NOVA SCHOOL OF
BUSINESS & ECONOMICS

The effect of monetary policy on US stock prices and industry sectors: An Impulse Response Analysis

Macro-Econometrics
May 2024

Professor
Paulo M. M. Rodrigues

Group 8:

Nicolas Yong Joon Lee – 43792
Giani Ranzetti – 58575

Literature Review

The main tenet of a central bank is to promote sustainable domestic real growth while maintaining a low inflation rate. It is clear in the macro-economic literature that monetary policy has causal and lasting effects on various real economic variables. For instance, Taylor (1995) and MacLennan et al. (1998) both uncover that monetary policy decisions affected real output movements for over two years after its implementation. Gargiulo et al. (2024) find that monetary policy has varied effects on prices and unemployment depending on the ex-ante inflationary levels.

One concern regarding monetary policy actions is how long it might take for those changes to have an impact in the real economy through the policy transmission mechanism. Financial markets, however, such as the stock market, react more quickly to new information and therefore could be used to identify the impacts of changes in monetary policy. Understanding the policy transmission mechanism through the stock market into other macro-economic variables is crucial to have a wholistic view of the impact of monetary policy on the real economy. Stock price can be linked to consumption spending through wealth effects, although empirical research showed those effects not to be very significant. Additionally, some view the stock market itself as a source of macroeconomic volatility (Bernanke and Kuttner (2005)). Stock prices according to the Discounted Cash Flow model are the present value of future expected free cash flows. Therefore, stock returns are both impacted by expectations regarding future economic situation and by the discount rate.

Nevertheless, economists have differing views on the effect of monetary policy on financial markets and stock prices: particularly with regards to the impact of asset prices on monetary demand. Should banks react directly to stock price movements especially during times of high volatility? Is the demand for money independent from asset price movements? Ioannidis and Kotonikas (2006) argue for inflation targeting and claims that focusing on inflationary pressures minimizes the negative side effects of short-run, volatile stock price movements without targeting them directly. As such, interest rates should be set depending on the difference between current inflation and its forecast. Monetary policy should react to stock prices only if they affect expected inflation in some way.

Li, Iscan and Xu (2010) have empirically researched the impact of monetary policy shocks in stock prices in the US and Canada using SVAR model with short run restrictions, through a Cholesky decomposition. They found that in the US, the immediate response of stock prices to a contractionary monetary shock to be large and the dynamic response to be relatively prolonged.

Studies such as Caruso (2006), Masih and De Mello (2009) and Lutkepohl and Netsunajev (2018) attempt to use cointegrated VAR models to measure the relationship between the demand for money and stock prices. Caporale and Soliman (2013) outline several limitations of this approach. First, this methodology is exposed to model misspecification due to the omission of key explanatory variables. For instance, results would be biased if there exists simultaneity; stock prices affect monetary policy decisions and vice versa. Second is the issue of identification of the structural parameters. Restrictions are imposed on the model's deviations from its reduced form representation (errors) to orthogonalize them and retrieve impulse response functions. One common and simple restriction is the Cholesky decomposition. It relies on assuming one of the variables as exogenous, setting its structural coefficient to 0. In certain cases, this may be quite a strong assumption to make, furthermore, it relies heavily on the ordering of the variables (from most to least exogenous). As a result, different impulse responses will be estimated based on different variable ordering. Alternatively, *a priori* restrictions can be set on the covariance matrix of the structural errors and on the impulse functions based on theoretical considerations and intuition. In practice, this process requires many restrictions and involves assuming that the structural errors are uncorrelated which is often not plausible. This method is recommended to only be implemented in small independent systems.

Initially, we set out to create a VECM based on the methodology of Wickens and Motto (2001). It incorporates long run restrictions from macro-economic theory and estimating a VAR model in first differences for the exogenous variables. The full system includes both sets of equations and can be used to compute the impulse responses to the structural shocks without the need for arbitrary restrictions other than the ones needed to identify the shocks to the exogenous variable. Nevertheless, the implementation of such a model proved difficult in the python programming language and poor co-integrating relationships were discovered in our sample data.

Jarocinski and Karadi (2018) propose a different methodology that tackles the same problem and simultaneity issue. When studying the casual effect of monetary policy, the economic fundamentals that the policy endogenously responds to must be controlled for. They suggest instrumentalizing monetary policy shocks using Central Bank (CB) announcements to overcome the identification problem. These announcements isolate the unexpected variation in policy and, thus, can be used to assess the effect on real activity and prices (Gertler and Karadi 2015; Nakamura and Steinsson 2018). However, often these announcements reveal information about more than just policy, it may reveal the CB's assessment of the economic outlook. If these central bank information shocks have a macro-econometric impact, then they must be differentiated from policy shocks to uncover the true effects.

For instance, on March 20th, 2001, the US Federal Open Market Committee (FOMC) unexpectedly announced a 50-basis point decrease in interest rates to 5%. Contrary to standard economic theory, the stock market showed a decline following the announcement (See Appendix 1). The positive co-movement occurred because the CB shared a negative economic outlook of the economy in the short-to-medium term. This pattern is not unique, between 1992 and 2024, around a third of FOMC announcements are accompanied by such a positive co-movement of interest rate and stock market changes. In fact, in Figure 1 visualizes this phenomenon, observations in quadrants I and III are anomalous.

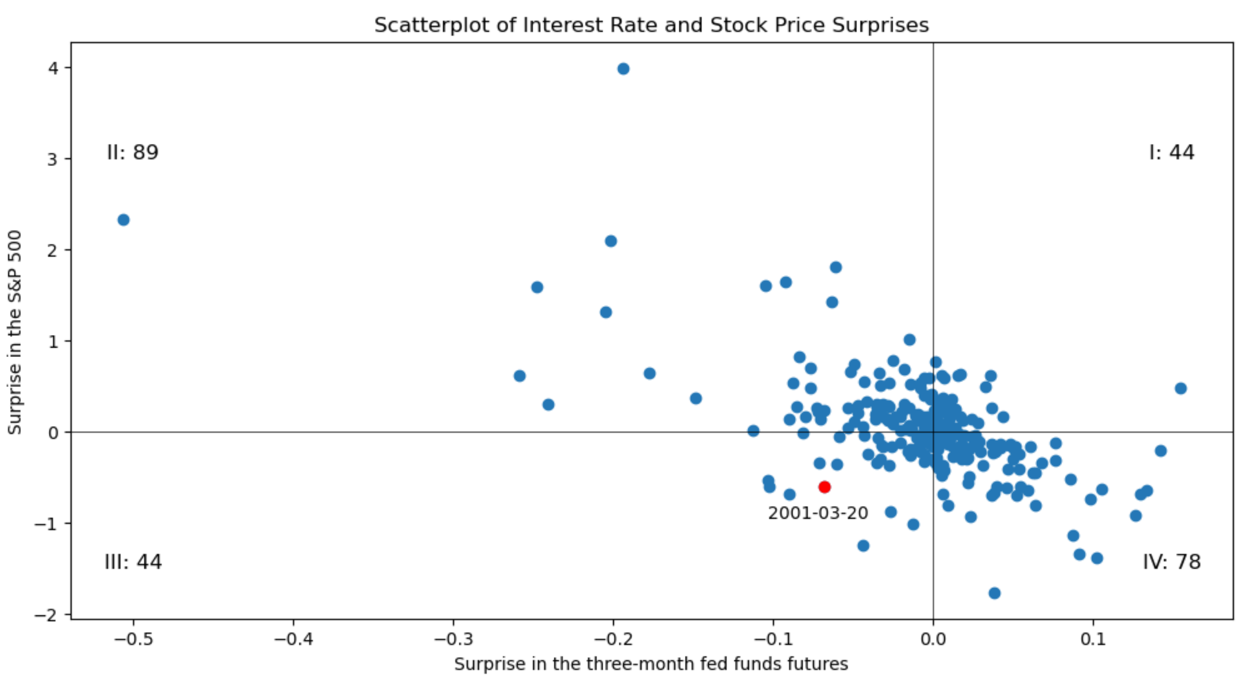


Figure 1: Scatterplot of stock price surprises vs. interest rate surprises

The separation of monetary policy shocks and CB information shocks are achieved by analyzing the co-movement of interest rates and stock prices around announcements (Miranda-Agrippino and Giovanni Ricco (2021)). Standard theory predicts that monetary policy tightening leads to lower 'fundamental' stock market valuations. This is because it reduces the present value of future dividends paid out by the stock. First by increasing the discount rate and second by reducing the expected dividend, given the deteriorating outlook.

