UNIVERSITA' DEGLI STUDI DI PADOVA

DIPARTIMENTO DI SCIENZE ECONOMICHE ED AZIENDALI
"M.FANNO"

CORSO DI LAUREA MAGISTRALE IN
ECONOMICS AND FINANCE

TESI DI LAUREA

"LONG-RUN EFFECTS OF MONETARY POLICY SHOCKS: AN EMPIRICAL INVESTIGATION FOR THE U.S"

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MATRICOLA N. 2009416

ANNO ACCADEMICO 2020 – 2021

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Firma (signature)

To my parents,

for their care, guidance, and support during this journey.

Acknowledgement

To complete the research, I would like to thank my family for supporting me throughout the entire research and praying that it would be a great success. This is only their blessing and encouragement that have helped me to ease myself on a different critical path. After that I would like to thank the university for providing such a great opportunity to develop new knowledge and skills. This has helped me develop the same. Also, I also want to thank the supervisor, **Efrem Castelnuovo**, who helped and encouraged me at various times to complete the research. Lastly, I would like to express my gratitude to one and all those who have always encouraged me and supported me when I needed it.

Abstract

The main purpose of the thesis is to investigate whether monetary policy shocks and information shocks can generate long-term effects through a significant response of the noncyclical unemployment rate (nrou) in the United States, which is referred to as 'hysteresis.' The Cholesky (recursive) VAR model is used in the study, using quarterly data from the Federal Reserve Economic Data (FRED) spanning from 1991Q1 to 2015Q4. The analysis focusses on examining the dynamic effects of policy shocks through the application of impulse response functions (IRFs). Overall, the response of unemployment to monetary policy shocks tends to have a positive effect, while the response to information shocks exhibits a negative effect overall. Furthermore, the study investigates the impact of these two shocks on other variables including output (Gross Domestic Product), inflation (Implicit Price Deflator), short-term (3-Month) Treasury bills and long-term government bonds using forecast error variance decomposition (FEVD) at two horizons, namely 12 and 24. The substantial interaction among the variables can be seen from the FEVD analysis.

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1. Introduction

The central question of the thesis is to know how well the economy responds to an exogenous monetary policy shock? To analyze these shocks and study their impact, economists employed the Vector Auto Regressions (VAR). This model is pioneered among the various structural economic models used to measure the impact of a monetary policy shock on the U.S. economy.

The main objective of the thesis is to understand whether two policy shocks, i.e., monetary policy and information shocks generate long-term effects through a significant response of the noncyclical unemployment rate. This long-term effect is known as "hysteresis" (Cerra et al., 2020).

Unlike the other identification schemes reported in the literature, we have employed the (Cholesky) recursive identification strategy in this study and examine the dynamic reaction of macroeconomic variables to identify monetary policy and information shocks. We find that both monetary policy and information shocks exert long-term effects on unemployment. The findings are consistent with the study of (Miranda-Agrippino & Ricco, 2021). The contribution of these shocks to the dynamics of the natural rate of unemployment is not negligible, specifically information, shocks, and concluded that a monetary contraction is unequivocally and significantly recessionary in the long run.

In this study, we followed the work of (Miranda-Agrippino & Ricco, 2021) who constructed an instrument for monetary policy shocks by projecting market-based monetary surprises on their own lags and on the central bank's information set using SVAR-IV approach aggregating monthly data for US data set.

To fulfil the research objectives in the study, we apply a Cholesky VAR analysis, which has been one of the most widely used tools for analyzing the dynamics of economic systems since Sims' influential work in 1980. The VAR framework provides a simple method of capturing the dynamics of multiple time series that allows macroeconomists

to describe, summarize, and forecast macroeconomic data and quantify the underneath structure of the economy, (Stock & Watson, 2001).
Two of the major applications of vector autoregressive (VAR) are to quantify the impulse responses to macroeconomic shocks, to obtain forecast error variance decomposition (FEVD), and to understand the contributions of each shock to the fluctuation of other variables. In this study, we have employed the same empirical approach.

The structure of thesis is as follows. Section 2 explains the relevant literature and history on the impact of monetary policy and information shocks on variables of interest. It reviews the literature inspired by the study of (Miranda-Agrippino & Ricco, 2021). It also covers the importance of hysteresis in the labor market, reviewing its literature on the long-term impact of policy shocks via the significant response of unemployment rates.

Section 3 explained theoretical concepts underpinning the analysis of VAR models, along with chosen identification schemes.

Section 4 includes data and empirical methodology including the source and structure. Outlining the steps to define empirical models such as VAR.

Section 5 deals with model specification and estimation including the variables and the lag structure. Explanation of identification schemes and the ordering of the variables.

In Section 6, we presented the empirical results obtained by implementing the VAR model displaying the Impulse Response Functions graphically and discussed the patterns we have observed. To prove the robustness of our results, we then construct the tables of Forecast Error Variance Decompositions analysis.

Lastly, in section 7, we draw conclusions and discuss the policy recommendations.

2. Relevant Literature

2.1 Overview of Macroeconomic Shocks

What exactly are the macroeconomic shocks we try to estimate empirically? The definition is ambiguous due to some researchers' use of the term '*shock*' or refer to innovation (i.e., the residual from a reduced form of VAR models) or instruments.
(Sims, 1980) equated innovation with macroeconomic shocks, although it is claimed to be atheoretical. Other researchers use the word *shock* when referring to instruments (e.g., (Cochrane, 2004)).

Although, (Ramey, 2016) view shocks, VAR innovations, and instruments to be different concepts, and identification schemes may associate them in many cases. These shocks are more closely associated with the structural disturbances in a simultaneous equation system. The same study adopted the concept of shocks used by economists such as (Blanchard & Summers, 1986), (Bernanke. B.S., 1986) and (J. H. Stock & Mark W. Watson, 2012).

According to (Bernanke. B.S., 1986):
Shocks are primitive external forces without any correlation between them and should have economic meaning.

2.2 Monetary Policy Shocks

All those monetary policy decisions that affect the economic environment causing shocks, give rise to monetary policy shocks (MPS). There are two types:

i. If the interest rate rises and attempts to stimulate private investment and household consumption push the economic cycle, it expands.

ii. Restrictive when interest rate increases, reduce the supply of money, making any kind of investment and production less convenient.

The central question in monetary economics is to know how does the economy responds to exogenous monetary policy shocks? In the literature, numerous explanations are presented. In this study, we have reviewed the literature on monetary policy shocks, their identification methods and how these shocks are related to the real economy, specifically unemployment. We also reviewed the literature on different identification schemes such as recursive decomposition scheme, narrative instruments, high-frequency instruments, and external policy instruments which later adopted by (Miranda-Agrippino & Ricco, 2021).

In this study, we have used recursive schemes to identify and estimate the impact of monetary policy shocks. Furthermore, we review the literature on persistent effects of monetary policy shocks on unemployment and review basic concept of hysteresis in the Global economy. The importance of hysteresis in the labor market of US and how these persistent effects remained after financial crisis. The literature is inspired by the studies of (Cerra, Fatas, and Saxena, 2020) and (Ramey, 2016).

In 1963, Friedman and Schwartz used historical data from the past to discuss the history of U.S. money and presented evidence that changes in money supply may have a real impact. On the other hand, James Tobin, in 1970 presented a paper on money and income, arguing that the well-known positive correlation between money and income does not imply causality. In addition, Tobin presented the Keynesian model in which central banks provide reserves to maintain fixed interest rates and banks provide credit and deposits in response to trade needs. In other words, income is the source of money.

The answer to Tobin's Grainger Causality was given by Sims in 1972 in his paper Money, Income and Causality. Sim's research has two objectives. One is to look at the real question: Does there have statistical evidence that money is exogenous? The second one is to present simple models that some time series methods are not now widely used. The main novelty in their methodology is the use of direct tests to prove the existence of a single causality. So empirical finding says that the causal relationship between money and income is consistent with American post-war data, and the hypothesis that the causal relationship between income and money is consistent is rejected.

Few years later, (Sims, 1980) in the paper of Econometrica "Macroeconomics and Reality" argued against the basic classification assumptions used in the main macroeconomic model, saying:

"It is my view, perhaps, that rational expectations are more intensely subversive of identification than has yet been documented."

It was the first time Vector Autoregression model (VAR) was introduced. Sims estimated a system and found that shocks to money accounted for a significant fraction of forecast error variance of output. He further explained that by including nominal interest rates in the VAR, it will significantly decrease the shocks to money to explain the output.

Afterwards, (Christiano et al., 1999) explored variety of specifications such as federal funds rate, nonborrowed reserves, etc. and mentioned the Federal Reserve's feedback rule, i.e., the rule which is related to the policymaker's actions to the state of the economy. The study pointed out the important identifying assumptions related to the feedback rule. One assumption is that the policy shock is orthogonal in nature to other macroeconomic variables. This refers to as the recursiveness assumption. This assumption implies that output and prices respond only with a lag to a monetary policy shock. The empirical results stated that monetary policy shocks had meaningful effects on output and are robust across almost all specifications. Authors like (Leeper et al., 1996); (Sims, 1986; Sims et al., 2012) (Sims & Zha, 1998) adopted the same recursive approach.

The second and third assumptions for the identification of monetary policy shocks do not involve explicitly modelling the Fed's feedback rule. (C. Romer & Romer, 1989) claimed that there were exogenous monetary policy shocks, while other authors assumed that these shocks can be measured by fluctuations in the federal fund rate. Finally, some authors claimed that all movements in prices reflect exogenous movements in monetary policy (Christiano et al., 1999).

The third assumption identifies that monetary policy shocks do not affect economic activity overall (see for example, (Friedman, 1968)). In general, policy shocks play a crucial role in macroeconomy and generally unobservable (Kilian & Lütkepohl, 2017).

Another important discussion in the study of (Christiano et al., 1999) is the price puzzle. (Sims, 1992) noted that in many specifications, prices increase short-term after a contraction in monetary policy shocks. Eichenbaum (1992) calls this "the price puzzle." As Sims argued that the Fed was reacting to future inflationary news. To manage this, it includes a commodity price index in the VAR.

2.3 Identification of Monetary Policy Shocks

The question arises in the empirical literature that why there is a need to identify shocks to monetary policy. Secondly, the question about the identification of monetary policy shocks has been asked many times. The sources of shocks are also of immense importance in empirical literature in the business cycle. Not only is it related to understanding the forces that cause economic fluctuations, but also to identifying the sources of shock. The answer lies in two explanations. One needs to establish causal effect on output. Another could be the explanation of the part of business cycles.

We start with a concise overview of the research on Handbook of Macroeconomic chapter by (Christiano et al., 1999). Furthermore, the study reviewed the specifications of Christiano, Eichenbaum and Evan's, focused on two notable types of externally identified monetary policy shocks: the narrative/Greenbook shocks (C. D. Romer & Romer, 2004) and (Gertler & Karadi, 2015)'s high-frequency identification (HFI) shocks. We focus on these shocks, because, despite the use of different identification methods and samples, both shocks have remarkably similar effects on production from monetary policy.

Most macro econometric literature that studies the effects of monetary and fiscal policy shocks is based on mechanisms and insights derived from full information and rational expectations. However, some empirical studies have shown that the existence of information frictions can change identification problems in several ways (Hubert &

Ricco, 2018). For example, (Blanchard et al., 2013) explained that in an economy without information friction, the econometricians must align the set of information of the econometric model with that of the representative agent. Conversely, when economic agents do not observe structural shocks in real time, economists may not be able to correctly identify the shocks.

To accurately identify structural shocks, econometrics must use a higher information set. Furthermore, if economic agents have different information sets, the concept of a representative agent is certainly misleading. Finally, the lack of fully informed representatives implies that economic policy decisions can reveal information about the policy makers of the state of the economy and transmit information to economic agents. This mechanism is known as the signaling channel for economic policy actions (see Melosi, 2017 and Romer & Romer, 2000).

2.3.1 The Recursiveness Approach

Few authors identified monetary policy shocks by considering different sets of endogenous variables and by applying different identification strategies. One of the most widely adopted approaches is to impose alternative sets of recursive zero restrictions on the contemporaneous coefficients (Ramey, 2016). The pioneer of this method is (Sims, 1980), and this approach is also known as triangularization. The assumption underlying the recursiveness assumption considers that the information set at time t does not respond to monetary policy shock realized at time t, but that it responds with a lag.

The Handbook of Macroeconomics chapter "Monetary Policy Shocks: What have we learned and to what end?" by (Christiano et al., 1999) shed light on the implications of many of the 1990s innovations in studying monetary policy shocks. Their benchmark model used a specific Cholesky decomposition method, in which it is assumed that the first components of GDP, inflation, and commodity prices not to respond to the shocks of monetary policy within a quarter (or month). They called it the "recursive assumption".

Conversely, they allowed contemporaneous values of the first-block variables to influence monetary policy decisions. The most important message of the chapter may have been the robustness of the findings that contractionary monetary policy shocks, measured with either federal funds rate or nonborrowed reserves, have a significant negative impact on output. On the contrary, the price puzzle continued to occur in some specifications.

The study also showed robustness of results that were generally consistent with traditional views on the effect of monetary policy shocks. (Ramey, 2016b) adopted the specification like (Christiano et al., 1999), however used (Coibion, 2012) macroeconomic variables for the first block. Specifically, they used monthly series including log industrial production, the unemployment rate, the log of the CPI, and the log of a commodity price index. In the second block, they used the federal funds rate. Likewise, in the third block they used log of nonborrowed reserves, total reserves, and M1. Thus, the innovation of federal funds rates (orthogonal to the current value of the first block variables and the lags of all variables) is identified as a monetary policy shock. SVAR model is applied in the study to estimate impulse responses for sample, 1965m1 – 1995m6.

The empirical findings show that the responses are identical to the classical effects of monetary policy shocks. The Federal funds rate jumps up temporarily but then falls back to 0 by 6 months because of prolonged recession. The unemployment rate and industrial production increase and peak around 23 months later but return to normal after 4 years. Prices increase slightly for a few months, but then follow a steady path down, settling at the new lower level after 4 years. Other variables such as nonborrowed reserves and money supply (M1) fall and then recover after 3 years.

