the M2 money are forced to react negatively to an increase in the rate. While the exchange rate is assumed to react negatively.

(3) The zero restrictions are imposed on the monetary policy rule in a way that the FED funds may react contemporaneously only to real GDP and the price level.

(4) The following part repeats for each draw. If at least one successful A_0 matrix is obtained, the results are recorded. The rotations are repeated until a reasonable number of successful matrices is obtained.

Taking into consideration the order of the variables, we implement the restrictions of para 3 above by creating a Z_1 matrix of size $N_0 \times K$, where N_0 is the number of the zero restrictions on the monetary policy rule. For the case of 8 variables and 5 zero impacts we have:

$$Z_1 = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 \end{bmatrix} \tag{6}$$

By multiplying this matrix by $[(A_0^*)^{-1}]'$ we cut off the three lower rows of the latter. And based on this matrix, say Θ, we begin to build up a matrix Q that shall allow us to obtain the next structural impact matrix. First, we find a null-space matrix, or kernel, for Θ (define as $Null(\Theta) \equiv \mathbf{x}$), that is such a matrix multiplying Θ by which we get zeros:

$$
\Theta \mathbf{x} = \begin{bmatrix} a & a & a & a & a & a & a & a \\ a & a & a & a & a & a & a & a \\ a & a & a & a & a & a & a & a \\ a & a & a & a & a & a & a & a \\ a & a & a & a & a & a & a & a \end{bmatrix} \begin{bmatrix} x & x & x \\ x & x & x \\ x & x & x \\ x & x & x \\ x & x & x \\ x & x & x \\ x & x & x \\ x & x & x \end{bmatrix} = \begin{bmatrix} 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix} \tag{7}
$$

where a-s and x-s are non-null values. Essentially, the values in $\mathbf{x}$ are the solution to the system of linear equations where on the right-hand side we have zeros.

Then, we obtain a $K \times 1$ vector q_j via:

$$
q_j = \mathbf{x} \frac{\mathbf{x}' x_j}{\|\mathbf{x}' x_j\|} \tag{8}
$$

where $\|z\|$ is the 2-norm of z (square root of the sum of the squares). q_j then is input in Q.

The rest of the q_j columns are drawn in the same way with the difference that $\Theta = Q'$. As the result $K \times K$ matrix Q is obtained. Multiplying $[(A_0^*)^{-1}]'$ by Q' gets us a new A_0' matrix.

What is left is to check if the sign restrictions for the structural monetary rule are satisfied. That is, that the 3 last elements of the first column of $[(A_0^*)^{-1}]'$ have the correct sign.

If that is through, I continue with checking that the IRFs obtained with this particular A_0 matrix are consistent with the sign restrictions within the specified horizon. If so we get our successful A_0 matrix as an output.

Once again, step (4) is iterated until we have the sufficient number of A_0-s to allow for ergodicity in the resulting distribution of responses which in my case is around 70 thousand successful A_0 matrices. And correspondingly 70 thousand IRFs. The first graph of the four below shows log real GDP three thousand individual responses to a shock.

Step 4: Obtaining impulse response functions and forecast error variance decompositions

I plot the responses of variables as means and probability bands (90% and 68%) of the distributions. This is implemented through sorting the IRFs at the cross-section of each period so that the individual lines do not overlap - compare the zoomed-in graphs above.

Then the relevant percentiles corresponding to the mean and the required probability bands are chosen. All the loan aggregates, M2 money and the exchange rate are made real. That is the CPI IRFs are deducted from the ones of those variables. All the responses then are normalized to the 0.25% hike in the interest rate - which is a common step for the FED funds rate.

The similar procedure is applied to forecast-error variance decompositions.