Ergo, we identify a monetary policy shock using a negative co-movement between interest rate and stock price changes. If, instead, interest rates and stock prices co-move positively, it will classify as a reflection of an information shock. Their respective impacts will be assessed using a Structural VAR model. The methodology resembles that of a proxy VAR (Stock and Watson 2012) that use interest rate surprises as external instruments to identify monetary policy shocks. Following Jarocinski and Karadi's methodology, we use sign restrictions on multiple surprises and identify multiple contemporaneous shocks.

The aim of this study is primarily to obtain impulse responses to monetary policy shocks that are purged from the effects of the information shock. These purged shocks should be directly comparable to shocks to monetary policy rules in standard models. As a secondary analysis, we will identify the impact of the central bank information shocks on financial markets and the macroeconomy. This sheds light on the presence and nature of any information transfer between the central bank and the public. Finally, we will assess if the findings are consistent between market prices of different industry indices.

Methodology

Standard Cholesky- identified SVAR

Before estimating a model that differentiates the monetary policy shock and the information shock, we estimated a structural VAR model with a single interest rate "shock" variable. By only accounting for a single shock, the model will serve as a baseline to investigate if information shocks indeed add noise to monetary policy announcement shocks. For the variables, an Augmented Dickey-Fuller test was performed to identify if variables were stationary or not. Then the necessary variables were transformed to reach stationarity.

The optimal number of lags was selected using the Akaike Information Criteria (AIC), and the value obtained was 3 lags. Some noticeable outliers were present in our dataset, and so a dummy variable was used for 3 months in 2008 and 3 months in 2020. The full model can be represented as follows:

(1) $$\Gamma_0 Y_t = \mu + \sum_{i=1}^{p} \Gamma_i Y_{t-i} + \varepsilon_t$$

where, Y_t is a 1 x k vector and k is the number of variables in the model and μ is a 1 x k vector of constants

In estimation, we can only retrieve the reduced form SVAR model:

(2) $$Y_t = A_0 + \sum_{i=1}^{p} \mathrm{A}_i Y_{t-i} + u_t$$

where, $A_0 = \Gamma_0^{-1}\mu$, $A_i = \Gamma_0^{-1}\Gamma_i$, for i=1, … ,p, and $u_t = B\varepsilon_t$, where B = Γ_0^{-1}

Defining values from matrices A allows us to uncover the true coefficients from equation (1). Given that we can estimate residuals u_t, we can decompose its variance-covariance matrix into a lower triangular and upper triangular matrix denoted by P and P'. However, given the symmetric properties of a variance covariance matrix, there are not enough equations to solve for the number of unknown parameters. Thus, the B-matrix is identified using the Cholesky decomposition. The covariance matrix of the reduced-form residuals, Σu, is decomposed into the product of a lower triangular matrix P times its transpose, as follows: $\Sigma u = \mathrm{PP}'$. The B-matrix is then the inverse of P and it describes the contemporaneous relationships between variables, it is represented by a lower triangular matrix with ones on the diagonal. This structure implies a recursive ordering where each variable can contemporaneously affect the variables that follow it in the specified order. The order of the variables in this analysis was: Surprise variable, Treasury 1Y (difference), S&P (difference of logs), GDP (difference of logs), Unemployment (difference), and M2 (difference of logs). Changing the order of the variables would result in different contemporaneous relationships and, consequently, different model outcomes.

Sign Restricted Structural VAR

We then proceed to our Bayesian structural VAR model, which followed the methodology proposed by Jarocinski and Karadi (2018). It is aims to distinguish between the monetary policy and information shocks. Given its 'Bayesian' nature, we must incorporate *prior* information about model parameters. This allows the model to account for the estimation uncertainty in the presence of missing observations, on months with no CB announcements. Given that Bayesian statistics are outside the scope of the project, we will not go into them in too much detail. We simply use the priors from Jarocinski and Karadi who themselves take it from Litterman (1979). The literature imposes a prior about the matrix B and the variance-covariance matrix of the residuals Σ that is independent normal-inverted Wishart distributed. The specifications of the prior from the replication code can be found in Appendix 2. Bayesian VARs can naturally handle set identification due to sign restrictions. The model is surprisingly simple; it can be written as:

$$(3) \qquad \begin{pmatrix} m_t \\ y_t \end{pmatrix} = \sum_{p=1}^{P} \begin{bmatrix} 0 & 0 \\ B_{YM}^{p} & B_{YY}^{p} \end{bmatrix} \begin{pmatrix} m_{t-p} \\ y_{t-p} \end{pmatrix} + \begin{bmatrix} 0 \\ c_y \end{bmatrix} + \begin{pmatrix} u_t^m \\ u_t^y \end{pmatrix}, \quad \begin{pmatrix} u_t^m \\ u_t^y \end{pmatrix} \sim \mathrm{N}(0, \Sigma)$$

where, y_t is a vector of N_y macroeconomic and financial variables observed in month t, m_t is a vector of N_m surprise variables observed in month t. c_y is a constant and N denotes a normal distribution.

To construct m_t, all intraday surprises occurring in month t on the days with FOMC announcements are aggregated. Note that m_t is zero in the months with no FOMC announcements. Our model is a VAR with the restriction that m_t does not depend on the lags of either m_t or y_t and has zero mean. As previously discussed, the literature has used these surprises variables, m_t, as instruments in proxy VARs (Caldara and Herbst (2019), Stock and Watson (2018)). Jarocinski and Karadi point out that these models asymptotically lead to the same impulse responses under regularity conditions. Treating the surprises through a simple SVAR instead of a *proxy* VAR significantly simplifies the methodology and inference.

The two structural shocks in m_t are transmitted through the CB announcements. The first shock called a '*negative co-movement shock*' is associated with a Monetary Policy shock. The second is a '*positive co-movement shock*' and identifies the CB information shock. The identification of the model and isolation of the shocks are achieved through two assumptions:

1. Announcement Surprises (positive and negative co-movements) are affected only by the 2 announcement shocks and no other shocks.

2. A negative co-movement shock is associated with an *interest rate increase* and a *drop in stock prices*. A positive co-movement shock with an *increase in both* interest rates and stock prices.

We can justify the first assumption because the surprises are recorded in a small-time interval before and after the announcements. It is unlikely that shocks unrelated to the CB announcements systematically occur at the same time. The second assumption represents the sign restriction that follows economic intuition. It separates the different announcements shocks; their orthogonality is a standard requirement. As previously outlined, an unforeseen increase in interest rates should decrease the present value of dividends and reduced asset prices. Hence a negative co-movement must imply that news is revealed about monetary policy. We approximate this to a Monetary policy shock. Conversely, a positive co-movement must reflect something in the central bank's announcement that is not news about monetary policy. We will call the positive co-movement shock a *central bank information shock*. These restrictions are visualized in Table 1.