The study of (Ramey, 2016) provide the overview of the most common identification schemes and argue about vast literature on identification perhaps many macroeconomists believe that monetary policy shocks themselves contribute little to macroeconomic outcomes. The reason is the identification of nonsystematic movements in monetary policy, so we can estimate causal effects of money on macroeconomic variables. (Sims & Zha, 1998) also stated in his response to (Rudebusch, 1998) criticism of the standard VAR methodology that we need instruments to identify key structural parameters such as real output, prices, and unemployment.

Monetary policy shock has an impact on economic activity and inflation through various channels, collectively known as transmission mechanisms of monetary policy (Gertler & Karadi, 2015). These shocks are identified by using the mpi_{ff4} instrument defined in next section. Results, in the form of dynamic responses, are obtained using a VAR model estimated with standard macroeconomic priors over the sample 1991Q1 – 2015Q4 due to data availability. Variables entered the VAR in log levels are real gross domestic product and inflation except for short term and long-term interest rate and unemployment.

2.3.2 Narrative Instruments:

Narrative methods involve building a series of historical documents to determine the cause of specific changes in variables or quantities. The classical example of using historical information to identify policy shock is the study of (M. Friedman, 1963). Other studies use the narrative methods are (J.M. Poterba, 1986) tax policy announcements, and (C. D. Romer & Romer, 2000, 2004) monetary shock series based on FOMC minutes.

In the study of (C. D. Romer & Romer, 2004) they constructed a new measure of monetary shocks based on two innovations, the use of Fed intensions (changes in federal funds rate targets). The other one is Greenbook forecasts.

However, (Coibion, 2012) found some issues from the study of (C. D. Romer & Romer, 2004). He finds that the estimation of Romer produced much higher effects on output than standard VAR methods. Their results are very sensitive to the inclusion of nonborrowed reserve targeting from 1979 to 1982. Embedding their shocks in a VAR produces medium term effects. The study of (C. D. Romer & Romer, 2004) failed to provide correct results. Without additional recursive assumptions, even narrative methods can produce confusing results. Later, through the mid-1990s many of the methods produced puzzles when estimated over later samples. Specifically, the tightening of monetary policy shocks has expansionary effects in the first year and the price puzzle is pervasive. One plausible explanation is the identification problem.

2.3.3 High Frequency Identification:

This high frequency identification strategy is first used by (Kuttner, 2011) to separate anticipated vs unanticipated monetary policy shocks, seem to look at only the effects on interest rates. This strategy further extended by (Campbell et al., 2012; Gürkaynak et al., 2005). These HFIs were also introduced by (Gertler & Karadi, 2015) who first, explains that these high frequency instruments are the measure of the revision of market-based expectations follow a monetary announcement, are predictable and autocorrelated (see also Ramey, 2016). In addition, (Gertler & Karadi, 2015) also used federal funds futures to identify these high frequency surprises around FOMC announcements (30 minutes window). Although there are many applications of these high frequency instruments, (Kuttner, 2011) found one issue that these instruments do not necessarily identify exogenous shocks.

2.3.4 External Policy Instruments

The "external instrument" method or "proxy SVAR" is a promising new method for incorporating external series to identify shocks. This methodology first developed by (J. Stock & Watson, 2008), then extended by (J. H. Stock & Mark W. Watson, 2012) and (Mertens & Ravn, 2013). This approach uses information developed "outside" of VAR, such as narrative-based series, shocks from estimated DSGE models or high-frequency information. The idea is that these external series are noisy measurements of real shocks.

Despite extensive research, there is still much uncertainty about the effects of monetary policy shocks (see (Ramey, 2016a)). Specifically, several studies have highlighted a counter-intuitive increase in production or in prices following a contractionary monetary policy known as output and prize puzzles. (Miranda-Agrippino & Ricco, 2017) pointed out that the lack of robust empirical results in existing literature may be due to the implicit assumption that both central banks and private agents can obtain full information about the economy.

Importantly, the transfer of macroeconomic information from central banks to private agents can generate price puzzles highlighted in literature. Therefore, the interpretation by private agents of monetary policy surprises is crucial to the determination of the signs and magnitude of the effects of monetary policy. Based on this intuition, (Miranda-Agrippino & Ricco, 2017) proposed a new method to investigate the impact of monetary policy shock, considering the problem faced by agents following the central bank policy announcements. In the United States, five years later, the Fed published its economists' macroeconomic forecasts (Green Book forecasts), which were used to inform previous monetary policy decisions.

(Miranda-Agrippino & Ricco, 2021) defined monetary policy shocks as the external changes in policy instruments that surprise market participants, which are unforecastable and are not the result of a systematic reaction of central banks to the information set. The study mentioned the explanations as documented in (Coibion, 2012) and in (Ramey, 2016b) on the estimations on the sensitivity to the choice of instruments, sample, and empirical specifications of the dynamic responses to monetary policy shocks. For these reasons, (Miranda-Agrippino & Ricco, 2021) give the explanations for such instabilities that is based on models of imperfect information and propose a new identification strategy for the analysis of unstable and puzzling economic results that is robust to the presence of information frictions in the economy.

The study provides evidence of the presence of information frictions that are relevant for monetary policy and discussed the implications for the identification of the shocks. Because of certain assumptions proposed by ((Melosi, 2017; C. D. Romer & Romer, 2000) that information asymmetries between public and central banks give rise to an information channel for monetary policy actions to informationally constrained agents, a policy rate hike can signal either a deviation of the central bank from its monetary policy rule i.e., contractionary monetary shock or stronger than expected fundamentals to which monetary authority endogenously responds.

(Melosi, 2017; and Romer & Romer, 2000) further claimed that empirical assessments that do not consider information frictions and do not disentangle these two scenarios, are likely to retrieve dynamic responses of monetary policy shocks which effect the economy, leading to the well-known price and activity puzzles.

(Gertler & Karadi, 2015; and Romer & Romer, 2004) shed light on popular instruments for monetary policy shocks that are constructed in leading identification schemes can be thought of as assuming that either the Central Bank or market participants enjoy perfect information. Under these assumptions, controlling the information set of the perfectly informed agent is sufficient to identify the shock. Nevertheless, if all agents in the economy enjoyed full information, different instruments would deliver identical results. Conversely, responses may diverge with dispersed information.

Hence, (Miranda-Agrippino & Ricco, 2021) reviewed the models of imperfect information (noisy and stick) and asymmetric information and built a new methodology on the insights provided by these models (example are (Woodford, 2001), (Mankiw & Reis, 2002) and (Maćkowiak & Wiederholt, 2009) and empirically combined insights from (C. D. Romer & Romer, 2004) narrative identification and the high-frequency identification (HFI) of (Gertler & Karadi, 2015).

Taking a stock of previous evidence, (Miranda-Agrippino & Ricco, 2021) construct a novel instrument as discussed previously known as external instrument of proxy SVAR for monetary policy shocks by projecting market-based monetary surprise on their own lags and the central bank's information set, as summarized by Greenbook forecasts. This instrument accounts for the presence of information frictions in the economy. The construction of this instrument triggered by policy announcements that is orthogonal to both the central bank's economic projections and to past market surprises. This composition consists of three steps. First, they project high-frequency market-based surprises in the fourth federal funds futures around FOMC announcements on Greenbook forecasts on output growth, inflation, and the unemployment rate, as in (C. D. Romer & Romer, 2004), controlling for the central bank's private information and hence for central bank information channel. By running regression at FOMC meeting frequency:

Equation 1:

$$FF4_m = \alpha_0 + \sum_{j=-1}^{3} \theta_j F_m^{cb} x_{q+j} + \sum_{j=-1}^{2} \vartheta_j \left[F_m^{cb} x_{q+j} - F_{m-1}^{cb} x_{q+j}\right] + MPI_m$$

Here, $FF4_m$ denotes the high-frequency market-based monetary surprise computed around the FOMC announcement indexed by m, $F_m^{cb} x_{q+j}$ denotes Greenbook forecasts for the vector of variables x at horizon q + j that are assembled prior to each meeting, and $[F_m^{cb} x_{q+j}$ - $F_{m-1}^{cb} x_{q+j}]$ denotes revisions to forecasts between consecutive FOMC meetings. These forecasts are expressed in quarters and q denotes the current quarter. These forecasts are also thought of as a proxy of the information set of the FOMC at the time of making the policy decision. Secondly, they constructed a monthly instrument by summing the daily MPI_m within each month, adopted in e.g., (J. H. Stock & Mark W. Watson, 2012) and (Caldara & Edward Herbst, 2016). The monthly monetary policy instrument MPI_t is constructed as the residuals of the following regression:

Equation 2:

$$\overline{MPI_t} = \emptyset_0 + \sum_{j=1}^{12} \emptyset_j \overline{MPI_{t-j}} + MPI_t$$

Where MPI_t is the result of the monthly aggregation. By estimating the above regression equation using observations that correspond to nonzero $\overline{MPI_t}$ readings for the dependent variable. In months without meetings, MPI_t is equal to zero.

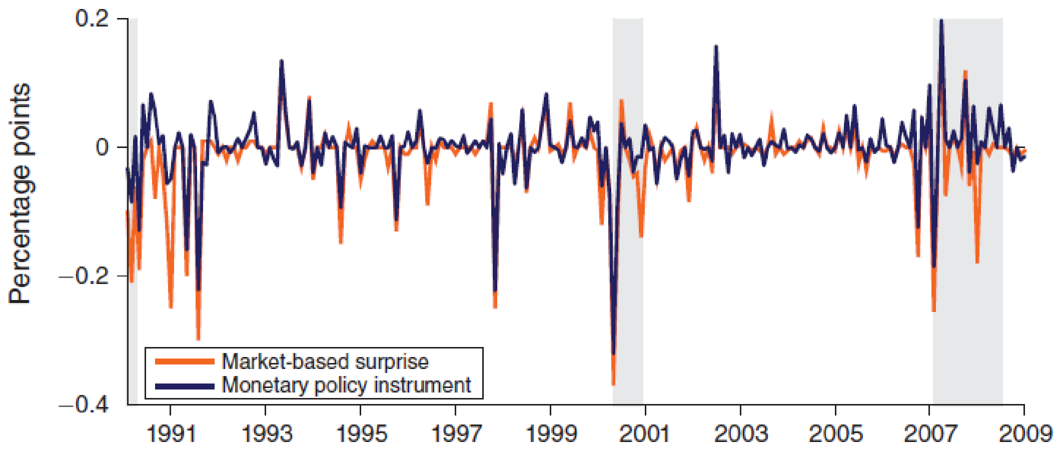

Figure 1: Monetary Policy Shocks as in Agrippino (2021)

The plot of market monetary surprise aggregated at monthly frequency by summing daily surprises ($FF4_t, orange\ line$) and the instrument constructed by (Miranda-Agrippino & Ricco, 2021) approach ($MPI_t, blue\ line$). The main point to note in the figure is the discrepancy between the two series specifically evident during the time of economic crisis.

2.4 Information Effect on Monetary Policy

There is a study of (Gai & Tong, 2022) who made use of state-of-the-art monetary policy shocks identified by (Bu et al., 2019) to extract the information shocks embedded in the announcements of the Federal Open Market Committee (FOMC), and then propagated these shocks in panel local projections (LPs) to a sample of 58 countries over the period 1994-2020. They also established that information shocks raise expectations of future global activity and proceed to document the findings of their research. The empirical findings suggest that pure monetary policy and information shocks generate opposite impulse response functions (IRFs). While a tightening in US monetary shocks lead to a higher unemployment rate, lower industrial production and lower asset prices around the world, information shocks delivered the opposite i.e., raising production, long-term government bond yields, and lowering the unemployment rate. Our results are consistent with the findings of (Gai & Tong, 2022).

Although both monetary and information shocks come from the Federal Reserve, they arise from different sources. Monetary policy surprises reflect shifts in the central bank's stance on inflation and unemployment targets, while information shocks reveal a state of economic fundamentals by the two types of shocks are assumed to be uncorrelated (Gai & Tong, 2022).

Conventionally, temporary demand-driven cyclical fluctuations required expansionary policies while supply-driven fluctuations required structural reforms (Cerra et al., 2020). For this purpose, (Blanchard & Quah, 1989) introduced decomposition, which became the basis for identifying the sources of shock. They assumed that only supply disturbances had a long-term effect on output, while demand shocks had no impact. This type of shock affects unemployment temporarily, but not permanently. These assumptions are important for the identification of the two types of shocks and their dynamic effects on output and unemployment.

In the article of (Wilkinson & Sanchez, 2023) published by FRED, during periods of recession and expansion, the Federal Reserve increases and decreases interest rates to fulfil its mandate of stable prices and maximum sustainable employment. When the Federal Reserve raises interest rates, it is called 'tightening' its monetary policy. Higher interest rates can help control high inflation because access to credit becomes more expensive (i.e., tightening of financial conditions), which lowers consumption and investment, as theory suggests. In turn, central banks adjust prices and inflation drops.

(Miranda-Agrippino & Ricco, 2021) study the information asymmetries between the public and the central bank that can give rise to an information channel for monetary policy actions. The term “information effect” was first introduced by Romer and Romer (2000) in their seminal research, who refer to the effect of FOMC announcements on private sector views of non-monetary economic fundamentals, such as output and growth of a country. (Miranda-Agrippino & Ricco, 2021) also show how macroeconomic and financial variables respond to the informational component of the monetary policy surprises, as captured by the fitted component of equation 01, aggregated at monthly frequency. The responses capture the effect of central bank information on the short-term macroeconomic outlook extracted from market participants at the time of the announcement. Using VAR model, and including the 10-year Treasury rate, the stock market index, and the effective dollar exchange rate. They estimated the impulse responses of monetary policy shock and information shocks and explain the differences among them evident in figure below.

