A Literature survey on Macroeconomic Forecasting with Mixed-Frequency Data

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ABSTRACT - *A dilemma that forecasters face is that not all data are sampled equally. Most macroeconomic data are sampled monthly (e.g. employment, CPI) or quarterly (e.g. GDP). Most financial variables (for example, interest rates and asset prices), on the other hand, are sampled daily or even more frequently. The challenge is how best to use the available data. We explained in this article how the macroeconomic data can be adjusted by using the X-13 ARIMA SEATS software. This review article provides a literature study on vector autoregression (VAR) for the time series observed at quarterly and monthly frequencies and also some common methods for dealing with mixed frequency data. In order to examine the relationship between inflation and money supply, as well as GDP in India, this study used annual time series data. In the last section of this article References based on Seasonal Adjustment, Inflation & GDP, FAN Chart and Nowcasting are provided for further study.*

Keywords* – *Macroeconomic Data, Seasonal Adjustment, Vector autoregression (VAR), Inflation, GDP, Nowcasting, FAN Chart

1. INTRODUCTION

1.1 Inflation Effect on GDP

The relationship between economic growth and inflation has been one of the most widely researched topics in macroeconomics. Inflation is defined as the increase in the level of prices and Gross Domestic Product (GDP) defines the economic growth of a country; It measures the market values of a country's final goods in a specified period. An increase in inflation means that prices have risen. With an increase in inflation, there is a turn down in the purchasing power of money, which reduces consumption and therefore GDP decreases. High inflation can make investments less advantageous because it creates insecurity for the future and it can also affect the balance of payments only because exports become more expensive. Hence, GDP is decreases further. So, we can say that GDP is negatively related to inflation. However, there are studies indicating that there might also be a positive relationship between Inflation and GDP. For example, The Phillips curve shows that high inflation is consistent with low unemployment rate, implying that there is a positive impact on economic growth.

1.2 Midas technique

A problem faced by forecasters is that not all data sampled at the same frequency. Most of the macro-economic data are sampled monthly or quarterly and most financial variables are sampled daily or even more frequently. So, in order to deal with mixed-frequency data, in some cases, simply averaging the higher-frequency data produces no distinct disadvantage. In other cases, however, using mixed data sampling may be more beneficial for forecasting purpose especially while constructing intra-period forecast.

MIDAS model to be evaluated is as follows:

$$Y_t = \alpha + \sum \beta_i L_i\, Y_t + \gamma \sum \phi\ (k;\, \theta) L^k_{HF} X_t + \epsilon_t$$

Where the function $\Phi(k;\theta)$ is a polynomial which determines the weights for temporal aggregation. The weighting function can have any number of functional forms. The goal here is to achieve flexibility while maintaining parsimony.

1.3 FAN chart

A fan chart illustrates the probability distributions for the forecast of inflation and output growth, based on the central projection, uncertainty and the risks surrounding them. One can assume that the possible outcomes for inflation will symmetrically spread out around a central value or most probable value and those values will more likely be closer to the centre than those further away. This leads to the assumption of bell-shaped normal distribution for the project distribution which is widely used in statistical analysis.

2. Objective

1. Seasonally adjusting the time series data using X-13 ARIMA SEATS software. i.e. processing the row data.
2. Checking the relationship between inflation and money supply as well as gross domestic product.
3. Forecasting Inflation in India for the upcoming years.
4. Technical details underlying the derivation of Fan Chart used in representing the uncertainty in inflation forecasts
5. Nowcasting Inflation using high frequency data.

3. Material and methods

3.1Dataset of the Macroeconomic variables

In order to examine the relationship between inflation and money supply as well as GDP in India, this study employed annual time series data. The data is available in the Central bank of India which the RBI. Inflation data is available in monthly basis and GDP is available in quarterly basis. Co integration test, Vector Error Correction Model and Granger causality tests will be applied in the analysis. Co integration test is applied to know the long run relationship among the variables, Vector Error Correction Model is applied to study the short run and long run dynamic relation. All the variables are expressed in terms of their real values in this study. The data is transformed into log linear specification to have consistent estimates and to apply econometric modelling which requires the same order of integration in the data set.

3.2 For seasonal adjustment

X-13ARIMA-SEATS implements the two most widely used seasonal adjustment methods- the moving average X-11 method and the ARIMA model-based SEATS method. It also offers a module for selecting pre-adjustment effects using regARIMA models. X-13ARIMA-SEATS produces basic and advanced diagnostics to evaluate the quality of the seasonal adjustment results.