	Shock		
Variable	Monetary Policy (negative co-movement)	CB Information (positive co-movement)	Other
m_t			
Interest rate	**+**	**+**	**0**
Stock Index	**-**	**+**	**0**
y_t	*Unrestricted*	*Unrestricted*	*Unrestricted*

Table 1: Identifying restrictions of the VAR model

Using the now defined restrictions, and the Bayesian priors, we can use an iterative simulation process called a *Gibbs Sampler* to compute the contemporaneous VAR effects. At each iteration, the *Gibbs sampler* samples from the conditional distribution of each parameter given the current values of all other parameters. After sampling from each conditional distribution, the values of the parameters are updated. The process continues for many iterations until the sampler reaches convergence. At this point, the sampled values stabilize around the true posterior distribution. By deriving the Bayesian posterior distributions of the shocks, we can subsequently calculate the impulse responses.

This process is conducted under the assumption of a uniform prior distribution over the space of rotations. More specifically, the first assumption implies a "block Cholesky" structure on the shocks with the surprises forming the first block. We impose the sign restrictions on the contemporaneous responses to the first two shocks. This can be written as:

(4)
$$Q = \begin{bmatrix} Q^* & 0 \\ 0 & I \end{bmatrix},$$

where, Q* is a 2x2 orthogonal matrix with elements drawn out from normal distribution, I is a square identity matrix with dimension of the number of endogenous variables.

For each draw of Σ, we compute its lower triangular Cholesky decomposition, C. We then multiply it by Q. We repeat this process until we find Q matrixes such that matrix CQ satisfies the sign restrictions. If the conditions are met, the impulse responses (IRFs), representing the dynamic propagation of a shock to the model residuals are plotted.

IRFs are a plot of the marginal effect of each lag after an initial condition is subjected to a shock. IRFs can be computed based on the following MA representation:

(5) $$Z_t = \epsilon_t + P_1 \cdot \epsilon_{t-1} + P_2 \cdot \epsilon_{t-2} + \ldots + P_{t-1} \cdot \epsilon_1 + C_0,$$

where, $Z = \begin{bmatrix} m \\ y \end{bmatrix}$ and $\epsilon = \begin{bmatrix} u^m \\ u^y \end{bmatrix}$ and P is the restricted error matrix CQ

We find by shifting equation (5) towards future values instead of using lagged values of Z_t, and the initial condition, C_0, becoming the last observation of the sample, that:

$$\frac{\partial Z_t}{\partial \epsilon'_t} = I_K, \qquad \frac{\partial Z_{t+1}}{\partial \epsilon'_t} = P_1, \qquad \frac{\partial Z_{t+2}}{\partial \epsilon'_t} = P_2$$

Presented as k x k matrixes with k being the number of variables in Z.

We save each successful draw of P and its contemporaneous impulse responses. By iterating the process N times, we predict N impulses. This simulation process allows to create confidence intervals around the *median* IRF.

This concludes the model specification; however, the methodology must be used in combination with tests to determine required characteristics of the variables. Namely, an Augmented Dickey-Fuller test is used to evaluate stationarity; a Breusch-Pagan Test for heteroskedasticity and a Shapiro-Wilk for normality and a Durbin-Watson on for serial autocorrelation.

Data Selection

We use the surprise variables available on Marek Jarocinski's website. The surprise in the policy indicator is the "1st principal component of the surprises in interest rate derivatives with maturities from 1 month to 1 year". The second is the surprise in the S&P500. Both surprises are measured in a half-hour window starting 10 minutes before and ending 20 minutes after the announcement. We assume that within this narrow window only two structural shocks, a monetary policy shock and central bank information shock, influence systematically the financial market surprises. Until February 1994 the FOMC did not issue press releases, so we drop all surprise observation pre-February 2024. Additionally, there are no surprises measured during the month of September 2021. These shock variables are originally high frequency data, but we aggregate them monthly. On months with no CB announcements, the surprise variables are equal to 0.

Regarding our endogenous variables, they are all in monthly frequency. We use the 1-year Treasury rate from the FRED database as our monetary policy indicator. We use a rate longer than the targeted Fed Funds Rate because it contains the impact of forward guidance which is also a relevant CB tool. Our baseline for the stock market index is the monthly average of the S&P 500 in log levels, this is sourced from Bloomberg. Later, we also use Bloomberg's first level decomposition of industries on the S&P 500.

Next, our measure of real activity is the S&P Global Market Intelligence's GDP index, it was used over an actual measure of GDP due to its monthly frequency. The price level is represented through the personal consumption expenditure index (PCEPI) from FRED. This variable represents the price level in 2017 terms. Finally, we use the spread between BAA corporate bonds and the 10-year treasury rate as an indicator of financial conditions. We call this time series the "excess bond premium" (EBP) and it is also sourced from FRED. Caldara and Herbst (2019) find that omitting credit spreads during Monetary policy modeling attenuates the response of all variables to monetary shocks. All variables are available for the period between 1st Jan 1992 to 1st Jan 2024. Finally, we will assume that the Fed will perform monetary policy only through interest rates and the monetary base. US monthly unemployment rate and M2 Monetary Supply were also retrieved from FRED.

Raw Variables	Model 1	Model 2	Stationary
Interest Rate Shock	X	X	I(0)
S&P 500 Shock		X	I(0)
S&P 500	X	X	I(1)
GDP	X	X	I(1)
1Y Treasury	X	X	Weakly
Price Level		X	I(1)
EBP		X	I(0)
Unemployment	X		I(1)
M2 Money Supply	X		I(1)

Table 2: Variable selection in each model and stationarity information

After conducting ADF-Tests on those variables, the following transformations were made in order to make them stationary. For S&P500, M2, and PCEPI we computed the log of their values multiplied by 100 and then differenced. For GDP, the same process was applied, except the variable was first deflated with the price level. For unemployment the first difference was taken. The 1-year Treasury rate was weakly stationary, as such model 1 took the first difference, while model 2 did not, to avoid losing information and potentially over differencing. The Excess Bond Premium was already stationary, so no transformation was needed. The surprise variables were stationary as expected. The specific selected variables selected for each model along with their stationarity is stored in Table 2. All data pre-processing and pre-testing is performed in Python.

Results

Standard Cholesky- identified VAR

Model 1 was implemented in the R programming language. Although this estimated model was found to be stable (inverse of AR roots all inside the unit circle, Appendix 3), several problems were found. The Jarque-Bera test of normality indicated the residuals were not normally distributed (Appendix 4), the test for heteroskedasticity using Breusch-Pagan rejected the null hypothesis of homoskedasticity (Appendix 5) and the Lagrange Multiplier test for autocorrelation using Breusch- Godfrey test (Appendix 6) also rejected the null hypothesis of no serial correlation. The autocorrelation and partial autocorrelation plots are found in Appendix 7. Nonetheless, the IRF (Appendix 8) shows that there is an immediate negative effect in S&P 500 returns following a higher than expected interest rate announcement by the FOMC and the effect converges to zero in the span of 3 to 6 months approximately.

The diagnostic test results indicate that our first model had misspecification problems. These issues suggest that the model did not fully capture the dynamics of the underlying data. Non-normality of residuals indicated the model did not adequately represent the distribution of the data, and accounting for additional outliers might have been required. Serial correlation suggests that additional lags or a different model specification might be necessary. Heteroskedasticity indicated that the variance of the residuals is not constant, suggesting the need for models that account for changing volatility, such as GARCH models. To mitigate these issues, one could use Heteroskedasticity and Autocorrelation Consistent (HAC) standard errors to obtain more robust inference despite the presence of these misspecifications.