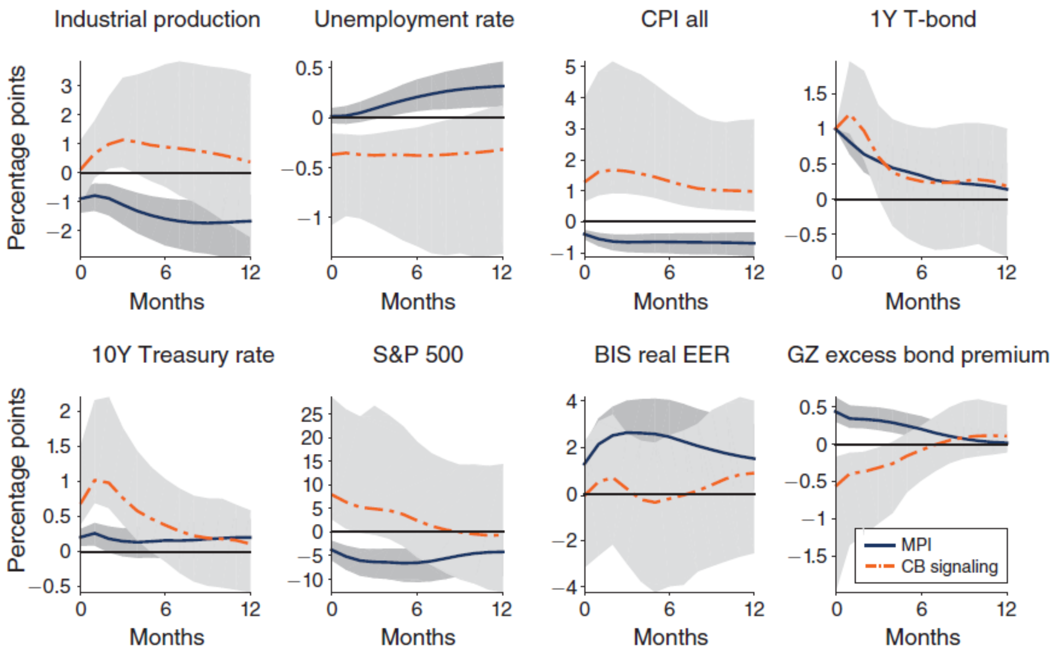

Figure 2: Monetary Policy Shocks vs Information Shock,

Estimated by (Miranda-Agrippino & Ricco, 2021)

In the figure, dashed lines are used for the responses to the information component, while solid lines are the responses to a monetary policy shock identified with MPI_t. The empirical findings show that the difference between the responses elicited by two shocks is large and strongly significant. Both shocks raise nominal interest rates in the same proportion, but information shocks are followed by economic expansion in the frequency of the business cycle, consistent with the view that rising interest rates can signal to market participants that the central banks are expecting a stronger economy to emerge. Quantities and prices have increased, the value of the stock market has increased, and credit conditions have eased.

These results support the view that market participants extract information from the announcements of central banks on aggregate demand shocks to which the central banks are likely to react. In a different but complementary methodology, the same conclusions were drawn in (Jarociński & Karadi, 2020). Monetary policy surprises that contain both policy shocks and demand shocks would mix the two effects illustrated in the figures and therefore produce puzzles. Similar evidence is documented in (Ramey, 2016b).

The empirical findings show that after monetary tightening, economic activity and price contracts, lending cools down and expectations follow the fundamental trends.
These results indicate that monetary policy is an important tool for economic and financial stability. The results have been robust in several tests.

In the next section, we will discuss the effects of monetary policy shocks on unemployment rate, either the effects are long term or short term and forming hysteresis. We also review the previous studies based on the concept of hysteresis in macroeconomic setting.

2.5 Hysteresis and Macroeconomic Outlook

The Great Recession of 2008 caused severe economic and financial crisis that have been characterized by an unusually slow recovery (Inaba et al., 2015). There are two kinds of issues posed about the causes of the insufficient recovery. Firstly, potential growth has weakened, reflected in the lack of supplies. Secondly, the production gap could be abnormally persistent, i.e., the economy may have difficulty absorbing demand deficits.

There are many models and evidence in microeconomics labor literature supporting the view that either employment levels, skill levels or wages can react persistently to the business cycle. The study of (Tella & MacCulloch, 2006) explained that unemployment can interact with the design of institutions which then provides a mechanism for unemployment to stay higher. (Yagan, 2019) and (Rinz, 2019) also discussed evidence from the context of the Great Recession.

Another study of (Saez et al., 2019) presented the evidence of persistent effects of changes in tax policies that impact labor demand. In contrast, some studies presented evidence of positive effects of a tight labor market such as (Hotchkiss & Moore, 2018).

These papers emphasize the idea that the effects of cyclical fluctuations can last for a long time, even a lifetime, and therefore the potential positive effects of their stability can be much greater than previously thought. GDP's path depends on its history, and it is this dynamic feature referred to as hysteresis.

The weakening of potential growth may be due to a lack of traditional factors (low productivity, increased social inequalities, aging active populations, globalization, shortage of raw materials, etc.) but also to hysteresis effects (Keightley et al., 2016) because the crisis could have "permanently damaged" production factors (reduction of human capital of the unemployed, damage of productive capital, drop in investment). Regarding the persistence of the production gap, this may indicate that the economy is not able to achieve full employment or at least frictional unemployment rates, so it is possible to assume that stagnation has become permanent enough to be considered "secular".

The severity of the recession has doubted the fact that it is simply a cyclical slowdown, although it is serious. The economists questioned then whether the economy would one day be able to return to the old level of activity. A widely adopted study, took up an old intuition of (Blanchard & Summers, 1986), which emphasized the role of hysteresis linked to long-term unemployment: workers who continue unemployed for prolonged periods of time lose their human capital, and when they finally stary working again, they will be less productive.

The policy makers and economists who have examined the consequences of these policy shocks are aware that the rise in unemployment experienced in the 1970s and 1980s appeared to have a very long-term effects in some countries via what was described then as unemployment hysteresis.

2.6 Overview of hysteresis

The term hysteresis was first introduced by (Clark, 1989) in the context of European labor markets in models during the 1970s and 1980s. Hysteresis refers to the increase in the actual rate of unemployment that leads to a rise in the underlying or equilibrium unemployment rate.

Consequently, any increase in the demand for labor is likely to create inflationary pressure in wages and prices well before unemployment returns to its pre-shock level. As a result, an increase in unemployment will have long-term effects, with substantial costs in terms of higher inflation and low output, incomes, and opportunities for millions of people (O'shaughnessy, 2011).

2.7 The Nature of Hysteresis in the Global Economy

(Cerra, Fatas, and Saxena, 2020) explained the presence of hysteresis in models where GDP is history dependent, i.e., all cyclical deviations have permanent effects on economic activity. They also argued that hysteresis arises due to path-dependence, structural factors, investment dynamics, and financial disturbances. It influences policy decisions by highlighting the long-lasting effects of shocks and the need for appropriate interventions. Ball (2009) addressed two issues in his study. The first is whether there is evidence of the effects of hysteresis. The second is the nature of hysteresis.

The focus of investigation in the 1980s and 1990s was neither about 'good' hysteresis nor the 'bad' hysteresis, but the insights into how the effects of hysteresis might operate are clearly valuable and have important policy implications. Traditionally, macroeconomic models and the policy holders usually ignore hysteresis effects. In Keynesian tradition, this comment is applicable and equally to New Keynesian models and the models on a real business cycle as well. (Cerra et al., 2020) have shown that this slow recovery from the monetary crisis means that economic growth today is clearly below its pre-crisis trend. There is enormous empirical evidence that GDP fluctuations (shocks) are persistent, and their effects are still with us years after it took place.

2.8 The Role of Hysteresis in the Long-Term Unemployment Movement

In various countries, hysteresis is central to the long-term unemployment movement. But what is the relative importance of these shocks and how can these shocks impact the unemployment level? This question is motivated by the following reasons. Firsty, the labor market and the unemployment rate have always been at the center of business cycle description. In this context, fluctuations are seen as changes in the degree of economic weakness, and unemployment rates are the most obvious indicators of this weakness as the Phillips curve indicates in the study of (Cerra, Fatas and Saxena, 2023).

The literature explains several reasons for the persistent effects of unemployment in Europe. They developed a theory explaining such persistence, based on the differences between insiders and outsiders wage bargaining. Though the problem of European unemployment can be solved by expansionary demand policies (Blanchard & Summers, 1986).

Some studies find the long run effect of monetary policy shocks on unemployment. The study of monetary shocks affect employment and therefore the pace of knowledge accumulation, which is the driver of long-term growth. Stiglitz (1993) demonstrated similar effects in a model where R&D expenditures respond to the state of the business cycle. Martin and Rogers (1997) developed a model where human capital accumulation, via learning by doing, is driving long-term growth.

Few studies found mixed results on the long-term impact of monetary policy shocks on unemployment. For example, (Cambazoğlu et al., 2012) found that changes in money stocks have an impact on employment and production through credit stocks.
(Christiano et al., 1994) found that contractionary monetary policy shocks have resulted in persistent declines in real GDP, employment, and rise of unemployment. (Wu & Xia, 2013) achieved that the Federal Reserve's efforts to stimulate the economy led to a one percent drop in unemployment in December 2013. Also, (Gambetti & Pistoresi, 2004) found that the expansion of total demand and deregulation policies that reduce the mark-up permanently reduce the Italian unemployment rate.

Overall, these papers suggest that monetary policy shocks may have a negative impact on employment and production, but expansionary policies may help reduce long-term unemployment.

3. Econometrics Framework and Methodology

3.1 Vector Autoregressions (VAR)

Christopher Sims (1980)'s work has made a significant contribution to the field of macroeconomics, a new framework that holds immense importance: vector autoregressions (VARs). It is a widely used model for the analysis of multivariate time series, consisting of a regression equation system. It differs from the simultaneous equation system, since there is no internal-external distinction of variables in any economic theory (Akkaya, 2021a). In addition, the lag value of the dependent variable in a VAR model allows for strong future predictions(Kumar et al., 1995). This model can be estimated by regressing each model variable on lags of its own as well as lags of other model variables up to some prespecified maximum lag order, p and are typically dependent upon monthly or quarterly data (Kilian & Lütkepohl, 2017).

The main goal of VAR modeling is not only to find the one-way relationship between variables but also the relationships between variables in terms of lags. The reason we implement VAR in this study is its simplest nature, as it measures the dynamic response of economic aggregates to a fundamental economic shock and used for data descriptions, forecasts, structural conclusions, and policy analysis (J. H. Stock & Watson, 2001).

Several advantages of VAR model compared to univariate time series models and structural models as discussed by (Kinal & Ratner, 1982) and (Brooks, 2008):

- This method is simple because it does not require determining which variables are endogenous and exogenous. For this reason, prediction of the structural model in a simultaneous equation depends on the definition of all variables in the system.
- Ordinary least square method is applicable, therefore easy to forecast.
- It does not require any restrictions.

However, it encounters some problems mentioned in the book of (Gujrati, 2009):

- Since VAR model uses less prior knowledge, it is more agnostic. As it does not make strong assumptions about the underlying data generating process.
- Selecting a suitable lag length is another major concern in VAR modeling. Since sample sizes are not too large, all parameters consume too much degree of freedom, so the estimations will be problematic (Akkaya, 2021).

In this study, we have adopted the methodology applied by (Christiano et al., 1999, 2005) and (Kilian & Lütkepohl, 2017).

3.1.1 Basic Linear VAR Model

Consider a *K*- dimensional time series, $y_t = (y_{1t}, \ . \ . \ . \ , \ y_{Kt})'$ and t = 1, . , *T*.
Under mild regularity conditions, the linear VAR process of order p (referred to as a VAR(*p)* model) of the form can be approximated by:

Equation 03:

$$Y_t \ = \ \boldsymbol{A_1} Y_{t-1} \ + \ . \ . \ . \ + \boldsymbol{A_p} Y_{t-p} \ + \ C\eta_t$$

where $A_{i,}\ i = 1, \ . \ . \ ., p,$ are $K \times K$ parameter matrices and nonnegative integer and the error process $\eta_t = (\eta_{1t,} \ . \ . \ ., \eta_{Kt})'$ is a 6-dimensional zero mean white noise process with covariance matrix $E(\eta_t \eta_t{}') \ = \ \sum\eta$ such that η_t ~ (0 , $\sum\eta$). It captures the sources of exogenous variation of policy shocks in the model. The matrix C is described as a 6 x 6 lower triangular matrix with diagonal terms equal to unity. Consistent estimates of the $A_i{}'s$ can be obtained by running ordinary least squares method on equation (03). This equation explains a system of equations. Each model variable in Y_t is regressed on its own lags as well as lags of the other model variables up to a lag order *p,* as discussed before. One can then estimate $\sum\eta$ from the fitted residuals (Christiano et al., 1999). One significant characteristic of a VAR(p) process is its stability. As it generates stationary time series with time invariant means, variances and covariances (Pfaff, 2008).
The matrix form of equation (1) can be represented as the matrix polynomial in the lag operator:

Equation 04:

$$A(L) = \ I_K - \ A_1 L - . \ . \ . \ - \ A_p L^p$$

and write the process as in compact form:

Equation 05:

$$A(L)Y_t = \eta_t$$

The VAR has two kinds: the reduced-form and the structural VAR. A detailed description of these two kinds is given below.

3.1.2 Structural VAR(p) Model

In applied work, it is significant to choose a suitable VAR specification, considering the properties of data. Structural VAR analysis is based on the premise that the data generating process (DGP) is well approximated by a reduced-form VAR model.
Consider the structural VAR(p) model used by (Kilian & Lütkepohl, 2017):

Equation 06:

$$B_0\, Y_t = \boldsymbol{B_1} Y_{t-1} + . . . + \boldsymbol{B_p} Y_{t-p} + w_t,$$

where, the K x 1 vector Y_t presumed to be zero mean. The dimension of B_i, i = 0, . . . p, is K x K. The K x 1 vector w_t is assumed to be white noise. This is a structural model in which elements of w_t is a K x 1 vector of structural errors, or shocks. By construction, the shocks are mutually uncorrelated. Additionally, they are serially uncorrelated, and the error vector has zero mean and variance-covariance matrix $\sum w$ is of full rank (i.e., the number of shocks is equal to the number of variables).
Mathematically, this means that:

$$E(w_t) = 0\,, \qquad E(w_t w_t{}') = \sum w = I_K$$

3.1.3 Reduced-form VAR Model

A reduced-form model expresses the current values of the data as a linear function only of its own lagged values and lagged values of the other model variables. It can be viewed as a finite-order approximation to a general linear process as depicted by (Kilian & Lütkepohl, 2017). The importance of this model in our study has proved useful for summarizing the properties of data, for forecasting, for testing for the existence of equilibrium relationships tying together two or more economic variables.