The forecast error at horizon $t+k$ conditional on all shocks is given by

$$\begin{aligned} Var[\hat{Y}_{t+k} - \hat{Y}_{t+k|t} | \text{All shocks}] &= \hat{V} + F\hat{V}F' + F^2\hat{V}(F^2)' + ... + F^{k-1}\hat{V}(F^{k-1})' \\ &= \sum_{j=0}^{k-1} F^j \hat{V}(F^j)' \end{aligned} \tag{9}$$

The fraction of the FEV of variable i at horizon $t+k$ due to shock j, for $i, j = 1, 2, 3, ..., N$, is

$$\frac{V^j_{k,(i,i)}}{V_k(i,i)} \tag{10}$$

with $\sum_{j=1}^{N} \frac{V^j_{k,(i,i)}}{V_k(i,i)} = 1$.

A.4 Matlab Code

Main Code

```
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
clear
%
path(path,'/Users/v.krasnogorskiy/Desktop/VKrasnogorskiy/MonetaryPolicyLoansAggregates')
path(path,'/Users/v.krasnogorskiy/Desktop/VKrasnogorskiy/MonetaryPolicyLoansAggregates/LoansData/')
path(path,'/Users/v.krasnogorskiy/Desktop/VKrasnogorskiy/MonetaryPolicyLoansAggregates/matprog/')
path(path,'/Users/v.krasnogorskiy/Desktop/VKrasnogorskiy/MonetaryPolicyLoansAggregates/gibbs/cogmorsar/')
path(path,'/Users/v.krasnogorskiy/Desktop/VKrasnogorskiy/MonetaryPolicyLoansAggregates/gibbs/CogleyPrimiceriSargent/')
path(path,'/Users/v.krasnogorskiy/Desktop/VKrasnogorskiy/MonetaryPolicyLoansAggregates/matprog/stats')
options = optimset;
```

```
options = optimset(options,'Display','off');
warning('off','all')
format short g
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
Delta=0.005;
Horizon=10*12; %Horizon=10*12;
Stationary='N';
NB = 50000; % Number of burn in iterations
NG = 1000; % Number of draws from Gibbs sampler per data file
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
HorizonForSignRestrictions=24;
LagOrder=6;
PriorSampleLength=8; %years
%
NumberOfDraws=15000;
NumberOfRandomRotationMatrices=1000;
%
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
% Loading time series:
X=xlsread('MonetaryPolicyLoansData.xlsx','USMonthly','C217:BB739');
%
[T,N]=size(X);
Time=X(:,1);
LogReserves=log(X(:,2));
LogM2=log(X(:,3));
LogConsumerLoans=log(X(:,4));
LogRealEstateLoans=log(X(:,5));
LogCommercialAndIndustrialLoans=log(X(:,6));
LogOtherLoans=log(X(:,7));
LogNEER=log(X(:,8));
FedFundsRate=X(:,9)/100;
LogRealGDP=log(X(:,10));
LogCPI=log(X(:,11));
LogPPI=log(X(:,13));
LogTotalReserves=log(X(:,14));
LogAggregateLoans=log(sum(X(:,4:6),2));
LogCPI2=log(X(:,15));
LogPPIa=log(X(:,16));
LogWTI=log(X(:,17));
LogSP500=log(X(:,12));
LogHousePrices=log(X(:,18));
LongRate=X(:,19)/100;
```

```
ShortRate=X(:,20)/100;
LogTotalBankCredit=log(X(:,26));
LogTotalLoans=log(X(:,25));
LogTotalCredit=log(X(:,30));
ThreeMTreasury=X(:,32)/100;
LongShortSpread=LongRate ThreeMTreasury;
LogCreditToGovt=log(X(:,27));
LogCreditToHH=log(X(:,28));
LogCreditToNFC=log(X(:,29));
LogSecurities=log(X(:,33));
%
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%
X=[LogReserves LogM2 LogTotalCredit LogSecurities LogNEER
    FedFundsRate LogRealGDP LogCPI];
%Variable at position 4 above is changed for the credit aggregate of
%interest
PositionReserves=1;
PositionM2=2;
PositionTotalCredit=3;
PositionCreditAggregate=4;
PositionNEER=5;
PositionFedFundsRate=6;