Sign Restricted Structural VAR

We run the sophisticated SVAR model using a slightly modified version of the replication code from Jarocinski and Karadi (2018) available publicly on the *American Economic Journal* website. The details of the main part of the code can be found in Appendix (9). The model is implemented in MATLAB.

In Figure 2, we plot the IRFs to the monetary policy and CB information shocks, using the S&P 500 as the market index. Confidence interval bands are denoted with different shades of blue, the light blue corresponds to 95% and the dark blue to 84%. The IRFs are plotted for 36 months which is equivalent to 3 years. We find that our variables have slightly different responses to the shocks providing evidence that monetary policy announcements generate not only monetary policy shocks. The positive co-movement of interest rates and stock prices around monetary policy announcements is informative about low-frequency outcomes. This is highlighted for example by the differences in IRFs of inflation and credit spread between the two shocks. Most importantly, as is the main goal of this paper, Monetary policy and Information shocks affect the S&P 500 differently.

In the first column, we investigate responses to a one standard deviation shock in monetary policy. This represents a surprise increase in interest rates or a monetary tightening, purged from any information transfer. In such a situation, the model predicts in contemporaneous 5 basis points (bps) increase in the 1-year treasury yields. Nevertheless, the yield reverts to zero in about 11 months to a 16% significance level. The S&P 500 decreases by around 40 to 60 bps and remains at this new equilibrium. Although, to a 5 percent significance, the monetary policy effects dissipate after around 2-3 months and remain statistically indifferent from zero. Regarding the real GDP, we note a persistent decline of about 5 to 15 bps over the span of 3 years to a 16% significance level. The credit spread increases significantly contemporaneously by 3 bps and eventually reverts to 0 in about 9 months to a 16% significance level.

The second column denotes the impulse responses to a CB information shock where they express a positive economic outlook in the short to medium term. We find that the 1-year treasury rate does not react contemporaneously but instead gradually rises by 6-7 bps over the first year. Then it declines back to zero over the following 2 years, this is much slower than in a monetary policy shock. The information shock has a mild contemporaneous negative effect of about 5 bps on the stock market but after about 3 months, the effect is statistically indifferent from zero. One aspect to note is that the confidence bands are significantly smaller for the information shock. This provides evidence that transmission of information reduces market uncertainty and thus volatility. Additionally, Jarocinski and Karadi test this model in a European context, they find that the stock market effects are significantly larger there as the ECB follows a much more transparent communication. The real GDP effects are similar to monetary policy shocks where there are no contemporaneous effects but experiences a persistent decline by about 0.5 to 1 basis point. The price level exhibits some negative effects but that are never statistically different from zero. The credit spread effects are difficult the interpret. Initially, the effect is negative but in the first year it becomes positive, in the second year it turns negative again and positive for the third year. These effects are never statistically significant.

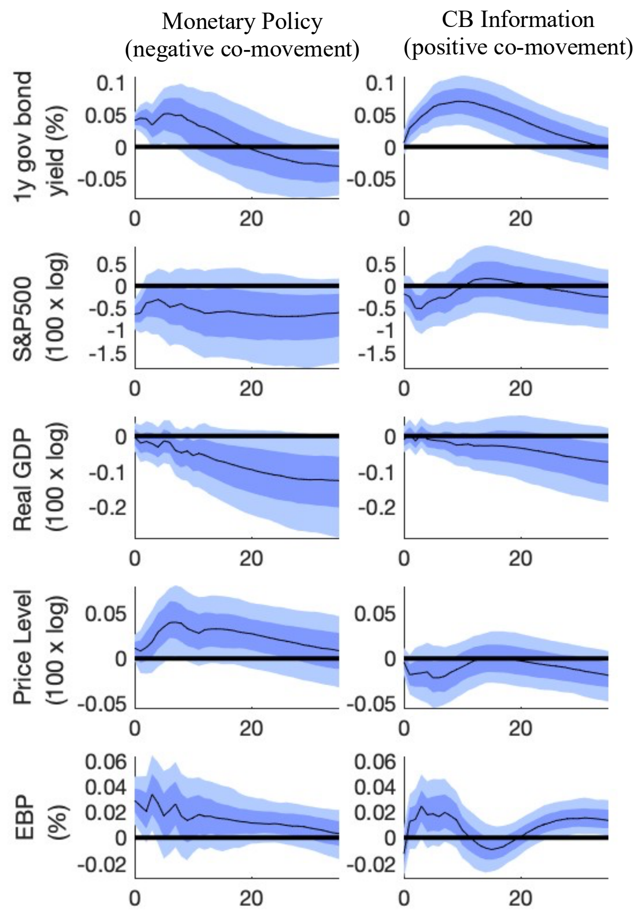


Figure 2: Impulse response to 1- standard deviation shocks using the S&P 500

We note that there are divergences between the IRFs from Figure 2 and the ones reported by Jarocinski and Karadi. The most flagrant difference is with the price level. The original paper finds negative price level and real GDP effect after a monetary policy shock and thus classifies these as "demand" shocks. We find a negative output effect but a positive price level effect. Several reasons can be attributed to this difference in findings. First, we include a more recent time range in our sample which includes the Covid crisis and its "supply shocks". This period contains the extreme inflationary pressures post-pandemic, and the unanticipated interest rate increases in an attempt to control the price level. This could explain the co-movement of the positive interest rate surprise and the short-term rise in inflation.

Next, we use Bloomberg's 1st level decomposition of the S&P 500 by industry as the market index inside the model as seen in Figure 3. There are 10 industries in this decomposition: *Consumer staples, Real Estate, Health Care, Materials, Information Technology, Industrials, Consumer Discretionary, Communications Services, Financials and Energy*.

The first three have a ‘positive’ price effect following an increase in interest rates. These industries provide essential goods and services that follow an inelastic demand. Even though consumer spending will reduce during a monetary tightening, the demand for these industries will generally remain unchanged. This argument should also hold for the *Energy* sector which shows negative price effects, however, as we will see later it is a capital intensive industry. The *Real Estate* sector in particular shows a strong positive contemporaneous effect to the shock of around 10 bps but returns to zero after 9 to 10 months. One reason why this industry is the best performing after a monetary tightening is that rising interest rates may also signal a strong economy, leading to increased demand for commercial real estate properties such as office buildings and retail spaces. Additionally, real estate investment trusts (REITs), which are commonly traded on stock exchanges, often offer attractive dividend yields, making them more appealing to investors seeking income during periods of monetary tightening.

