UNIVERSITY OF COPENHAGEN
FACULTY OF SOCIAL SCIENCES

Bachelor thesis

The Global Financial Cycle Revisited

The Spillover Effects of US Monetary Policy to the Global Economy

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Submitted: May 3, 2024
Number of characters: Approximately 43,510 (18.12 normal pages)

Abstract

This thesis analyzes the effects of the monetary policy spillovers from the US on the global economy. I use a recursive VAR with seven variables influenced by Rey's (2013) seminal paper to answer my research question. While Rey (2013) focuses on the period 1990Q1-2012Q4, my period is 2001Q4-2023Q3 and analyze if my results differ from hers. The variable for the US monetary policy shock is the short-term interest rate, the effective federal funds rate. By estimating impulse response functions, I analyze how a shock to the effective federal funds rate impacts the global risk, as measured by the VIX. Also, how the VIX impacts the global financial cycle. The variables for the global financial cycle of the recursive VAR's are the leverage of European banks, global domestic credit, and cross-border credit flows (Rey, 2013).

The findings of my thesis points to continued existence of monetary policy spillovers from the US to the global economy. However, the spillovers are smaller in the COVID-19 period possible due to more efficient regulation. A US monetary loosening, for instance, is found to decrease global risk, thereafter increasing the leverage for European banks. However, in the COVID-19 sample, a lower global risk will result in lower global domestic credit and lower cross-border credit flows. These newer results might be a result of the increased regulations to reduce excessive risk-taking (Saft, 2016). My results highlights the crucial role of US monetary policy in creating financial stability of the global economy.

Keywords: Financial integration, Monetary Policy Spillovers, The Global Financial Cycle.

JEL classification: E52, E58, F02, F33, G15

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1 Introduction

In the decades after a harsh period with the Great Depression and two world wars, financial integration seemed to be a blast from the past. However, since 1990, policymakers have again worked to open the financial markets to other countries (Rey, 2013). Financial integration might be here to stay and will play a more significant role in the future, especially with the potential expansion of the EU. This realization raises an exciting question for tomorrow's policymakers: Is financial integration merely a bed of roses, or are there some negative consequences? The Global Financial Crisis shattered the international consensus that financial integration was a win-win game. Academic discussions on the potential effects resurfaced, and a new aspect emerged: the loss of financial stability. Hence, I aim to answer the same question Rey (2013) raises: *"How does the US monetary policy affect the global financial cycle?"* And: *"Are the monetary policy spillover effects still as large as in Rey (2013)?"*

Hélène Rey's (2013) research found that European economies experienced spillover effects from US monetary policy through the global risk measured by the VIX to the leverage of the European banks. Her results became a beacon of academic recognition. Her analysis, focused on the Global Financial Crisis, was internationally acknowledged by academic peers and international organizations such as the IMF, further highlighting the importance of her findings. The US monetary policy propagates to the global financial cycle via the risk-taking channel of monetary policy (Bruno & Shin, 2012). In some countries, the US monetary policy spillover effects are even larger than the domestic effects in the US (Georgiadis, 2015).

Since Rey's (2013) important work, many economic events have occurred, most notably the COVID-19 crisis and the Russian Invasion of Ukraine. The macroeconomic tools have also changed, with policymakers focusing more on regulation and macroprudential policies. It would be interesting to update Rey's (2013) recursive VAR with newer data and analyze if her conclusions have changed.

To answer the research question, I take considerable inspiration from Rey's (2013) recursive VAR. However, I use data for the period 2001Q4-2023Q3. The structural shocks in the recursive VAR are derived using Cholesky decomposition, with the variables ordered higher being: European banking sector leverage, the effective federal funds rate, and the volatility index, the VIX. From the orthogonalized errors, I estimate structural impulse response functions (Killian & Lütkepohl, 2016). From the shocks to the system, I analyze how the variables for the global financial cycle respond to a FED loosening.

My empirical findings point to the importance of US monetary policy in determining the global financial cycle but to a lesser extent than in Rey's (2013) recursive VAR. A US monetary policy shock will propagate to the global economy via the global financial cycle. The propagation is as follows: a US monetary policy loosening will decrease global market risk measured by the VIX. If the VIX decreases, then the European Banking Sector Leverage will increase. However, the US monetary policy spillovers are lower in the COVID-19 period. Moreover, an increase in the leverage of the European banks further lowers the

VIX. Furthermore, the decrease in the VIX will decrease both the credit inflow and global domestic credit. These latter two results differ from Rey's (2013) findings, as she finds that a decrease in the VIX will increase credit and credit inflow. These new dynamics and the lower US monetary spillover effects might be due to more developed international financial markets because of more efficient regulation (Saft, 2016). Additionally, I find that higher leverage for European banks and credit growth will lead to a fall in the VIX. This result is consistent with the risk-taking channel of monetary policy (Bruno & Shin, 2012).

2 Macroeconomic background

This section provides an overview of the empirical studies that have shaped my analysis and influenced the academic research on US monetary policy spillovers.

2.1 The methodological issues

Empirical results from papers find no robust causality between financial integration and economic growth. One reason is the issue of reverse causality. The countries that have opened their financial markets are also highly developed (Edison et al., 2002). Another reason is endogeneity issues because it is complex to account for all determinants of growth (Rey, 2013). Furthermore, a recent theoretical study by Coeurdacier et al. (2020) finds that the effects of financial integration are heterogeneous. The effects are heterogeneous since they depend on how large the economies are and their level of capital before they integrate their financial markets with other economies (Coeurdacier et al., 2020). This acknowledgment is vital, as most empirical papers focus on average rather than the effects for the individual economies. Finally, economists use many different methods of measuring financial integration. As a result of the methodological challenges, recent papers on financial integration focus on the US monetary policy spillovers.

2.2 The Global Financial Cycle

Financial integration has changed the dynamics of the international financial markets by making them more interdependent. For instance, introducing the euro has increased the interdependence between the euro-area countries and the US (Lane, 2008). This interdependence on the financial markets has given rise to a modern phenomenon known as the *'Global Financial Cycle'* (Rey, 2013). The *'Global Financial Cycle'* refers to the contemporaneous movement of prices for financial assets, banks' leverage, global domestic credit, and cross-border credit flows (Rey, 2013). It also involves a synchronization of global risk aversion and uncertainty, often measured by the VIX (Forbes & Warnock, 2012). A *'global factor'* triggers these co-movements (Rey, 2013). However, what exactly drives this global factor? US monetary policy is the answer, as it is the center economy in the financial markets. For example, the dollar is the anchor currency, the global economy's primary reserve currency (Rey, 2013). Kalemli-Özcan (2019) also finds strong evidence that US monetary policy affects global risk, which propagates to domestic credit costs. Moreover, they find that the spillovers from US monetary policy are larger in emerging markets (Kalemli-Özcan, 2019).

2.3 The international transmission channels of monetary policy

Two main channels of monetary policy transmit to the global financial cycle: the risk-taking channel (Borio & Zhu, 2008) and the credit channel (Bernanke & Gertler, 1989). Before the Global Financial Crisis, central bankers overlooked how short-term interest rates affect banks' financial intermediation (Borio & Zhu, 2012). However, Borio and Zhu (2008) found a new monetary policy transmission channel. The monetary policy from the US propagates to the VIX via the risk-taking channel, which impacts the financial markets more directly than the other channels. The risk-taking channel of monetary policy operates in this cycle: A US monetary policy loosening will make it cheaper for foreign banks to fund their investment and lending using the dollar. Decreased costs for the banks impact their incentives, making them less risk-averse. Their incentives change as they borrow given the short-term interest rate, whereas they lend given the long-term interest rate. So, a lower short-term rate will make the yield curve more steep. As a result of the decreased risk aversion, international banks increase their leverage by financing their assets to a greater extent via debt rather than equity. The currencies in the economies the capital flows into will appreciate because of higher demand for the US dollar. The appreciated currencies strengthen the domestic borrowers' balance sheets in the capital flow-recipient economies, decreasing the risk for international banks' loans. Ultimately, this will create a cycle where the leverage of the international banks increases again (Borio & Zhu, 2012).

Empirical evidence on the matter also confirms these channels. The seminal paper from Rey (2013) finds that the US monetary policy spillovers transmit to the global economy via cross-border credit and leverage. Bruno and Shin (2012) also find evidence for the risk-taking channel, as a FED loosening will increase banking sector capital flows because of the bank's leverage. Results from a global VAR also find that the two channels are the same for unconventional US monetary policy (Georgiadis, 2015). Finally, US monetary policy spillovers remain significant after the Global Financial Crisis (Miranda-Agrippino & Rey, 2020).

2.4 Optimal monetary policy in an interconnected world

The international transmission channels of US monetary policy led to a sudden shift from the impossible trinity. Instead, an 'irreconcilable duo' arises where economies with floating and fixed exchange rates face a dilemma: they must use capital controls or macroprudential policies to implement independent monetary policy (Rey, 2013). Macroprudential policies are policies that aim to create financial stability in an economy (Milne, 2009). Such policies are necessary for central bankers to implement optimal monetary policy, where they can stabilize the domestic output gap and inflation. If the non-center economies do not implement the policies, all economies except the US will, in principle, have fixed exchange rate regimes.

Implementing financial integration has both positive and negative effects. Financial integration poses an economic trade-off between a faster transition to a steady state and financial stability (Georgiadis, 2015). This trade-off is also why some economists argue that financial integration is only efficient when combined with government regulation. Otherwise, banks will become too leveraged because of profitable transactions. A leverage that is too high can cause systemic risk, like during the Global Financial Crisis (Stiglitz, 2010). Central banks, including the European Central Bank, have implemented macroprudential policies to lower banks' leverage and excessive risk-taking to prevent these systemic risks.

3 Description of Data

This section describes the collected data and the calculated variables (see Appendix A for a technical understanding). The seven variables in my model are the same as Rey (2013) uses in her seminal paper. They are given by GDP, GDPDEF, CREDIT, INFLOW, EULEV, EFFR, and the VIX (Rey, 2013). The variables are essential in the dynamics of the global financial markets, and some are predictors of financial crises (Rey, 2013). My sample is more recent, spanning from 2001Q4 to 2023Q3. I collect data for GDP, GDPDEF, EFFR, and the VIX from the Federal Reserve of Saint Louis. Moreover, I collect data for CREDIT, INFLOW, and EULEV from IFS. Three of the seven variables are relevant: the European banking sector leverage (EULEV), the effective federal funds rate (EFFR), and the CBOE volatility index (VIX). Look at Appendix A for a description of the other variables, calculation, and citation for all variables.

3.1 The Effective Federal Funds Rate (EFFR)

The US monetary policy variable in my recursive VAR is the effective federal funds rate (EFFR). The Federal Reserve calculates the effective federal funds rate as the median of the effective overnight rate at which banks in the US borrow reserves on the interbank market. I use the effective federal funds rate, as it is a short-term rate, which implies that it is affected more directly by monetary policy (Bruno & Shin, 2012). If I used a long-term rate instead, the changes would depend more on other factors than monetary policy. I collect the effective federal funds rate as monthly data, which I aggregate into quarterly data by taking the quarterly average.