The reduced-form representation is obtained by multiplying both sides of equation 1 by B_0^{-1}:

Equation 07:

$$\boldsymbol{B_0^{-1}} Y_t = \boldsymbol{B_0^{-1}} \boldsymbol{B_1} Y_{t-1} + \ldots + \boldsymbol{B_0^{-1}} \boldsymbol{B_p} Y_{t-p} + \boldsymbol{B_0^{-1}} w_t,$$

such that the reduced-form error covariance matrix is:

$$E(\eta_t \eta_t{}') = \sum \eta = B_0^{-1} B_0^{-1\prime}$$

Given that $\eta_t = B_0^{-1} w_t$, this matrix allows us to express the mutually correlated reduced-form innovations (η_t) as weighted averages of the mutually correlated structural innovations (w_t), with the elements of B_0^{-1} serving as the weights. In addition, reduced form VAR can be seen as a data generation process (DGP) from structural VAR (J. H. Stock & Watson, 2001).

3.2 Estimation and Identification of VAR model

One of the objectives of the Box–Jenkins methodology is to provide a parsimonious modeling approach. It is preferable to provide accurate short-term forecasts by eliminating estimates of irrelevant parameters from the model. (Sims, 1980) criticized the identification restrictions of structural models and supported alternative estimation strategies known as Cholesky (recursive) identification.

The VAR model identification can be done by finding the matrix and multiplying it by its transpose, producing the covariant matrix for VAR innovations or shocks. This matrix is used to build orthogonal shocks from innovations and to calculate the dynamic reactions of each variable to each shock (Leeper et al., 1996).

Another interesting point is to know whether the variables in a VAR need to be stationary. (Sims, 1980) did not recommend differencing, even if the variables contain a unit root. Since the goal of VAR analysis is not parameter estimates, but the purpose of determining the interrelationships between variables.

(Enders, 2015) also mentioned the main disadvantage for differencing, as it throws away information concerning the movements in the data. It is also argued that the data need not be detrended. Because in a VAR a trending variable is well approximated by a unit root plus drift. For these reasons, all variables in this study are assumed to be stationary.

3.2.1 Cholesky (Recursive) VAR

The Cholesky decompositions of the variance-covariance matrix $\sum \eta$ has been implemented in this study as it was first introduced by (Sims, 1980):

$$PP' = \sum \eta \text{ , } P \text{ lower triangular}$$

This decomposition orders the n variables in the VAR system (i.e., n! orderings), which sometimes referred to as Cholesky orderings. They are widely acceptable as they are easy to calculate, and a unique decomposition exists for each order. [1]

3.2.2 Identification and Estimation with Policy Instruments

Instruments are also known as proxy variables and are widely used in semi structural analysis. (Plagborg-Møller & Wolf, 2021) proved the equivalence of the Cholesky VAR model, which first placed the shock proxy and the proxy-VAR (instrumental variable VAR) and presented evidence that both approaches provide the same identification of the structural vector autoregressions. They also proved that the structural estimation of the instrument (proxy) can be performed by first ordering the instrument in a recursive VAR, even without invertibility.

[1] See Proof in the chapter 4: titled ‘Uniqueness of the Triangular Factorization’ (Hamilton, 1994)

3.3 Impulse Response Function (IRF)

In VAR modelling, impulse response functions play a significant role in determining the dynamic relationship between the variables examined and in finding symmetrical relations. These functions are standard in one of the random errors (Akkaya, 2021b). The IRF traces the response of current and future values of each variable to a one-unit increase in the value of one of the VAR shocks η_t at time t, assuming that it will return to zero in the following periods and keeping all other shocks constant at value zero. Since we are using a recursive identification scheme in estimating VARs, impulse responses can be useful in this scenario. Because when the error terms are uncorrelated across equations, altering one error while keeping the other constant fixed makes the most sense (Kilian & Lütkepohl, 2017).

3.4 Forecast Error Variance Decomposition (FEVD)

According to (J. H. Stock & Watson, 2001), forecast error variance decomposition (FEVD) is the percentage of the variance of the error term w_t, made in predicting a variable, caused by a specific shock η_t at a given horizon h. In this study, FEVD analysis is used to see the impact of those two FF4 shocks on the other variables focusing on two horizons i.e., 12 and 24.

4. Empirical Methodology

4.1 Data Collection

In this study, there are seven endogenous variables and quarterly data covering the periods 1991 to 2015. The data gathered from the Federal Reserve Economic data (FRED) site.

Table 1: Variables Description

Variables	Description	Source
lrgdp	Real Gross Domestic Product	https://fred.stlouisfed.org/series/GDPC1
lpgdp	Gross Domestic Product: Implicit Price Deflator	https://fred.stlouisfed.org/series/GDPDEF
sr	3-Month Treasury Bill Secondary Market Rate, Discount Basis	https://fred.stlouisfed.org/series/DTB3#0
lr	Long-Term Government Bond Yields: 10-year: Main (Including Benchmark) for United States	https://fred.stlouisfed.org/series/IRLTLT01USM156N#0
nrou	Noncyclical Rate of Unemployment	Noncyclical Rate of Unemployment (NROU) | FRED | St. Louis Fed (stlouisfed.org)
$\mathbf{mpi_{ff4}}$	Monetary policy shocks (Quarterly series constructed by cumulating monthly realizations of the shock)	Estimated by Miranda Agrippino and Ricco (2021 AEJM)
$\mathbf{info_{ff4}}$	Information shock (Quarterly series constructed by cumulating monthly realizations of the shock)	Estimated by Miranda Agrippino and Ricco (2021 AEJM)

4.2 Macroeconomic Variables

The study comprises of five macroeconomic variables and two policy shocks. The dataset is composed of 1) real GDP for output, 2) GDP deflator for the price level, 3) short term and long-term interest rates, 4) non-cyclical unemployment rate, while the policy instruments are 5) monetary policy shock, and 6) central bank information shock. The first two series are entered as log-levels (times 100). The reason to use log transformation in time series regressions and macroeconomic forecasts is rooted in the normality assumption of classical econometrics approaches (Mayr & Ulbricht, 2007).

4.2.1 Gross Domestic Product

Real Gross Domestic Product (GDP) is the value of all finished goods and services produced in a particular economy over a given period. GDP can be measured in real or nominal terms. The difference between the two is that real GDP is adjusted to inflation. Nominal GDP is not. In this study, we have used Real Gross Domestic Product (GDPC1) for measuring output. The series was retrieved from FRED database. It is the inflation adjusted value of the goods and services produced by labor and property located in the United States.

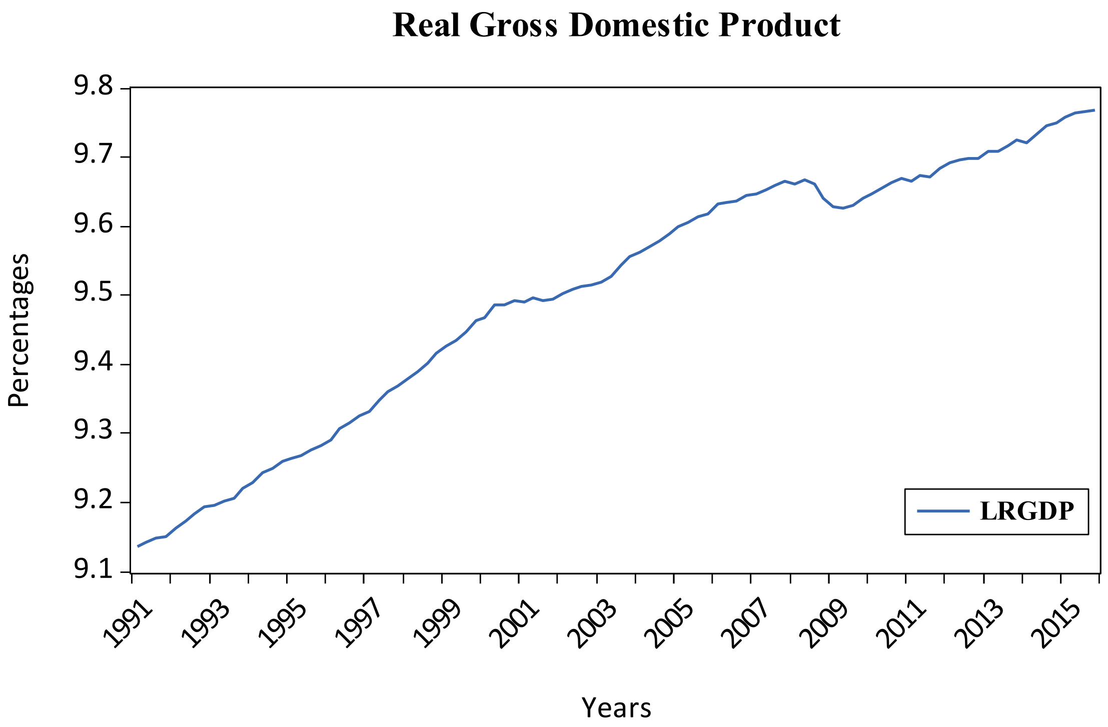

Figure 3: GDP By Author

4.2.2 GDP Deflator

It is an economic indicator that measures the overall price level of an economy. It calculates the ratio between nominal GDP and real GDP, showing the impact of price movements rather than volume changes in production. Thus, GDP inflation is a measure of economic inflation. The GDP deflator series (GDPDEF) is also extracted from FRED.

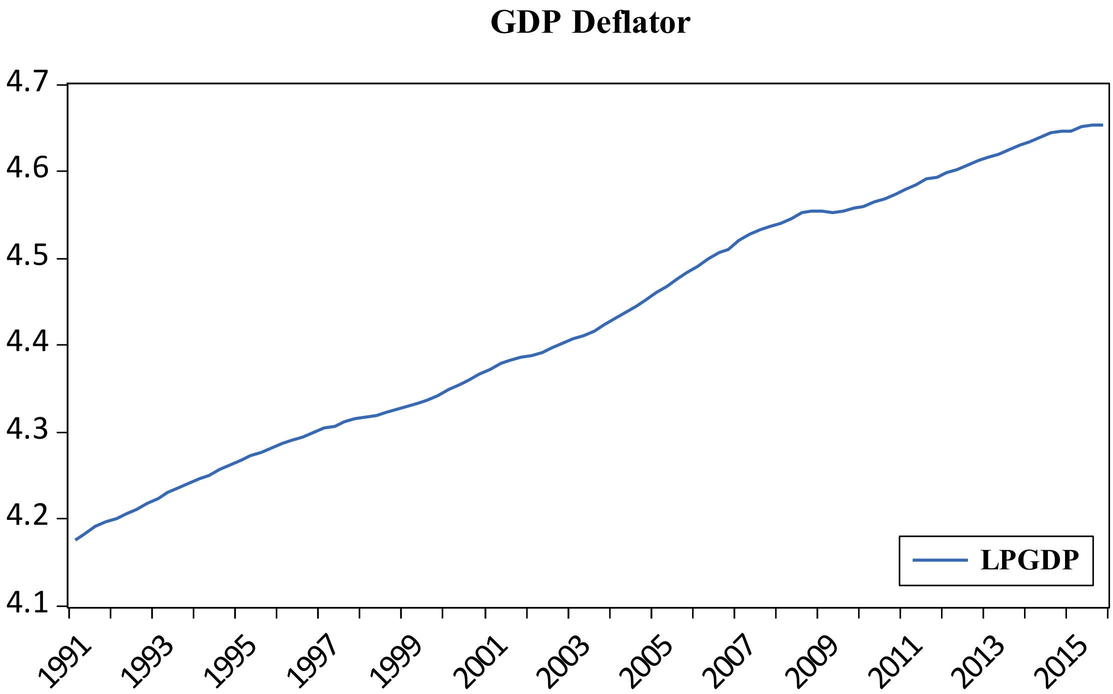

Figure 4: Inflation (Source: By Author)

4.2.3 Interest rates

For the case of interest rates, the quarterly series of the Three-Month Treasury Bill (sr) and Long-Term Government Bond Yields for 10-year have been taken as measures of interest rates in the study. All these data sets were collected from the St. Louis Fed. DTB3 is the interest rate on a three-month U.S. Treasury bill that is often used as one of the risk-free rates for U.S. based investors (Salimullah, 2020).