PositionGDP=7;
PositionCPI=8;
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
time=Time;
y=X;
Tau=minindc(abs(time (time(1)+PriorSampleLength)));
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
[T,N] = size(y);
% Selecting lag length:
L=LagOrder;
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
% initial estimates through T0
T0 = Tau   L;
% adaptive estimation through T1
T1 = T L;
%
% lagged dependent variables: X1 = [y(t 1) y(t 1) ... y(t L)]
X1 = zeros(T L,1+(N*L));
X1(1:T L,1) = ones(T L,1);
```

```
for i = 1:L,
    X1(1:T L,2+(N*(i 1)):1+(i*N)) = y(1+L i:T i,:);
end
Y = y(1+L:T,:)';
%
[rx1,cx1] = size(X1');
[rx2,cx2] = size(X1');
[rx3,cx3] = size(X1');
[rx4,cx4] = size(X1');
[rx5,cx5] = size(X1');
[rx6,cx6] = size(X1');
[rx7,cx7] = size(X1');
[rx8,cx8] = size(X1');
%
data = [X1';X1';X1';X1';X1';X1';X1';X1'];
rd = size(data,1);
onemat = zeros(rd,size(y,2));
onemat(1:rx1,1) = ones(rx1,1);
onemat(rx1+1:rx1+rx2,2) = ones(rx2,1);
onemat(rx1+rx2+1:rx1+rx2+rx3,3) = ones(rx3,1);
onemat(rx1+rx2+rx3+1:rx1+rx2+rx3+rx4,4) = ones(rx4,1);
onemat(rx1+rx2+rx3+rx4+1:rx1+rx2+rx3+rx4+rx5,5) = ones(rx5,1);
onemat(rx1+rx2+rx3+rx4+rx5+1:rx1+rx2+rx3+rx4+rx5+rx6,6) = ones(rx6,1)
    ;
onemat(rx1+rx2+rx3+rx4+rx5+rx6+1:rx1+rx2+rx3+rx4+rx5+rx6+rx7,7) =
    ones(rx7,1);
onemat(rx1+rx2+rx3+rx4+rx5+rx6+rx7+1:rd,8) = ones(rx8,1);
%
clear X
for i = 1:cx1
    temp(:,:,i) = ndgrid(data(:,i),ones(1,N));
    X(:,:,i) = temp(:,:,i).*onemat;
end
clear rx1 cx1 rx2 cx2 rx3 cx3 rx4 cx4 rx5 cx5 rx6 cx6 rx7 cx7 rx8 cx8
    data rd onemat temp
%
% partitioning the data
Y0 = Y(:,1:T0);
YS = Y(:,1+T0:T1);
X0 = X(:,:,1:T0);
XS = X(:,:,1+T0:T1);
X01 = X1(1:T0,:);
```

```
XS1 = X1(1+T0:T1,:);
time = time(1+T0:T1,:);
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
% Following Primiceri, we assume that the prior for the parameters of the VAR (the states) is normal with mean
% equal to the OLS estimates of the time invariant VAR over the first years of data, and variance equal to
% 4 times its estimated variance:
[B,VARB,U,COV]=varp(Y0',L,'Y');
PriorMU=vec(B'); % Prior for the state
PriorCovarianceMU=VARB; % Prior for its covariance matrix as in Primiceri
max(abs(varroots(L,N,B)))
clear B
InversePriorCovarianceMU=MyInverse(PriorCovarianceMU);
%
% An inverse Wishart prior for the VAR's covariance matrices for the 2 sub samples:
df = N+1; % Prior degrees of freedom
DF = df + T1   T0; % Posterior degrees of freedom
%
COV0 = COV; % Prior covariance matrix
TQ0 = df*COV0; % Prior scaling matrix
TQ = TQ0; % Initialize posterior covariance matrix
% clear initial sample
clear y Y X Y0 X0 X01 T0 T1
[T,N] = size(YS');
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%                          Initialize Gibbs arrays:
% State vector:
BBBB = zeros(N*(1+N*L),NG); % Draws of the state vector
% Covariance matrices:
VVVV = zeros(N,N,NG);
% Reduced form VAR residuals:
UUUU=zeros(T,N,NG);
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
% Initial draw of VAR's coefficients:
[PosteriorMU,PosteriorCovarianceMU]=GetPosteriorMeanCovarianceMUBySubSample(PriorMU,InversePriorCovarianceMU,YS,XS,N,L,T,TQ0); %this is from Luetkepohl page 224, formula 5.4.6.
% CholPosteriorCovarianceMU=sqrt(PosteriorCovarianceMU);
```

```
[VV,DD]=eig(PosteriorCovarianceMU);
CholPosteriorCovarianceMU=VV*DD.^0.5;
MeanPosteriorDraw=zeros(size(PosteriorMU));
CovariancePosteriorDraw=eye(size(PosteriorCovarianceMU));
MU=PosteriorMU+CholPosteriorCovarianceMU*MultivariateNormalRandomDraw
    (MeanPosteriorDraw,CovariancePosteriorDraw,1)';
MaxAbsRoot=max(abs(varroots(L,N,reshape(MU',1+N*L,N)')))
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
VVVV(:,:,1)=TQ0;
%
%
    %%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
DFILE=['/Users/v.krasnogorskiy/Desktop/VKrasnogorskiy/
    MonetaryPolicyLoansAggregates/Results/Securities_BurnIn'];
% Variables to be saved:
varname(1,:) = ['BBBB'];
varname(2,:) = ['VVVV'];
varname(3,:) = ['UUUU'];
varname(4,:) = ['RSNO'];
varname(5,:) = ['RSUN'];
varname(6,:) = ['FILE'];
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%%                              Begin MCMC burn in:
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%
file=1;
while file<=NB/NG
    iter = 2;
    while iter <= NG
        [NB/NG file+1 NG iter+1]
        %
            %%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
        % (1) Drawing the VAR's coefficients:
        [PosteriorMU,PosteriorCovarianceMU]=
            GetPosteriorMeanCovarianceMUBySubSample(PriorMU,
            InversePriorCovarianceMU,YS,XS,N,L,T,VVVV(:,:,iter 1));
        [VV,DD]=eig(PosteriorCovarianceMU);
        CholPosteriorCovarianceMU=VV*DD.^0.5;
        MU=PosteriorMU+CholPosteriorCovarianceMU*
            MultivariateNormalRandomDraw(MeanPosteriorDraw,
```

```
            CovariancePosteriorDraw,1)';
        if file==1
            MaxAbsRoot=1;
        else
            MaxAbsRoot=max(abs(varroots(L,N,reshape(MU',1+N*L,N)'))));
        end
        if abs(MaxAbsRoot 1)<Delta
            BBBB(:,iter) = MU;
            SA=[];
            for tt=1:T
                SA=[SA MU];
            end
            UUUU(:,:,iter)=innovm(YS,XS1,SA,N,T,L)';
            U=UUUU(:,:,iter);
            TQ = TQ0 + U'*U; % Posterior estimate
            VVVV(:,:,iter) = gibbs2Q(TQ,DF,N,L); % Drawing V2
            iter=iter+1;
        end
    end
    % Reinitialize gibbs arrays (buffer for back step)
    BBBB(:,1) = BBBB(:,NG);
    UUUU(:,:,1) = UUUU(:,:,NG);
    VVVV(:,:,1) = VVVV(:,:,NG);
    %
    RSNO=randn('state');
    RSUN=rand('state');
    FILE=file;
    %
    save(DFILE,varname(1,:),varname(2,:),varname(3,:),varname(4,:),
        varname(5,:),varname(6,:),' v7.3');
    %
    file=file+1;
end
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%
clear DFILE varname A0 MU BB UU
DFILE=['/Users/v.krasnogorskiy/Desktop/VKrasnogorskiy/
    MonetaryPolicyLoansAggregates/Results/Securities_Results'];
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
% Variables to be saved:
varname(1,:) = ['MU'];
varname(2,:) = ['BB'];
```

```
varname(3,:) = ['UU'];
varname(4,:) = ['A0'];