3.2 CBOE Volatility Index (VIX)

I use the CBOE Volatility Index (VIX) to measure global risk in my recursive VAR. The VIX measures the expected forward-looking volatility of the stock market. Generally, a lower VIX will cause an increase in the prices of stocks. Chicago Board Options Exchange (CBOE) calculates it by the options prices in the S&P500 index. I use the daily calculated VIX (VIXCLS), the closing value. I aggregate the VIX into quarterly data by taking the average for each quarter. This definition contrasts Rey as she uses quarterly data provided by CBOE. I take the natural logarithm of the VIX to normalize the impulse response functions. The VIX is essential in my recursive VAR, as it is synchronized with the global financial cycle (Rey, 2013).

3.3 European Banking Sector Leverage (EULEV)

One of my variables for the global financial cycle in the recursive VAR is the European Banking Sector Leverage (EULEV). Banking Sector Leverage is the ratio between a banking sector's debt relative to the sector's capital (Rey, 2013). A high banking sector leverage implies that the banks finance their assets using loans rather than equity. Higher leverage can be a cause of concern, as it is one of the indicators of instability in the financial sector (Bruno & Shin, 2012). The focus is on the European banks, as the Euro Area is highly financially integrated with the US (Lane, 2008). Furthermore, a high degree of financial development often implies a higher leverage, and the Euro Area has one of the most developed financial markets (Georgiadis, 2015).

3.4 Descriptive statistics of the variables

I create times series plot in Figure 3.4.1 to inspect the stationarity of my variables.

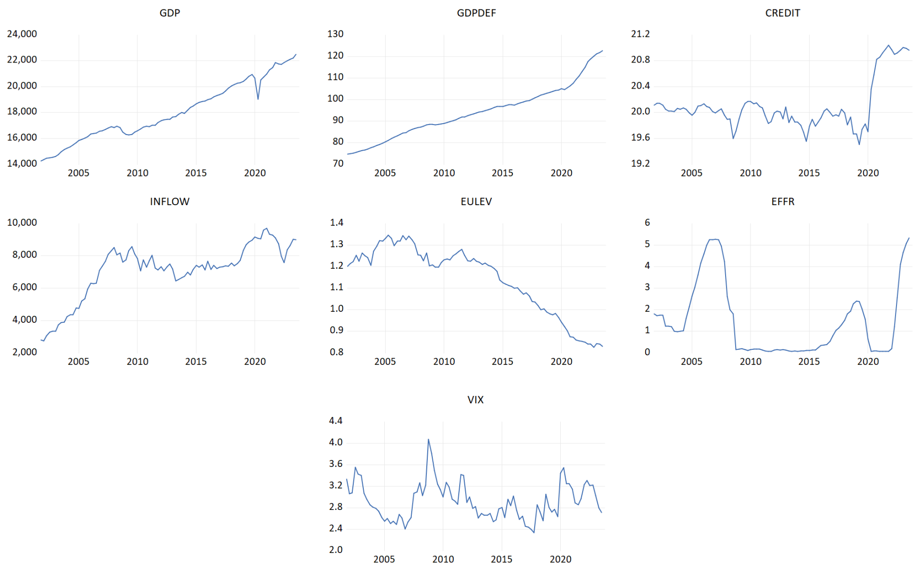

Figure 3.4.1: Times series plots for the variables

The descriptive statistics for the variables can be seen in Table 3.4.1.

	GDP	**GDPDEF**	**CREDIT**	**INLFOW**	**EULEV**	**EFFR**	**VIX**
Mean	18029.38	94.14	20.1	7071.89	1.13	1.45	2.92
Median	17479.75	93.65	20.02	7374.6	1.2	0.99	2.85
Maximum	22490.69	122.76	21.04	9710.6	1.34	5.33	4.07
Minimum	14253.57	74.79	19.5	2710.6	0.82	0.07	2.33
Std. Dev.	2245.8	12.03	0.37	1709.51	0.15	1.66	0.34
Skewness	0.27	0.44	1.37	-0.99	-0.69	1.16	0.7
Kurtosis	2.02	2.7	4.05	3.28	2.18	3.12	3.36
Observations	88	88	88	88	88	88	88

Table 3.4.1: Descriptive statistics of the variables in the recursive VAR analysis

4 Econometric model

This section explains my recursive VAR, its importance, and its limitations in answering my research question. The model's econometric theory is from Killian and Lütkepohl's textbook (2016). I take considerable inspiration from Rey's (2013) recursive VAR to analyze the spillovers from a US monetary policy shock.

4.1 Reduced form Vector Autoregression

In order to estimate my recursive VAR, I have to first estimate a reduced form VAR. My general reduced form VAR equation is:

$$\underset{7\times 1}{y_t} = \underset{7\times 7}{A_1}\underset{7\times 1}{y_{t-1}} + \underset{7\times 7}{A_2}\underset{7\times 1}{y_{t-2}} + \cdots + \underset{7\times 7}{A_p}\underset{7\times 1}{y_{t-p}} + \underset{7\times 1}{u_t} \tag{4.1.1}$$

The endogenous variables of my reduced form VAR correspond to that of Rey (2013):

$$\underset{7\times 1}{y_t} = \begin{pmatrix} \mathrm{GDP}_t \\ \mathrm{GDPDEF}_t \\ \log(\mathrm{CREDIT}_t) \\ \mathrm{INFLOW}_t \\ \mathrm{EULEV}_t \\ \mathrm{EFFR}_t \\ \log(\mathrm{VIX}_t) \end{pmatrix} \tag{4.1.2}$$

My model's coefficients are in the 7×7 A-matrix.

$$\underset{7\times 7}{A_1} = \begin{pmatrix} a_{11} & a_{12} & a_{13} & a_{14} & a_{15} & a_{16} & a_{17} \\ a_{21} & a_{22} & a_{23} & a_{24} & a_{25} & a_{26} & a_{27} \\ a_{31} & a_{32} & a_{33} & a_{34} & a_{35} & a_{36} & a_{37} \\ a_{41} & a_{42} & a_{43} & a_{44} & a_{45} & a_{46} & a_{47} \\ a_{51} & a_{52} & a_{53} & a_{54} & a_{55} & a_{56} & a_{57} \\ a_{61} & a_{62} & a_{63} & a_{64} & a_{65} & a_{66} & a_{67} \\ a_{71} & a_{72} & a_{73} & a_{74} & a_{75} & a_{76} & a_{77} \end{pmatrix} \tag{4.1.3}$$

The errors for my reduced form VAR are:

$$\underset{7\times 1}{u_t} = \begin{pmatrix} u_t^{\mathrm{GDP}} \\ u_t^{\mathrm{GDPDEF}} \\ u_t^{\mathrm{CREDIT}} \\ u_t^{\mathrm{INFLOW}} \\ u_t^{\mathrm{EULEV}} \\ u_t^{\mathrm{EFFR}} \\ u_t^{\mathrm{VIX}} \end{pmatrix} \tag{4.1.4}$$

4.2 Inference

To analyze the properties of my estimator, I conduct misspecification tests, where I use a significance level of five percent.

4.3 Structural Vector Autoregression

A recursive VAR is a special type of a Structural Vector Autoregression (SVAR). SVARs are VAR models, where the shocks in the model are theoretically grounded (Killian & Lütkepohl, 2016). The SVAR is given by:

$$\underset{7\times7}{B_0}\underset{7\times1}{y_t} = \underset{7\times7}{B_1}\underset{7\times1}{y_{t-1}} + \underset{7\times7}{B_2}\underset{7\times1}{y_{t-2}} + \ldots + \underset{7\times7}{B_p}\underset{7\times1}{y_{t-p}} + \underset{7\times7}{B_0^{-1}}\underset{7\times1}{w_t} \tag{4.3.1}$$

4.4 Cholesky decomposition

The errors must be mutually uncorrelated to estimate a recursive VAR, referred to as orthogonalization. I orthogonalize the errors, u_t, using Cholesky decomposition, ordering variables like Rey (2013). The order is a causal chain that makes it recursive. The VAR is recursive since the variable ordered first will only respond to shocks to the variable ordered first in the first quarter. In the first quarter, the variable ordered second will only respond to a shock in the variable ordered first and the variable itself. The equation for the last order variable will consist of its lagged values and all the lower variables. The causal chain should be grounded in theoretical considerations (Killian & Lütkepohl, 2016). My order is GDP, GDPDEF, CREDIT, INFLOW, EULEV, EFFR, and the VIX. For a visualization of the contemporaneous effects; see Figure B.2.

I describe the theoretical rationale based on institutional knowledge for ordering the variables in the recursive VAR. The variable ordered first is the US GDP, a more long-run variable that will only respond contemporaneously to shocks to itself. The second ordered variable is the GDP Deflator because US inflation should respond contemporaneously to US GDP. The theoretical rationale behind this ordering is due to Okun's law, which is the inverse relationship between observed unemployment and GDP (Okun, 1962). So, an increase in US GDP causes US unemployment to fall. From the fall in unemployment, salaries will increase such that inflation increases cf. the Phillips curve (Phillips, 1958).
The variable ordered third is global domestic credit. Global domestic credit should respond within the first quarter to US GDP, as a higher US GDP will increase the demand for global credit, which leads to credit growth (Gillchrist et al., 2014). Furthermore, global domestic credit should rise when there is a positive US inflation shock. Higher US inflation will, ceteris paribus, lead to a depreciation of the US Dollar. From this, international firms' currency risks will decrease, as the global reserve currency is the US dollar (Rey, 2013). Also, since the debt is lower then banks more may be willing to lend. These relationships are due to financial integration, where a domestic shock to a large economy such as the US transmits to the international financial markets. The variable ordered fourth is the cross-border credit flow.
However, the ordering of global domestic credit and cross-border credit flow does not matter for my interpretations, as I will show in my robustness checks. It is just an assumption that Rey (2013) uses to build the recursive VAR, and this approach is called partial identification. This is because I am primarily interested in the three last-ordered variables. I use the exact ordering as Rey (2013) either way to better compare my results to hers.
The variable ordered fifth is the European Banking Sector Leverage. The leverage of the European banks should increase from a positive shock to cross-border

credit flow and global domestic credit since more credit is available. The variable ordered second-last is the effective federal funds rate such that it can respond contemporaneously to all variables but not the VIX. The effective federal funds rate responds to a contemporaneous shock to the leverage of European banks. This is because the financial markets are interconnected, and thereby, leverage might transmit to the effective federal funds rate by changing the demand for money (Georgiadis, 2015). The variable ordered last is the VIX, which will respond contemporaneously to shocks from all variables in the recursive VAR. The VIX is ordered last, as the effective federal funds rate can affect global risk by signaling the future economic situation to investors. Moreover, the VIX responds to contemporaneous shock to the leverage of European banks via the risk-taking channel of monetary policy (Section 2.3). With this causal chain in the recursive VAR, it will be possible to analyze how a US monetary policy shock propagates to the global financial cycle.