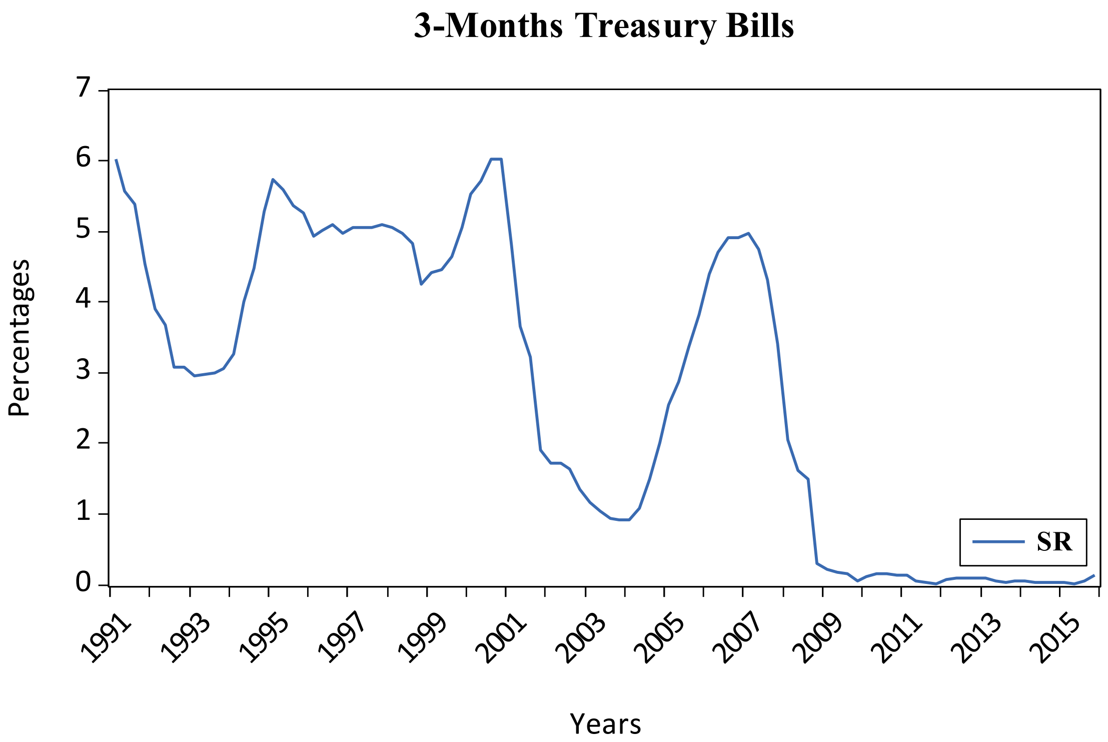

Figure 5: Short-term Interest Rates (Author)

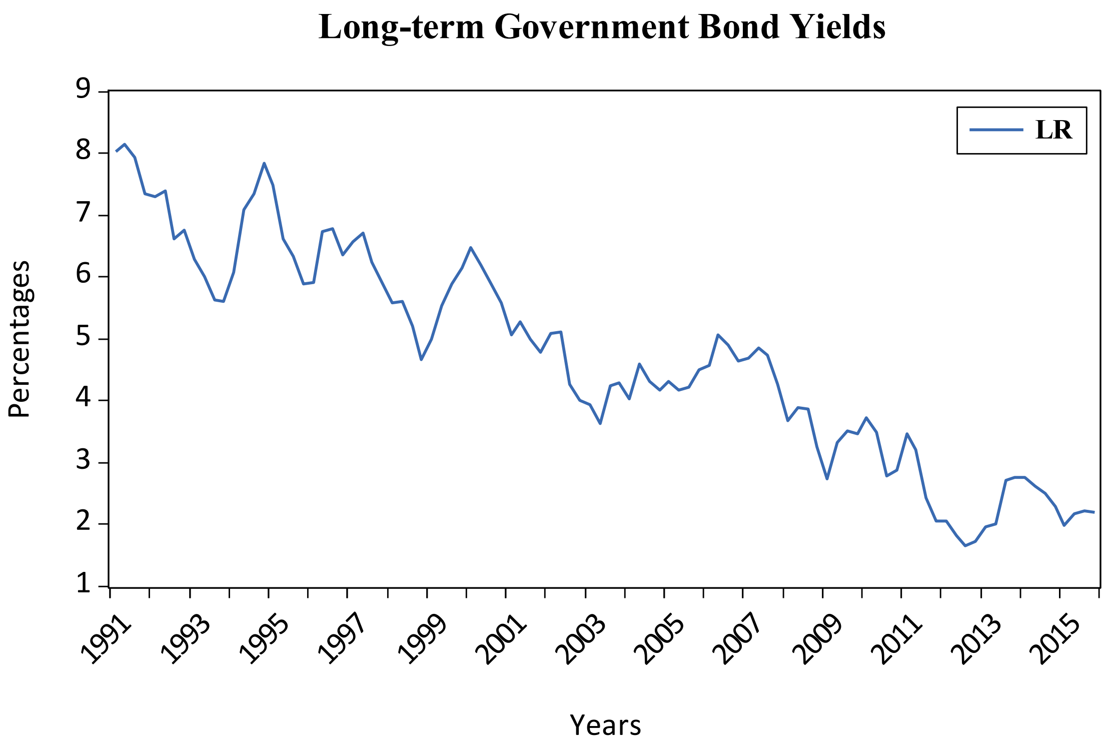

Figure 6: Long-Term Rates Source: Author

4.2.4 Unemployment

The contents of the article address the concept of "natural unemployment" proposed by the economist Milton Friedman in 1968. According to Friedman, natural unemployment, also known as non-cyclical unemployment rate, refers to a specific level of unemployment occurring within the economy. This level is determined by the functioning of labor and commodity markets, considering various realities and deficiencies in those markets. The natural rate of unemployment (NAIRU) is the rate of unemployment arising from all sources except fluctuations in aggregate demand. Estimates of potential GDP are based on the long-term natural rate.

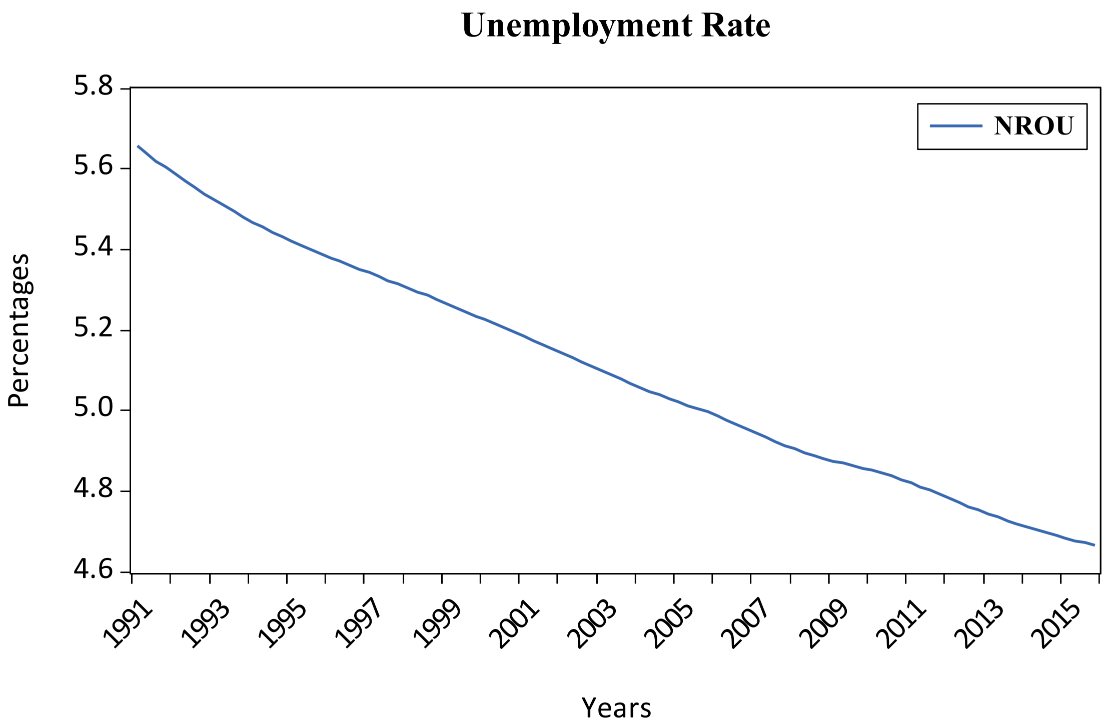

Figure 7: non-cyclical unemployment (Source: Author)

4.3 Proxy of shocks

We consider two alternative measures of identified U.S. monetary policy shocks. These shocks are not our own but were constructed by (Miranda-Agrippino & Ricco, 2021). The original monetary policy shocks are monthly. To match the sampling frequency of our economic data, we cumulate these monthly observations to a quarterly frequency. The study also analyzed how surprises in the Federal Funds Rate around FOMC meetings affect economic conditions of US.

4.3.1 Monetary Policy shocks (mpi_{ff4})

Monetary policy shocks are known as informationally robust instruments, including decisions on interest rates, money supply, and other policy instruments. Informationally robust instruments refer to variables that provide accurate and reliable information on currency policy shocks (Gürkaynak et al., 2005). Exogenous changes in the policy instrument that surprised market participants are unpredictable and are not caused by the central bank's systematic response to its assessment of macroeconomic prospects. (Miranda-Agrippino & Ricco, 2021) has already constructed monetary policy shock tools by projecting market-based monetary surprises based on its own lags and the information set of central banks, summarized in the Greenbook forecasts.

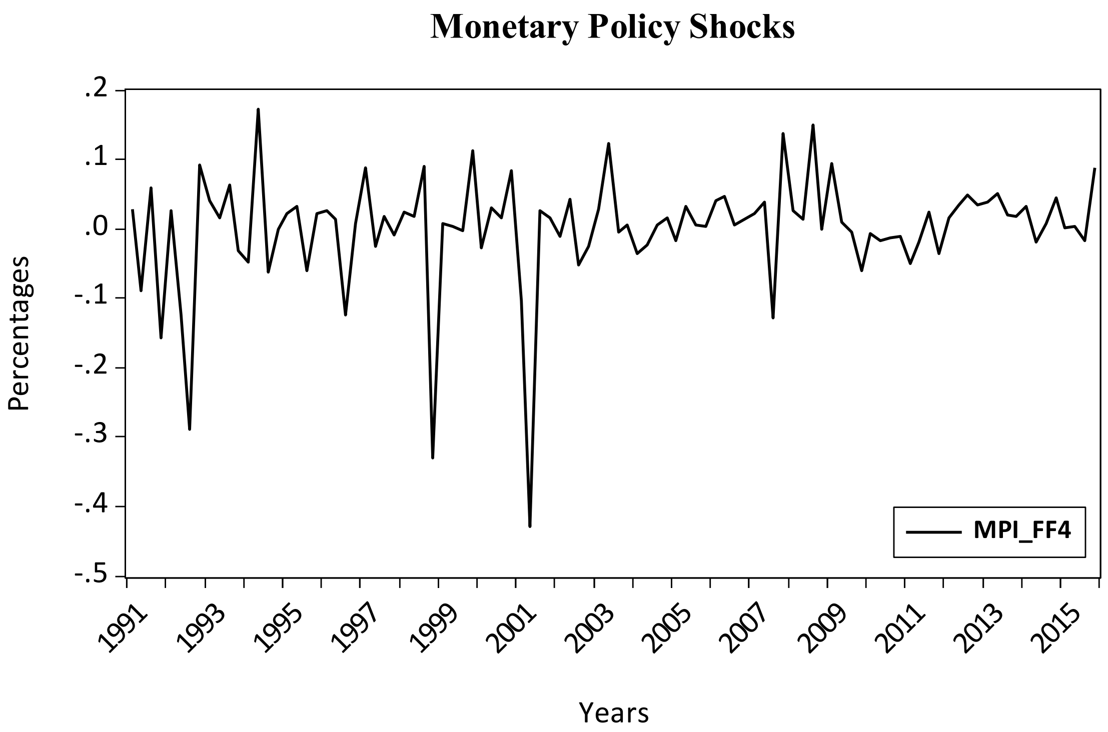

Figure 8: Monetary Policy shocks Source: Author

4.3.2 Information shocks ($info_{ff4}$)

These are information components of monetary policy surprises, calculated by monthly frequency estimates (Miranda-Agrippino & Ricco, 2021). These responses are based on the impact of the Central Bank's information on market participants' short-term macroeconomic prospects, which was obtained at the time of the announcement. According to (Gertler & Karadi, 2015), policy shocks are future surprises in Fed Funds that occur during the days of the Federal Open Market Committee (FOMC). To isolate the impact of news on monetary policy, futures interest rate surprises are usually measured in a narrow window (e.g., 30 minutes) after FOMC's decision. The dependent variables in the event study are usually the same day responses in many interest rates and asset returns. One of the main assumptions is that the economic news on FOMC Day has no impact on policy decision making. Only the information available the previous day is important. Miranda Agrippino and Ricci, 2021, examined the information symmetries between the public and central banks, creating an information channel ($info_{ff4}$) for monetary policy actions.

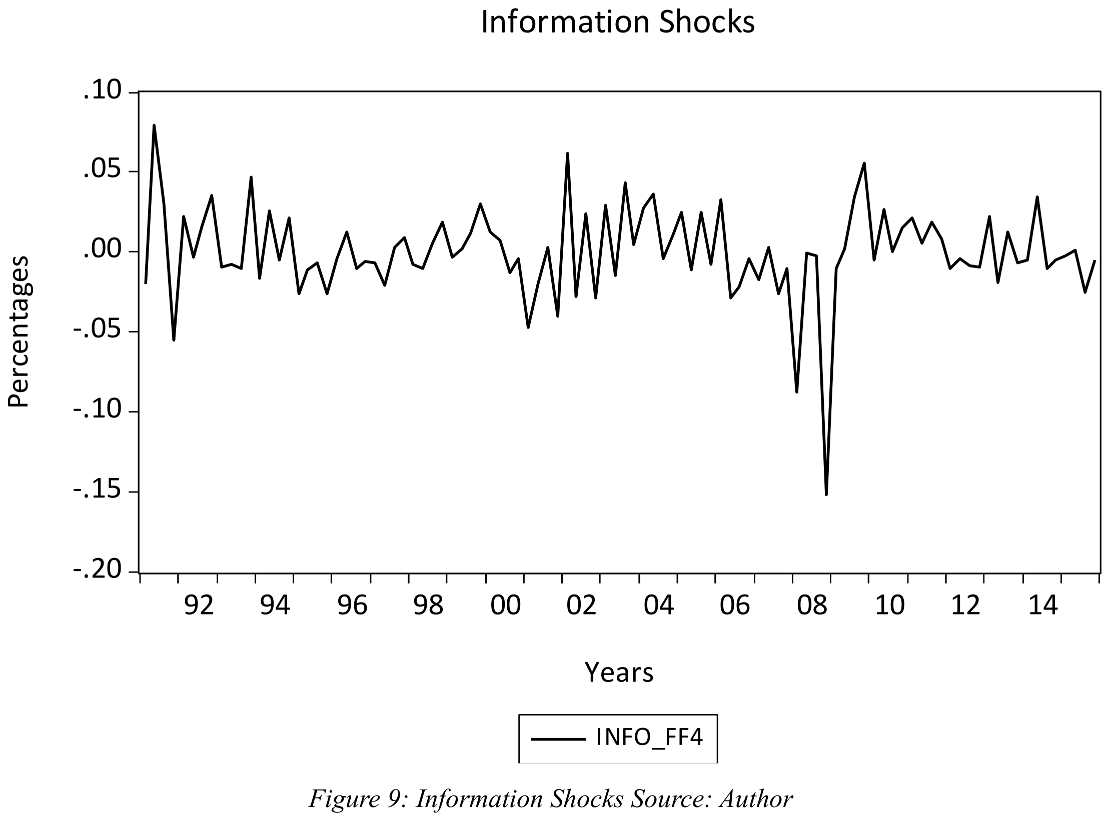

Figure 9: Information Shocks Source: Author

4.4 Model Specification

The VAR contains 2 lags of each variable. I model a parsimonious representation of the US macroeconomy (Christiano et al. 1999 and Kilian & Lütkepohl, 2017).

