Chapter - III

Research Methodology

This chapter offers a comprehensive overview of the theoretical framework, data collection, and empirical methodology employed in the study. The chapter commences with a detailed explication of the theoretical approach employed to select the variables utilized in the research. Subsequently, it provides an account of the variables employed, including their sources. This is followed by an elucidation of the empirical method utilized. The chapter provides an exhaustive overview of the selected methodology, delving into the reasons for choosing the model and the identification approach used to address the research questions.

3.1 Theoretical framework

The theoretical framework of the model is derived from the objectives of monetary and fiscal policies.

The existing literature shows that utility functions for monetary and fiscal authorities are commonly developed with three variables: inflation, unemployment, and potential output growth. However, studies by Andlib et al. (2012) and Raj et al. (2011) have shown that the weights assigned to each macroeconomic variable differ between these authorities, reflecting their distinct preferences for macroeconomic outcomes. Fiscal authorities tend to prioritize low unemployment over inflation, while monetary authorities give greater weight to reducing inflation. This difference in weighting can be attributed to the central bank's primary objective of maintaining price stability, whereas the fiscal authority is responsible for promoting output growth, which in turn impacts employment levels. In India, the dominant objective of monetary policy has been price stability Mohanty, D. (2011).

Using the methodology described by Nordhus (1994), as outlined in Andlib et al. (2012), the following utility functions are specified based on the underlying assumptions:

$$U^M = f(\mu, \hat{\pi}, \theta) \tag{3.1}$$

$$U^F = f(\hat{\mu}, \pi, \theta) \tag{3.2}$$

where U^F and U^M are the utility functions of fiscal and monetary authorities respectively; μ, π and θ are unemployment rate, inflation rate and potential output growth respectively.

The unemployment gap is a closely linked with the output gap in economic literature. The difference between the unemployment rate and the non-accelerating inflation rate of unemployment

(NAIRU) is connected to the deviation of actual output from its potential level as explained by long run Philips curve. Additionally, Okun's law establishes a negative relationship between changes in gross domestic product (GDP) and unemployment that remains relatively stable over time (Jahan and Mahmud, 2017). Therefore, Okun's law can be used to represent the unemployment rate in terms of the output gap. Both fiscal and monetary policies have an impact on the output level in the economy, as demonstrated in the IS-LM analysis. Thus, the output gap can be modelled as a function of the two policies - interest rate (r) and fiscal balances (s). The current fiscal balance is calculated as the difference between current revenue and current expenditure. Accordingly , fiscal balance depends upon the two tools of the fiscal policy (ie. taxation (t) and expenditure (g)). Therefore, unemployment can be modelled as a function of interest rate and fiscal balance. That is, $\mu = g(r,s)$

Thus, equations (3.1) and (3.2) can be rewritten as:

$$U^M = f(r,s,\hat{\pi},\theta) \qquad 3.3$$

$$U^F = f(r,s,\pi,\hat{\theta}) \qquad 3.4$$

The utility functions of the monetary and fiscal authorities, as represented in equations (3.3) and (3.4), respectively, are influenced by policy targets and instruments. Equation (3.3) demonstrates that when policy instruments are used in place of the unemployment rate, fiscal authorities display a preference for potential output growth, as denoted by the hat on q.

The fiscal authorities encounter a growth maximization problem that is limited by constraints originating from the external and monetary sectors of the economy (as seen in IS-LM-BP analysis). In contrast, the monetary authorities are confronted with the challenge of minimizing inflation, subject to constraints arising from the external (as shown in IS-LM-BP analysis) and fiscal sectors (as seen in non- ricardian assumption of FTPL, Christ (1968) macroeconomic model).

The above mentioned constrained can be expressed as the reaction function of both the authorities:

$$r = h(\pi, s, e, v) \qquad 3.5$$

$$s = h(r, \theta, g, t) \qquad 3.6$$

where equation (5) can be defined as monetary policy reaction function with interest rate (monetary policy variable) is a function of inflation, fiscal balance (s) , exchange rate depreciation/ appreciation (e) and external reserves/ GDP growth. Here s captures the effect of fiscal policy variables on the monetary policy variables. To incorporate concerns regarding fluctuations in the exchange rate and external reserves in a managed-float regime, e and v are taken into account when developing the monetary policy reaction function. On the other hand, equation (6) defined the fiscal policy reaction with fiscal balance as function of interest rate (r) , output gap (θ) , government expenditure (g) and government taxes (t). Here interest rate captures the effect of monetary policy variable on the fiscal variable.