I estimate a lower-triangular Cholesky decomposition matrix for the contemporaneous shocks in the recursive VAR:

$$\underset{7\times 7}{B_0}^{-1} = \begin{pmatrix} b_{11} & 0 & 0 & 0 & 0 & 0 & 0 \\ b_{21} & b_{22} & 0 & 0 & 0 & 0 & 0 \\ b_{31} & b_{32} & b_{33} & 0 & 0 & 0 & 0 \\ b_{41} & b_{42} & b_{43} & b_{44} & 0 & 0 & 0 \\ b_{51} & b_{52} & b_{53} & b_{54} & b_{55} & 0 & 0 \\ b_{61} & b_{62} & b_{63} & b_{64} & b_{65} & b_{66} & 0 \\ b_{71} & b_{72} & b_{73} & b_{74} & b_{75} & b_{76} & b_{77} \end{pmatrix} \tag{4.4.1}$$

With Cholesky decomposition, the orthogonalized standard errors for my just-identified model, becomes:

$$\underset{7\times 1}{u_t} = \underset{7\times 7}{B_0^{-1}} \underset{7\times 1}{w_t} \tag{4.4.2}$$

In matrices, the orthogonalized errors are (Killian & Lütkepohl, 2016):

$$\begin{pmatrix} u_t^{\text{GDP}} \\ u_t^{\text{GDPDEF}} \\ u_t^{\text{CREDIT}} \\ u_t^{\text{INFLOW}} \\ u_t^{\text{EULEV}} \\ u_t^{\text{EFFR}} \\ u_t^{\text{VIX}} \end{pmatrix} = \begin{bmatrix} b_0^{11} & 0 & 0 & 0 & 0 & 0 & 0 \\ b_0^{21} & b_0^{22} & 0 & 0 & 0 & 0 & 0 \\ b_0^{31} & b_0^{32} & b_0^{33} & 0 & 0 & 0 & 0 \\ b_0^{41} & b_0^{42} & b_0^{43} & b_0^{44} & 0 & 0 & 0 \\ b_0^{51} & b_0^{52} & b_0^{53} & b_0^{54} & b_0^{55} & 0 & 0 \\ b_0^{61} & b_0^{62} & b_0^{63} & b_0^{64} & b_0^{65} & b_0^{66} & 0 \\ b_0^{71} & b_0^{72} & b_0^{73} & b_0^{74} & b_0^{75} & b_0^{76} & b_0^{77} \end{bmatrix} \begin{pmatrix} w_{1t} \\ w_{2t} \\ w_{3t} \\ w_{4t} \\ w_{5t} \\ w_{6t} \\ w_{7t} \end{pmatrix} \tag{4.4.3}$$

Equation (4.4.3) shows how the contemporaneous shocks are ordered in the causal chain. The coefficients not on the main diagonal are the contemporaneous responses from shocks in my causal chain, whereas the main diagonal shows the effects of a shock on the given variable. Each coefficient, b, shows the contemporaneous effect of a shock on the variables. The zeros indicate that the given variable does not respond to the contemporaneous shock.

4.4.1 Advantages and limitations of the recursive VAR

I use a recursive VAR to interpret the causal short-run relationships between my variables. If I used a reduced form VAR to analyze the short-run relationships, it would be hard to interpret the causal relationships since all of my variables would respond to each other within the first quarter. Consequently, I could not analyze the propagation of a US monetary policy shock. Furthermore, using the recursive VAR, I can decompose the forecast error variance of the VIX (Killian & Lütkepohl, 2016).

Generally, macroeconomists often use recursive VARs to analyze short-run dynamics. However, they do pose some challenges. One of the challenges is to analyze the sensibility of the ordering. In my recursive model, I have seven different orders, but I cannot be sure about the precise Cholesky ordering of the variables (Killian & Lütkepohl, 2016). Rey (2013) bases the ordering on assumptions from institutional knowledge, which I have argued for in Section 4.4. For my recursive VAR, there are $7! = 5040$ possible orderings. However, I will ignore this consideration for the empirical analysis and assume that the ordering of the last-ordered variables is still correct.

4.5 Structural Impulse Response Functions

I estimate the structural shocks based on the orthogonalized errors from equation (4.4.3). There are seven shocks in my recursive VAR, as I assume that the number of shocks equals the number of variables (Killian & Lütkepohl, 2016). The number of structural impulse response functions in my model is $7^2 = 49$. The x-axis is denoted by the quarters i = 0,1,2,...,20. From the responses and shocks, I estimate the structural impulse response functions as follows:

$$\frac{\partial y_t}{\partial w'_{t-i}} = \frac{\partial y_{t+i}}{\partial w'_t} = \Theta_i, \quad i = 0,1,2,...,20 \tag{4.5.1}$$

Since my recursive VAR is linear, the opposite response will occur if I analyze a negative structural shock instead of a positive one (Killian & Lütkepohl, 2016). I will utilize this property in my empirical analysis of the propagation of a US monetary policy loosening.

4.5.1 Bootstrap estimation of confidence intervals

I estimate the confidence intervals for the responses in my impulse response functions by bootstrapping. Bootstrapping is a method used to approximate a sampling distribution based on the observed data. I use 1000 bootstrap replications, $\hat{\theta} = (\theta_1^*, \theta_2^*, \ldots, \theta_{1000}^*)$. Here, the confidence interval of 95 percent will be given by: $[\theta_{25}^*, \theta_{975}^*]$. Ultimately, when using bootstrapping, I want to approximate the distribution of the sample by a bootstrap distribution, $\hat{\theta}_B - \hat{\theta}$ (Singh & Xie, 2010). Furthermore, I use Hall's (1992) percentile, where the *"Edgeworth expansion"* term is added. This extra term accounts for the skewness of the data, thereby increasing the accuracy. I chose this method as an assumption of asymptotic confidence intervals because I do not know the asymptotic distribution of the data.

5 Empirical results

In this section, I find the empirical results for my research question by estimating the impulse response functions from the recursive VAR.

5.1 Unit root analysis

I begin by examining the stationarity of the variables included in the recursive VAR. This procedure is essential because stationarity of the VAR is required for the impulse response functions (Killian & Lütkepohl, 2016). Based on graphical inspection, it could be the case that my variables are trend-stationary. Therefore, I include a time trend in the reduced-form VAR to eliminate the trend effects. Also, by removing the variables' common trend components, I decrease their correlation. By decreasing their correlation, I avoid multicollinearity and ensure more accurate estimates (Table B.8).

I conduct Augmented Dickey-Fuller tests to test for the presence of unit roots, and thereby non-stationarity, in the variables; see Table B.1. I impose a maximum of four lags in the test, as my data are quarterly, and the criterion used is the Schwarz info criterion; see Table B.3. All the tests conducted on the level variable with an intercept and a time trend do not lead to a rejection of the null hypothesis of a unit root.

Usually, I make all of my variables stationary by taking their differences to ensure my estimates are consistent and avoid spurious correlations. However, in my recursive VAR, I ignore the non-stationary of my variables if and only if my reduced form VAR is stable. This is first and foremost because I am only interested in the short-run dynamics. Second, if I take the differences of first order, then there is a risk of my estimates becoming inconsistent because of white noise (Georgiadis, 2015). I would lose information, and it would be harder to interpret the short-run dynamics from the impulse response functions. Furthermore, the variables would adjust to their equilibria too quickly compared to Rey's (2013) impulse response functions.

5.2 Estimation of the reduced-form VAR

I estimate the reduced form VAR after describing my empirical considerations about the stationarity of my variables. The suggested lag length is at two lags based on the lag length criteria (LR, FPE, AIC, SC, and HQ) (Figure B.2). This is because LR, FPE, and AIC are lowest at two lags, while SC and HQ are lowest at one lag. Therefore, my preferred reduced form VAR is VAR(2) since it had lower information criteria than VAR(1). Adding more lags also increases the risk of instability in my impulse response functions (Bruno-Shin, 2012).

I create a graph for the inverse roots of the Autoregressive characteristic polynomial to ensure the stationarity and stability of my reduced form VAR (see Figure B.1). All inverse roots are inside the unit circle in the complex plane; therefore, my reduced form VAR is stable, and the VAR residuals are stationary. This result is no coincidence, as it suggests some co-integrating relationships between the variables in my reduced-form VAR rather than spurious relationships.

I conduct a Johansen unrestricted cointegration rank test (Table B.7). Based on the trace tests, I find five co-integrating equations in my reduced-form VAR.

5.2.1 Misspecification tests

I conduct misspecification tests to investigate the properties of my variables and VAR. First, I test for autocorrelation using a Lagrange Multiplier test and find that my residuals are not serially correlated (Table B.3). The next tests are normality tests with Cholesky of covariance as the orthogonalization method. The residuals in US GDP and Effective Federal Funds Rate are non-Gaussian distributed. Next, I conduct heteroskedasticity tests with no cross terms. The residuals in US GDP, US GDP Deflator, CREDIT, Effective Federal Funds Rate, and my model suffer from heteroskedasticity. The non-gaussian and heteroskedastic residuals may result in biased and inefficient estimates, and a better estimator will exist. Inefficiency occurs because I estimate the reduced-form VAR(2) using Quasi-Maximum Likelihood.

Furthermore, the effective federal funds rate shows signs of ARCH effects (Table B.6). The ARCH effects affect my model, as I need to estimate it using a heteroskedasticity robust estimator such as the MLE or QMLE. Finally, I conduct a RESET test for the correct functional form. With a test statistic of 3.58, my variables might have a misspecified functional form. I want to keep the failed RESET test in mind, but I do not transform my variables further, as I want my results to be comparable to Rey's (2013) results.

5.3 The structural impulse response functions

I use Cholesky decomposition on the variables in this order: US GDP, US GDP Deflator, Global Domestic Credit, Global Inflow, and European Banking Sector Leverage (Rey, 2013). The ordering has been chosen based on institutional knowledge, which I account for in Section 4.4

Furthermore, I use the degrees of freedom adjusted Cholesky ordering with a one standard deviation shock (Table 3.4.1). The standard errors are estimated as bootstrap errors using Hall's percentile. The errors are bootstrap since I reject normality in my residuals and do not know the asymptotic distribution. Using bootstrap errors, I ensure that the errors are robust. In addition, the percentile method is the Hall's percentile since it is more robust to skewed data than the standard percentile (Hall, 1992). The 95 percent confidence interval is computed using 1000 single bootstrap replications. The total number of quarters is 20, which makes it easier to compare to Rey (2013) in section 7. I have included the essential impulse response functions in Figures 5.4.1 to 5.4.5, while the other results are in Figure B.3.

