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Understanding the Dynamic Effects of Information Shocks: An Empirical Analysis

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Abstract

This study employs a Structural Vector Autoregressive (SVAR) model to investigate the dynamic responses of key economic variables to a positive information shock. The analysis employs Cholesky Vector Autoregressions (VARs) with a proxy variable and incorporates impulse response functions and the forecast error variance decomposition to identify the variables most affected by the shock.

1 Introduction:

1.1 Issue Outline: A major obstacle in identifying the effects of shocks in the market has been the neglect of information asymmetries between the public, the central bank, and the private sector. The paper by Miranda-Agrippino and Ricco (2021) highlights the importance of considering the impact of information frictions and their consequences on potential shocks. Imperfect and asymmetric information are the norm in monetary policy, an example could be the case of forward guidance policies, where central banks communicate future policy intentions, the impact of these announcements can vary significantly depending on the information available to market participants. A misinterpretation of central bank's signals due to information frictions, could lead to unintended economic consequences, such as misaligned expectations about future interest rates or inflation.
Although the literature includes several theoretical attempts to incorporate informational imperfections into the modeling of monetary policy (for example the role of expectation in the Barro-Gordon Model), these have been largely disregarded in the empirical identification of shocks. Most monetary policy shocks constructed in leading identification schemes assume that either the central bank or market participants have perfect information. However, these assumptions can distort the model, potentially leading to inaccurate representations of reality and ineffective monetary policy operations.

1.2 Motivation: This project aims to shed light on the response of key U.S. economic variables to information shocks by implementing a Cholesky SVAR with a proxy. An empirical analysis will be conducted using the VAR toolbox developed by Ambrogio Cesa-Bianchi[1] to retrieve empirical evidence of the importance of information shocks. The VAR toolbox provides a robust framework for estimating the impact of information shocks on U.S. economic variables. This brief paper seeks to address questions such as:

- How does interest rate GS1 adjust when unexpected information emerges?
- What happens to the consumer price index and to the RGDP?
- Are there spillover effects?

Ultimately, this brief paper aims to bridge the gap between theoretical models and empirical reality enhances the effectiveness of monetary policy operations.

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[1] More details on the VAR toolbox, refer to: Ambrogio Cesa-Bianchi

2 Data and Methodology

2.1 Data and Variables: The analysis conducted in this paper is based on quarterly data spanning from April 1st, 1991, to October 31st, 2017. The dataset includes various variables such as GS1, BAA10Y, CPIAUCSL100LOG and RGDP100LOG; these variables will be considered endogenous in order to determine their response to the information shock.

GS1 describe the market yield on U.S. Treasury Securities at 1-Year constant maturity, quoted on an investment basis, so, it describes the 1- Year interest rate; "CPIAUCSL100LOG": is a variable representing the logarithm (log) transformation of the Consumer Price Index (CPI), with an additional scaling factor of 100. Price Index (CPI) serves as a metric for monitoring the fluctuation in prices paid by urban consumers for a standardized basket of goods and services over time, making it a key indicator of market inflation. Inflation (deflation) refers to the general increase (decrease) in prices of goods so, effectively captured by changes in the CPI. RGDP100LOG and BAA10Y are respectively the real GDP transformed using a logarithmic scale and a scaling factor, and the interest rate spread that measures the risk premium between BAA-rated corporate bonds and 10-year U.S. Treasury bonds.

The dataset contains also a series called "mar_info_extended_1", this is a proxy for the information shock constructed by Silvia Miranda Agrippino and Giovanni Ricco. To understand the process and the analysis it's important to focus on how and why this instrument was ideated. The proxy is built to capture the part of high-frequency market reactions to policy announcements that is unrelated to the central bank's economic projections and past market surprises. The instrument is built firstly by considering Greenbook forecasts and their revisions around FOMC (Federal Open Market Committee) announcements, as benchmarks for expected economic conditions, and then by projecting these forecasts onto the high-frequency market-based surprises (The Greenbook is a publication by the Federal Reserve that provides economic forecasts for key variables, such as real output growth, inflation, and unemployment).

