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Application of VAR Model in Macro-econometric Analysis

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Abstract:- One of the most critical roles of macro-econometricians is to provide advice to policymakers by describing and summarizing macroeconomic data, making macroeconomic forecasts, estimating how much stakeholders understand concerning the macroeconomy's underlying structure. Various methods were used in to perform these activities in the 1900s. The most notable ones were policy analysis, forecasting and inference structure. Researchers investigated a wide scale of these techniques, from vast frameworks with numerous complex equations to simple one-variable time series models and single-equation interactions models. However, none of these methods proven to be particularly reliable after the macroeconomic instability of the 1970s. Christopher Sims (1980) introduced a novel macro-econometric paradigm, vector autoregressions (VARs), two decades ago, and it was immediately well received. As the name suggests, the current value of a single variable is explained by the residual of that same variable, which is known as a univariate autoregression. To put it another way, it constitutes a linear regression of n-equation and variable in which each component is described based on its individual lagged numbers, as well as present and previous values of the rest of the n - 1 additional variables. The VAR statistical toolset proved to be effective for use and analysis and it provided a systematic technique to detect dynamics in many time series. In a series of significant early works, Sims (1980) and others claimed that VAR had the promise of providing a consistent and plausible model for policy analysis, structural inferences, and data description.

Keywords:- ***vector autoregressions; univariate autoregression; macro-econometric analysis.***

I. INTRODUCTION

There are different varieties of VAR which can be applied in macro econometric analysis including; structural, recursive and reduced VAR. In the case of reduced VAR, each component is expressed as an equation of its historical record and a sequentially independent error term. The VAR that will be given precedence in this paper therefore includes; present redundancy levels as a component of previous levels of unemployment, interest and inflation rates and current inflation as an equation of past inflation, joblessness, and rates of interest. [1] The same case will apply for interest rates. Ordinary least squares regression is used to estimate each equation. There are several ways to determine the quantity of delayed variables to incorporate in each computation. In a bid to maintain simplicity of findings this paper will utilize a series of four lags. The error terms of regression variables can be understood as the variables' "unexpected" moves after accounting for their previous values.

The standard errors in each regression model are designed to be mutually independent with the error terms in the preceding regression equations in a recursive VAR. This is accomplished by strategically incorporating recent data as predictors in the model. This can be illustrated using an example of a three-variable VAR composed of inflation, unemployment, and interest. [2] Lagged values of all three variables are used in the initial computation of the recursive VAR in which inflation is depicted as the dependent variable. This equation uses the lags of the selected variables, coupled with the presiding inflation rate, as regressors to predict the unemployment rate.

This equation's dependent variable is the interest rate, and the regressive components are the current inflation rate and the current unemployment rate. Ordinary least squares estimation yields standard errors that are statistically independent between individual equations. VAR residuals, coefficients, and equations are all affected by the variables' order, and there exist n! n! recursive VARs to represent all conceivable orderings. Economic theory is used to identify the temporal relationships among the variables in a structural VAR. [3] In order to interpret correlations causally, structural VARs necessitate the use of "identifying assumptions. "Through the use of instrumental variables and regression, it is possible to estimate the contemporaneous linkages. In the above examples, attention will be directed at two structural VARs that are correlated to each other. Each assumes that monetary policy influences unemployment, inflation, and interest rates in a different way. [4] The Federal Reserve is depicted as setting interest rates derived from previous levels of unemployment and inflation in the "Taylor rule" approach. In this arrangement, the Federal Reserve determines the federal funds rate R in accordance with the regulation that reads:.

$$R_t = r^* + 1.5(\bar{\pi}_t - \pi^*) - 1.25(\bar{u}_t - u^*) + \textit{ lagged values of } R,\ \pi,\ u + \varepsilon_t,$$

(1)

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To better understand the equation above, r* is the intended real interest rate; Xt and ut are the goal levels redundancy and inflation; Et constitutes the error in the linear formula. The structural VAR uses this relationship as the basis for its interest rate equation. When the equation error, Et, is taken into account, it might be considered a "monetary policy shock," representing how far interest rates depart from the Taylor rule. [5] Researchers have suggested that the Federal Reserve's behavior is better characterized as "forward-looking" rather than "backward-looking" given that it responds to data from the past, such as the average of the prior fiscal quarter of unemployment and inflation.