4. REVIEW OF LITERATURE

4.1 Papers on Seasonal adjustment:

Tucker Mcelroy; (US census Bureau) in his paper "Time Series Seasonal Adjustment Using Regularized Singular Value Decomposition" proposes a new seasonal adjustment method which is based on the Regularized Singular Value Decomposition (RSVD) of the matrix obtained by reshaping the seasonal time series data. The method is flexible enough to capture the fixed seasonality and the time-varying seasonality. They have used the real seasonality's extracted from three seasonal economic time series for conducting the simulation. Those series are Industrial Production Index, Total Nonfarm Payrolls, and the Inflation rate calculated from Consumer Price Index for all Urban Consumers. These data's are available on FRED website. RSVD represents the time-varying seasonality by a linear combination of several seasonal patterns. This proposed method applies to seasonal time series data with a stationary or nonstationary non-seasonal component.

Rudrani Bhattacharya, Radhika Pandey∗, Ila Patnaik, Ajay Shah in their paper **"Seasonal adjustment of Indian macroeconomic time-series"** have shown the full process for seasonal adjustment for four important Indian time-series. They have shown the complete steps of the seasonal adjustment process for analysing four monthly time-series, the Index of Industrial Production, exports, the Consumer Price Index and the Wholesale Price Index using X-13 ARIMA SEATS software developed by US census bureau. This involves calendar adjustment, detection and correction for outliers, fitting models, conducting diagnostic tests, etc. They found that Eid does not have a significant effect on the IIP but Diwali does. They found that at the risk of failure for some time series, significant reductions of variance are obtained by using black box seasonal adjustment. Systematic knowledge about seasonal adjustment yields more reliable answers, and a roughly 15% improvement in the unpredictability of month-on-month changes.

David F. Findley, Demetra P. Lytras and Agustin Maravall in their paper **"Illuminating Model-Based Seasonal Adjustment with the First Order Seasonal Autoregressive and Airline Models"** yields new results, including relative smoothness results based on autocorrelation comparisons of same-calendar-month subseries before and after seasonal adjustment. They presented the results of their investigation of residual seasonality detection properties of three types of diagnostics - regression, spectrum and positive seasonal autocorrelation, six diagnostics in all. These are available in widely used software TRAMO-SEATS, X-13ARIMA-SEATS and JDemetra+. All were applied to a set of sixteen under adjusted U.S. Census Bureau Monthly Retail Trade Survey series. They developed the Wiener-Kolmogorov signal extraction filter formula for a deeper analysis of the SAR(1) decomposition and for generalizations to ARIMA model-based decompositions. These formulas and their ARIMA generalizations by Bell (1984) are also applied in various ways.

D. F. Findley, K.C. Wills, J. A. Aston, R. M. Feldpausch, and C. C. Hood ;(U.S. Census Bureau) in their paper **"Diagnostics for ARIMA-Model-Based Seasonal Adjustment"** present two types of diagnostics for SEATS and similar programs. They started with modifications of the diagnostic used by SEATS to detect overestimation or underestimation, meaning inadequate or excessive suppression of frequency components near the target frequencies, e.g. the seasonal frequencies in the case of seasonal adjustment. They have shown that the SEATS diagnostic is substantially biased toward indicating underestimation even when the estimation is optimal. The second type of diagnostic which is considered is an adaptation of the widely used sliding spans diagnostic of X-12-ARIMA SEATS. The adaptation is a method in order to determine the span length for model-based-adjustment as a function of the ARIMA model's seasonal moving average parameter.

4.2 Papers on Inflation and GDP

Joshua Chan and Gary Koop in their paper "**A New Model of Inflation, Trend Inflation, and Long-Run Inflation Expectations"** adds to the growing literature which uses survey-based long-run forecasts of inflation to estimate trend inflation. Authors have presented an international comparison using data from Italy, Japan, and the UK. They have chosen these countries in part because the forecast data go back as far as 1990 and in part because the survey-based long-run forecasts show some noticeable time variation. They developed a bivariate model of inflation and long-run forecasts of inflation which allows for the estimation of the link between trend inflation and the long-run forecast. Thus, their model allows for the possibilities that long-run forecasts taken from surveys can be equated with trend inflation, that the two are completely unrelated, or anything in between. They used their model with a variety of inflation measures and survey-based forecasts for several countries. They have found that long-run forecasts can provide substantial help in refining estimates and fitting and forecasting inflation. The same evidence indicates it is less helpful to simply equate trend inflation with the long-run forecasts.