The projection is given by the following regression:

$$FF4_m = \alpha_0 + \sum_{j=-1}^{3} \theta_j F_m^{cb} \boldsymbol{x_{q+j}} + \sum_{j=-1}^{3} \vartheta_j \left[F_m^{cb} \boldsymbol{x_{q+j}} - F_{m-1}^{cb} \boldsymbol{x_{q+j}}\right] + MPI_m$$

$FF4_m$[2] is the high-frequency market-based monetary surprise around FOMC announcements, it's explained by central bank's economic projections and others independent information ($\approx MPI$).

$F_m^{cb} \boldsymbol{x_{q+j}}$ are forecasts for the vector of variables **x** (Greenbook forecasts and their revisions).

MPI_m is the daily residual.

The sum of the residual (MPI_m) within each month from this projection serves as the instrument for monetary policy information shock. To address the gradual absorption of information by agents, Silvia Miranda Agrippino and Giovanni Ricco eliminated the autoregressive component from the monthly surprises, refining the instruments used in the analysis.

2.2 Modeling Approach: The analytical framework employed in this study entails a Cholesky Structural Vector Autoregression (SVAR) with a proxy. Cholesky SVAR models serve as effective tools for disentangling the intricate dynamics among economic variables after exogenous shocks. By employing a triangular decomposition of the covariance matrix, this method establishes a structured hierarchy among variables, thereby facilitating the discernment of causal effects. Developed by influential economists such as Stock and Watson (2012) and Mertens and Ravn (2013), with further

[2] FF4 are federal funds futures, are financial futures contracts based on the federal funds rate and traded on the Chicago Mercantile Exchange (CME). The prices of Fed funds futures reflect market expectations about future changes in the Fed funds rate. For more details: Miranda-Agrippino and Ricco (2021).

refinement highlighted in Montiel Olea, Stock, and Watson (2020), Proxy-SVARs emerge as robust model suitable for addressing endogeneity and identification challenges. The incorporation of a proxy into the Cholesky SVAR model augments its analytical prowess by furnishing a mechanism to discern and isolate specific shocks. Moreover, the orthogonality nature of the instrument allows for the elimination of endogeneity issues and the rectification of identification challenges.

3 Estimation and Results

3.1 VAR model: In line with what said before, the first step to create the model is to estimate the VAR model, starting by creating the vector of endogenous variables $\boldsymbol{y}$.

$$\boldsymbol{y} = \begin{pmatrix} mar\_info\_extended\_1 \\ GS1 \\ BAA10Y \\ CAPIAUCSL100LOG \\ RGDP100LOG \end{pmatrix}$$

The structural representation of a VAR model is:
$B(L)y_t = w_t$
Where $B(L)$ is a $(n \times n)$ matrix of lag-length L, representing impulse-response functions of the shocks to the elements of y_t, w_t is the vector of structural shocks.
To estimate the SVAR model, the previous equation is multiplied by B_0^{-1} (inverse matrix of B_0) obtaining: $w_t = u_t B_0^{-1}$, where u_t is the reduced-form errors that are not mutually uncorrelated (the variance covariance matrix is not diagonal).
To retrieve the vector of shocks, we implement the Cholesky approach by transforming B_0^{-1} into a lower triangular matrix. This approach assumes that the shocks to the variables do not have any contemporaneous impact on the preceding ones. Therefore, we construct $\boldsymbol{y}$ with the proxy for information as the first variable.

3.2 Impulse Response Functions: An Impulse Response Function (IRF) is a tool used in time series analysis, particularly within the framework of vector autoregressive (VAR) models, to analyze how a variable responds to a shock or impulse in another variable over time. It helps in forecasting the future behavior of variables in response to shocks, allowing analysts to anticipate the impacts of sudden changes. The shock is usually a one-unit change, such as a one-standard deviation increase, in the error term of the equation for that variable and the IFRs calculates the impact of this shock on the current and future values of all variables in the model.
In this analysis, the Impulse Response Functions[3] (IRFs) are the main object of interest, particularly with regard to the response of RGDP100LOG and CAPIAUCSL100LOG to a positive information shock.
As illustrated in Figure 1, both real GDP and inflation exhibit a similar response to the shock. The impulse response starts from a positive value, indicating an initial increase in GDP and an inflationary trend triggered by the shock. In the initial steps, there is a phenomenon known as the price puzzle, where the reactions of these variables are not clear. This ambiguity is followed by a decreasing trend, characterized by some degree of persistence[4]. The persistence of the shock's effects over time can be