Model 1:

$$y_{1t} = \left(mpi_{ff4}, lrgdp, lpgdp, sr, lr, nrou\right)'$$

Model 2:

$$y_{2t} = (info_{ff4}, lrgdp, lpgdp, sr, lr, nrou)'$$

4.4.1 Lag structure

The VAR model does not specify a variable that is endogenous or exogenous; in this study, all variables considered were endogenous. Variables evaluated both by their own lags and by the lagged values of other variables. When using VAR analysis, the ideal lag length must first be determined according to the appropriate lag length criteria. The best approach to select the appropriate lag length in VAR is to use information criteria (Enders, 2015). Three different criteria are used, namely the Akaike Information Criteria (AIC), the Hannan-Quinn Information Criteria (HQ), and the Final Prediction Error (FPE). The model with the smallest information criteria is the best model (Seddighi et al., 2000). According to all three criteria, the lag length selected in this study is two.

Table 2: VAR lag length criteria model 1

Lag	LogL	LR	FPE	AIC	SC	HQ
0	414.38	NA	5.62e-12	-8.878	-8.713	-8.811
1	1366.16	1758.73	1.27e-20	-28.786	-27.635	-28.321
2	1536.68	292.86	6.89e-22*	-31.711*	-29.572*	-30.848*
3	1563.372	42.35	8.65e-22	-31.508	-28.383	-30.247
4	1604.51	59.92*	8.12e-22	-31.619	-27.508	-29.960

Notes: *indicates lag order selected by the criterion.

Table 3: Var lag length criteria model 2

Lag	LogL	LR	FPE	AIC	SC	HQ
0	512.066	NA	6.72e-13	-11.001	-10.837	-10.935
1	1501.012	1827.399	6.78e-22	-31.718	-30.566	-31.253
2	1668.984	288.474*	3.88e-23*	-34.587*	-32.449*	-33.724*
3	1697.382	45.066	4.70e-23	-34.421	-31.297	-33.160
4	1731.966	50.373	5.08e-23	-34.391	-30.279	-32.731

Notes: *indicates lag order selected by the criterion.

4.4.2 Cholesky ordering

Cholesky decomposition is popular in literature because it is easy to calculate (Uhlig, 2005). This method requires the selection of variables in order and the choice of variables that are interpreted as monetary policy shocks.

It is a widely used strategy to identify a monetary policy shock in a recursive structure of the contemporaneous relationships of the variables included in the vector. Since, this strategy is based on the recursiveness assumption, according to which monetary policy shocks are orthogonal to the information set of monetary authority.

Another advantage is that it does not require the researchers to take a position on the identification of other shocks (Castelnuovo & Palolo, 2010). In this study, the order of the variables is mpi_{ff4}/infoff4, lrgdp, lpgdp, sr, lr, nrou.

We use the ordinary Least Square (OLS) method to perform regressions with EViews software. OLS is a regression method that allows you to find functions that are represented in the regression curve as close as possible to data points. In particular, the function discovered must minimize the sum of the square of the distance between the observed data point and the curve representing the function itself.

In addition, when estimating a parameter in statistics, of is often not enough to find a single value. Therefore, it is advisable to accompany the estimate with an interval of plausible values for that parameter, known as the confidence interval (Gujrati, 2009). In this study a confidence interval of 68 percent is used.

5. Empirical Analysis

Introduction

This chapter provides the empirical estimates by implementing our VAR model of using impulse response functions and forecast error variance decompositions. The explanation of impulse response functions is important and is the fundamental part for the understanding of the final phenomenon. In general, IRF refers to the reaction of a dynamic system over time to some external change. In the field of economics, specifically in macroeconomic modelling, the impulse response functions explain how the economy reacts to exogenous shocks over time. Additionally, they try to understand the reaction of macroeconomic variables such as output, inflation, interest rates and unemployment at the time of the shock and after it.

5.1 Impulse Response Functions Results

Figure 10 illustrates the impulse response functions for the estimated VAR model, ordered as mpi_{ff4}, $lrgdp$, $lpgdp$, sr, lr, $and\, nrou$. The vector of endogenous variables includes output, inflation, interest rates and unemployment. The blue solid lines report the responses to a monetary policy shock identified using informationally robust instrument of (Miranda-Agrippino & Ricco, 2021) - $\mathrm{mpi}_{\mathrm{ff4}}$. The red dotted lines are 68 percent confidence bands (+/-).

The overall response of the five macroeconomic variables to monetary policy shock (mpi_{ff4}) tends to decline over the long term. The ±1 standard error bands are displayed, giving an approximate 68 percent confidence interval for each of the impulse responses. Estimated impulse reactions show persistent common variation patterns.

Similarly, GDP price deflator falls quickly following the contractionary monetary policy shock which is also consistent with the study of (Uhlig, 2005). It is also observed that inflation moves somewhat above zero first before declining below zero after a monetary policy shock, referred to as the “price puzzle” pointed out by Sims (1992) as well. An unexpected rise in output and inflation slowly fades away over twenty-four quarters and is associated with a persistent increase in unemployment and interest rates.

However, the mpiff4 shock has an increasingly positive effect on the long run unemployment rate (nrou) from first quarter to twenty-four quarters ahead.

Figure 11 shows the responses to the central bank information shocks ordered as $info_{ff4}$, $lrgdp$, $lpgdp$, sr, lr, $and\ nrou$. The vector of endogenous variables includes output, inflation, interest rates and unemployment. The blue solid lines report the responses to an information shock identified using informationally robust instrument of (Miranda-Agrippino & Ricco, 2021) - $\mathrm{info}_{\mathrm{ff4}}$. The red dotted lines are 68 percent confidence bands (+/-).

The shock leads to an increase of up to four basis points in the short-term treasury bills (sr) and a 2-quarter increase in long-term government bonds (lr) before declining persistently up to twenty-four quarters ahead. Unemployment (nrou) affected negatively both in the short run and long run respectively.

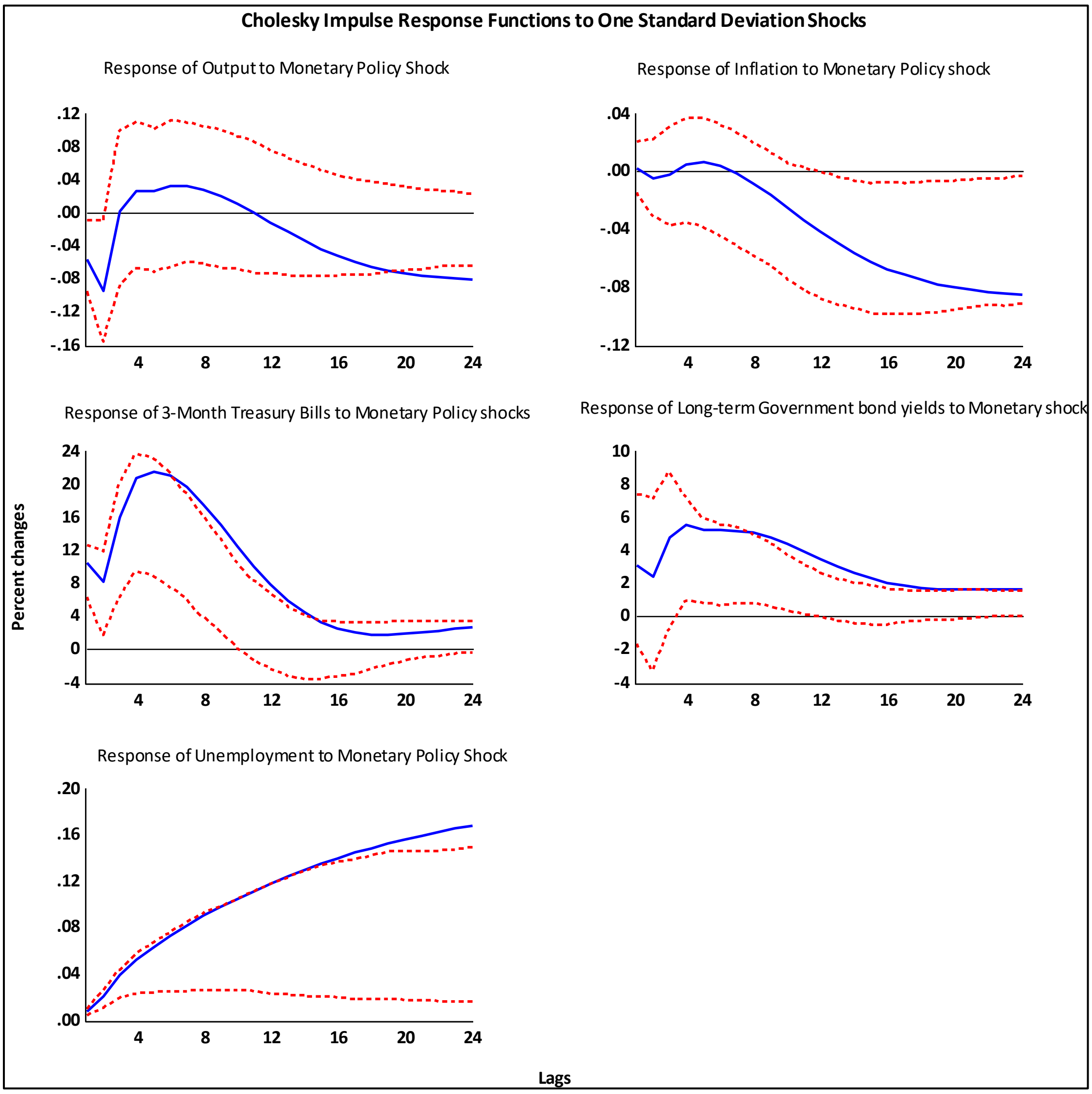

Figure 10: Impulse Response Function to Monetary Policy Shocks.

(Source: Author)

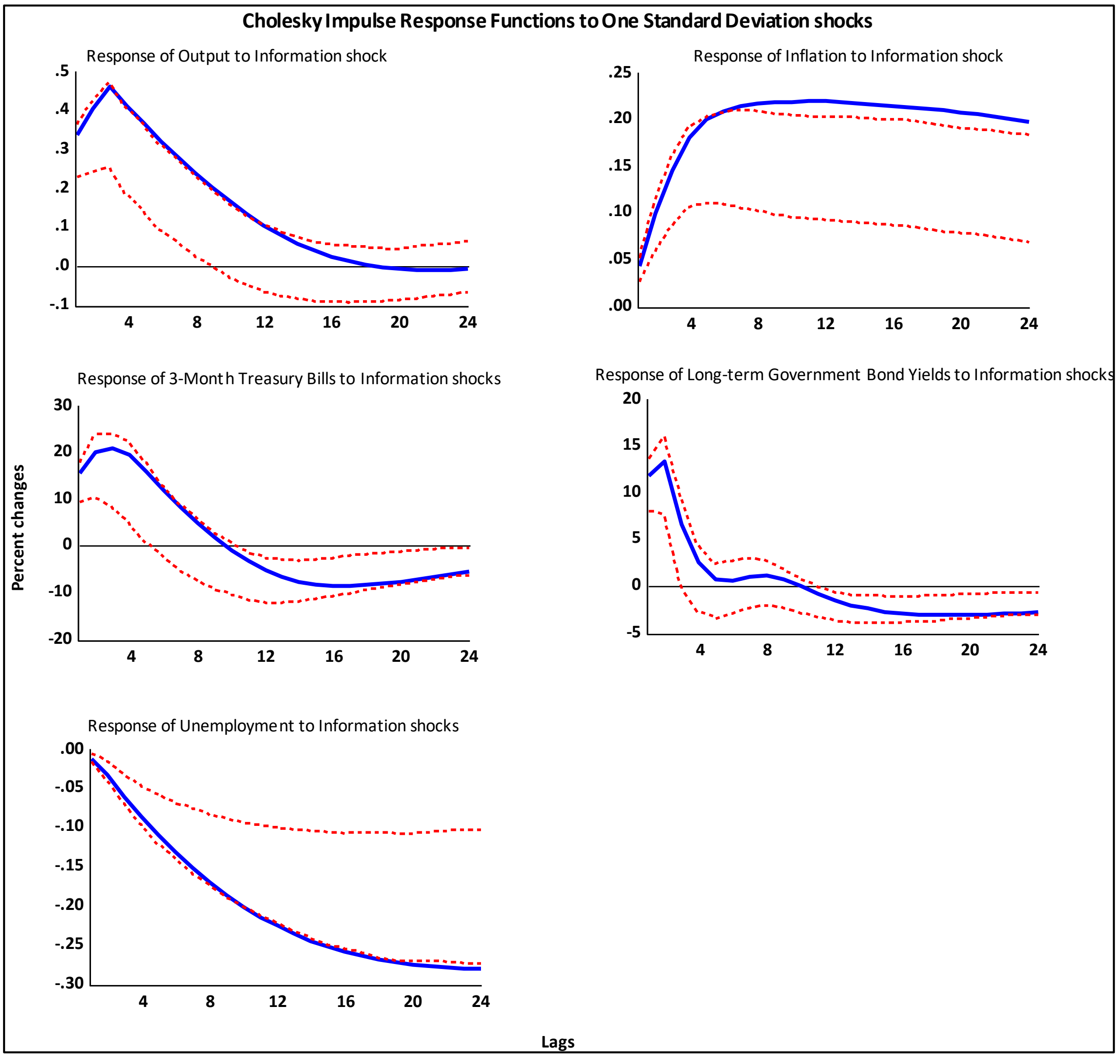

Figure 11: Impulse Response Functions to Information Shocks.

(Source: Author)

5.2 Forecast Decomposition Error Variance Analysis (FEVD)

5.2.1 Percentage variation due to (mpi_{ff4}) shock:

In table 4, the percentage of the variance of the error made in forecasting a variable due to a specific shock at a given horizon known as forecast error decomposition (J. H. Stock & Watson, 2001).