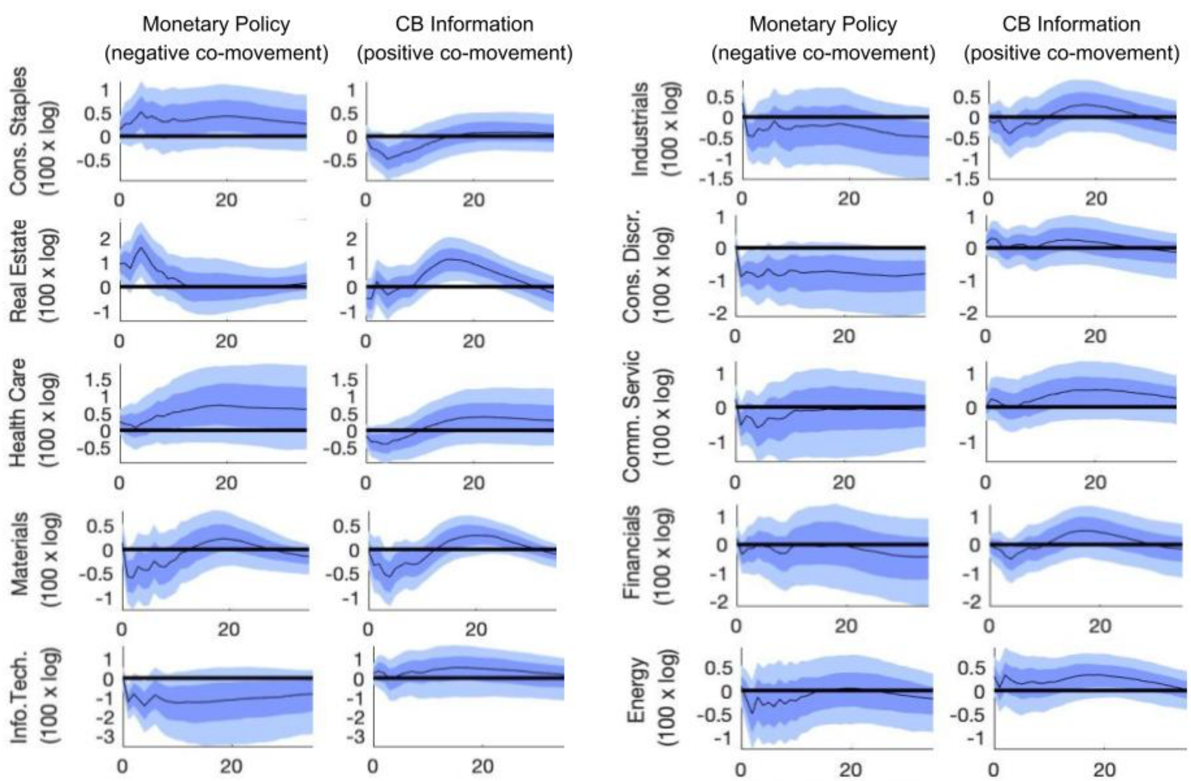


Figure 3: Impulse response to 1- standard deviation shocks breaking down the S&P 500 by industry

All other industries exhibit negative price effects following a surprise interest rate increase. The same argument as before except for elastic demand can be made to explain the price effect on *Consumer Discretionary* goods, *Information Technologies* or *Communications Services*. These are the first goods that consumers cut from their spending when required, investors may anticipate a reduction in earnings causing the market price to decrease. Additionally, capital intensive industries like the *Financials, Materials, Industrials* and *Energy* may suffer during a monetary tightening as they hold a lot a debt which becomes more expensive. Regarding a positive information shock transmitted by the FED announcement, most industries seem to display a positive response although in most cases it occurs 6 and 18 months after the shock, but the effects are never significantly different from zero.

Finally, to evaluate the performance and validity of our model, we perform various diagnostic tests as mentioned in the *Methodology* section. The results for the Breusch-Godfrey test for heteroskedasticity, Shapiro test for normality and Durbin Watson test for autocorrelation are tabulated in Table 2. For the first two tests, a p-value below a standard significance level will indicate heteroskedasticity and non-normality respectively. For the Durbin Watson test, no autocorrelation is demonstrated by a DW statistic of 2, values greater than 2 indicate positive autocorrelation and values below 2 indicate negative autocorrelation.

	Diagnostic Test Results				
	Breusch-Pagan Test		Shapiro-Wilk Test		Durbin-Watson Test
Variable	**LM Statistic**	**LM p-value**	**T-stat**	**p-value**	**DW Statistic**
1-year Treasury Yield	146.50	0.00	0.70	0.00	1.86
S&P log-returns	107.01	0.00	0.77	0.00	2.16
Real GDP growth	5.49	0.06	0.68	0.00	1.82
Inflation Rate	3.86	0.15	0.96	0.00	2.00
Corporate Credit Spread	0.46	0.79	0.45	0.00	2.08

Table 3: Diagnostic Test Results for the Bayesian SVAR

The Results from Table 3 demonstrate that only the corporate credit spread, and the inflation rate displayed no heteroskedasticity. The real GDP growth showed heteroskedasticity at a 6% significance level. All variables fail the normality test, displaying negligible p-values. Finally, all variables show adequate values of the Durbin-Watson statistic showing evidence of no or low autocorrelation. These results harm the interpretability of the impulse response functions. heteroskedasticity-consistent (HC) errors could be implemented to correct for the VAR regressions that displayed heteroskedasticity in the residuals. To correct for normality, deterministic variables or dummy for structural breaks in the data could be implemented. Additionally, adjusting the priors of the distribution could potentially accommodate non-normality in the residuals. The probability distribution of each endogenous variable in yt can be found in Appendix 10 to compare with the diagnostic test results. Given that there is little to no autocorrelation displayed in the residuals, we do not have to correct for it.

Given the time constraints and the use of replicating code to run the Bayesian VAR, we were not able to implement corrections. While it does harm the standard errors of the residual, it should have a limited effect on the main conclusions of the paper.

Discussion

Having shown that there are differences in reactions to 'purified' and 'standard' monetary shocks on US data we must assess what this entails about the channels of monetary transmission. First and foremost, it is crucial to define exactly what "central bank information" is. It is not clear in the literature that central banks have superior information about the fundamentals of the economy. If it were the case, the CB information shock IRFs are simply a materialization of said fundamentals. The central bank does not cause the responses it simply predicts them. In other words, economic agents would have figured out anyways that an economic expansion/ contraction is coming, the central bank announcement just informs them about the fundamentals earlier. Another possibility is that these announcements are self- fulfilling. The mere act of releasing a public signal influences the equilibrium level. In either case, these "CB information shocks" should not be referred to as a separate policy tool that the central bank can exploit.

Otherwise, central banks may have the incentive to withhold information which may in turn harm its trustworthiness leading to a potential economic disaster.

One possible limitation to the methodology is that the fed fund futures used to contract the interest rate surprise variable may be a poor representation of monetary policy. This is exemplified in a situation where the economy always has a good state and a bad state. If the central bank follows the Taylor Rule shown by the following equation:

$$Target\ rate = real\ rate + Inflation + 0.5(inflation\ gap) + 0.5(\boldsymbol{output\ gap})$$

Then, in the good states the interest rates must increase due to the output being above the long run target output. Being in the 'good state' also implies that the stock market must be increasing. In such a scenario, identifying positive co-movement occurrences, falling in quadrant I and III of Figure 1, is not evidence of 'superior central bank information' but rather just that monetary policy works. If this is the true mechanism, it may put into question the validity of this paper.

Conclusion

We attempt to investigate the effect of monetary policy on the stock market. Our approach evolved from initially using Wickens and Motto's (2001) VECM methodology, into implementing a Bayesian SVAR model as described by Jarocinski and Karadi (2018). This second model incorporated priors of the parameters and allowed us to refine our identification of the two types of shocks—monetary policy and central bank information shocks. Through this model, we were able to isolate and analyze the distinct impacts of these shocks, thereby providing an impulse response analysis on monetary policy shocks purged of any announcement information noise. We find that a 'purged' monetary shocks leads to a decrease in real output, an increase in the price level and the S&P 500 reaches a new lower equilibrium value. Dissecting the Market index into industries, we find that industries with inelastic demand for their products tend to perform better after an interest rate increase. On the other hand, capital intensive industries with elastic demand for their product are by far the worst performers following a monetary policy shock.