II. CAPITALIZING ON VAR MODEL FOR FORECASTING

A. Setting goals and objectives

Setting goals and objectives is the first step in every forecasting process, and provides a much clearer understanding of the successive steps. Questions like the targeted individuals that will be using the framework and why will arise as a result of this decision. Models are created by forecasters in accordance with the needs of their clients. Accordingly, the president of the Federal Reserve Bank is the primary target audience for the VAR model. Helpful models for forecasting key economic aggregates should be developed for application by policymakers, such as inflation, employment, and real production, to support their responsibilities in making policy decisions.[6] According to the VAR model presented in this work, the real GDP, will be employed as a measure for the levels of unemployment, inflation, and interest rates. It also includes two other monetary variables, the ideal federal funds rate (FF), which the FOMC has direct control over, and the M2 money supply, which FOMC has a less direct control over given that it was built to help guide policy. Finally, a series of commodity prices must be incorporated in the category of variables in order to allow commodity prices to play a part in predicting future inflation..

B. Mixed Frequency Data

Although actual GDP is included in the model, it is only calculated on a quarterly basis. One of the most difficult challenges is integrating data from different frequencies into one single-frequency model. In this scenario, real GDP would constitute the quarterly framework in which the other components would serve as averages of the daily, weekly, and monthly data points. [7] This reflects on the need for the construction of GDP forecasts. Incorporating timely monthly data, on the other hand, has been shown to improve forecasts of quarterly data. Judgmental forecasts are often cited as one of the key reasons for employing high-frequency data in VAR.

Using Chow and Lin's (1971) distribution method, it is possible to construct a 30-day series of real GDP. When constructing monthly real GDP estimates, the regression model is utilized to guarantee that the monthly average of the approximated GDP meets the accompanying monthly data of the same parameter. [8] Revisions to this variable and the quarterly indicator series are made on a regular basis. As a result, the entire index might be re-estimated on a monthly basis following the collection of new GDP data.

C. Estimation and Specification of the VAR

Predicted values for each series can be projected by summarizing the patterns of correlation observed among the data sets and using this summary to anticipate future quantities for each series. In this regard, the VAR delivers an estimate of each value in the m series as a function of the weighted average of the recent history of all the series coupled by a term that includes all other impacts on the current values, in a mathematical manner. It can be summarized as:

$$y_t = \nu + B_1 y_{t-1} + \cdots + B_p y_{t-p} + u_t, \tag{2}$$

All except the interest and unemployment rates are expressed as natural logarithms in the VAR for the period t, where yt signifies the m 3 1 vector. There is a function of the strength to which the current value of yt cannot be determined as a linear combination of previous y variables with weights given by static coefficients n and Bl, l = 1...p. Because the number of lagged occurrences of y to be included in the VAR, p, as well as the corresponding coefficient values, are unknown, there is uncertainty about the value of ut. [9] A random vector with zero mean, a positive-definite error covariance matrix S, and ut being uncorrelated with lagged values of yt are used to operationalize the uncertainty regarding ut.

Many estimated coefficients with significant standard errors can be found in VAR framework ideally fitted to the type of data needed by the researcher. Based on the fact that the coefficients are zero, they may appear to be larger than they are in the real sense. Nonzero coefficients, on the other hand, may not be accurately estimated due to a lack of data. [10] The problem becomes critical if the parameters are not precise. This is the case given the fact that inaccurate forecasts are prone to arise from high uncertainty estimations. This assertion is supported by the finding that extreme projections of uncertainty can yield inaccurate results.

Because the number of parameters is generally higher the set of observations, it is likely that obtaining inaccurate estimates of parameters in a VAR will be a regular issue. In utilizing the quantity 13 as the value for p, a total of 79 coefficients will be computed in each linear equation in the event that there were 6 variables in the VAR. [11] Overfitting VAR models has been addressed in forecasting research using a number of different approaches, all of which include restricting the coefficient values of the model before they are calculated, in order to use less data when estimating the coefficients' values. Accordingly, this prior constraint serves as non-data information concerning coefficient values.

By utilizing a null value for coefficients, predetermined values can help reduce the coefficient uncertainty. This move is inevitable especially considering the fact that prior embedment of VAR models to the obtained data may fail to deliver the required outcomes. For instance, a maximum lag order pmax might be specified in advance and the p pmax value that diminishes a given criterion could be chosen as an example. [12] Using this criterion, one is not penalized for the fact that they are embedding additional coefficients to a constant number of observations. It is also possible to pre-

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differentially compare data series that show drifts across a given period before embedding the VAR with coefficient limitations. [13] An exact constraint on VAR coefficients in data levels would be equivalent to this technique in terms of math. Imposing less-than-perfect preconditions can be an alternate strategy. It is also possible to directly incorporate the degree of inaccuracy in the pre-differencing restrictions into the coefficient estimate technique.