Alexander Bick in his paper "***Threshold effects of inflation on economic growth in developing countries***" introduces a generalized panel threshold model by allowing for regime intercepts. He investigated the relationship between inflation and growth for a balanced panel of 40 developing countries during the period from 1960 to 2004. The empirical application to the relation between inflation and growth confirms that the absent variable bias of standard panel threshold models can be statistically and economically significant. Regime intercepts are introduced and the potential bias of omitting these readily available regressors for both, regression slope and threshold estimates is discussed in the paper. The regime intercept is important in the inflation-growth nexus and affects the results in significant ways.

Sthanu R Nair, Leena Mary Eapen in their paper "***Food Price Inflation in India (2008 to 2010) : A Commodity-wise Analysis of the Causal Factor"*** analyses the causes of the high inflation experienced in 12 food commodities between January 2008 and July 2010. It is shown that due to domestic supply-side constraints, a majority of the commodities were subject to inflationary pressures. They include meat, fish, spices, pulses, fruits, vegetables, tea, coffee and sugar. The primary reason for rising prices of milk and eggs was cost escalation. Complex interaction causes the high inflation of rice of factors. But this paper finds no solid evidence to support the popular view that the higher food prices in recent years was the outcome of a "secular shift" in food consumption patterns towards high-value agriculture products.

Hongyi Li and Heng-fu Zou* in their paper "***Inflation, Growth, and Income Distribution: A Cross-Country Study***" uses a newly compiled cross-country panel data on income distribution to explore the impact of inflation on income distribution and economic growth. They used averaged data over 5-year periods in the empirical analysis. Although for most of the variables they had yearly observations, their data on Gini's coefficients were more limited – many countries have less than 10 observations, whereas only a few countries have more than 20 observations. By using a 5-year average they obtain a more balanced data set. The time period they covered was from 1950 to 1992 and the inflation data are from the International Financial Statistics of the International Monetary Fund (IMF). Finally, they have found that inflation worsens income distribution; increases the income share of the rich; has a negative but insignificant effect on the income shares of the poor and the middle class reduces the rate of economic growth.

Michelle T. Armesto, Kristie M. Engemann, and Michael T. Owyang in their paper "***Forecasting with Mixed Frequencies***" examined a few common solutions to the mixed-frequency problem. To compare the three methods for time- aggregating higher-frequency data, they used two different sets of sampling rates i.e., monthly data to forecast quarterly data and daily data to forecast monthly data. In all cases, they used lags of the forecasted variable in addition to a single predictor. First, they compared forecasts of the quarterly GDP growth rate using the monthly payroll employment growth rate as the predictor. Then, they compared forecasts of the monthly CPI inflation growth rate, monthly employment growth rate and monthly IP growth rate, using daily predictors. The daily effective federal funds rate for CPI inflation and the daily term spread which is the difference between the 10-year Treasury note yield and the 3-month Treasury bill yield for IP and employment. Each vintage of real-time data is seasonally adjusted and thus uses a different set of seasonal factors. They used real-time data for the GDP growth rate, CPI inflation rate, employment growth rate and IP growth rate. Interest rates are not revised, thus their initial data releases are used. It is also assumed that the most recent data vintages of the variables are the true value and use these vintages to compute the forecast errors. For our forecasting experiments, the data they used are log growth rates of the seasonally adjusted annual rate of nominal GDP from the Bureau of Economic Analysis, seasonally adjusted nonfarm payroll employment and seasonally adjusted CPI from the Bureau of Labour Statistics, and seasonally adjusted IP from the Board of Governors of the Federal Reserve System. Interest rate data are also used from the Board of Governors. The real-time data vintages used are December 1990 through September 2009. For the monthly forecasts using daily data, their initial in-sample estimations run from July 1975 to November 1990 and the out-of- sample forecasts begin in December 1990. For the GDP forecasts using employment data, their in- sample estimations run from the third quarter of 1975 to the fourth quarter of 1990 and the out-of- sample forecasts begin in the first quarter of 1991. They demonstrated time aggregation, which transforms by means of summation either weighted or unweighted higher frequency data to allow standard regression techniques to be used.