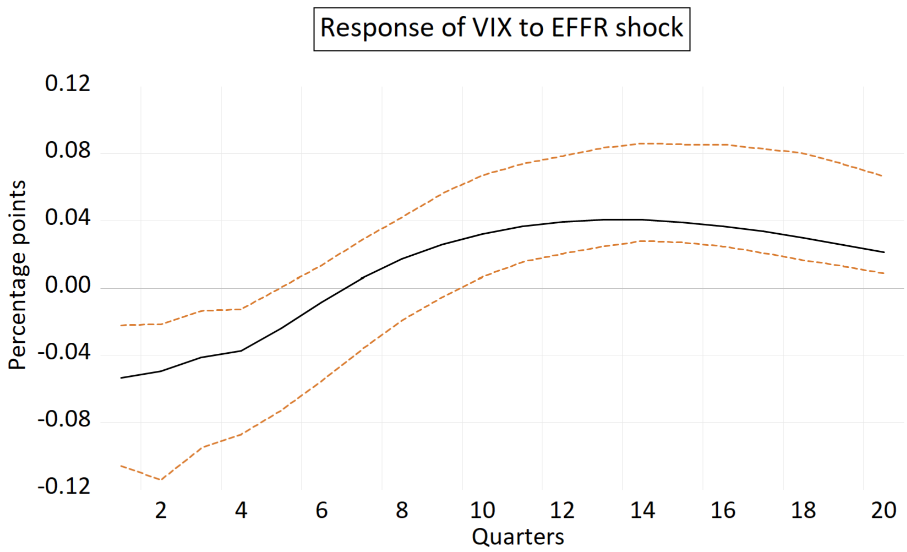

Figure 5.4.1: Response of VIX to a shock in the Effective Federal Funds Rate

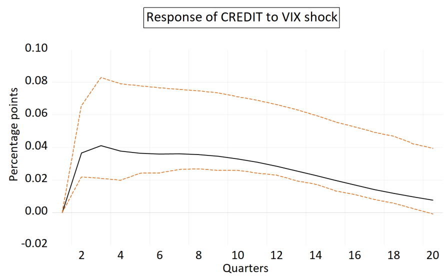

Figure 5.4.2: Response of global domestic credit to a shock in the VIX

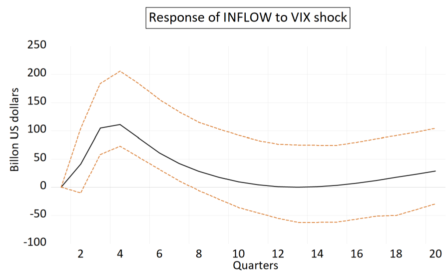

Figure 5.4.3: Response of cross-border credit flow to a shock in the VIX

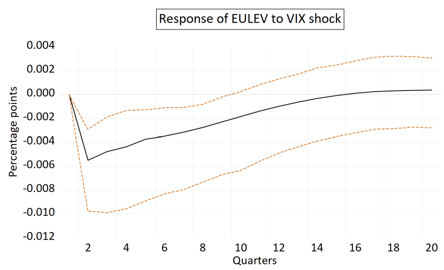

Figure 5.4.4: Response of European Banking Sector Leverage to a shock in the VIX

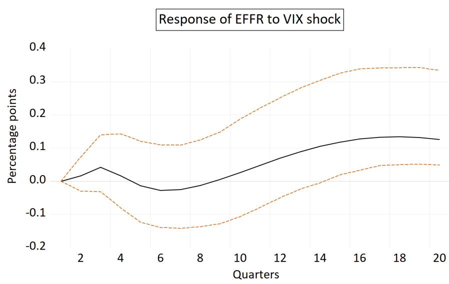

Figure 5.4.5: Response of Effective Federal Funds Rate to a shock in the VIX

5.4 Empirical findings

In this subsection, I list my impulse response functions' most important significant results. Impulse response functions are significant when the confidence interval does not contain zero. From the impulse response function in Figure 5.4.1, I find that the VIX initially will decrease until the five quarters from a 1.66 bonus point shock (Table 3.4.1) in the effective federal funds rate. Hereafter, the VIX will increase from 10 quarters. From a positive VIX shock, the leverage of European banks will decrease until ten quarters, as seen in Figure **??**. A positive shock to the VIX increases global domestic credit until 19 quarters, as seen in Figure **??**. A negative shock to the VIX results in a decrease in the cross-border credit inflow until eight quarters.

The following results can be found in the impulse response functions in the appendix (Figure B.3). A positive shock to the VIX will increase the effective federal funds rate after 14 quarters. The leverage of the European banks will decrease in quarters 12 to 16 after a US monetary policy shock. A positive shock to European banking sector leverage will decrease the global domestic credit until 19 quarters. A positive shock to the effective federal funds rate will decrease European banks' leverage in quarters 12 to 15. A positive shock to the effective federal funds rate increases the global domestic credit after 13 quarters. A positive shock to European banking sector leverage decreases the VIX until ten quarters. A positive shock to the European banking sector leverage decreases global domestic credit. A positive shock to the VIX will cause the US GDP Deflator to increase after five quarters. A positive shock to CREDIT will decrease VIX until five quarters and increase after 15 quarters.

5.5 The impact of a US monetary policy shock on the VIX

To further analyze the impact of the effective federal funds rate on the VIX, I decompose the forecast error variance for the VIX into shocks of the variables using my recursive VAR in Figure 5.6.1 (Killian & Lütkepohl, 2016). I estimate the standard errors using 1000 Monte Carlo repetitions. For over 20 quarters, the impact of the effective federal funds rate shocks on the variance in VIX is, on average, approximately 12 percent. However, the impact is insignificant since the confidence interval contains zero.

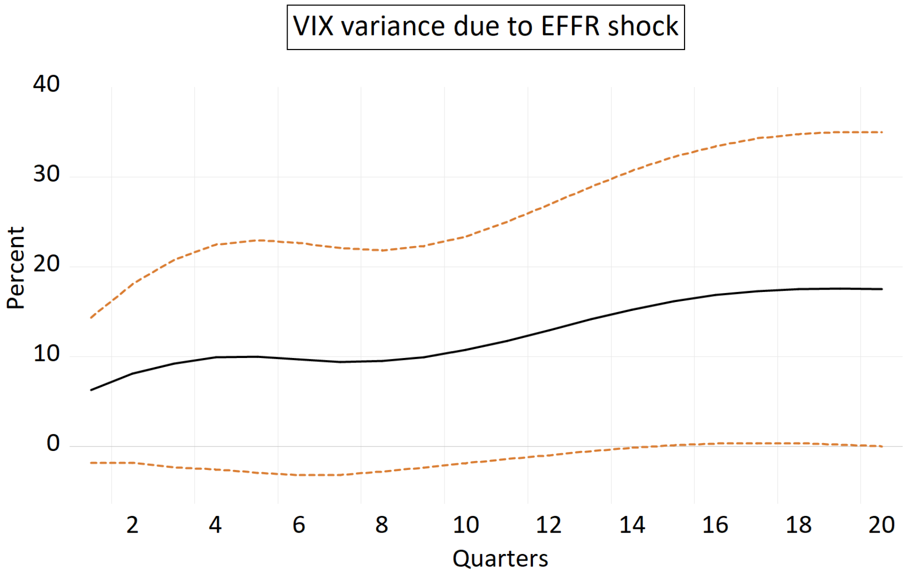

Figure 5.6.1: Variance decomposition of VIX due to EFFR shocks

6 Robustness

I perform the same robustness checks as Rey (2013) to check if my empirical results are robust and consistent. First, I check if the results are robust in a different time sample by selecting the pre-COVID-19 period, 2001Q4-2019Q4 (Figure C.1). I still get the same results, but cross-border credit flow now responds negatively to a positive shock in the VIX, as in Rey's (2013) paper. The impact of the effective federal funds rate on the variance in the VIX is on average 8 percent but also insignificant in the pre-COVID-19 sample (Figure C.7). Next, I check if my model is over-fitted since a too complex model will have low bias but high variance. I do this by removing the financial variables global domestic credit, European banking sector leverage, and cross-border credit flow (Figure C.2). In the four variable VAR in the pre-COVID-19 period, the impact is now approximately 18 percent but still insignificant. I also do robustness checks for the lag structure in Figure C.3, where I look at my impulse response functions with one lag. Still, I get the same results with one lag. Finally, examining a period similar to Rey (2013) is interesting. In the last robustness check, I estimate the impulse response functions for the period 2001Q4-2012Q4 (Figure C.4). Here, I find that a shock to the VIX will decrease global domestic credit, and a VIX shock will decrease cross-border credit flow, consistent with Rey (2013).

All in all, the dynamics between European banking sector leverage, effective federal funds rate, and the VIX are robust. On the other hand, the dynamics regarding global domestic credit and cross-border credit flow are not robust.

7 Discussion

In this section, I analyze how a US monetary policy shock will propagate to the global financial cycle, relate the results to the literature, and provide criticisms of my recursive VAR. In parts of my discussion, I interpret the different results based on my assessments since the research in my period is limited.

7.1 The propagation of a US monetary policy shock

The effects of the US monetary policy spillover on the global financial cycle persist. I analyze how a US monetary policy shock will propagate to the global financial cycle in this subsection. Initially, a US monetary policy loosening increases global risk, inconsistent with Rey (2013). Miranda-Agrippino and Rey (2020) analyze the US monetary policy spillovers after the Global Financial Crisis until 2019 and find a similar result. The mechanism behind this result is an information effect: A combination of US monetary policy loosening and the FED communicating pessimistic news about the projections for the economy will initially increase the VIX. During the COVID-19 pandemic, US monetary policy loosened, and a bad economic outlook also occurred (Condon, 2020).

After nine quarters, the global risk decreases by improving the confidence of global investors (Forbes & Warnock, 2012). The lower global risk propagates to the European banks by making them less risk-averse, resulting in the banks acquiring more debt. As a result of this, their leverage increases. Furthermore, the US monetary policy loosening also propagates to lower costs for European banks after 12 quarters (Bruno & Shin, 2012). Lower costs for banks change their risk attitudes because they want to maintain the same risk of absorbing losses (Value-at-risk) (Adrian & Shin, 2010). There is heterogeneity between the risk attitudes of the European banks, such that primarily, the more risk-taking European banks will higher their leverage even more (Miranda-Agrippino & Rey 2020). The increased leverage will lead to even lower global risk. Lower global risk further loosens the US monetary policy, and the responses reoccur.

All in all, a feedback cycle exists between US monetary loosening, leverage of European banks, and the VIX in the impulse response functions, consistent with Rey's (2013) paper and the international risk-taking channel of monetary policy. However, increased VIX from higher cross-border credit flow in my recursive VAR are inconsistent with the cycle from the risk-taking channel of monetary policy (Bruno & Shin, 2012).

My findings from Section 5.4 show that in my recursive VAR, the impact of the effective federal funds rate on the variance of the VIX is on average 12 percent. Compared to Rey (2013), this impact is significantly higher, as she finds an impact of only 4 percent.

7.2 Is the VIX dead?

Some of my empirical findings differ from Rey (2013). In my recursive VAR, a positive shock to the VIX increases the global domestic credit until 19 quarters and cross-border credit flow until seven quarters, whereas Rey finds a negative response. My results contradict the existing empirical literature. Here is why: volatility shocks widen credit spreads, meaning the costs for a firm's borrowing increase. Firms respond by a "wait-and-see"-strategy, where they reduce investments in new capital and instead focus on paying off their debt. Firms implement the strategy because they are often risk-averse (Sung, 2005) and want to avoid bankruptcy. A positive volatility shock ultimately results in lower credit demand (Gilchrist et al., 2014). In addition, firms lower their demand for credit, as in periods with positive volatility shocks, it is often harder to insure against losses, as evidence from the Global Financial Crisis shows (Arellano et al., 2016). In the period 2001Q4-2012Q4, I find that these mechanisms hold, consistent with Rey (2013) (Section 6).