[3] Result shows with little uncertainty due to the Bayesian VAR method and 68% coverage bands.
[4] In Figure 5 it's possible to spot the differences with the stationary impulse responses

attributed primarily to the non-stationary nature of some underlying processes. Non-stationarity implies that the statistical properties of the process, such as mean and variance, change over time, which can lead to prolonged effects from shocks. The positive information shock causes a decrease of the 10 Y spread that stabilize after approximately 12 steps. Furthermore, the market yield on U.S. Treasury Securities (GS1) shows a pronounced response to the shock. There is an initial increase in yields, indicating that investors demand higher returns due to perceived higher risk or inflation expectations. This is followed by a significant decrease, possibly reflecting the market's reassessment of the long-term impact of the shock or shifts in monetary policy expectations.

Figure 1

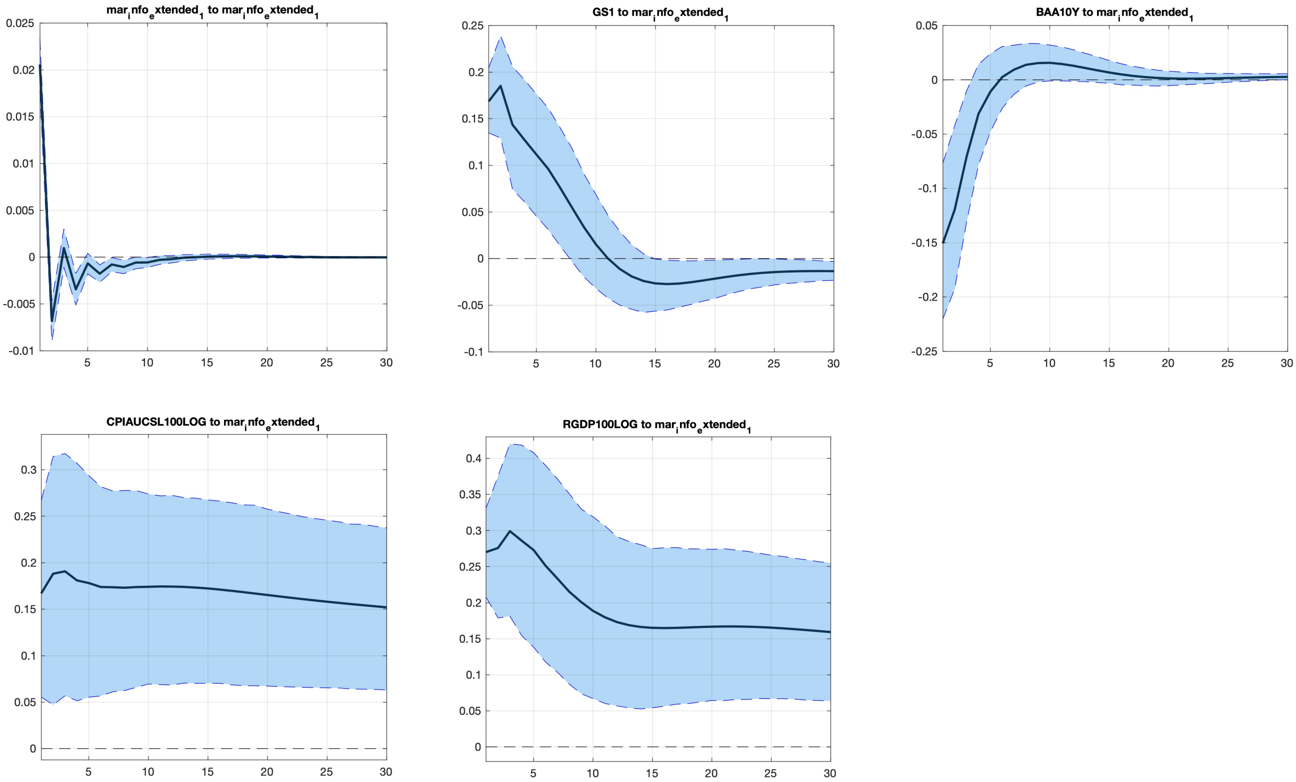
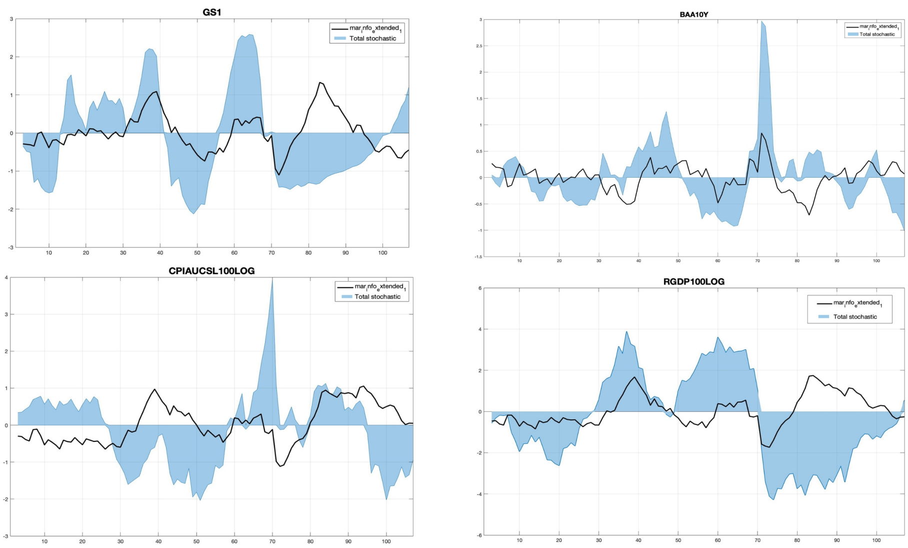