By optimizing the utility functions of both monetary and fiscal authorities in terms of inflation and potential output, respectively, while accounting for their policy constraints (as represented by their respective reaction functions), the following equation is derived:

$$\theta = F(r, g, t, \pi, \lambda) \quad 3.7$$

$$\pi = F(r, g, t, \theta, e, \lambda) \quad 3.8$$

Equation (3.7) states that potential output in the economy is a function of interest rate , government expenditure , government taxes and inflation.

Equation (3.8) states that equilibrium inflation rate is a function of interest rate , government expenditure , government taxes, exchange rate and output growth.

The constraint coefficient lambda (λ) in equations (3.7) and (3.8) refers to the marginal utility of adjusting policy instruments and serves to constrain the utility functions of both equations.

It should be noted that the objectives of equations (3.7) and (3.8) are different. While the former aims to maximize potential output growth, the latter seeks to minimize the rate of inflation. To convert both equations into minimization problems, equation (7) can be rewritten by substituting output gap for potential output growth. This reduces the problem to determining the optimal values for interest rate, government spending and taxes, inflation, changes that minimize the output gap. Based on the optimisation problem and the research objective the study used six variables- interest rate (monetary policy instrument) , government expenditure and taxes (fiscal policy instrument), inflation , output gap , exchange rate.

3.2 Description of Data

This section presents a description of the data and details on the methodology used to calculate the model variables for the SVAR model. The model was constructed using six variables, namely, output gap, government expenditure, government taxes, inflation, interest rate, and exchange rate. Among these variables, real expenditure and real taxes were considered as fiscal policy instruments, interest rate was considered as a monetary policy variable, and output gap, inflation rate, and exchange rate were non-policy macroeconomic variables.

All the data used in this study were collected at a quarterly frequency and spanned from the first quarter of 1991 to the second quarter of 2016. The study pertains to the time period during which India implemented a multiple indicator approach, whereas at present, it follows an inflation targeting regime. However, due to inadequate availability of data points, a rigorous analysis with data from inflation targeting period in India is unfeasible, and consequently, the analysis considers only the period until 2016Q2. Moreover, owing to significant events such as demonetization and the Covid-19 pandemic, the impact of inflation targeting cannot be ascertained with the available data. The summary of data description and source is provided in Table 3.2 in Appendix 3.1. Further the graph of the variables in baseline modelling is also reported.

The description of the variables included in the model is given below:

Output Gap

The output gap refers to the difference between the actual and potential output of an economy, with potential output representing the maximum amount of goods and services an economy can produce at maximum efficiency and capacity. To estimate the output gap, a simple slicing method, as outlined in Hill and Fox's (1997) approach, was employed to combine real GDP series with varying bases. Subsequently, the Hodrick-Prescott filter, a widely used statistical tool introduced by Hodrick and Prescott (1997), was utilized to estimate the output gap using the real GDP. The HP filter generates estimates based on a weighted moving average of the observations, unlike linear regression techniques that assign equal weight to all observations. To prioritize observations closer to the beginning and end of the sample period, the filter assigns greater weight to them (Bhoi and Behera, 2016). In this study, the value of the smoothing parameter for the HP filter, denoted by λ, was set to 1600, as proposed by Ravn and Uhlig (2002) for quarterly data. The output gap has been deseasonalized using moving average, centered moving average, seasonal irregular value, seasonal index and deseasonalized value for output gap, most of the negative values become positive.