What could explain this positive relationship in the COVID-19 period? More regulation and macroprudential policies might be the answer. Central bankers have implemented these policies since the Global Financial Crisis to prevent excessive risk-taking in the risk-taking channel of monetary policy (Saft, 2016). Such policies include the Basel III reforms, which implemented capital buffers and stress tests (Gale et al., 2011). Georgiadis (2015) analyzes the determinants of US monetary policy spillovers, where he finds that financial development in the domestic economy is a significant determinant. Regulation might increase financial development, as efficient policies decrease the risks of financial crises. As a result of the regulation, the VIX, global domestic credit, and cross-border credit flow have all been low in the post-2009 period. Avdjiev et al. (2017) find that the dollar might better determine cross-border credit flows during the post-Global Financial Crisis period. Since 2014, the VIX has been insignificant in determining the 3-month cross-currency basis when they add the dollar to the regression. In their regression, the dollar has a negative effect. So, when the dollar appreciates, the cross-currency basis will fall, indicating a currency mismatch on the balance sheets of international banks. This currency mismatch causes international banks to deleverage because of higher currency risk, and the banks' risk-taking will fall (Avdjiev et al., 2017).

Some investors have also begun criticizing the VIX as a measure of global risk after the Global Financial Crisis. They argue that the VIX is too low, especially after the Russian Invasion of Ukraine. The reason for a lower-than-normal VIX is the increase in the demand for options that expire within the same day one invests in them (0DTE options). My VIXCLS measures the options that expire within a month, so it does not account for 0DTE options. CBOE is now calculating the VIX1D to counter the increased trading, which they calculate multiple times daily (Cruz, 2023).

7.3 The size of the US monetary policy spillovers

The response of the VIX to a US monetary policy shock in my impulse response function is challenging to compare to Rey (2013) in percentage points. Rey normalizes her monetary policy shock to 25 bonus points, whereas mine is only 1.66. Therefore, I calculate the scaled responses to a 25 bonus point shock to the effective federal funds rate in Table B.9. The response for the VIX from a shock to the effective federal funds rate is not as large as Rey's (2013). Also, changes in VIX still lead European banks to take on more leverage, but to a lesser extent compared to Rey (2013). These two results are likely because of more regulation.

7.4 Criticisms of my analysis

A challenge for my model is that none of the variables account for the unconventional monetary policies central banks implemented during the COVID-19 pandemic. However, empirical studies show that such analyses are complex (Miranda-Aggripino & Rey, 2020). Also, it is hard to compare my responses for US GDP and cross-border credit flow directly to Rey (2013), as she normalizes these responses to percentage points.

There is also a potential problem regarding my confidence intervals in the impulse response functions. The confidence intervals could be inaccurate because of skewness in some of my variables; see Figure C.5, as I use percentile bootstrapping (Rousselet et al., 2021). Hence, if I had more time to familiarize myself with advanced bootstrapping methods, then I would try the Bias-Corrected and accelerated bootstrap. This is because BCa bootstrap often estimate more the confidence interval more precise (DiCiccio & Efron, 1996).

My two average-aggregated variables, the effective federal funds rate and the VIX, also likely smooth out the short-run fluctuations, which could withhold important information. Finally, my sample has only 88 observations, with the earliest observations being in 2001Q4. Finally, factors other than US monetary policy might affect effective federal funds, such as the demand for money (Georgiadis, 2015).

8 Conclusion

My thesis aimed to discover if there are still spillovers from US monetary policy. There are still spillovers from US monetary policy. However, the magnitude of the spillovers is lower in the COVID-19 period compared to Rey's (2013) period. A US monetary policy loosening will propagate to the global economy by decreasing the global risk and increasing the leverage of the European banks. Moreover, the higher leverage of the European banks will further decrease the VIX, which again increases the leverage. Although European banks have deleveraged since the Global Financial Crisis, the central banks should still monitor the leverage. My robustness checks show that my results cannot be generalized to different periods. However, my thesis might provide worthful information about how the US monetary policy propagates to the global economy during global lockdowns like the COVID-19 pandemic. This thesis also contributes to the literature on why the COVID-19 pandemic did not become another global financial crisis. This might be because of higher cross-border credit flows, not further lowering the VIX and because of lower VIX not increasing global domestic credit and cross-border credit flows (the cycle in the risk-taking channel) due to regulation and macroprudential policies (Saft, 2016). Examining how unconventional US monetary policy propagates to the global financial cycle via leverage, credit growth, and cross-border credit flows in the COVID-19 period could be interesting. Finally, future research could analyze if the dollar is a better measurement for global risk than the VIX and check if the dynamics might change (Avdjiev et al., 2017).

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Appendix A

This appendix explains the data and variables used in the empirical analysis in the recursive VAR. I describe the technical information about the collection and transformation of the seven variables. All my data is collected quarterly from 2001Q4 to 2023Q3.

	Description
GDP	Real US GDP
GDPDEF	US GDP Deflator, 2017=100
CREDIT	Global Domestic Credit
INFLOW	Cross-border credit flow
EULEV	European Banking Sector Leverage
EFFR	Effective Federal Funds Rate
VIX	CBOE Volatility Index

Table A.1: Description of my variables

US GDP (GDP)

The US GDP-variable (GDP) is the Real Gross Domestic Product of the United States, and the unit is billions of US Dollars, which are chained to the year 2017. Moreover, it is a seasonally adjusted annual rate.

Citation: I retrieve the data from the Federal Reserve Bank of St. Louis (FRED) (Link: https://fred.stlouisfed.org/series/GDP), collected February 6$^{\text{th}}$, 2024. The FRED collected it from the US Bureau of Economic Analysis.

US GDP Deflator (GDPDEF)

The US GDP Deflator (GDPDEF) is the implicit price deflator for the United States. The US GDP Deflator is also adjusted for seasonality. The base year is 2017, where the index is equal to 100.

Citation: US Bureau of Economic Analysis, Gross Domestic Product: Implicit Price Deflator [GDPDEF], I retrieved the data from the Federal Reserve Bank of St. Louis (FRED) (Link: https://fred.stlouisfed.org/series/GDPDEF), collected February 10$^{\text{th}}$ 2024. The FRED collected it from the US Bureau of Economic Analysis.

Global Domestic Credit (CREDIT)

Global domestic credit (CREDIT) is one of my variables for the global financial cycle. I first calculate the domestic credit for the individual countries as the total domestic claims in the Depository Corporations, except for the Central Bank. I calculate the domestic claims as Claims on the Private Sector, Public Non-Financial Corporations, other Financial Corporations, and Net Claims on Central or General Government (Rey, 2013). I then calculate the Global

Domestic variables as follows:

$$\text{CREDIT} = \sum_{i=1}^{70} \textbf{Domestic Credit}_i \tag{A.1}$$

I then take the natural logarithm of the global domestic credit to normalize it into credit growth.
Citation: I have received the data on the CREDIT-variable from: Other Depository Corporation Survey and Deposit Money Banks Survey; Monetary Statistics; IFS, (Link: https://data.imf.org/regular.aspx?key=63243614). The data is collected in the national currencies of the given countries.

Countries included in the Global Domestic Credit variable

The collected data is the original data in national currencies, where I exclude aggregate measures such as currency areas.
The list of countries becomes: Albania, Algeria, Angola, Argentina, Australia, Belize, Benin, Bolivia, Bosnia and Herzegovina, Botswana, Brazil, Bulgaria, Burkina Faso, Cabo Verde, Colombia, Côte d'Ivoire, Czechia, Denmark, Dominican Republic, Arab Republic of Egypt, Kingdom of Eswatini, Republic of Fiji, Georgia, Guatemala, Guinea-Bissau, Honduras, Hungary, Iceland, Indonesia, Israel, Jamaica, Japan, Jordan, Republic of Kazakhstan, Kenya, (South) Korea, Malaysia, Mali, Mexico, Republic of Moldova, Morocco, Republic of Mozambique, Nambia, New Zealand, Nicaragua, Niger, Republic of North Macedonia, Norway, Pakistan, Panama, Paraguay, Philippines, Republic of Poland, Romania, Rwanda, Senegal, Republic of Serbia, Sierra Leone, Solomon Islands, South Africa, Republic of South Sudan, Sweden, United Republic of Tanzania, Thailand, Trinidad and Tobago, Türkyie, Uganda, Ukraine, Uruguay, Vanuatu, and Zambia.

Citation: I retrieved the data from the IMF website; Other Depository Corporation Survey and Deposit Money Banks Survey; Monetary Statistics; IFS (Link: https://data.imf.org/regular.aspx?key=63243614), collected 14^{th} February 2024.

Cross-border credit flow (INFLOW)

Another variable for the global financial cycle is cross-border credit flow (INFLOW), which is the net amount of credit flowing into an economy. The variable aggregates credit flow for a total of 54 countries.

$$\text{Cross-border credit flow} = \sum_{i=1}^{54} \text{Direct Cross-Border Credit}_{54} \tag{A.2}$$

Where Direct Cross-Border Credit for the individual country is defined as (Rey, 2013):

$$\text{Direct Cross-Border Credit} = \text{Claims} - \text{Liabilities} \tag{A.3}$$

Countries included in the cross-border credit flow variable

I select the same sample countries in the global credit inflow panel variable as in Rey's (2013) paper. However, since Serbia is no longer a BIS-reporting country, I choose Albania as an alternative for Serbia because of their similar economies. Also, Czechia, Türkyie, and Hong Kong SAR have changed their names since 2013.
My list, therefore, is: Albania, Argentina, Austria, Belarus, Belgium, Bolivia, Brazil, Bulgaria, Canada, Chile, Colombia, Costa Rica, Croatia, Cyprus, Czechia, Denmark, Ecuador, Finland, France, Germany, Greece, Hong Kong SAR, Hungary, Iceland, Indonesia, Ireland, Italy, Japan, (South) Korea, Latvia, Lithuania, Luxembourg, Malaysia, Malta, Mexico, Netherlands, New Zealand, Norway, Poland, Portugal, Romania, Russia, Slovakia, Slovenia, South Africa, Spain, Sweden, Switzerland, Thailand, Turkey, United Kingdom and United States.

Citation: I retrieved the data from the BIS data portal; Table A3: Cross-border positions, by residence and sector of counterparty (Link: https://data.bis.org/topics/LBS/tables-and-dashboards/BIS,LBS_A3,1.0), collected 20^{th} February 2024.

European Banking Sector Leverage (EULEV)

European Banking Sector Leverage (EULEV) is the median for the 12 initial Euro Area countries (Rey, 2013). Contrary to Rey's (2013) EULEV variable, I omit the Banking Sector Leverage for the United Kingdom, as Brexit happened in 2020. The data is in the euro currency instead of the national currencies Rey (2013) uses. The banking sector leverage for the individual country is given by:

$$\text{Banking Sector Leverage} = \frac{\text{Claims on Private Sector}}{\text{Transferables} + \text{Other Deposits}} \tag{A.4}$$

Citation: I retrieved the data from the Other Depository Corporations Survey; Monetary Statistics, International Financial Statistics database; IFS (Link: https://data.imf.org/regular.aspx?key=63243614), collected 14^{th} February 2024.