At the forecast horizon of twelve quarters, 0.497 percent of the change in GDP forecast errors was due to the mpi_ff4 shock. This means that economic shocks will have moderate impacts on GDP forecasts in the short term. Conversely, in the twenty-four-quarter forecast, the impact increased to 1.288 percent, indicating a more pronounced long-term impact.

For inflation, 0.465 percent of the deviations in forecast error in 12 quarters of the horizon can be caused by the shock mpi_{ff4}. This indicates that shocks have a small impact on price deflator forecasts, like GDP estimates. On the contrary, the impact on the 24-quarter horizon increased significantly to 3.749 percent, indicating a long-term impact on the price deflation forecast.

The 3-month Treasury bills show a substantial reaction to the mpi_{ff4} shock, with 17.906 percent of the forecast error variance attributable to the 12-quarter horizon shock. This suggests that the shock has a substantial and immediate effect on short-term interest rates. Similarly, at the 24-quarter horizon, the influence is still high at 16.275 percent, indicating that the effects of the shock will also persist over the long term.

Bond yields show medium term responses to the mpi_{ff4} shock, with 6.837 percent of the forecast error variance attributed to the 12-quarter horizon. This means that the shock has a remarkable but not overwhelming impact on long-term bond yields. At the 24-quarter horizon, the affect increases slightly to 7.221percent, suggesting that the impact of the shock persists but does not increase significantly over the long term.

The unemployment rate responds to the mpi_{ff4} shock, with 9.208 percent of the forecast error variation at the 12-quarter horizon attributed to the shock. This implies it has a meaningful impact on short-term unemployment forecasts. Likewise, at the 24-quarter horizon, the influence remains high at 9.444 percent, indicating that the effects of the shock persist, although they do not increase over the long term.

Table 4: FEVD Analysis of Monetary Policy Shocks.

Percentage variation due to (mpi_{ff4}) shock:		
Forecast Horizon	12 quarters ahead	24 quarters ahead
Gross Domestic Product	0.497	1.278
	(3.279)	(4.770)
Implicit Price Deflator	0.465	3.749
	(3.433)	(6.704)
3 - Month Treasury Bill	17.906	16.275
	(8.597)	(8.103)
Long-term Government	6.837	7.221
Bond yields	(5.544)	(6.073)
Unemployment Rate	9.208	9.444
	(9.318)	(10.591)

Note: The numbers in parentheses are the boundaries of the associated 68 percent Confidence bands.

Summary:

Overall, these forecast error deviation decompositions provide insights into how the mpi_{ff4} shock affects various economic variables at different forecast horizons. The explanation suggests the degree of sensitivity and persistence of these variables in response to shocks. Variables, such as short-term interest rates and unemployment, have more immediate and substantial reactions, while GDP, inflation, and bond yields, have moderate responses that persist over time.

5.2.2 Percentage variation due to ($info_{ff4}$) shock:

Table 5 shows that GDP has significant reactions to the $info_{ff4}$ shock but has less effect than inflation and unemployment. The percentage in 12 quarters was 38.9 percent, and in 24 quarters it was 21.95 percent, respectively.

In the 12th and 24th horizons, the implicit price deflator is the most effective due to the shocks $info_{ff4}$. It represents a considerable proportion of the forecast error deviations, 47.479 percent in 12 quarters and 50.674 percent in 24 quarters showing greatest influence from the shock.

The unemployment rate also showed large effects, with 32.278 percent in 12 quarters and 31.542 percent in 24 quarters respectively. As the labor market continues to influence by the $info_{ff4}$ shocks.

The long-term interest rates show a moderate impact, with 10.593 percent in 12 quarters and 12.136 percent in 24 quarters. However, these effects are smaller than the implicit price deflator, unemployment rate and GDP.

These short-term interest rates exhibit the smallest effect of the variables studied, with 12.094 and 14.846 percent for 12 and 24 quarters, respectively. Although shocks still have an impact, but it is smaller than other variables.

Table 5: FEVD Analysis of Information Shocks.

Percentage variation due to (INFO_FF4) shock:		
Forecast Horizon	12 Quarters ahead	24 Quarters ahead
Gross Domestic Product	30.865	21.095
	(11.673)	(9.694)
Implicit Price Deflator	47.479	50.674
	(12.039)	(13.042)
3 - Month Treasury Bill	12.094	14.846
	(8.063)	(9.604)
Long-term Government Bond	10.593	12.136
yields	(6.653)	(7.459)
Unemployment Rate	32.278	31.542
	(14.339)	(16.259)

Note: The numbers in parentheses are the boundaries of the associated 68 percent Confidence bands.

Summary:

To summarize, inflation and unemployment rates have the largest effect due to $info_{ff4}$ shock, indicates high sensitivity to these shocks. Moreover, GDP also responds significantly, but to a slightly smaller extent. Long-term government bond yields are moderately sensitive, and the 3-month Treasury Bill shows the lowest sensitivity among the variables considered. The findings suggest that the $info_{ff4}$ shocks have different effects on different economic variables.

6. Analysis of Empirical Results and Discussion

This section talks about the empirical results and thus the impact of monetary policy shocks on macroeconomic variables.

6.1 IRF Results for Monetary Policy shocks vs Information Shocks

From the thesis, we draw important findings from the results. In line with the theory, we find that agents expect both inflation and production to slow down over time due to a contractionary monetary policy shock. The empirical results of the study also suggest that the contraction in GDP is sudden, larger, and significant compared to previous literature. Our results also indicate that there is no evidence of price puzzle, which means the tightening in output also accompanied by inflation tightening. Similar evidence is documented in (Miranda-Agrippino & Ricco, 2021).

The impulse response functions (IRF) generated by information shocks shows the tightening of information shocks in the United States decreases output and unemployment rates. In contrast, a pure monetary shock caused a contraction of the economy. The tightening of the monetary policy shock led to a significant decline in the price level for about eight quarters, while information shocks led to a small and transitional decline. Similarly, contractionary monetary policy shocks in government bonds lead to a fall in the expected short-term interest rates, resulting in a decline in long-term yields.

On the other hand, information shocks reveal higher future short-term rates and, therefore, long-term rates. These findings are consistent with the literature on sign restriction vector autoregressions, if the current increase in bond yield is a response to monetary and demand shocks (Kilian & Lütkepohl, 2017). These findings also compliment with the study of (Gai & Tong, 2022) and (Jarociński & Karadi, 2020), information shocks lead to decrease in unemployment rate.

The study found that monetary policy shocks lead to higher short and long-term interest rates, making investment and consumption more expensive. This, in turn, reduces demand and causes the unemployment rate to increase. Similar findings also reported by (Romer & Romer, 2004) and (Uhlig, 2005). On the other hand, information shocks have a positive impact on the economy. These shocks bring confidence to the system showing “good news” in terms of Federal Reserve forecasts for the next business cycle. As a result, they stimulate consumption and investment, leading to an increase in aggregate demand and a decrease in the unemployment rate.

6.2 FEVD Results for Monetary vs Information Shocks

From the forecast error variance decomposition analysis, the percentages attributed to mpi_{ff4} and $info_{ff4}$shocks. Based on the results from tables above, 3-month treasury bills at both the 12 and 24 – quarter horizons, exhibit the largest effect indicating most strongly influenced by mpi_{ff4}shocks. On the other hand, output and inflation show smaller effects. This suggests that labor market conditions are significantly affected by these shocks.

7. Conclusion and Policy Implementation

7.1 Conclusion

The growing interest in hysteresis has been sparked by the persistence of the Global Financial Crisis, as there is still a perception that many advanced economies have suffered the negative consequences. The crisis has left scars on organizations, labor market, investors, and consumers as well.

In this study, the main purpose is to understand whether two policy shocks, i.e., monetary policy and information shocks generate long-term effects through a significant response of the noncyclical unemployment rate known as hysteresis. We have employed Cholesky VAR methodology on quarterly data set of US. The data set contains seven endogenous variables such as output, inflation, short term and long-term interest rates and unemployment.

The main comparison between these two types of shocks is the magnitude of their impact on unemployment. The $info_{ff4}$ shock has a downward and positive impact on unemployment, means the low level of unemployment indicates an excess demand for labor, which will eventually lead to an increase in real wage rates.

On the contrary, the mpi_{ff4} shock has negative and increasing effect, indicates a surplus of labor supply, resulting in a downward pressure on real wages.
Importantly, the analysis of the impulse responses of interest rates at short and long maturities found important but very short-lived effects of policy.

7.2 Recommendations

Using impulse response functions and forecast error variance decomposition analysis, we conclude that both monetary policy shocks and information shocks exert long-term effects through the natural rate of unemployment. The contribution of these shocks to the dynamics of the natural rate of unemployment is not negligible, particularly information shocks.

To sum up, the responses of a monetary policy shock obtained with the recursive identification are consistent with standard macroeconomic theory. This theory suggests that a contractionary monetary policy shock brings a contraction in output, a rise in unemployment rate, and a reduction in inflation rate.

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Appendix

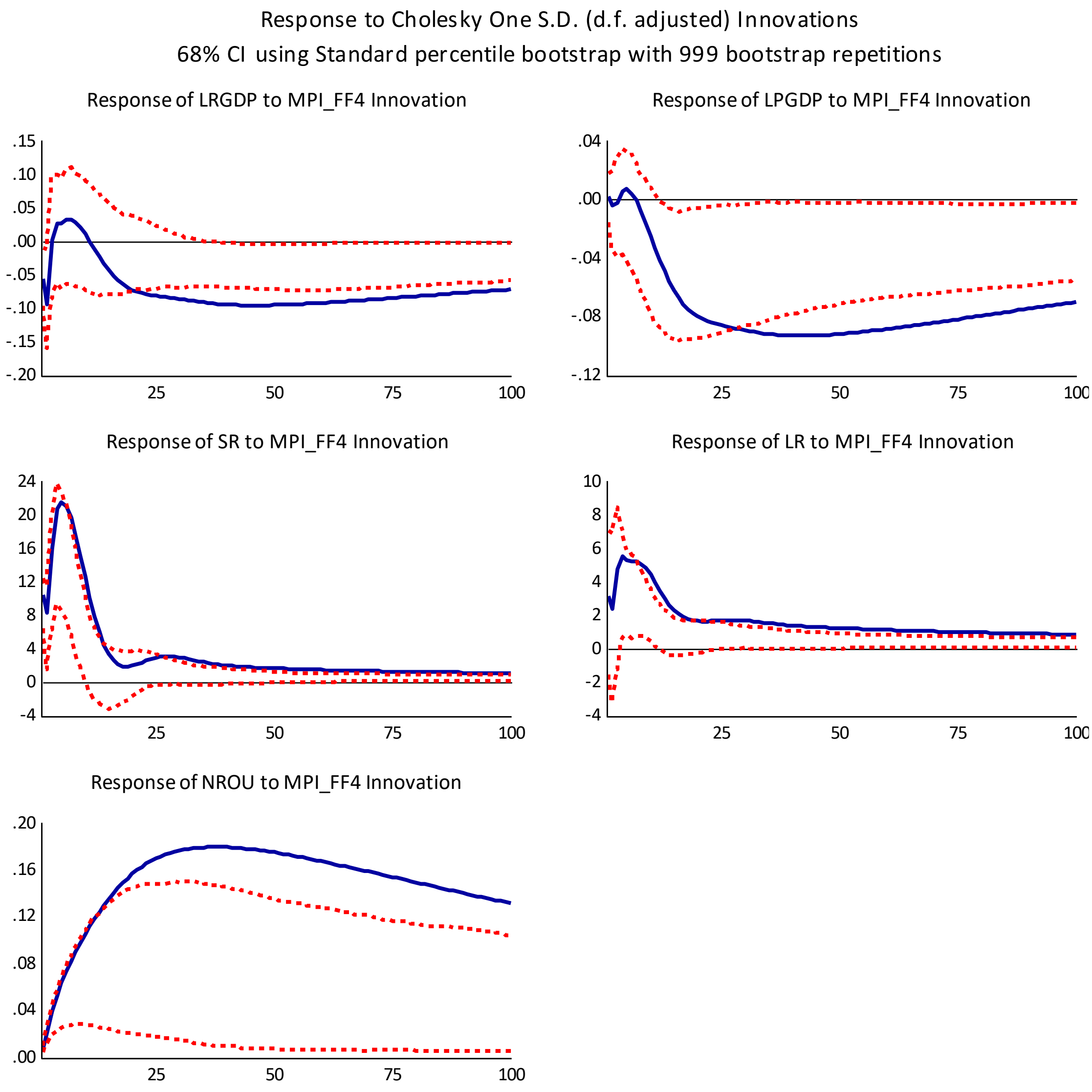

Figure 12: IRF to Monetary Policy shocks for 100 years horizon

(Author)