III. RESPONSE TOWARDS STAGGERED TIMING OF DATA RELEASE

An additional issue with data is the irregularity with which it is released. For instance, the value of average interest rate is typically determined at the end of every quarter. However, it is not until the midst of the next month that an estimate of the money stock for the previous month can be obtained. Although the real GDP series is distributed monthly, fresh GDP observations can only be approximated at the end of the month. Using this paradigm, the values for all series that have not yet been observed are designated as "conditional" on all parameters for which measurements are made. [14] A sample with complete data on all of the constructs in the model is used for estimation purposes in the vector autoregression framework. By the end of January, the VAR would have been approximated using data obtained in the course of the previous year. The VAR is then used to forecast all of the variables for January as if no new data had been collected. Even though the January values of the commodity prices and Federal Funds are readily available, more accurate estimates are impossible to derive without using this information. The degree to which the commodity prices and federal funds for the month of January can be used to estimate the other series' values for that month will determine the level of the enhancements achieved by the January forecast.

IV. DETERMINING FORECAST ACCURACY

In choosing a framework for specification, the researcher must consider forecast evaluation. The forecast loss function or preferences determines the accuracy criterion. RMSE or MAE are the most commonly used accuracy measures in forecasting. However, there are a plethora of additional options that can be used for this purpose. This study's results are based on the RMSE, although secondary projection metrics for accuracy have the potential of producing diverse model standings, as noted in the previous sections. [15] Most forecasters use historical data to demonstrate the model's accuracy and reliability when presenting the ultimate specification to a client. Due to the time spent on historical out-of-sample forecasting experiments, it is likely that this evidence will be a byproduct of the model selection process, which requires a significant investment in time and effort.

A. Advantages of VAR

One of the advantages of the VAR model constitutes ease of implementation. It is relatively simple to estimate the coefficients of the overall system using ordinary least squares (OLS) for each equation in the VAR because all equations have the same range of parameters on the right-hand side. [16] This ease of execution is further amplified by the fact that standard asymptotic properties apply to the OLS estimator. The OLS estimator is asymptotically normally distributed in large samples. Secondly, VAR promotes classical reasoning. A linear limitation can be tested using the standard F and t variables with the OLS estimator given that it contains typical asymptotic features. [17] In the event that the first equation fails to incorporate the second lag despite its relevance, the researcher will still be able to achieve meaningful outcomes.

Testing for constraints using several equations is also an option. Suppose a researcher aims to investigate whether the coefficients correlating to Y t-2 are alike across the equations: H 0:12 = 22. An F-statistic will be suitable for this scenario. Statistical testing or the minimization of some information criteria may also be used to determine the lag duration p. [18] In this example, assuming that p = 2 and using H 0: p= 2 while H 1: p = 3, one can express the null hypothesis as p = 2 and the alternative hypothesis as H 1: p = 3. An F statistic or an asymptotic likelihood test can be used to test the null and alternative hypotheses for the VAR model, which is estimated and established by comparing the sum of squared residuals.

V. LIMITATIONS AND CONCLUSION

A. Limitations of the VAR Model

VAR is problematic when it comes to ordering of variable. The impulse-response functions depend on the ordering of the variables when the innovations 1t and 2t are contemporaneously connected. Transforming innovations so that they are no longer associated is a typical solution (e.g., using the Cholesky decomposition). [19] In other words, the system's response to a shock in innovation may now be studied separately from the system's other advances without interfering with them. There are ramifications for the system specification as well, as the first equation no longer has a single current invention but rather two. The second equation on the other hand contains three. has three. As a result, it is critical to pay attention to the variables' sequence of appearance. It is the researcher' role to decide how to arrange the variables. While economic theory can provide some insight, the forecaster's ultimate goal will determine the order in which the data is sorted. [20] Furthermore, structural VAR modeling is divided on the issue of the identification of restrictions. Ideally, economic theory should govern which limits are imposed on business practices. However, researchers maintain that this theory is not helpful in determining accurate limits.

B. Conclusion

Finance and economics are some of the most critical disciplines that determine the ability of world nations to attain continued growth and development. In order to ensure that a country or an organization’s economic model proceeds smoothly, there is a need to ensure that favorable models of analysis are applied appropriately. The VAR mode is suggested as one of the approaches that can be used to identify inconsistencies in market structures and deliver meaningful projections that can be capitalized on to make informed decisions. This paper has presented a critical and detailed

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analysis of the application of the VAR model in macroeconomics as well as its advantages and disadvantages.

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