Inflation

The Consumer Price Index (CPI) was widely recognized as the primary measure of inflation in most countries. However, CPI data at the all India level was only available from 2011 after the introduction of the new all-India CPI (rural and urban combined in February 2011) (Patnaik et al., 2011). Therefore, the study used Wholesale Price Index (WPI) as a measure of inflation in India. WPI data was available for all commodity groups on a monthly basis, and so the quarterly data was obtained by calculating the average of monthly data for the respective quarter. The WPI series utilized three bases for the study period, namely WPI (base 1981-82), WPI (1993-94), and WPI (2011-2012). To address this issue, a simple slicing technique was employed to convert the WPI series into a single base of 2011-2012.

Government Taxes

Data on government net taxes data was available on monthly basis so the quarterly data was obtained on basis of sum of monthly values. The pre 1997 missing data on quarterly basis was calculated using Denton (1971) proportional method from the annual data available for that period. The Denton method is a popular benchmarking technique that is commonly utilized to convert low-frequency to high frequency time series (Macro-Integration - Denton's Method (Pdf File) - CROS - European Commission, 2013).The government net taxes were converted into real terms using GDP deflator. GDP deflator was calculated on basis of GDP series at current and constant prices with base year 2011-12 using the formula mentioned below:

$$GDP\ deflator = \frac{Nominal\ (current\ price)\ GDP}{Real\ (constant\ price)\ GDP}$$

Government Expenditure

Data on government expenditure was available on monthly basis so the quarterly data was obtained on basis of sum of monthly values. The pre 1997 missing data on quarterly basis was calculated using Denton (1971) proportional method from the annual data available for that period. The Denton method is a popular benchmarking technique that is commonly utilized to convert low-frequency to high frequency time series (Macro-Integration - Denton's Method (Pdf File) - CROS - European Commission, 2013).The government expenditure were converted into real terms using GDP deflator.

Interest rate

Interest rate was measured using nominal weighted average call money rate. The rate at which short-term funds are borrowed and lent in the money market is known as the call money rate. Two main reasons why call money rate was taken as measure of interest rate for the study period is that (a) call money rate is the overnight inter-bank rate which is the first point of transmission of monetary policy (Kumar et al., 2017) (b) The data was available for the entire study period. The quarterly data on call money rate was obtained by calculating average of the monthly values.

Exchange rate

Exchange rate was measured by 36 currency based real trade weighted index ie. Real Effective Exchange Rate (REER).

3.3 Empirical methodology

The first step in conducting time series analysis is to perform a stationarity check on the data using appropriate statistical tests. The stationarity of a time series refers to the constancy of its statistical properties over time. Non-stationarity in the data can lead to biased or inconsistent results in statistical analyses.

To evaluate the stationarity of the time series in this study, the Phillips-Perron test was employed in the study . The Phillips-Perron test is a widely used statistical test that examines the null hypothesis of unit root presence against the alternative hypothesis of stationarity.

3.3.1 Unit Root test

The log-series analysis is in progress in context to tests involving stationarity. Developing models comprising of non-stationary data and using the same could result in spurious regressions entailing with misleading results. Hence, it requires transferring non-stationary time-series data into stationary in pursuit of obtaining the accurate models and outcomes. To have this operation in place, the necessity is to employ the Phillips-Perron test. The common version of the Phillips-Perron test without any trend is:

$$\Delta y_t = \beta^{'} D_t + \pi y_{t-i} + u_t \qquad 3.9$$

where u_t is I(0) and may be heteroskedastic. The PP tests immediately alter the test statistics t $\pi = 0$ and $T\pi$. to directly adjust for any serial correlation and heteroskedasticity in the errors u_t of the test regression.

3.3.2 Vector Autoregressive (VAR) Model

In 1980, Sims introduced the vector autoregressive (VAR) methodology as an alternative to traditional large scale macro econometric modelling. Sims identified several objections to the traditional approach, including the arbitrary imposition of exclusion restrictions and the lack of solid economic or econometric arguments for identification. In particular, Sims argued that in a world of rational forward-looking agents, no variable can be considered exogenous. To address these issues, Sims proposed treating all variables as endogenous and first estimating an unrestricted model in a reduced form.