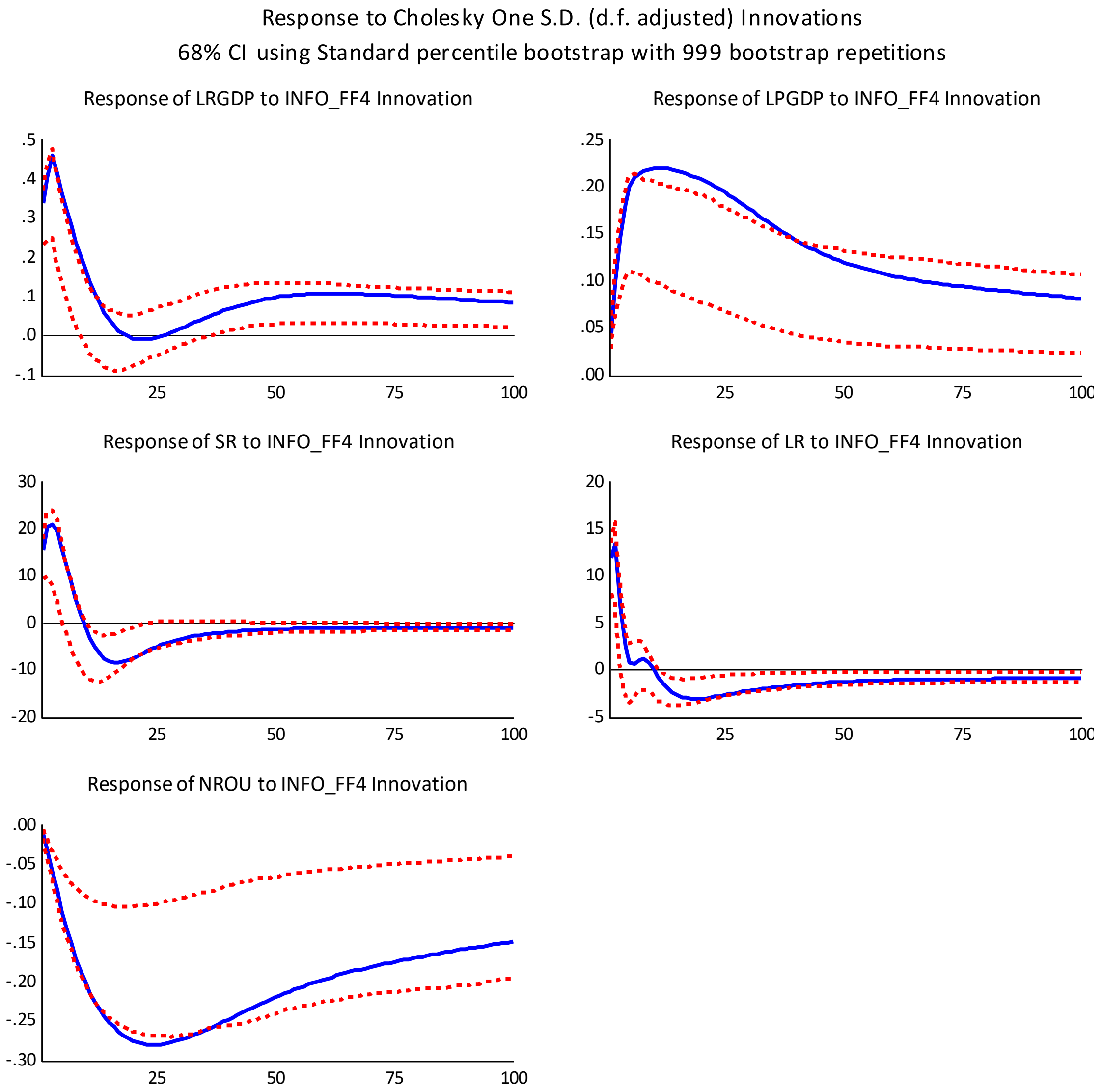

Figure 13: IRF responses to information shocks for 100 years horizon

(Author)

These figures represent the cholesky recursive VAR to one standard deviation showing impulse responses to monetary policy shocks with the horizon of hundred years.

Vector Autoregression Estimates
(MODEL 1)

Vector Autoregression Estimates
Date: 09/15/23 Time: 02:26
Sample (adjusted): 1991Q3 2015Q4
Included observations: 98 after adjustments
Standard errors in ( ) & t-statistics in [ ]

	MPI_FF4	LRGDP	LPGDP	SR	LR	NROU
MPI_FF4(-1)	-0.216228	-0.006411	-0.001302	-0.977630	-0.184615	0.001110
	(0.11628)	(0.00727)	(0.00220)	(0.38002)	(0.46730)	(0.00058)
	[-1.85954]	[-0.88160]	[-0.59156]	[-2.57257]	[-0.39507]	[1.9132]
MPI_FF4(-2)	-0.096603	0.011428	0.001769	1.045039	0.309082	0.000710
	(0.10570)	(0.00661)	(0.00200)	(0.34546)	(0.42479)	(0.00053)
	[-0.91390]	[1.72876]	[0.88439]	[3.02508]	[0.72760]	[1.3463]
LRGDP(-1)	-1.043307	1.140461	0.085366	8.612407	3.472896	-0.003877
	(1.84596)	(0.11544)	(0.03493)	(6.03288)	(7.41837)	(0.00921)
	[-0.56518]	[9.87910]	[2.44389]	[1.42758]	[0.46815]	[-0.4207]
LRGDP(-2)	1.575318	-0.203607	-0.066691	-6.320131	-1.121148	0.001010
	(1.75790)	(0.10993)	(0.03326)	(5.74508)	(7.06448)	(0.00877)
	[0.89614]	[-1.85208]	[-2.00490]	[-1.10009]	[-0.15870]	[0.11508]
LPGDP(-1)	-5.371871	-0.437133	1.292670	1.887507	-8.563666	0.006938
	(5.49420)	(0.34359)	(0.10396)	(17.9558)	(22.0795)	(0.02742)
	[-0.97773]	[-1.27224]	[12.4338]	[0.10512]	[-0.38786]	[0.2530]
LPGDP(-2)	6.570926	0.270008	-0.299441	1.761783	13.43521	-0.008625
	(5.52657)	(0.34562)	(0.10458)	(18.0616)	(22.2096)	(0.02758)
	[1.18897]	[0.78123]	[-2.86335]	[0.09754]	[0.60493]	[-0.3126]
SR(-1)	0.063416	0.002883	0.001057	1.570229	0.084708	-0.000265
	(0.03036)	(0.00190)	(0.00057)	(0.09921)	(0.12200)	(0.00015)
	[2.08896]	[1.51874]	[1.84052]	[15.8268]	[0.69434]	[-1.7465]
SR(-2)	-0.067421	-0.001912	-0.001220	-0.650885	-0.021157	0.000251
	(0.02980)	(0.00186)	(0.00056)	(0.09738)	(0.11975)	(0.00015)
	[-2.26268]	[-1.02629]	[-2.16462]	[-6.68387]	[-0.17668]	[1.6850]
LR(-1)	-0.004651	-0.000387	-4.58E-05	0.039250	0.953166	5.61E-05
	(0.02784)	(0.00174)	(0.00053)	(0.09098)	(0.11188)	(0.00014)
	[-0.16707]	[-0.22247]	[-0.08689]	[0.43139]	[8.51965]	[0.4038]

LR(-2)	-0.005818	-0.000934	0.000304	-0.140468	-0.406053	-2.45E-05
	(0.02743)	(0.00172)	(0.00052)	(0.08964)	(0.11023)	(0.00014)
	[-0.21213]	[-0.54428]	[0.58504]	[-1.56703]	[-3.68382]	[-0.1789]
NROU(-1)	1.927802	-0.526603	-0.339943	52.32638	43.66391	1.928996
	(7.64201)	(0.47791)	(0.14461)	(24.9752)	(30.7109)	(0.03814)
	[0.25226]	[-1.10188]	[-2.35081]	[2.09513]	[1.42177]	[50.574]
NROU(-2)	-0.914297	0.404264	0.346317	-47.57031	-37.15009	-0.931954
	(7.11279)	(0.44482)	(0.13459)	(23.2456)	(28.5842)	(0.03550)
	[-0.12854]	[0.90884]	[2.57308]	[-2.04642]	[-1.29967]	[-26.251]
C	-15.41988	1.970316	-0.181318	-61.07628	-74.80690	0.049084
	(14.0645)	(0.87956)	(0.26614)	(45.9649)	(56.5210)	(0.07020)
	[-1.09637]	[2.24012]	[-0.68130]	[-1.32876]	[-1.32352]	[0.6992]
R-squared	0.108205	0.999277	0.999890	0.985286	0.963919	0.999998
Adj. R-squared	-0.017695	0.999175	0.999874	0.983209	0.958825	0.999998
Sum sq. resids	0.598298	0.002340	0.000214	6.390284	9.662481	1.49E-05
S.E. equation	0.083898	0.005247	0.001588	0.274189	0.337159	0.000419

Vector Autoregression Estimates (MODEL 1)

F-statistic	0.859453	9788.031	64313.26	474.3156	189.2327	3454250.
Log likelihood	110.7771	382.4322	499.5821	-5.276723	-25.53684	630.1874
Akaike AIC	-1.995450	-7.539432	-9.930246	0.372994	0.786466	-12.59566
Schwarz SC	-1.652547	-7.196528	-9.587342	0.715898	1.129370	-12.25276
Mean dependent	0.000622	9.510619	4.432012	2.674529	4.631327	5.092444
S.D. dependent	0.083165	0.182641	0.141615	2.115962	1.661566	0.273732
Determinant resid covariance (dof adj.)		3.55E-22				
Determinant resid covariance		1.51E-22				
Log likelihood		1627.598				
Akaike information criterion		-31.62444				
Schwarz criterion		-29.56702				
Number of coefficients		78				

Vector Autoregression Estimates (MODEL 2)

Vector Autoregression Estimates
Date: 09/15/23 Time: 02:27
Sample (adjusted): 1991Q3 2015Q4
Included observations: 98 after adjustments
Standard errors in ( ) & t-statistics in [ ]

	INFO_FF4	LRGDP	LPGDP	SR	LR	NROU
INFO_FF4(-1)	-0.260952	0.009420	-0.002053	-4.638620	0.193047	-0.004028
	(0.14141)	(0.02826)	(0.00852)	(1.52952)	(1.79984)	(0.00220)
	[-1.84530]	[0.33333]	[-0.24100]	[-3.03273]	[0.10726]	[-1.8326]
INFO_FF4(-2)	0.042264	0.034617	0.002225	-1.433877	-0.999183	-0.004659
	(0.11120)	(0.02222)	(0.00670)	(1.20270)	(1.41526)	(0.00173)
	[0.38008]	[1.55776]	[0.33209]	[-1.19222]	[-0.70601]	[-2.6958]
LRGDP(-1)	0.715601	1.112400	0.091905	22.66982	3.512842	0.002833
	(0.67634)	(0.13516)	(0.04075)	(7.31525)	(8.60814)	(0.01051)
	[1.05805]	[8.22998]	[2.25534]	[3.09898]	[0.40808]	[0.2694]
LRGDP(-2)	-0.747546	-0.176686	-0.073550	-20.64326	-1.477019	-0.005993
	(0.64806)	(0.12951)	(0.03905)	(7.00931)	(8.24813)	(0.01007)
	[-1.15352]	[-1.36425]	[-1.88370]	[-2.94512]	[-0.17907]	[-0.5950]
LPGDP(-1)	-2.184116	-0.484059	1.295987	13.01435	-5.123508	0.015800
	(1.75383)	(0.35050)	(0.10567)	(18.9692)	(22.3218)	(0.02726)
	[-1.24534]	[-1.38107]	[12.2646]	[0.68608]	[-0.22953]	[0.5796]
LPGDP(-2)	1.708897	0.329897	-0.302120	-10.11625	9.316930	-0.019024
	(1.77119)	(0.35397)	(0.10671)	(19.1570)	(22.5428)	(0.02753)
	[0.96483]	[0.93200]	[-2.83110]	[-0.52807]	[0.41330]	[-0.6911]
SR(-1)	0.001125	0.001848	0.000932	1.537848	0.070240	-5.94E-05
	(0.00904)	(0.00181)	(0.00054)	(0.09776)	(0.11504)	(0.00014)
	[0.12451]	[1.02319]	[1.71126]	[15.7312]	[0.61060]	[-0.4230]
SR(-2)	-0.007742	-0.000580	-0.001091	-0.655312	-0.008731	4.23E-06
	(0.00936)	(0.00187)	(0.00056)	(0.10127)	(0.11917)	(0.00015)
	[-0.82689]	[-0.31015]	[-1.93434]	[-6.47082]	[-0.07327]	[0.0290]
LR(-1)	0.005528	-0.000538	-2.08E-05	0.099241	0.957815	0.000108
	(0.00893)	(0.00178)	(0.00054)	(0.09660)	(0.11367)	(0.00014)
	[0.61898]	[-0.30136]	[-0.03857]	[1.02732]	[8.42592]	[0.7795]
LR(-2)	-0.005348	-0.001177	0.000275	-0.152112	-0.396426	-1.70E-05
	(0.00871)	(0.00174)	(0.00053)	(0.09425)	(0.11090)	(0.00014)

	[-0.61377]	[-0.67606]	[0.52336]	[-1.61398]	[-3.57452]	[-0.1254]
NROU(-1)	-1.416820	-0.373225	-0.329815	45.73679	42.35498	1.910061
	(2.45242)	(0.49011)	(0.14776)	(26.5252)	(31.2132)	(0.03811)
	[-0.57772]	[-0.76152]	[-2.23211]	[1.72428]	[1.35696]	[50.1167]
NROU(-2)	1.185366	0.258041	0.336312	-41.69972	-36.48128	-0.914298
	(2.28225)	(0.45610)	(0.13751)	(24.6845)	(29.0473)	(0.03547)
	[0.51939]	[0.56576]	[2.44580]	[-1.68930]	[-1.25593]	[-25.778]
C	3.597527	1.890144	-0.181676	-51.88922	-65.62747	0.064786
	(4.47604)	(0.89452)	(0.26968)	(48.4124)	(56.9687)	(0.06956)
	[0.80373]	[2.11303]	[-0.67367]	[-1.07182]	[-1.15199]	[0.9313]
R-squared	0.206735	0.999263	0.999889	0.983917	0.963883	0.999998
Adj. R-squared	0.094745	0.999159	0.999873	0.981646	0.958784	0.999998
Sum sq. resids	0.059709	0.002385	0.000217	6.984935	9.672143	1.44E-05
S.E. equation	0.026504	0.005297	0.001597	0.286663	0.337328	0.000412

Vector Autoregression Estimates (MODEL 2)

F-statistic	1.846006	9604.112	63566.04	433.3325	189.0365	3570121.
Log likelihood	223.7031	381.5034	499.0095	-9.636602	-25.58582	631.8041
Akaike AIC	-4.300064	-7.520477	-9.918561	0.461971	0.787466	-12.62866
Schwarz SC	-3.957160	-7.177573	-9.575657	0.804875	1.130369	-12.28575
Mean dependent	-0.000605	9.510619	4.432012	2.674529	4.631327	5.092444
S.D. dependent	0.027856	0.182641	0.141615	2.115962	1.661566	0.273732

Determinant resid covariance (dof adj.)	1.98E-23
Determinant resid covariance	8.42E-24
Log likelihood	1769.104
Akaike information criterion	-34.51233
Schwarz criterion	-32.45491
Number of coefficients	78