Bibliography

Taylor, John B. 1995. "The Monetary Transmission Mechanism: An Empirical Framework." Journal of Economic Perspectives, 9 (4): 11-26.
https://www.aeaweb.org/articles?id=10.1257/jep.9.4.11

Pesaran, H. Hashem & Shin, Yongcheol, 1998. "Generalized impulse response analysis in linear multivariate models," Economics Letters, Elsevier, vol. 58(1), pages 17-29, January.
https://www.sciencedirect.com/science/article/abs/pii/S0165176597002140

Maclennan, Duncan & Muellbauer, John & Stephens, Mark, 1999. "Asymmetries in Housing and Financial Market Institutions and EMU," CEPR Discussion Papers 2062, C.E.P.R. Discussion Papers.
https://www.jstor.org/stable/23606482

Rapach, David E., 2001. "Macro shocks and real stock prices," Journal of Economics and Business, Elsevier, vol. 53(1), pages 5-26.
https://www.sciencedirect.com/science/article/abs/pii/S0148619500000370

Michael R. Wickens & Roberto Motto, 2001. "Estimating shocks and impulse response functions," Journal of Applied Econometrics, John Wiley & Sons, Ltd., vol. 16(3), pages 371-387.
https://onlinelibrary.wiley.com/doi/abs/10.1002/jae.617

Anthony Garratt & Kevin Lee & M. Hashem Pesaran & Yongcheol Shin, 2003. "A Long run structural macroeconometric model of the UK," Economic Journal, Royal Economic Society, vol. 113(487), pages 412-455, April.
https://www.jstor.org/stable/3590326

Ben S. Bernanke & Kenneth N. Kuttner, 2005. "What Explains the Stock Market's Reaction to Federal Reserve Policy?," Journal of Finance, American Finance Association, vol. 60(3), pages 1221-1257, June.
https://onlinelibrary.wiley.com/doi/full/10.1111/j.1540-6261.2005.00760.x

Christos Ioannidis & Alexandros Kontonikas, 2006. "Monetary Policy and the Stock Market: Some International evidence" Working Papers 2006_12, Business School - Economics, University of Glasgow.
https://www.gla.ac.uk/media/Media_219105_smxx.pdf

Li, Yun Daisy & Iscan, Talan B. & Xu, Kuan, 2010. "The impact of monetary policy shocks on stock prices: Evidence from Canada and the United States," Journal of International Money and Finance, Elsevier, vol. 29(5), pages 876-896, September.
https://www.sciencedirect.com/science/article/abs/pii/S0261560610000422

Guglielmo Maria Caporale & Alaa M. Soliman, 2013. "Stock Prices and Monetary Policy: An Impulse Response Analysis," International Journal of Economics and Financial Issues, Econjournals, vol. 3(3), pages 701-709.
https://dergipark.org.tr/en/download/article-file/362809

Lucia Alessi, & Mark Kerssenfischer, 2016 "The response of asset prices to monetary policy shocks: Stronger than thought", Working Papers 2016, Journal of Applied Econometrics, 2019, vol. 34, issue 5, 661-672
https://www.ecb.europa.eu/pub/pdf/scpwps/ecbwp1967.en.pdf

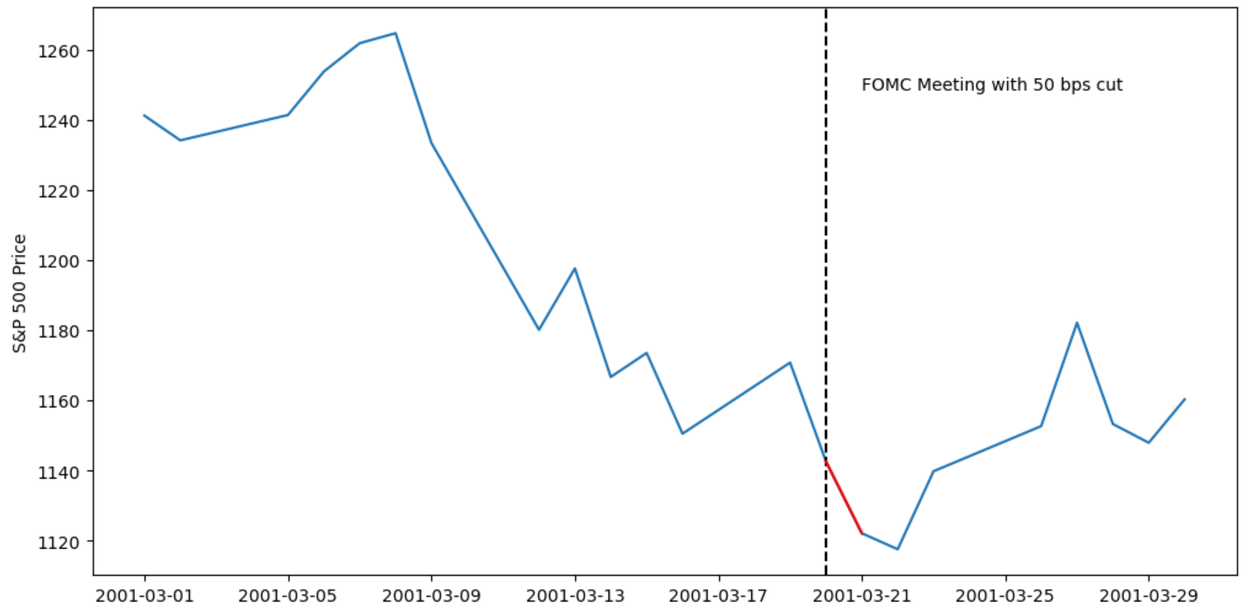
Olli-Matti Laine, 2023. "Monetary Policy and Stock Market Valuation," International Journal of Central Banking, International Journal of Central Banking, vol. 19(1), pages 365-416, March.
https://www.ijcb.org/journal/ijcb23q1a8.pdf

Jarociński, Marek & Karadi, Peter, 2018. "Deconstructing monetary policy surprises: the role of information shocks," Working Paper Series 2133, European Central Bank.
https://www.ecb.europa.eu/pub/pdf/scpwps/ecb.wp2133.en.pdf

Silvia Miranda-Agrippino & Giovanni Ricco, 2021. "The Transmission of Monetary Policy Shocks," American Economic Journal: Macroeconomics, American Economic Association, vol. 13(3), pages 74-107, July.
https://warwick.ac.uk/fac/soc/economics/research/workingpapers/2017/twerp_1136_ricco.pdf

Appendix

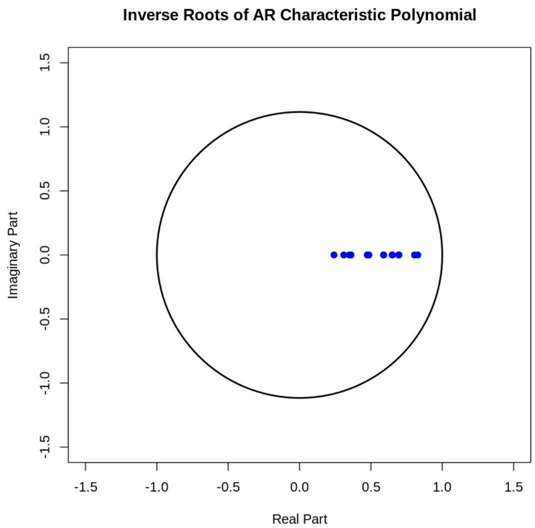
<u>Appendix 1</u>: Market reaction to rate cut on 20th march 2001



<u>Appendix 2:</u> Minnesota prior specifications used in Bayesian VAR taken from the replication code

```
% PRIOR
prior.lags = 12;
prior.minnesota.tightness = .2;
prior.minnesota.decay = 1;
prior.Nm = length(mnames);
```

Appendix 3: Stability Test (Model 1 without shock differentiation)



Appendix 4: Jarque-Bera Normality Test (Model 1 without shock differentiation)

```
        JB-Test (multivariate)

data:  Residuals of VAR object var_model
Chi-squared = 16623, df = 12, p-value < 2.2e-16
```