The VAR (k - equation k- variable linear model) is a time series model of the economy where each variable is explained by its own lagged values, plus current and past values of the remaining k - 1 variables, estimated using ordinary least squares. The dynamic characteristics of empirical model are illustrated through impulse response functions and variance decompositions, which are commonly used in VAR analysis (Keating, 1992). Sims (1980) and other prominent researchers contended in their early influential publications that VARs had the potential to offer a consistent and reliable technique for data description, structural inference, forecasting, and policy analysis (Stock and Watson, 2001).

Initially, the dynamic indicators of the VAR were generated through a mechanical technique that was perceived as having little relationship to economic theory. However, Cooley and LeRoy (1985) contended that this so-called atheoretical method actually implies a particular economic structure that is difficult to reconcile with economic theory (Keating, 1992). The VAR approach, therefore, provides a more flexible and theoretically grounded way to identify the causal relationships between economic variables.

However, the VAR approach has faced criticism for lacking economic content. The only role is to suggest the variables to include in the model, after which the procedure becomes almost mechanical. Due to the limited economic input in the VAR approach, it is not unexpected that the resulting analysis may also lack economic content. While innovation accounting necessitates ordering the variables, the selection of this ordering is often ad hoc (Enders, 2010).

This criticism of the VAR approach prompted the development of a "structural" VAR approach by Bernanke (1986), Blanchard and Watson (1986), and Sims (1986). The structural VAR technique enables researchers to incorporate economic theory into the reduced-form VAR model by converting it into a system of structural equations. The primary distinction between atheoretical and structural VARs is that the latter produce impulse responses and variance decompositions that can be interpreted in structural terms (Keating, 1992). This allows researchers to explore the causal relationships between economic variables in a more theoretically rigorous manner, compared to the mechanical approach of the traditional VAR methodology . Therefore , a structural VAR uses economic theory to determine the variables' contemporaneous relationships (Bernanke, 1986; Blanchard and Watson, 1986; Sims, 1986) (Stock,2001).

3.3.3 Structural VAR model

Structural Vector Autoregression (SVAR) is a widely used statistical model in macroeconomics and finance, allowing for the identification and analysis of the underlying shocks that drive the dynamics of the system. The SVAR framework involves a system of equations that are simultaneously estimated, with the aim of uncovering the structural relationships between the endogenous variables of interest.

SVAR models are useful for addressing a wide range of economic questions, such as the effects of monetary policy shocks, fiscal policy shocks, and other economic disturbances. The model allows researchers to study the transmission mechanisms of these shocks and to make predictions about their future impact on the economy.One key feature of the SVAR model is that it is able to account for the endogeneity of variables in the system, making it a powerful tool for modeling dynamic relationships between variables.

3.3.4 Advantages of SVAR Model

The structural vector autoregressive (SVAR) model has several advantages over other econometric models, particularly in the context of macroeconomic research.

Firstly, SVAR models can provide a flexible framework for analyzing the causal relationships between variables in the system. This is because they allow for the identification of structural shocks, which are exogenous variables that capture the unanticipated changes in the economic system. By examining the impulse response functions generated from these shocks, researchers can gain insights into the causal relationships between variables in the system and the impact of exogenous shocks on these variables.

Secondly, SVAR models are able to account for feedback effects between variables in the system, which is important in many macroeconomic applications. This is because the model allows for the simultaneous determination of all variables in the system, rather than assuming that some variables are exogenous and others are endogenous.

Thirdly, SVAR models can be used to analyze a wide range of macroeconomic questions, such as the effects of monetary policy on the economy, the impact of fiscal policy on output and inflation, and the transmission of shocks across different sectors of the economy. This is because the model can incorporate a large number of variables and can be used to test a wide range of hypotheses.

Fourthly, SVAR models allow for the incorporation of prior information about the economic system, which can improve the accuracy and efficiency of the estimates. This is particularly important in cases where there is limited data available or when the data is noisy or unreliable.

Overall, the flexibility, ability to account for feedback effects, wide range of macroeconomic applications, and incorporation of prior information make SVAR models a powerful tool for analyzing the complex interactions between economic variables.

3.3.5 Representation of SVAR model

A general form SVAR appears in the following format:

$$B_o y_t = B_1 y_{t-1} + \ldots.. + B_p y_{t-p} + w_t \qquad 3.10$$

where y_t is the k x1 vector of observed time series data $(y_{1t}, \ldots y_{kt})'$, t= 1,…,T. It contains endogenous variables. For this study the set of endogenous variables are government expenditure, government taxes, interest rate, inflation rate, output gap and exchange rate.