varname(5,:) = ['IN'];
IN=1;
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%%                    The ergodic distribution:
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%
Draw=0; %Draw=0;
dd=1; %dd=1;
while dd<=(NumberOfDraws/NG)
    iter = 2; %iter = 2;
    while iter <= NG
        %%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
        % (1) Drawing the VAR's coefficients:
        [PosteriorMU,PosteriorCovarianceMU]=GetPosteriorMeanCovarianceMUBySubSample(PriorMU,InversePriorCovarianceMU,YS,XS,N,L,T,VVVV(:,:,iter 1)); % formula 5.4.6.
        [VV,DD]=eig(PosteriorCovarianceMU);
        CholPosteriorCovarianceMU=VV*DD.^0.5;
        BBBB(:,iter)=PosteriorMU+CholPosteriorCovarianceMU*MultivariateNormalRandomDraw(MeanPosteriorDraw,CovariancePosteriorDraw,1)';
        MaxAbsRoot=max(abs(varroots(L,N,reshape(BBBB(:,iter)',1+N*L,N)'))));
        if abs(MaxAbsRoot 1)<Delta
            SA=[];
            for tt=1:T
                SA=[SA BBBB(:,iter)];
            end
            UUUU(:,:,iter)=innovm(YS,XS1,SA,N,T,L)';
            U=UUUU(:,:,iter);
            TQ = TQ0 + U'*U; % Posterior estimate
            VVVV(:,:,iter) = gibbs2Q(TQ,DF,N,L); % Drawing V2
            %
            bb=reshape(BBBB(:,iter)',1+N*L,N)';
            mu=bb(:,1);
            bb=bb(:,2:size(bb,2));
            Sigma=VVVV(:,:,iter);
            [VV,DD]=eig(Sigma);
            A0Start=VV*DD.^0.5;
```

```
                %
                [a0,IND]=GetA0_MPLA(N,LagOrder,A0Start,bb,
                    NumberOfRandomRotationMatrices,
                    HorizonForSignRestrictions);
                %
                if size(IND,1)>0
                    Draw=Draw+1;
                    Index=sum(IND);
                    MaxAbsRoot=max(abs(varroots(L,N,reshape(BBBB(:,iter)
                        ',1+N*L,N)')));
                    [(NumberOfDraws/NG) dd+1 NG iter+1 Draw sum(IN)
                        MaxAbsRoot]
                    A0(:,:,1:Index,Draw)=a0;
                    IN(Draw,1)=Index;
                    MU(:,:,Draw)=mu;
                    BB(:,:,Draw)=bb;
                    UU(:,:,Draw)=UUUU(:,:,iter);
                end
                iter=iter+1;
            end
        end
        save(DFILE,varname(1,:),varname(2,:),varname(3,:),varname(4,:),
            varname(5,:),'v7.3');
        % Reinitialize gibbs arrays (buffer for back step)
        BBBB(:,1) = BBBB(:,NG);
        UUUU(:,:,1) = UUUU(:,:,NG);
        VVVV(:,:,1) = VVVV(:,:,NG);
        %
        dd=dd+1;
end
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
[(NumberOfDraws/NG) dd+1 NG iter+1 Draw sum(IN) MaxAbsRoot]
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%%                        Impulse response functions
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
NNN=sum(IN);
NN=length(IN);
%
MonetaryPolicyShock=1;
%
IRFs=zeros(Horizon+1,N,NNN);
%
```

```
xx=0;
Draw=1;

        while   Draw<=NN
                bb=BB(:,:,Draw);
                Index=IN(Draw);
                zz=1;
             while  zz<=Index
                    xx=xx+1;