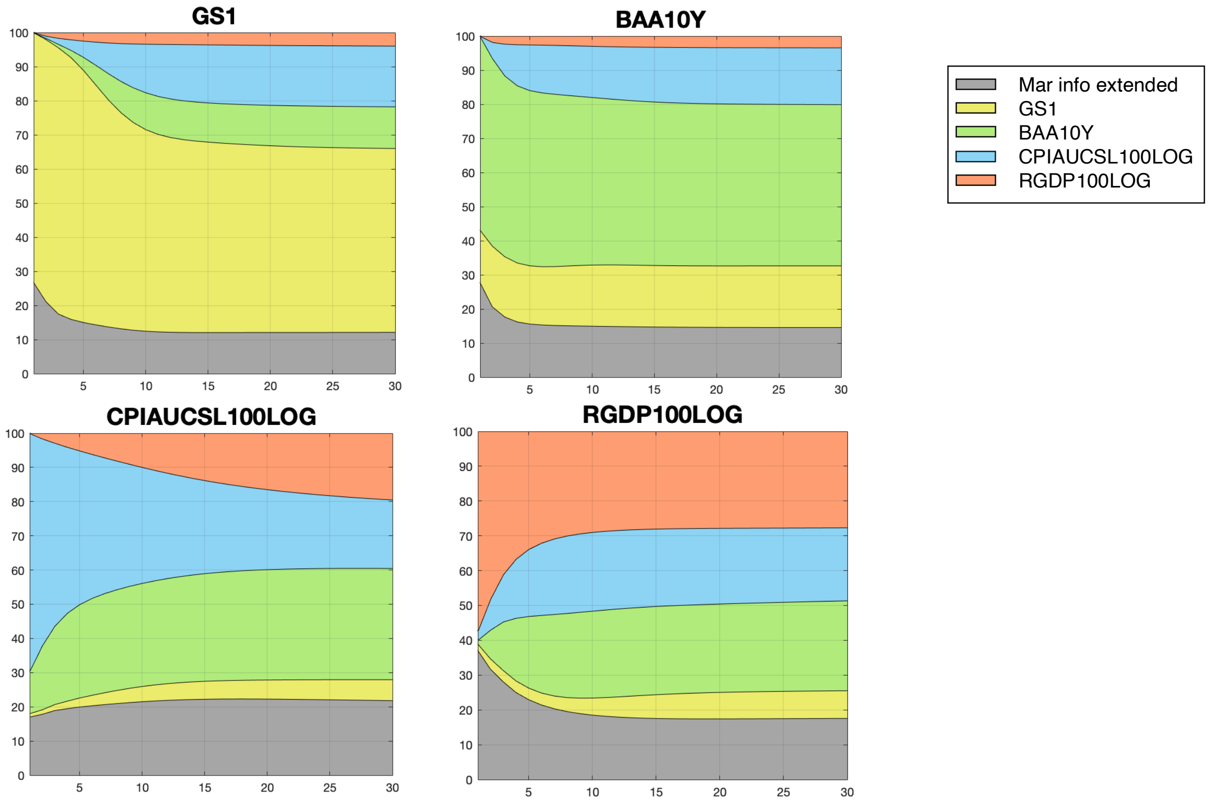
Figure 2 presents the Historical Decomposition, offering a detailed interpretation of the historical fluctuations, within the modeled time series, by analyzing the influence of the identified structural shocks.