B_0 is a k x k matrix, which reflects the contemporaneous relationship between the variables.

Further, B_i , $i = 1,...,p$, is a k x k matrix of autoregressive slope coefficients where the cross-variable coefficients captures the interaction between the variables.

B_o^{-1} captures the impact effects of each of structural shock on each of the variables in the model. w_t is serially uncorrelated and has a diagonal covariance matrix

$\sum_w$ of full rank. The structural shocks can be recovered from the reduced - form representation.

Equivalently the model can be written as

$$B(L)y_t = w_t \tag{3.11}$$

where $B(L) = B_0 - B_1L - B_2L^2 - \ldots - B_pL^p$ is the autoregressive lag polynomial.

The problem with form of SVAR model shown in equation (3.10) is that it cannot be estimated using standard estimation technique such as OLS. The inherent feedback in the system prevents direct estimate of these equations, as the variables of interest (y_t) are associated with the error term (w_t). This correlation poses a challenge, as the standard estimation techniques are based on the assumptions that the regressors are uncorrelated with the error term ie. $cov(y_{it}, w_{it}) \neq 0$ (Enders, 2010).

Therefore, in order to estimate the SVAR model and to obtain its true structural parameter requires transforming the primitive system into its standard reduced form VAR model. This reduced form model can be obtained by premultiplying both sides of the equation (3.10) by B_0^{-1}.

Thus, reduced form representation of the model can be written as

$$y_t = A_1y_{t-1} + \ldots.. + A_py_{t-p} + u_t \tag{3.12}$$

where $A_i = B_0^{-1}B_i$ and $u_t = B_0^{-1}w_t \sim (0, \sum_u$. Equivalently the model can be represented by:

$$A(L)y_t = u_t \tag{3.13}$$

where $A(L) = I_K - A_1 L - A_2 L^2 - \ldots - A_p L^p$ is the autoregressive lag polynomial.

The coefficients of this reduced form can be estimated through either Ordinary Least Squares (OLS) or Maximum Likelihood (ML) estimation methods, since only predetermined variables are expressed as a function of y_t. Similarly, this would also generate the residuals u_t.

Once A_i matrix and the residuals u_i are estimated , from $A_i = B_0^{-1} B_i$ $u_t = B_0^{-1} w_t$ the structural parameters B_i and and structural shocks w_t can be estimated. However, to recover the parameters of the structural model requires the knowledge of the structural impact multiplier matrix B_0^{-1}. The estimation of B_0^{-1} or B_0 requires economically credible restrictions be imposed on B_0^{-1} or B_0 to identify the structural shocks. Given these restrictions and data, if B_0^{-1} or B_0 can be solved, it can be confirmed that the parameters of the structural VAR model, denoted as (B_0 , B_1 , . . . Bp, $\sum_w$), have been identified (Kotzé). Alternately, we can state that structural shocks, denoted by $w_t = B_0 u_t$, have been identified. Identification of structural shocks from reduced form residual is the essence of SVAR.

3.3.6. Identification

Various techniques have been suggested in the literature for this purpose, which are discussed below:

Short run restrictions

The short-run constraints in Structural Vector Autoregression (SVAR) models impose normalization and certain restrictions on some of the contemporaneous feedback effects among the variables to orthogonalize the shocks, as described in the seminal works of Bernanke (1986), Blanchard and Watson (1986), and Sims (1986) (Guay and Pelgrin, 2007). One of the most common ways of imposing these restrictions is the Cholesky decomposition, which involves decomposing the covariance matrix of the structural shocks into a lower-triangular matrix of orthogonal factors (for example, Stock and Watson, 2001). This imposes a causal ordering on the variables, making it a recursive system. However, this approach has faced criticism for being "atheoretical" and for often necessitating the imposition of unrealistic assumptions about the timing of responses (Arora, 2017). This criticism led to the development of alternative identification strategies, such as non-recursive restrictions imposed by Sims (1986), Bernanke (1986), Blanchard and Watson (1986), Blanchard and Perotti (2002), and Keating (1992). However, non-recursive VAR models suffer from the challenge of weak identification, as they require strong instruments to accurately estimate causal effects in the data.