Girijasankar Mallik and Anis Chowdhury* in their paper **"Inflation and Economic Growth: Evidence from Four South Asian Countries"** seeks to examine the relationship between inflation and GDP growth for four South Asian countries (Bangladesh, India, Pakistan and Sri Lanka). A comparison of empirical evidence is obtained from the cointegration and error correction models using annual data collected from the IMF International Financial Statistics. Authors finds evidence of a long-run positive relationship between GDP growth rate and inflation for all four countries. There are also important feedbacks between inflation and economic growth. These results have important policy implications. Faster economic growth feeds back into inflation; moderate inflation is helpful to growth. Thus, these countries are on a knife-edge.

4.3 Papers on FAN chart

Kenneth F. Wallis* in his article **"Asymmetric Density Forecasts Of Inflation And The Bank Of England's Fan Chart"** examines the statistical issues surrounding the Bank of England's density forecast of inflation and its presentation as a "fan chart". An alternative fan chart based on central prediction intervals is presented, better reflecting the extent to which the overall balance of risks is on the upside of the inflation target. Loss function "all-or-nothing" is seen to be implicit in the Bank's choices of statistical measures, but is unrealistic.

Emerson Abraham Jackson and **Edmund Tamuke Leone** in their paper **"Probability Forecast Using Fan Chart Analysis: A case of the Sierra Leone Economy"** addresses both theoretical and empirical practicalities of probability forecasting, more so covering areas pertaining to Time Series Econometrics and its combination with Fan Chart distribution of projected outcomes using confidence intervals. They made use of ARIMAX methodology in producing probability forecast from Fan Chart analysis for the Sierra Leone economy. In view of the estimation technique used to determine best model choice for outputting the Fan Chart, the outcomes have shown the importance of Exchange Rate variable as an exogenous component in influencing Inflation dynamics in Sierra LeoneBrier Score probability was also used to ascertain the accuracy of the forecast methodology.

Nivedita Banerjee and Abhiman Das in their paper **"Fan Chart: Methodology and its Application to Inflation Forecasting in India"** have presented the technical details underlying the derivation of Fan Chart used in representing the uncertainty in inflation forecasts. The uncertainty in the macro-economic variables is based on their historical standard deviation of the forecast errors, but they allowed these to be subjectively adjusted. Thus, the methodology presented in their paper shows how the balance of risk for various macroeconomic variables like WPI, IIP etc. can be linked with inflation uncertainty. In this paper, it is also seen that the fan chart presentation is a combination of interaction of uncertainty and subjective judgment, intertwined with solid statistical foundations. Their main objective of using fan chart is to focus on the whole forecasting distribution rather than on small changes to the central projection.

Kevin Dowd* in his paper **"Too Good to be True? The (In)credibility of the UK Inflation Fan Charts"** presents some simple methods in order to estimate the probability that realized inflation will fail to observe a given inflation target range over a specified period which is based on the Bank of England's RPIX inflation forecasting model and also the Monetary Policy Committee's forecasts of the parameters on which this model is constructed. This paper explains the density function used by the Bank to forecast inflation probabilities then sets out three simple ways for obtaining a no-breach probability from the Bank's published 2PN parameter forecasts. Author collected data of UK Inflation rate for the period May 1997 to December 2003 for the above-mentioned purpose.

4.4 Papers on Nowcasting

Edward S. Knotek II and Saeed Zaman in their working paper **"Nowcasting U.S. Headline and Core Inflation"** propose a new and parsimonious model for nowcasting headline and core inflation in the U.S. consumer price index (CPI) and price index for personal consumption expenditures (PCE) that relies on relatively few variables. The model's nowcasting accuracy improves as information accumulates over a month or quarter, outperforming statistical benchmarks. In real-time comparisons, the model's headline inflation nowcasts significantly outperform those from the Blue-Chip consensus and the Survey of Professional Forecasters.

Domenico Giannone, Francesca Monti, and Andrej Sokol in their paper **"A New Approach to Nowcasting with Mixed-Frequency Bayesian VARs"** proposes a new approach to nowcasting with mixed-frequency Bayesian Vector Auto-Regressive (BVAR) models using US GDP data. They mapped a BVAR estimated on quarterly data into a carefully selected monthly state-space representation that allows them to incorporate information available at monthly frequency using standard Kalman filtering techniques. They have performed a pseudo-real-time exercise, evaluating the performance of the Model exploiting the monthly data flow and comparing the models' forecasts to those of the SPF for a set of key macro variables.