Effective Federal Funds Rate (EFFR)

For the Effective Federal Funds Rate (EFFR), I calculate quarterly averages based on monthly data that are not seasonally adjusted.

$$\text{EFFR}_t = \frac{\text{EFFR}_{t=1} + \text{EFFR}_{t=2} + \cdots + \text{EFFR}_{t=n}}{n} \tag{A.5}$$

Citation: Board of Governors of the Federal Reserve System (US), Federal Funds Effective Rate [FEDFUNDS]. I have received the EFFR-data from the Federal Reserve Bank of St. Louis (FRED); (Link: https://fred.stlouisfed.org/series/FEDFUNDS), collected February 9^{th} 2024, H.15 Selected Interest Rates.

CBOE Volatility Index (VIX)

For the VIX, I calculate quarterly averages based on daily close readings (CLS) for the Chicago Board Options Exchange Volatility Index, which is non-seasonally adjusted.

$$\text{VIX}_t = \frac{\text{VIX}_{t=1} + \text{VIX}_{t=2} + \cdots + \text{VIX}_{t=n}}{n} \tag{A.6}$$

Citation: I retrieve the VIX-data from the FRED, Federal Reserve Bank of St. Louis; (Link: https://fred.stlouisfed.org/series/VIXCLS), and the FRED collected them from Chicago Board Options Exchange, I collected the data on February 8$^{\text{th}}$ 2024.

Appendix B

This is the model appendix. The software I use to estimate, is primarily Eviews12, however, OxMetrics9 has been used to test for hetereoskedasticity of the model and ARCH-effects for the variables.

Misspecification tests

	Test statistic	**p-value**
GDP	-2.68	0.2444
GDPDEF	-1.58	0.7895
CREDIT	-1.32	0.8762
INFLOW	-2.1	0.5334
EULEV	-2.53	0.3125
EFFR	-2.01	0.5835
VIX	-3.46	0.0494

Table B.1: Unit root tests (Augmented Dicky-Fuller tests) for my level variables

Lag	**LR**	**FPE**	**AIC**	**SC**	**HQ**
1	1146.56	4.2	21.29	23.11*	22.02*
2	83.41*	4*	21.23*	24.47	22.53
3	43.49	6.85	21.68	26.34	23.56
4	61.37	8.04	21.71	27.79	24.16

Table B.2: Information criteria at the different lag lengths

Lag	**LRE statistic**	**Degrees of freedom**	**p-value**
1	42.34	49	0.7408
2	35.03	49	0.9345
3	46.49	49	0.5790
4	60.45	49	0.1288

Table B.3: Test for autocorrelation (Lagrange Multiplier) at the different lag lengths

	Jarque-Bera test-statistic	**p-value**
GDP	2131.01	0.0000
GDPDEF	4.66	0.0972
CREDIT	1.9	0.3738
INFLOW	1.43	0.4875
EULEV	13.12	0.0014
EFFR	25.24	0.0000
VIX	12.04	0.0024
Joint test	2189.488	0.0000

Table B.4: Normality tests (Jarque-Ber) for the variables and VAR(2)

	Chi-sqaure	**p-value**
GDP	3.22	0.0001
GDPDEF	4.15	0.0000
CREDIT	2.85	0.0004
INFLOW	0.74	0.8079
EULEV	1.5	0.0950
EFFR	2.64	0.0009
VIX	1.51	0.0923
Joint test	952.1415	0.0042

Table B.5: Heteroskedasticity tests (White) for the variables and my VAR(2)

	Test statistic	p-value
GDP	0.07	0.9897
GDPDEF	0.63	0.6449
CREDIT	0.84	0.5025
INFLOW	1.94	0.1114
EULEV	1.62	0.1768
EFFR	6.3	0.0002
VIX	0.12	0.9745

Table B.6: ARCH tests for the variables

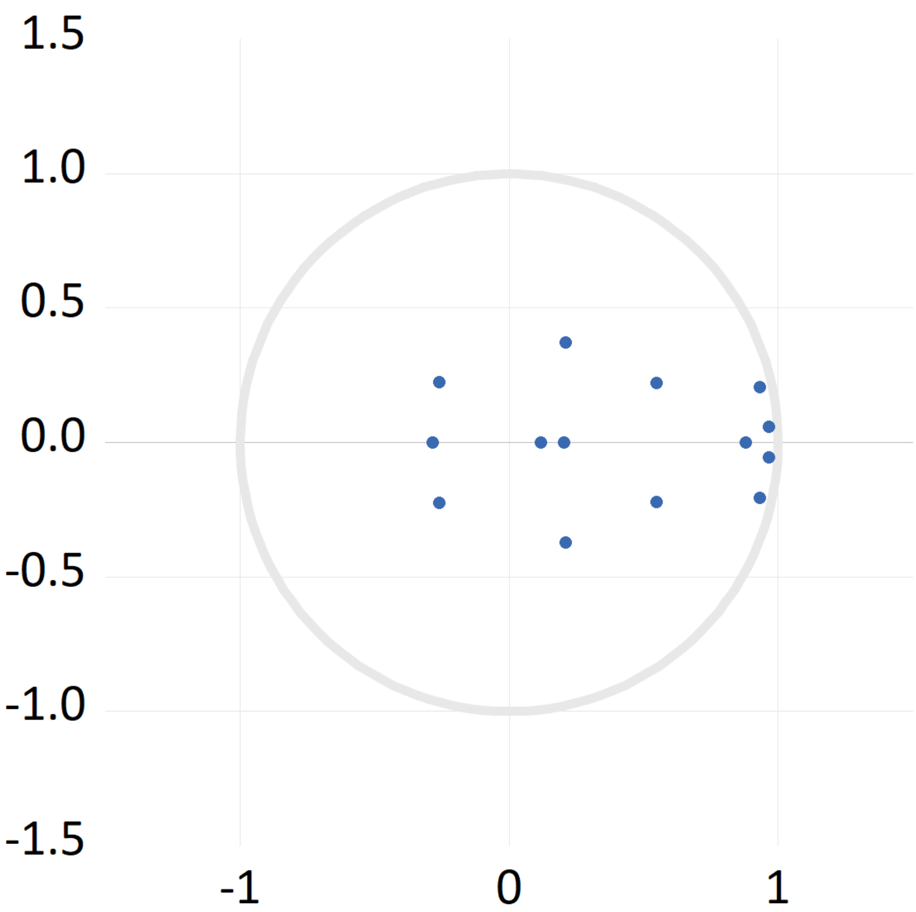

Figure B.1: Inverse roots of the characteristic polynomial

	Eigenvalue	**Trace statistic**	**Critical value**	**p-value**
0**	0.44	170.32	125.61	0.0000
1**	0.37	120.45	95.75	0.0004
2**	0.25	79.97	69.81	0.0062
3**	0.22	54.76	47.85	0.0098
4**	0.19	32.61	29.79	0.0231
5	0.12	14.32	15.49	0.0744
6	0.03	3.14	3.84	0.0762

Table B.7: Johansen cointegration rank test

Corr (p-value)	GDP	GDPDEF	CREDIT	INFLOW	EULEV	EFFR	VIX
GDP	1						
GDPDEF	0.97 (0.0000)	1					
CREDIT	0.46 (0.0000)	0.53 (0.0000)	1				
INFLOW	0.76 (0.0000)	0.77 (0.0000)	0.27 (0.0091)	1			
EULEV	−0.9 (0.0000)	−0.9 (0.0000)	−0.59 (0.0000)	−0.59 (−0.0000)	1		
EFFR	−0.02 (0.8421)	−0.04 (0.6856)	0.14 (0.1680)	−0.06 (0.5418)	0.1 (0.3178)	1	
VIX	−0.12 (0.2580)	−0.02 (0.8000)	0.16 (0.1350)	0.06 (0.5661)	−0.11 (0.2851)	−0.27 (0.0095)	1

Table B.8: Correlation matrix for the variables

The dynamic short-run relationship

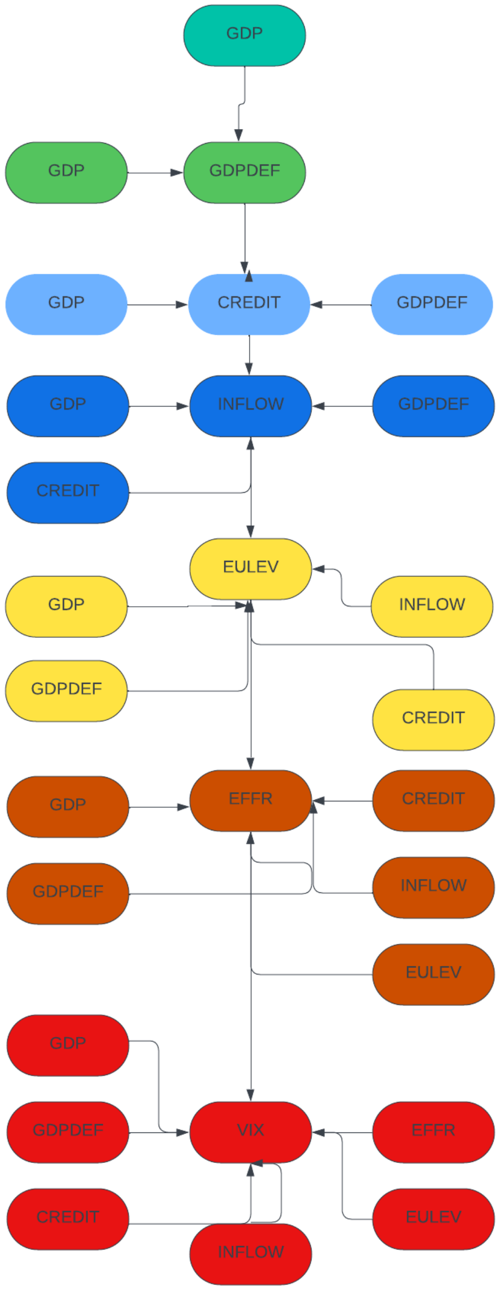

Figure B.2: Dependency graph for my ordering

The arrows in the middle indicate when the order is changing.