Figure 2



Variance decomposition: Variance decomposition, also known as forecast error variance decomposition (FEVD) quantify the contribution of each structural shock to the variance of the forecast error of each variable at different forecast horizons; essentially, it helps to understand how much of the variability in a given variable is explained by each shock over time. In Figure 3 is presented the stacked area graph, each area represents the contribution of a different shock; for this analysis it's important to focus on the "mar info extended" part. The variance decomposition analysis indicates that the information shock significantly impacts the ten-year spread, real GDP, and the GS1 variable, while its effect on the consumer price index (CPI) is less significant[5].

Figure 3



4 Diagnostic Testing

4.1 Stationarity: In the presented model, non-stationary autoregressive (AR) processes are observed; specifically, the Augmented Dickey-Fuller test (Figure 5) identified a unit root for the variables GS1-RGDP100LOG and CAPIAUCSL100LOG. Those results are in contrast with the classical literature, that require the stationarity of the model, the problem should have been overcome from the modern literature that requires only the stationarity in the residuals from the key VAR variables (Canova 2007 and A. Sims, H. Stock, W. Watson 1990[6]).
The residuals plot in Figure 4 clearly indicates the absence of any noticeable trends; instead, they seem to conform to a white noise process. These results allow to continue with the analysis without resorting to the difference that could alter the response of the variables to the shock (Figure 6 shows the impulse responses with the model made stationary by first differencing).

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[5] Note that the FEVD of the shock is omitted as it does not contribute to our analysis. Notice also that the greatest area of each graph is the variable itself that is not relevant in relation to the others.
[6] For more details about the stationarity: A. Sims, H. Stock, W. Watson 1990

4.2 Lag selection: To identify the appropriate number of lags to consider in the model, information criteria were employed. These criteria serve as a means to balance bias and variance, or accuracy (fit) and simplicity (parsimony). The results of the model selection are as follows: 2 lags according to the Akaike information criterion (AIC) and 1 lag according to the Schwarz information criterion (BIC). In this case, the AIC criterion proves to be more suitable since it exhibits lower bias in small samples and is less parsimonious.