                    a0=A0(:,:,zz,Draw);
                    irfs=GetIRFs(bb,a0,N,LagOrder,Horizon,MonetaryPolicyShock);
                    irfs(:,PositionTotalCredit)=irfs(:,PositionTotalCredit) irfs(:,PositionCPI);
                    irfs(:,PositionCreditAggregate)=irfs(:,PositionCreditAggregate) irfs(:,PositionCPI);
                    irfs(:,PositionM2)=irfs(:,PositionM2) irfs(:,PositionCPI);
                    irfs(:,PositionReserves)=irfs(:,PositionReserves) irfs(:,PositionCPI);
                    irfs(:,PositionNEER)=irfs(:,PositionNEER) irfs(:,PositionCPI);
                    IRFs(:,:,xx)=irfs;
                    zz=zz+1;
             end
             Draw=Draw+1;
             Draw
        end
%
SortedIRFs=sort(IRFs,3);
HOR=(0:1:Horizon)';
%
Percentiles=fix(NNN*[0.5 0.16 0.84 0.05 0.95]');
%
PercentilesIRFs=SortedIRFs(:,:,Percentiles);
PercentilesIRFs=(PercentilesIRFs/PercentilesIRFs(1,PositionFedFundsRate,1))*(0.01/4)*100;
%
for xx=1:N
             Perc=squeeze(PercentilesIRFs(:,xx,:));
             figure(1)
             subplot(2,8,xx)
```

```
            fill_color = [.96 .81 .81];
            plot(HOR,Perc(:,4),'Color',[.96 .81 .81],'LineWidth',0.01);
            plot(HOR,Perc(:,5),'Color',[.96 .81 .81],'LineWidth',0.01);
            x1 = [HOR;flipud(HOR)];
            inBetween=[(Perc(:,4));flipud(Perc(:,5))];
            fill(x1, inBetween, fill_color);
            hold on;
            fill_color = [.87 .51 .51];
            plot(HOR,Perc(:,2),'Color',[.87 .51 .51],'LineWidth',0.01);
            plot(HOR,Perc(:,3),'Color',[.87 .51 .51],'LineWidth',0.01);
            inBetween=[(Perc(:,2));flipud(Perc(:,3))];
            fill(x1, inBetween, fill_color);
            hold on;
            plot(HOR,zeros(size(HOR)),'k:',HOR,Perc(:,1),'k','LineWidth',2);
            xlim([0 Horizon])
 %
            if xx==PositionFedFundsRate
                title('Fed rate')
            elseif xx==PositionTotalCredit
                title('Log real total credit')
            elseif xx==PositionCreditAggregate
                title('Credit Aggregate')
            elseif xx==PositionGDP
                title('Log real GDP')
            elseif xx==PositionCPI
                title('Log CPI')
            elseif xx==PositionNEER
                title('Log real NEER')
            elseif xx==PositionReserves
                title('Log real reserves')
            elseif xx==PositionM2
                title('Log real M2')
            else
            end
end
%
subplot(2,8,1)
```

```
ylabel('IRFs')
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%                    Fractions of Error Variance
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
FractionsOfVariance=zeros(Horizon+1,N,NNN);
%
xx=0;
Draw=1;
while Draw<=NN
    mu=MU(:,:,Draw);
    bb=BB(:,:,Draw);
    Index=IN(Draw);
    zz=1;
    while zz<=Index
        xx=xx+1;
        a0=A0(:,:,zz,Draw);
        FractionsOfVariance(:,:,xx)=GetFractionOfVariance([mu bb],a0,N,LagOrder,Horizon,MonetaryPolicyShock);
        zz=zz+1;
    end
    Draw=Draw+1;