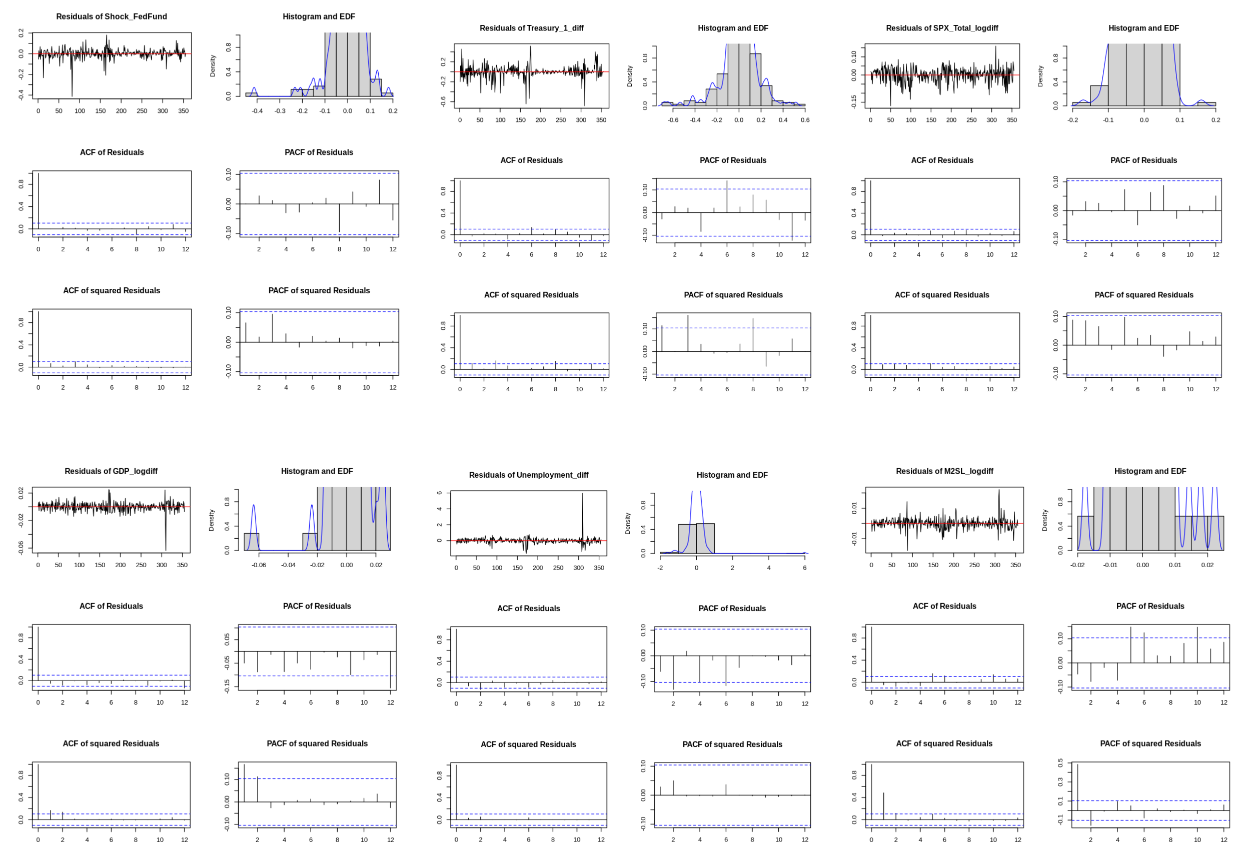
Appendix 5: Breusch-Pagan Heteroskedasticity test (Model 1 without shock differentiation)

```
        studentized Breusch-Pagan test

data:  residuals(var_model) ~ fitted(var_model)
BP = 154.62, df = 6, p-value < 2.2e-16
```

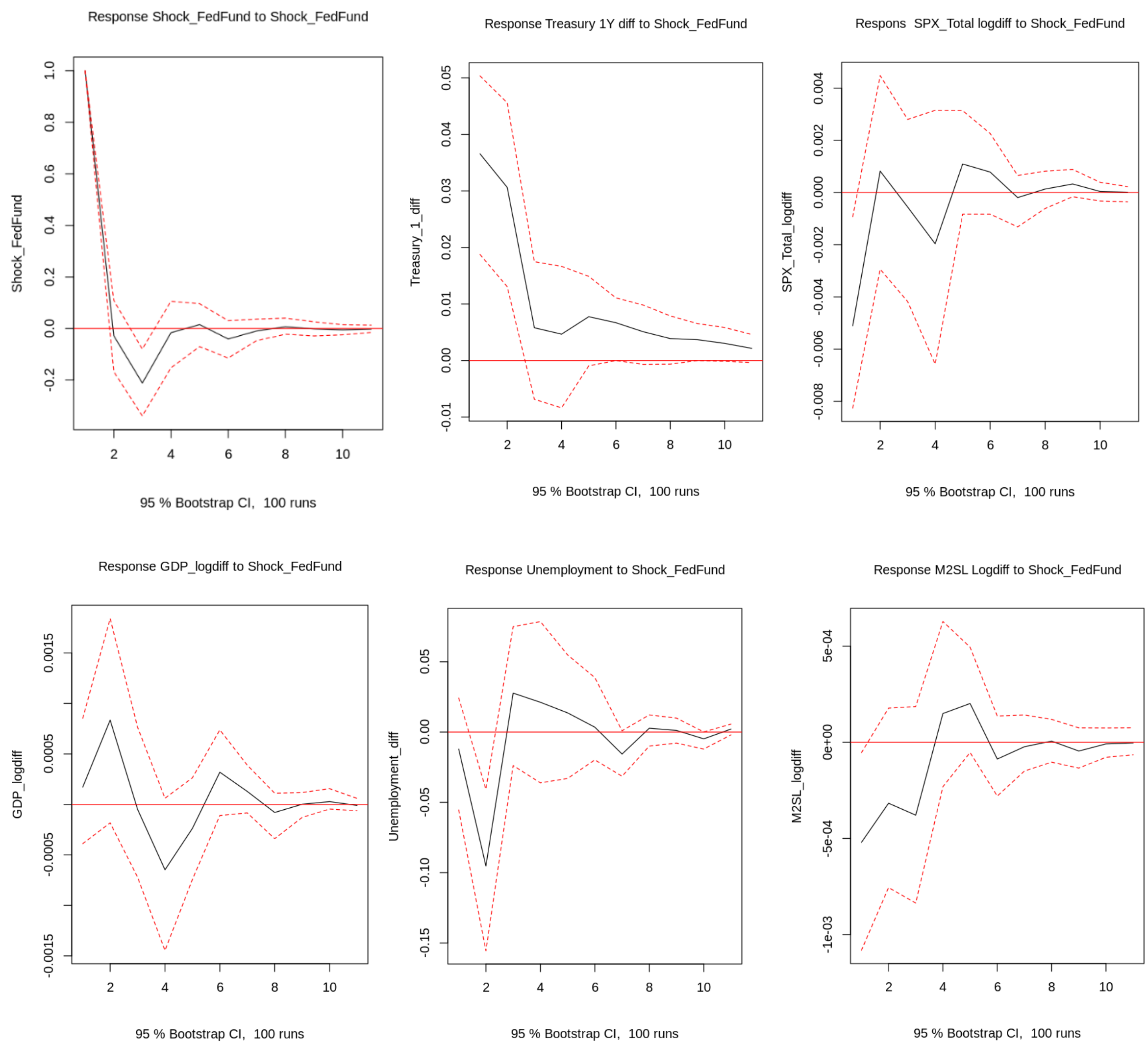
Appendix 6: Breusch-Godfrey autocorrelation test (Model 1 without shock differentiation)

```
	Breusch-Godfrey LM test

data:  Residuals of VAR object var_model
Chi-squared = 388.71, df = 180, p-value < 2.2e-16
```

Appendix 7: ACF and PACF plots (Model 1 without shock differentiation)