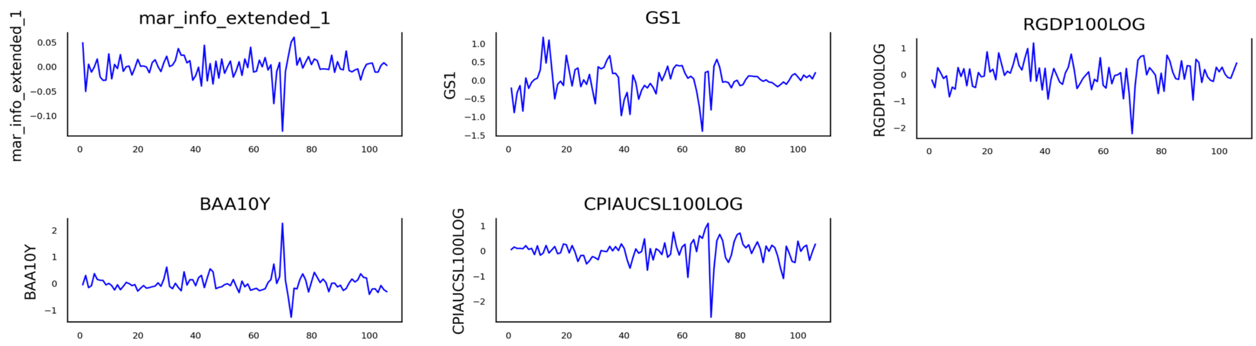
4.3 Heteroskedasticity and autocorrelation: In VAR estimation using OLS, it is crucial that the residuals do not exhibit heteroskedasticity or serial correlation, as these properties can distort parameter estimates and compromise the reliability of the model's results. However, there are some limitations to this analysis. Specifically, the VAR model used has low complexity and suffers from both autocorrelation and heteroskedasticity in the residuals. Notably, heteroskedasticity is evident in the GS1 variable (Figure 7), indicating a potential issue of misspecification in the VAR model.

4.4 Stability: A VAR process is stable if: $\det\left(I_{kp} - Bz\right) \neq 0 \; for \; all \; |z| \leq 1$, this means that the process is stable only when all eigenvalues of the companion-form matrix B have modulus less than or equal to one.
It's important to note that the concepts of stability and stationarity are distinct. While a stationary process is always stable, a stable process is not necessarily stationary. Stability ensures that the model accurately represents the time series behavior over the sampling period.
In this analysis, the estimated model's eigenvalues do not all lie within the unit circle. Some eigenvalues are on the complex unit circle, indicating that the model could be not stable. The eigenvalues are reported in Table 1.[7]

Table 1
VAR eigenvalues:

-0.50678	+0i
-0.029364	+0i
0.19696	+0.20086i
0.19696	-0.20086i
0.49128	+0.1659i
0.49128	-0.1659i
0.78408	+0.15312i
0.78408	-0.15312i
0.96165	+0i
0.99157	+0i

Figure 4 *Residuals plot*



The residuals have constant mean and variance $[\sim WN]$

[7] For the stability check look at the Appendix

Figure 5

```
    Augmented Dickey-Fuller Test on "GS1"
    ----------------------------------------------
Null Hypothesis: Data has unit root. Non-Stationary.
Significance Level    = 0.05
Test Statistic        = -1.6958
No. Lags Chosen       = 4
Critical value 1%     = -3.496
Critical value 5%     = -2.89
Critical value 10%    = -2.582
=> P-Value = 0.4333. Weak evidence to reject the Null Hypothesis.
=> Series is Non-Stationary.
```

```
    Augmented Dickey-Fuller Test on "CPIAUCSL100LOG"
    ----------------------------------------------
Null Hypothesis: Data has unit root. Non-Stationary.
Significance Level    = 0.05
Test Statistic        = -2.0952
No. Lags Chosen       = 2
Critical value 1%     = -3.495
Critical value 5%     = -2.89
Critical value 10%    = -2.582
=> P-Value = 0.2464. Weak evidence to reject the Null Hypothesis.
=> Series is Non-Stationary.
```

```
    Augmented Dickey-Fuller Test on "RGDP100LOG"
    ----------------------------------------------
Null Hypothesis: Data has unit root. Non-Stationary.
Significance Level    = 0.05
Test Statistic        = -1.9634
No. Lags Chosen       = 2
Critical value 1%     = -3.495
Critical value 5%     = -2.89
Critical value 10%    = -2.582
=> P-Value = 0.3028. Weak evidence to reject the Null Hypothesis.
=> Series is Non-Stationary.
```