    [Draw xx zz]
end
%
SortedFractionsOfVariance=sort(FractionsOfVariance,3);
HOR=(0:1:Horizon)';
%
PercentilesFractionsOfVariance=SortedFractionsOfVariance(:,:,Percentiles);
%
for xx=1:N
            Perc=squeeze(PercentilesFractionsOfVariance(:,xx,:));
            subplot(2,8,N+xx)
            fill_color = [.79 .91 .98];
            plot(HOR,Perc(:,4),'Color',[.79 .91 .98],'LineWidth',0.01);
            plot(HOR,Perc(:,5),'Color',[.79 .91 .98],'LineWidth',0.01);
            x1 = [HOR;flipud(HOR)];
            inBetween=[(Perc(:,4));flipud(Perc(:,5))];
            fill(x1, inBetween, fill_color);
            hold on;
```

```
            fill_color = [.50 .75 .87];
            plot(HOR,Perc(:,2),'Color',[.50 .75 .87],'LineWidth',0.01);
            plot(HOR,Perc(:,3),'Color',[.50 .75 .87],'LineWidth',0.01);
            inBetween=[(Perc(:,2));flipud(Perc(:,3))];
            fill(x1, inBetween, fill_color);
            hold on;
            plot(HOR,Perc(:,1),'k','LineWidth',2);
            axis([0 Horizon 0 1])
end
subplot(2,8,N+1)
ylabel('FEVs')
%
savefig(figure(1),'/Users/v.krasnogorskiy/Desktop/VKrasnogorskiy/MonetaryPolicyLoansAggregates/Results/Securities_.fig');
clear varname
DFILE=['/Users/v.krasnogorskiy/Desktop/VKrasnogorskiy/MonetaryPolicyLoansAggregates/Results/Securities_Graphs'];
save(DFILE,'PercentilesIRFs','PercentilesFractionsOfVariance','v7.3');
[NN NNN NN/NNN]
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
% Percentiles difference between credit aggregate IRFs and GDP IRFs
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%
HOR=(0:1:Horizon)';
%
Percentiles=fix(NNN*[0.5 0.16 0.84 0.05 0.95]');
%
PercentilesIRFs=SortedIRFs(:,:,Percentiles);
PercentilesIRFs=(PercentilesIRFs/PercentilesIRFs(1,PositionFedFundsRate,1))*(0.01/4)*100;
%
IRFsGDP=squeeze(IRFs(:,PositionGDP,:));
IRFsRealHousePrice=squeeze(IRFs(:,PositionCreditAggregate,:));
DifferenceOfIRFs=IRFsRealHousePrice IRFsGDP;
PercentilesDifferenceOfIRFs=ExtractPercentiles(sort(DifferenceOfIRFs'),[0.5 0.16 0.84 0.05 0.95]')';
%
figure(2)
%
```

```
fill_color = [.97 .87 .67];
plot(HOR,PercentilesDifferenceOfIRFs(:,4),'Color',[.97 .87 .67],'LineWidth',0.01);
plot(HOR,PercentilesDifferenceOfIRFs(:,5),'Color',[.97 .87 .67],'LineWidth',0.01);
x1 = [HOR;flipud(HOR)];
inBetween=[(PercentilesDifferenceOfIRFs(:,4));flipud(PercentilesDifferenceOfIRFs(:,5))];
fill(x1, inBetween, fill_color);
hold on;
fill_color = [.94 .75 .34];
plot(HOR,PercentilesDifferenceOfIRFs(:,2),'Color',[.94 .75 .34],'LineWidth',0.01);
plot(HOR,PercentilesDifferenceOfIRFs(:,3),'Color',[.94 .75 .34],'LineWidth',0.01);
inBetween=[(PercentilesDifferenceOfIRFs(:,2));flipud(PercentilesDifferenceOfIRFs(:,3))];
fill(x1, inBetween, fill_color);
hold on;
plot(HOR,zeros(size(HOR)),'k:',HOR,PercentilesDifferenceOfIRFs(:,1),'k','LineWidth',1);
xlim([0 Horizon])
title('Credit Aggregate')
savefig(figure(2),'/Users/v.krasnogorskiy/Desktop/VKrasnogorskiy/MonetaryPolicyLoansAggregates/Results/SecuritiesLeverage_.fig');
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
```