Long run restrictions

Shapiro and Watson (1988) and Blanchard and Quah (1989) introduced an alternative approach to identifying structural shocks in Structural Vector Autoregression (SVAR) models, which involves imposing identifying restrictions on the long-run multipliers. This approach allows for the determination of short-run dynamics based on the data, conditional on a particular long-run model, without imposing contemporaneous restrictions (Keating, 1992). In economic theory, there is a general tendency for a greater degree of predictability of events in long run as compared to short run. For example, economists generally agree that demand shocks such as monetary policy shocks are neutral in the long run.

One example of a long-run restriction is the Gali (1999) model, which assumes that only technology shocks have long-run effects on labor productivity. Another example is Fisher's (2006) "A Model of Neutral and Investment-Specific Technology Shocks," which identifies the model on basis of two permanent shock in a growth model.These long-run restrictions can help improve the accuracy of forecasts and policy analyses and provide a more complete understanding of the underlying economic relationships. However, the validity of these restrictions depends on the underlying economic theory and empirical evidence, and incorrect or inappropriate restrictions can lead to biased or unreliable results.

Sign restrictions

Faust (1998), Canova and De Nicolo (2002), and Uhlig (2005) were the pioneers of the sign restriction method for identification of structural VAR models.

Theoretical explanation of sign restriction approach:

$$B_o y_t = B_1 y_{t-1} + \ldots\ldots + B_p y_{t-p} + w_t \qquad 3.14$$

such that $E(w_t w_t') = \sum_w = I_K$

Putting $u_t = P\eta_t$, where u_t is the reduced -form VAR and P is the lower triangular Cholesky decomposition of $\sum_u$. For the unknown structural shock A solution w_t^* is constructed from a large number of combinations of the shocks η_t of the form.

$w_t^* = Q'\eta_t$

Where Q' is a square orthogonal matrix such that $Q'Q = QQ' = I_k$ and

$u_t = PQQ'\eta_t = PQw_t^*$.

Out of the possible constructed solutions w_t^* , the ones where the structural impact matrix PQ satisfy the restrictions imposed on B_0^{-1} are retained. The comprehension of PQ facilitates the computation of all pertinent structural impulse response coefficients from the estimates of the reduced-form slope parameters. At the same time, the capability to generate numerous candidate matrices Q from the entire set of orthogonal matrices is vital for constructing sign-identified VAR models. The orthogonal matrix Q is constructed using givens rotation matrices and the householder transformation. This study used the household transformation approach by Rubio-Ramirez, Waggoner, and Zha .

3.3.7 Identification of the shocks in the study

To address the issue of weak policy signals for fiscal policy, the study employs a combination of the sign restriction approach and the zero magnitude approach. The sign restriction method is a partial identification technique that does not require restrictions to be placed on every variable. Rather, it is used solely to identify the structural shock that the study seeks to investigate, in order to achieve its research goals.The sign restrictions and zero restriction imposed on the variables in the study are discussed below:

Identification of monetary and fiscal shocks:

Table 3.1: Identification of Shocks

Shock\ Variable	Inflation	Output Gap	Interest rate	Expenditure	Taxes
Monetary Policy Shock	–	–	+		
Tax shock		_			0[+]
Government Expenditure		+		0[+]	
Aggregate demand shock	+	+			
Aggregate Supply shocks	+	–			
(+) and (-) sign in the model represents positive and negative value. (0) represents zero restriction. Blank spaces represents no restriction on the variable					

The sign restriction are placed in line with economic theory and on basis of approach identified in the economic literature.

A positive monetary policy shock, which involves an increase in interest rates, is typically associated with a negative effect on both the output gap and inflation. This is because higher interest rates tend to reduce borrowing and spending by consumers and businesses, which in turn can lead to lower levels of economic activity and inflation (Arora, 2018 and Büyükbaşaran et al., 2020).