Figure 6

Impulse responses (2 lags) first difference

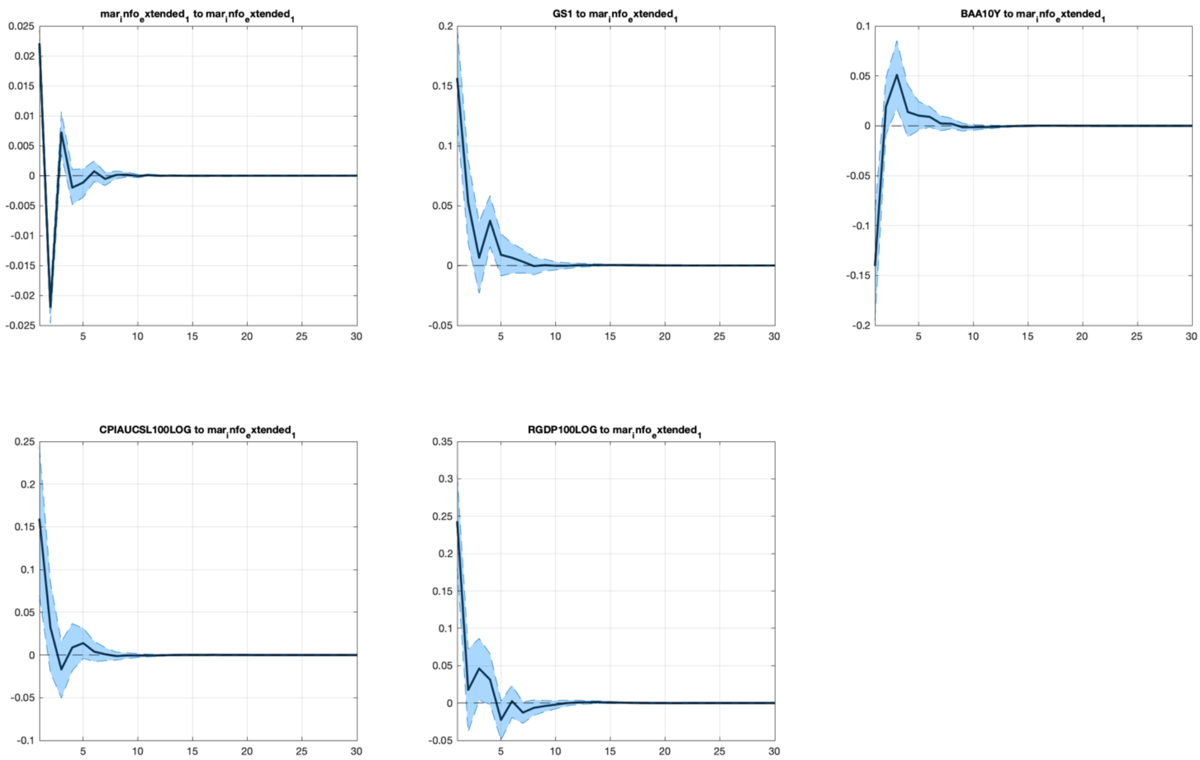


Figure 7

```
Heteroskedasticity Test for mar_info_extended_1
LM Statistic: 1.0760479865134365
LM-Test p-value: 0.5839009053002395
F-Statistic: 0.5281584446830496
F-Test p-value: 0.5912782534386106

Fail to reject the null hypothesis (homoskedastic).
```

```
Heteroskedasticity Test for GS1
LM Statistic: 6.440279753383402
LM-Test p-value: 0.039949469870139594
F-Statistic: 3.3314116037857837
F-Test p-value: 0.03963298846467828

Reject the null hypothesis (heteroskedastic).
```

```
Heteroskedasticity Test for BAA10Y
LM Statistic: 1.9705317428251983
LM-Test p-value: 0.3733399533194684
F-Statistic: 0.9755157500624663
F-Test p-value: 0.3804533718129528

Fail to reject the null hypothesis (homoskedastic).
```

```
Heteroskedasticity Test for CPIAUCSL100LOG
LM Statistic: 3.9019207505100546
LM-Test p-value: 0.14213750067888684
F-Statistic: 1.9681948977729837
F-Test p-value: 0.14492819726972517

Fail to reject the null hypothesis (homoskedastic).
```

```
Heteroskedasticity Test for RGDP100LOG
LM Statistic: 2.30647053550547
LM-Test p-value: 0.3156140199759222
F-Statistic: 1.1455221284487587
F-Test p-value: 0.3220759340147082

Fail to reject the null hypothesis (homoskedastic).
```