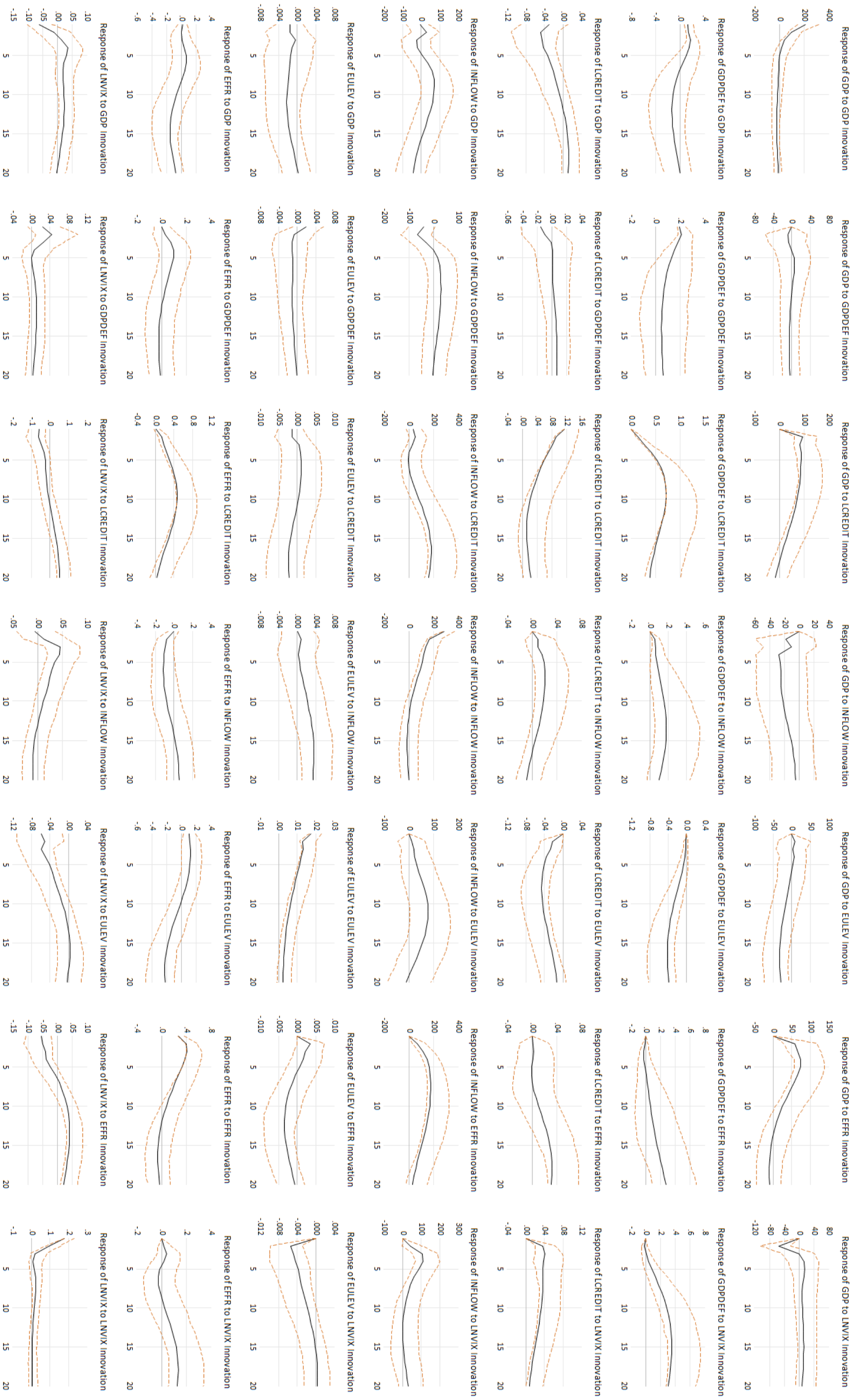

Figure B.3: Impulse response functions

Quarter	**Scaled response**
1	-0.81
2	-0.74
3	-0.62
4	-0.56
5	-0.36
6	-0.13
7	0.09
8	0.26
9	0.39
10	0.48
11	0.55
12	0.59
13	0.61
14	0.61
15	0.59
16	0.55
17	0.51
18	0.45
19	0.39
20	0.32

Table B.9: Scaled responses for VIX for 25 bonus point increase in EFFR

Appendix C - Robustness checks

Impulse response functions

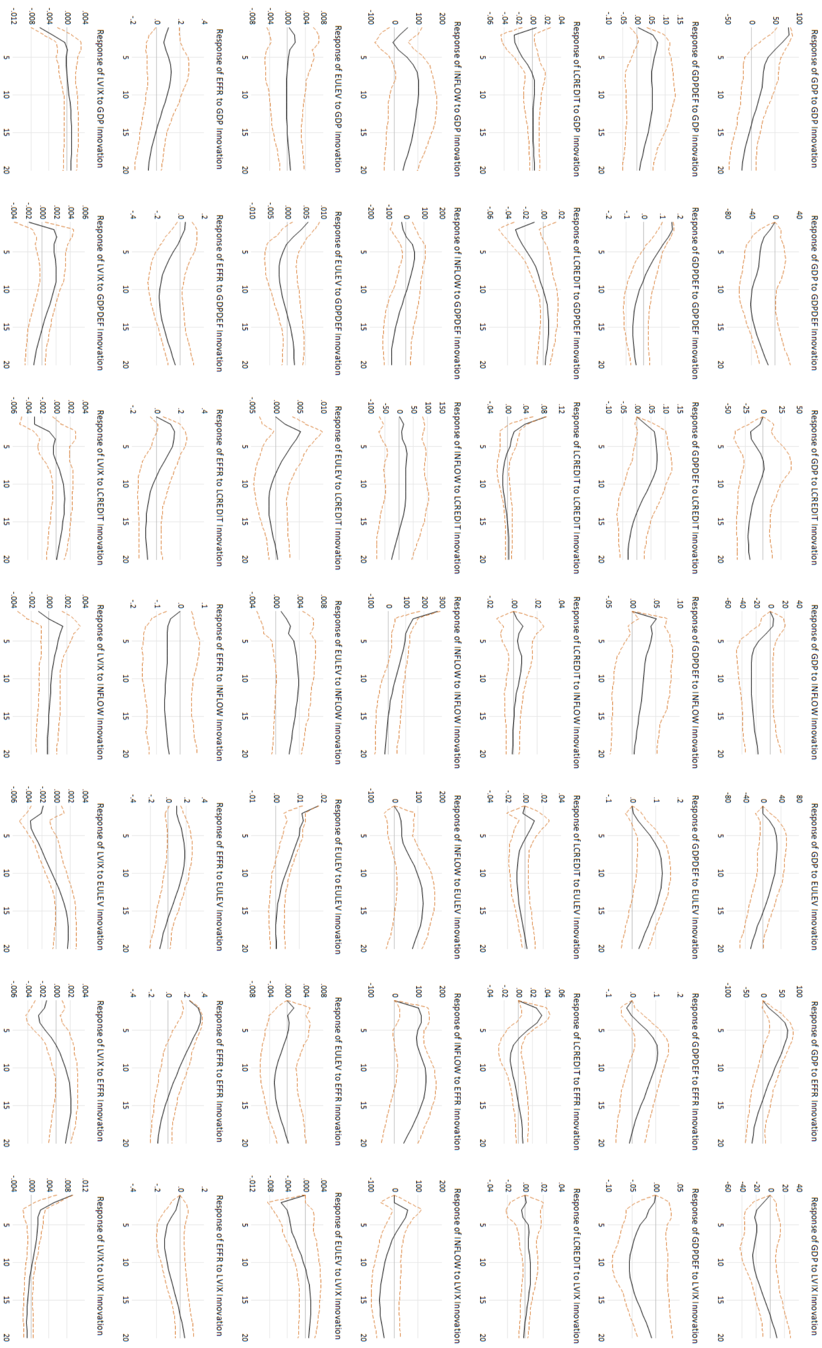

Figure C.1: Impulse response function for the pre-COVID-19 sample

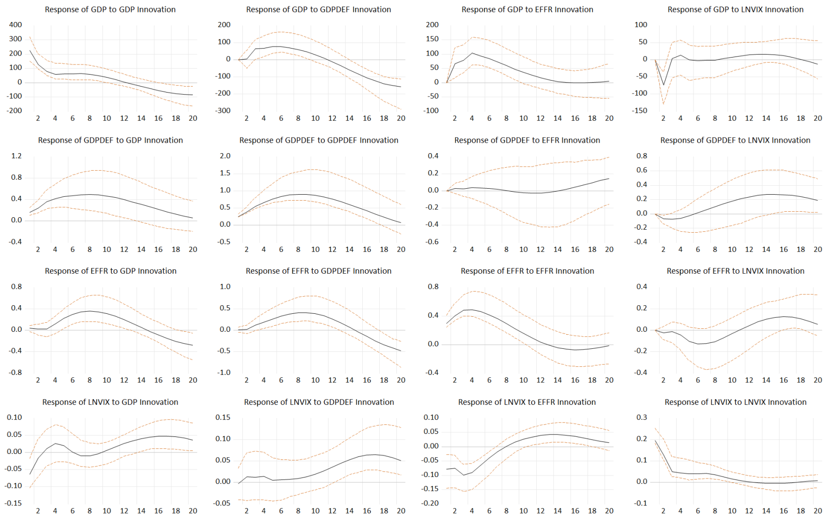

Figure C.2: Impulse response functions in the four variable VAR

Note: The y-axis is measured as units in the response variable, and the x-axis is quarters.