The identification of fiscal policy shocks in SVAR models poses a challenge due to the difficulty in disentangling the effects of fiscal policy from other macroeconomic shocks. This problem arises because fiscal policy shocks are often correlated with other shocks, such as monetary policy, productivity, or oil price shocks. As a result, a fiscal policy shock can be misidentified as another type of shock in the absence of clear identification restrictions. To address this issue, various identification strategies have been proposed, such as the use of institutional and historical information, sign restrictions, and external instruments. This study uses identification strategies similar to Canova and Pappa (2007), Gerba and Hauzenberger (2013), Mountford and Uhlig (2009) and Arora (2018). They have proposed the use of sign restriction along with zero restriction to deal with such issues (Arora, 2018). A positive tax shock is characterized by a tax hike , resulting in positive values for the tax shock during the initial period. An expenditure shock is associated with an expenditure increase, with no restrictions on the first periods and a positive value after that period.

The identification of aggregate demand and aggregate supply shocks is based on the Keynesian aggregate demand and supply analysis. Typically, the aggregate demand schedule is downward sloping, while the aggregate supply schedule is upward sloping in the short run.

An aggregate demand shock is characterized by an upward movement of the aggregate demand schedule, leading to an increase in both demand and prices. Conversely, a positive aggregate supply shock results in a leftward shift of the aggregate supply curve, causing an increase in output and a decrease in price. Therefore, Aggregate demand gap is identified by a positive impact on both output and inflation. While an aggregate supply gap is identified on the basis of positive impact on output but negative impact on inflation.

As sign and zero restrictions are imposed on the variables of interest in the case of sign and zero restriction techniques, additional clarity on the individual impact on these variables was obtained through the use of variance decomposition with Cholesky decomposition. Hence, variance decomposition with Cholesky decomposition is also reported in order to gain a better understanding of the variations in variables of interest.

3.7.8 Impulse response and Variance decomposition

The evaluation of SVAR analysis results is commonly done through Impulse Response Functions (IRFs) and Variance Decomposition. The IRFs are particularly useful as they provide a dynamic depiction of the effect of a shock on a particular variable of interest over time. This technique enables policymakers and researchers to examine the direction, size, and persistence of the effects of a particular shock, compare the relative importance of different shocks, and evaluate the effectiveness of policy responses to various shocks such as fiscal and monetary policy. Furthermore, the IRFs offer a more nuanced understanding of the complex interactions between macroeconomic variables, making it a valuable tool for decision-making.

To calculate an IRF in SVAR, the model is first estimated using a set of identified structural shocks. A one-unit shock is then applied to a particular variable of interest while holding all other variables constant, and the impulse response function is computed by observing how each endogenous variable responds to the shock over time.

The impulse response function is obtained by recursively applying the restrictions to the estimated coefficients of the model. Specifically, the impulse response function at time t is obtained by multiplying the impulse at time zero with the coefficient matrix raised to power t. The resulting matrix represents the dynamic effects of the impulse on each variable at time t.

The impulse response function is typically presented graphically, with the vertical axis representing the percentage change in the variable of interest, and the horizontal axis representing time. The shape of the impulse response function provides important information about the dynamic effects of the shock on the variable of interest, which can be used to inform policy decisions. Overall, the IRFs are an essential tool for researchers and policymakers to understand the complex interactions of macroeconomic variables and design effective policy responses.

Variance Decomposition is a statistical technique used in SVAR analysis to quantify the contribution of each shock to the variation in the endogenous variables over a specific time horizon. This technique involves decomposing the forecast error variance into the proportion of the variance that can be attributed to each shock. The variance decomposition provides insights into the relative importance of each shock in explaining the variability of the endogenous variables. It helps to identify the main drivers of economic fluctuations and to evaluate the effectiveness of policy responses to different shocks. A high contribution of a particular shock to the variance of a variable implies that the shock has a significant impact on the variable, while a low contribution suggests that the shock has limited effects.

Overall, IRFs and Variance Decomposition are valuable tools for policymakers and researchers to understand the relative importance of different shocks and their impact on the economy. They help to inform policy decisions and to design effective strategies to mitigate the adverse effects of economic fluctuations.