5. Conclusions

The analysis demonstrate that the information shock has an initial positive effect on the variables: RGDP100LOG, CAPIAUCSL100LOG and GS1, indeed, has a negative effect on the BAA10Y. The initial positive effect on RGDP100LOG suggests that the positive information shock likely increases consumer and business confidence. This boost in confidence can lead to higher spending and investment, driving up the overall economic output, this increases the demand for goods and services and as demand increase, prices tend to rise, reflected in a higher CPI. The positive effect on interest rates can be explained by the central bank's response to the increased economic activity and inflationary pressures. To prevent the economy from overheating and to keep inflation at the right level. A possible explanation for the negative effect on the BAA10Y spread is that the positive information shock reduces the perceived risk of corporate bonds, making the investors more confident about the ability of companies to pay off their debt, this lowers the risk premium, reducing so the spread.

These results are consistent with the use of the information proxy developed by Miranda-Agrippino and Ricco (2021). The FEVD denotes that the information shock is an important factor and contributes in a significant way in the changing of the variables, furthermore the HD were employed to illustrate how the information shock influenced the variance of these variables over time. However, the model presents some limitations, such as the presence of heteroskedasticity and some eigenvalues belonging to the complex unit circle, which could lead to small imperfections and bias in the estimated results.

In conclusion, the Cholesky VAR with proxy model, implemented in this analysis, effectively highlighted the significant impact of information shocks on key economic variables. Ongoing model evaluation and adjustment are crucial to addressing the identified limitations and ensuring the robustness of the results.

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Appendix

```
Stability check
Roots of Characteristic Polynomial
Endogenous variables:
  mar_info_extended_1 GS1 BAA10Y
  RGDP100LOG CAPIAUCSL100LOG
```

Root	Modulus
-0.50678 +0i	0.50678
-0.02936 +0i	0.029364
0.19696 +0.20086i	0.19777
0.19696 -0.20086i	0.19777
0.49128 +0.1659i	0.51672
0.49128 -0.1659i	0.51672
0.78408 +0.15312i	0.79503
0.78408 -0.15312i	0.79503
0.96165 +0i	0.96165
0.99157 +0i	0.99157

```
No modulus lies outside the unite circle
VAR satisfies the stability conditions
```

Lag selection

Lag Order 1 AIC : -15.85066764860334 BIC : -15.09686413140181 FPE : 1.3073911892577204e-07 HQIC: -15.545146981258677	Lag Order 2 AIC : -16.388585504591067 BIC : -14.998415797365697 FPE : 7.659550004852361e-08 HQIC: -15.825261314251026	Lag Order 3 AIC : -16.204987115646873 BIC : -14.170840270153512 FPE : 9.281347410572821e-08 HQIC: -15.380894449131448
Lag Order 4 AIC : -16.169561195465235 BIC : -13.483672421056385 FPE : 9.777620861277131e-08 HQIC: -15.081684277170925	Lag Order 5 AIC : -16.0765918701113 BIC : -12.73103828455292 FPE : 1.1040318434794427e-07 HQIC: -14.721863163131308	Lag Order 6 AIC : -15.887027199151603 BIC : -11.873723435682344 FPE : 1.3955588212917758e-07 HQIC: -14.262326463018804

```
Ljung-Box Tests
serial correlation in residuals

mar_info_extended_1
     lb_stat  lb_pvalue
 2  1.632494   0.442088
 No serial correlation detected (p-value = 0.4421)

GS1
      lb_stat   lb_pvalue
 2  19.657335   0.000054
 Serial correlation detected (p-value = 0.0001)

BAA10Y
     lb_stat   lb_pvalue
 2  7.721427   0.021053
 Serial correlation detected (p-value = 0.0211)

RGDP100LOG
     lb_stat  lb_pvalue
 2  4.927777   0.085103
 No serial correlation detected (p-value = 0.0851)

CAPIAUCSL100LOG
     lb_stat  lb_pvalue
 2  2.007551   0.366493
 No serial correlation detected (p-value = 0.3665)
```