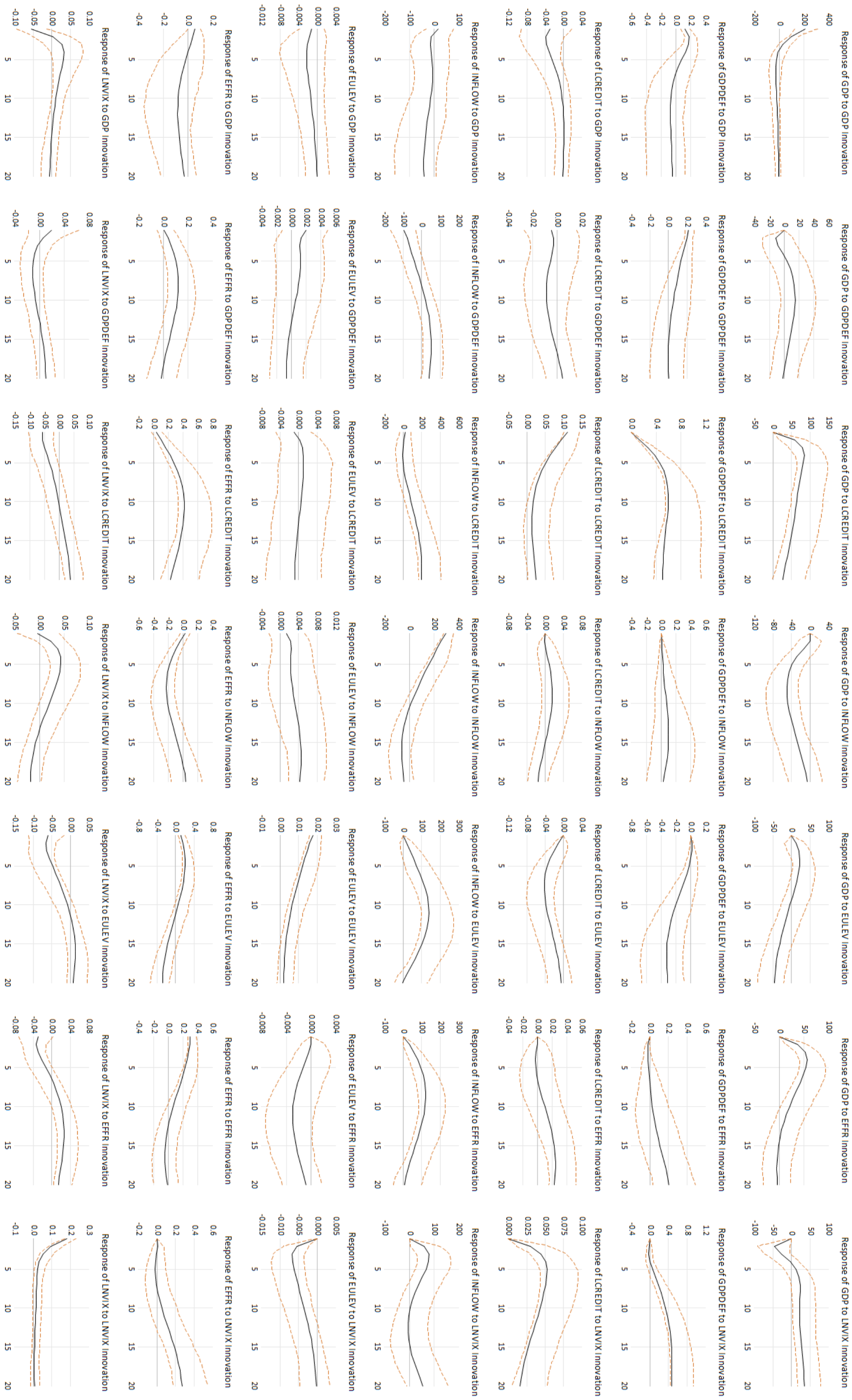

Figure C.3: Impulse response functions for VAR(1) with seven variables

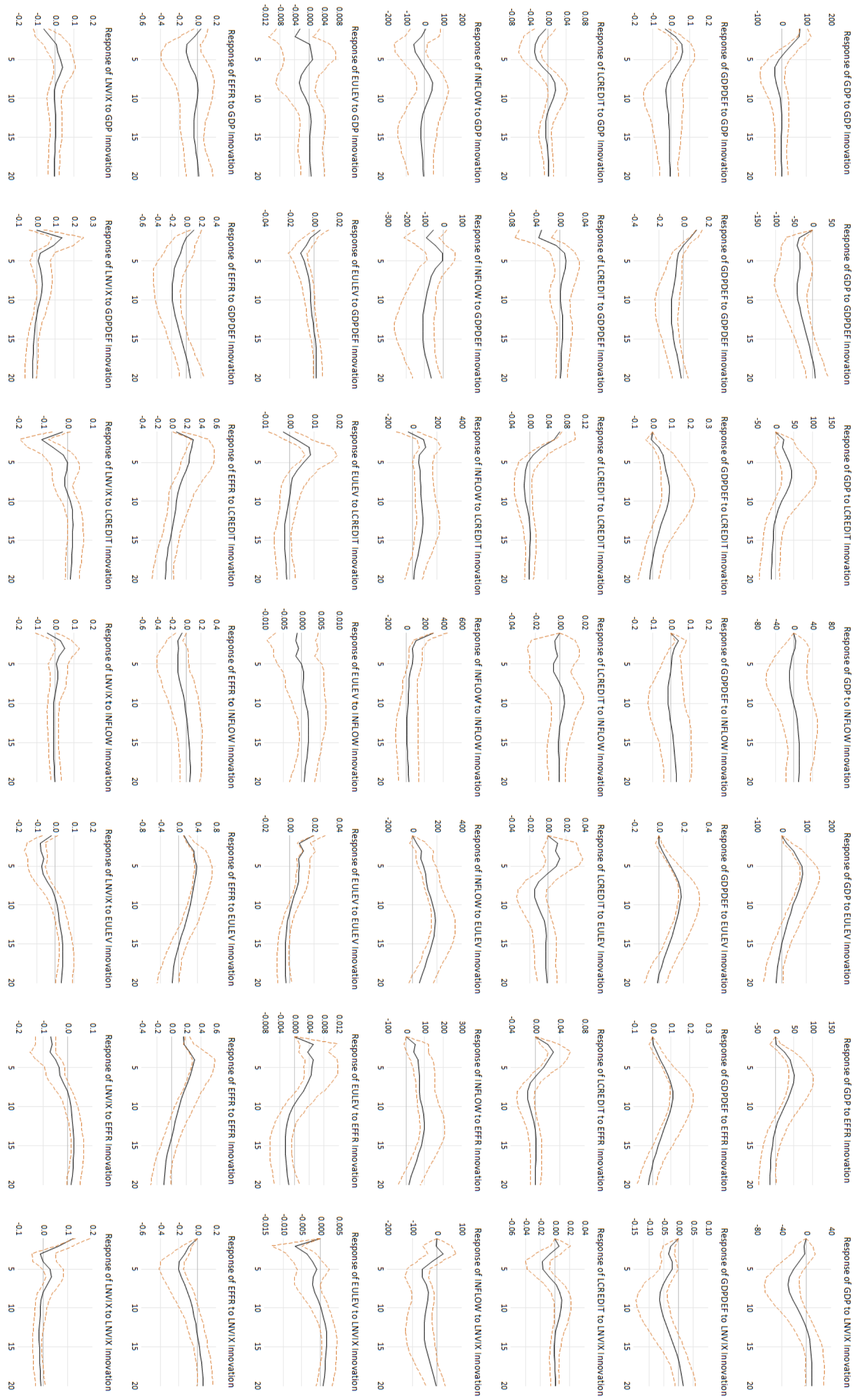

Figure C.4: Impulse response functions for period 2001Q4-2012Q4

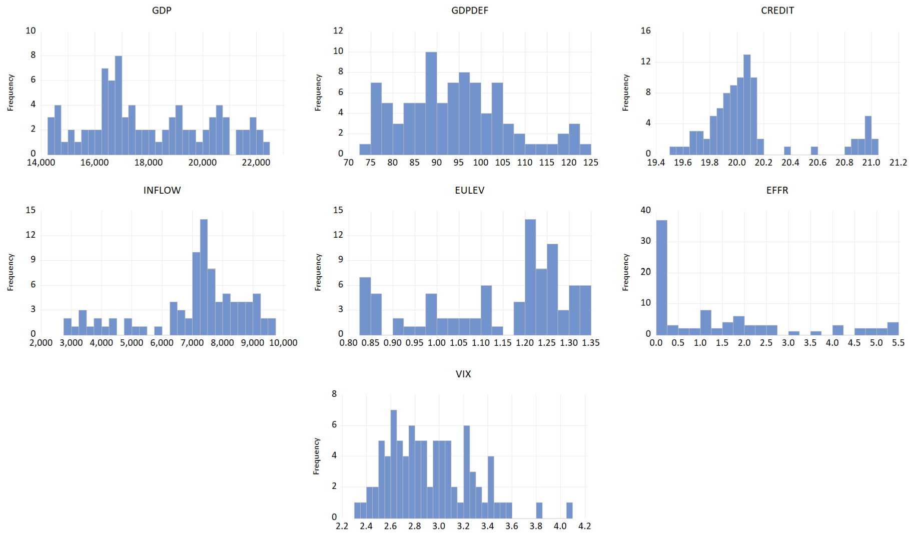

Figure C.5: Histograms for the variables

Variance decompositions

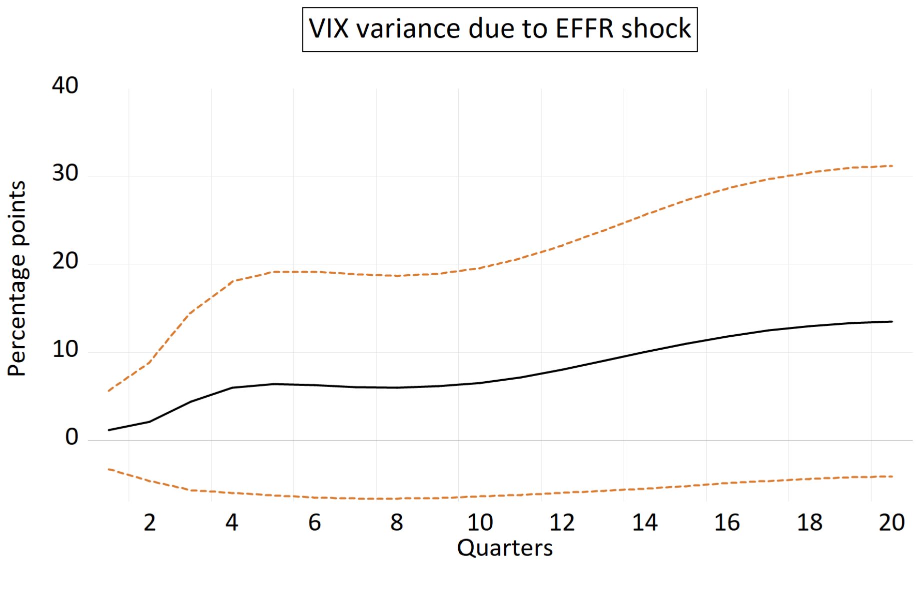

Figure C.6: Variance decomposition of VIX due to EFFR shocks in pre-COVID-19 sample

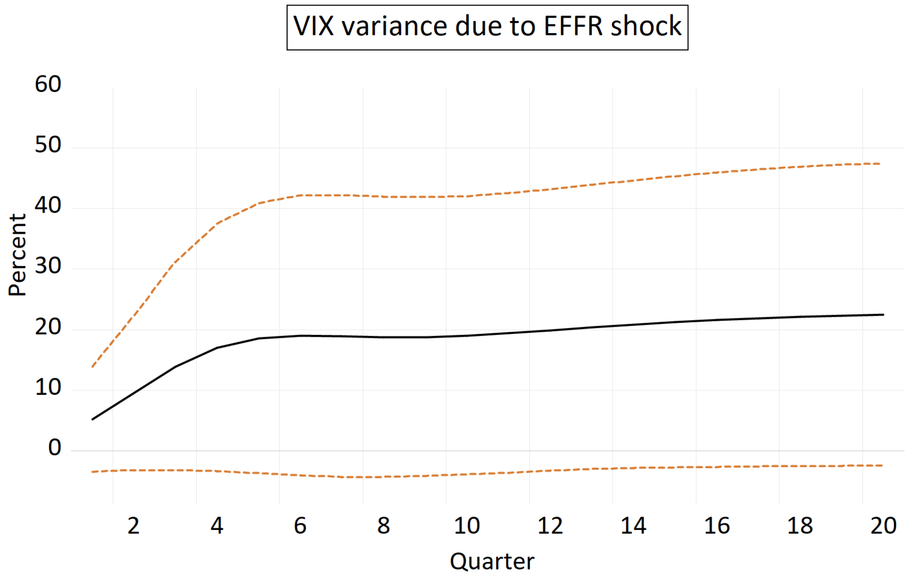

Figure C.7: Variance decomposition of VIX due to EFFR shocks in four variable VAR in pre-COVID-19 sample