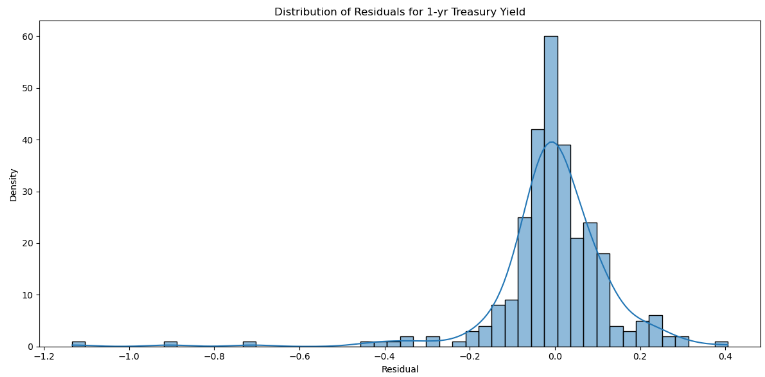
<u>Appendix 8</u>: Impulse Response Function plots (Model 1 without shock differentiation)

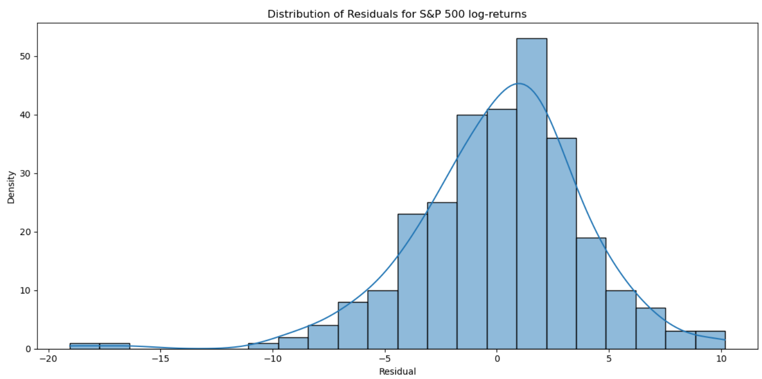


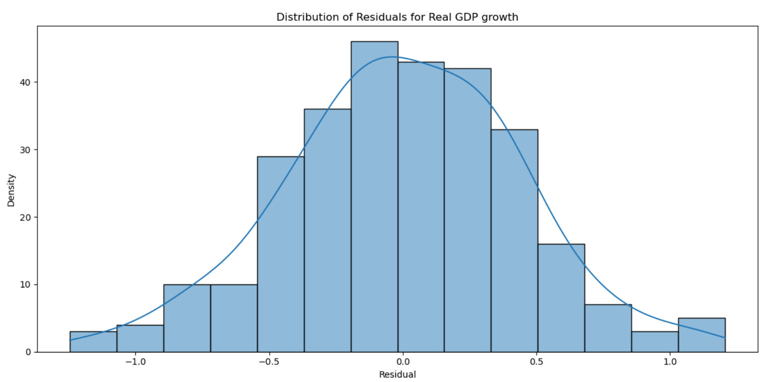
Appendix 9: Description of the main modelling function in the replication code. The original MATLAB codes along with the new python and R scripts will all be available inside the submission folder

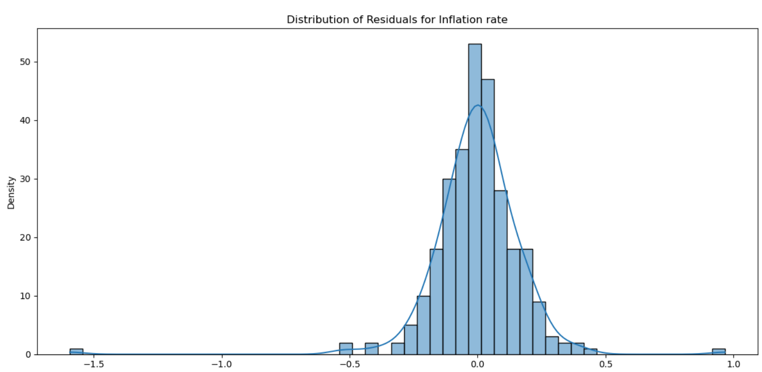
```
% result = VAR_withiid(data, prior, gssettings, printout)
% PURPOSE: inference in a VAR with some i.i.d. variables
%
% The VAR model with parameters B,Sigma is
%   M = Um
%   Y = X B + Uy
% where X = [ lagged M's and Y's, W ] and each row of U is N(0,Sigma).
%
% INPUTS:
% data - structure with variables
% data.y - T x Ny data on endogenous variables
% data.m - T x Nm data on i.i.d variables (the same number of observations as y)
% data.w - T x Nw data on exogenous variables (the same number of observations as y)
% data.names - cell array with names of the variables, m first, y second
% prior - structure with prior hyperparameters + n. of lags
% gssettings - settings of the Gibbs sampler
% printout (optional) - controls much printout, default=1
%
% DESCRIPTION OF prior:
%
% compulsory field:
% prior.lags - number of lags
%
% prior.minnesota - settings of the Minnesota prior
% example of the prior.minnesota struct:
% prior.minnesota.mvector = [1 1 0 1 0 0]; % means of own lags
% prior.minnesota.tightness = 0.2;
% prior.minnesota.decay = 1;
% prior.minnesota.sigma_deg = N+2; % degrees of freedom of p(Sigma)
%   p(Sigma) = IW(S,sigma_deg)
%   need sigma_deg > N-1 for the prior to be proper
%   need sigma_deg > N+1 for the E(Sigma) to exist
%   optional, default: sigma_deg = N+2
%
% RETURNS: result - struct with various posterior results
% result.data - data
% result.prior - prior
% result.logdensy - log marginal likelihood
% result.beta - posterior mean of the reduced form VAR parameters, K by N
% result.sigma - posterior mean of the reduced form error variance, N by N
% result.beta_draws - draws of beta from the posterior, K by N by ndraws
% result.sigma_draws - draws of sigma from the posterior, N by N by ndraws
% result.dens_draws - ndraws by 2, where:
%            the first column contains log prior p(B,Sigma) for each draw
%            the second column contains loglikelihod for each draw
%
% DEPENDS: kfsim_nan_VAR->kfsim_nan, MLMGD_VARwithiid->MLMGD
% SUBFUNCTIONS: varlags, multgammaln, logdet
%
% Marek Jarocinski 2016-Jul; 2016-Sep; 2017-Jun;
% 2019-Jan - marginal likelihood
```

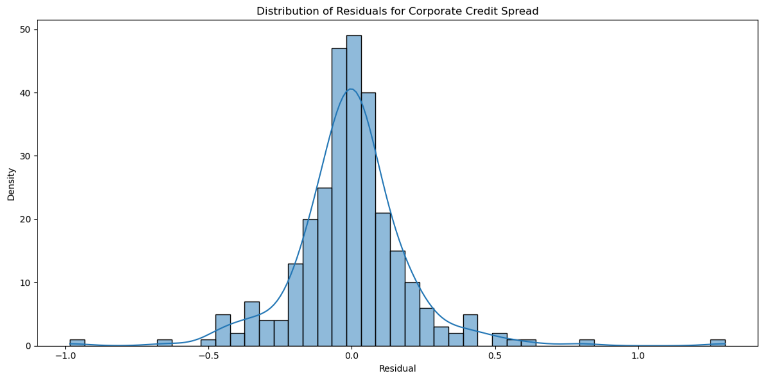
Appendix 10: Probability distributions of endogenous variables










Distribution of Residuals for Corporate Credit Spread
Density
Residual
0
10
20
30
40
50
−1.0
−0.5
0.0
0.5
1.0