Obtaining A0 Matrices

```
function [AA00,A0IN]=GetA0_MPLA(N,LagOrder,A0Start,bb,NumberOfRandomRotationMatrices,HorizonForSignRestrictions)
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
% [1] LogReserves
% [2] LogM2
% [3] LogTotalCredit
% [4] LogCreditAggregate
% [5] LogNEER
% [6] FedFundsRate
% [7] LogRealGDP
% [8] LogCPI
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
PositionReserves=1;
PositionM2=2;
```

```
PositionNEER=5;
PositionCPI=8;
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
MonetaryPolicyShock=1;
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
InvA0StartPrime=(MyInverse(A0Start))';
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%                              Monetary policy rule:
% [6] FedFundsRate
% [7] LogRealGDP
% [8] LogCPI
PositionsElementsOfMonetaryRule=[6:8]';
SignsElementsOfMonetaryRule=[1 1 1]';
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%                               Sign restrictions:
% [1] LogReserves
% [2] LogM2
% [5] LogNEER
PositionOfSignRestrictions=[1 2 5]';
SignRestrictions=[1 1 1]';
%
K=length(SignRestrictions);
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%                              Zero restrictions:
% [1] LogReserves
% [2] LogM2
% [3] LogConsumerLoans
% [4] LogCreditAggregate
% [5] LogNEER
NumberOfZeroImpacts=5;
Z1=zeros(NumberOfZeroImpacts,N);
Z1(1:NumberOfZeroImpacts,1:NumberOfZeroImpacts)=eye(
    NumberOfZeroImpacts);
%
AA00=zeros(N,N,NumberOfRandomRotationMatrices);
A0IN=zeros(NumberOfRandomRotationMatrices,1);
%
zz=1;
while zz<=NumberOfRandomRotationMatrices
    Q=[];
    jj=1;
    while jj<=N
```

```
        if jj==MonetaryPolicyShock
            RjofA0ApPlus=[Z1*InvA0StartPrime; Q'];
        else
            RjofA0ApPlus=[Q'];
        end
        NN=null(RjofA0ApPlus);
        xj=randn(N,1);
        qj=NN*((NN'*xj)/norm(NN'*xj,2));
        Q=[Q qj];
        jj=jj+1;
    end
    InvA0Prime=InvA0StartPrime*Q;
    % Here we check that the sign restrictions for the structural monetary rule are satisfied:
    Signs=sign(InvA0Prime(PositionsElementsOfMonetaryRule,MonetaryPolicyShock));
    if any(Signs SignsElementsOfMonetaryRule)==0
        IND=1;
    elseif any( Signs SignsElementsOfMonetaryRule)==0
        InvA0Prime= InvA0Prime;
        IND=1;
    else
        IND=0;
    end
    %
    if IND==1
        A0=MyInverse(InvA0Prime');
        a0=A0;
        a0([PositionReserves PositionM2 PositionNEER],MonetaryPolicyShock)=a0([PositionReserves PositionM2 PositionNEER],MonetaryPolicyShock) a0(PositionCPI,MonetaryPolicyShock);
        % Here we check that the impact of the monetary shock at t=0 has the right sign for the relevant variables:
        if any(sign(a0(PositionOfSignRestrictions,MonetaryPolicyShock)) SignRestrictions)==0
            % Given that it has the right sign, we now check that the IRFs have the right sign:
            irfs=GetIRFs(bb,A0,N,LagOrder,HorizonForSignRestrictions,MonetaryPolicyShock);
            irfs(:,PositionReserves)=irfs(:,PositionReserves) irfs(:,PositionCPI);
```

```
                irfs(:,PositionM2)=irfs(:,PositionM2)  irfs(:,PositionCPI);
                irfs(:,PositionNEER)=irfs(:,PositionNEER)  irfs(:,PositionCPI);
                for xx=1:K
                    if sum(sign(irfs(2:HorizonForSignRestrictions+1,PositionOfSignRestrictions(xx))))==SignRestrictions(xx))<HorizonForSignRestrictions
                        IND=0;
                    end
                end
                if IND==1
                    AA00(:,:,zz)=A0;
                    A0IN(zz)=1;
                end
            end
        end
        zz=zz+1;
end
%
Index=find(A0IN);
%
AA00=AA00(:,:,Index);
A0IN=A0IN(Index);
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
```

B Statement of Authorship

I hereby declare that I have written this thesis without any help from others and without the use of documents and aids other than those stated above. I have mentioned all used sources and cited them correctly according to established academic citation rules. I am aware that otherwise the Senat is entitled to revoke the degree awarded on the basis of this thesis, according to article 36 paragraph 1 letter o of the University Act from 5 September 1996.

Vladimir Krasnogorskiy