Modugno, Michele in their Working Paper **"Nowcasting inflation using high frequency data"** proposes a methodology to nowcast and forecast inflation using data with sampling frequency higher than monthly. Their paper exploits data with weekly and daily frequency in order to produce more accurate estimates of inflation for the current and followings months. Weekly Oil Bulletin Price Statistics for the euro area, the Weekly Retail Gasoline and Diesel Prices for the US and daily World Market Prices of Raw Materials are used in this paper. The findings in this paper suggests that the chosen weekly and daily data are important to improve the forecast accuracy for both the euro area overall HICP and the US total CPI inflation.

Andrea Carriero, Queen Mary, Todd E. Clark in their paper **"Realtime nowcasting with a Bayesian mixed frequency model with stochastic volatility"** develops a method for producing current quarter forecasts of gross domestic product growth with a range of available within-the-quarter monthly observations of economic indicators like employment and industrial production and financial indicators, such as interest rates and stock prices. They used Bayesian approach to estimate the model. They have provided results on the accuracy of nowcasts of real-time gross domestic product growth in the USA from 1985 through 2011. In terms of point forecasts their proposal improves significantly on auto-regressive models and performs comparably with survey forecasts.

5. References

1. **"Time Series Seasonal Adjustment Using Regularized Singular Value Decomposition"** with Wei Lin and Jianhua Z. Huang and Tucker McElroy**;** Journal of Business \& Economic; year = 2019; publisher = Taylor & Francis
2. "**Seasonal adjustment of Indian macroeconomic time-series**," with Rudrani Bhattacharya, Radhika Pandey, Ila Patnaik, Ajay Shah; NIPFP Working paper series; 20-Jan-16
3. "**Illuminating Model-Based Seasonal Adjustment with the First Order Seasonal Autoregressive and Airline Models**"; with David F. Findley Demetra P. Lytras Augustin Maravall1; research report series; Bank of Spain
4. "**Diagnostics for ARIMA-Model-Based Seasonal Adjustment**" with D. F. Findley, K.C. Wills, J. A. Aston, R. M. Feldpausch, and C. C. Hood"; U.S. Census Bureau
5. "**A New Model of Inflation, Trend Inflation, and Long-Run Inflation Expectations**" with Joshua Chan, Todd Clark and Gary Koop; May 10, 2017
6. "**Threshold effects of inflation on economic growth in developing countries**" with Alexander Bick; Elsevier; 30 April 2010
7. **"Food Price Inflation in India (2008 to 2010) : A Commodity-wise Analysis of the Causal Factor"**; Sthanu R Nair, Leena Mary Eapen; Economic and Political Weekly; MAY 19, 2012
8. **"Inflation, Growth, and Income Distribution: A Cross-Country Study"** with Hongyi Li and Heng-fu Zou*; ANNALS OF ECONOMICS AND FINANCE 3; 2002
9. "**Forecasting with mixed frequencies** " with Michelle T. Armesto, Kristie M. Engemann, and Michael T. Owyang; Federal Reserve Bank of St. Louis Review, November/December 2010
10. **"Inflation And Economic Growth: Evidence From Four South Asian Countries"** with Girijasankar Mallik and Anis Chowdhury; Asia-Pacific Development Journal; June 2001
11. **"Asymmetric Density Forecasts Of Inflation And The Bank Of England's Fan Chart"** with Kenneth F. Wallis; National Institute Economic Review, 1999
12. **"Probability Forecast Using Fan Chart Analysis: A case of the Sierra Leone Economy"** With Emerson Abraham Jackson and Edmund Tamuke Leone; MPRA; 31th August,2018
13. **"Fan Chart: Methodology and its Application to Inflation Forecasting in India"** with Nivedita Banerjee and Abhiman Das; Reserve Bank of India Working Paper; 2011
14. **"Too Good to be True? The (In)credibility of the UK Inflation Fan Charts''** with Kevin Dowd; Journal of Macroeconomics, 2007 - Elsevier
15. **"Nowcasting U.S. Headline and Core Infl ation"** with Edward S. Knotek II and Saeed Zaman; Journal of Money, Credit and Banking; 2017
16. **"A New Approach to Nowcasting with Mixed-Frequency Bayesian VARs"** with Domenico Giannone, Francesca Monti, and Andrej Sokol; NewYork Fed and Bank of England; February 14, 2018
17. **"Nowcasting inflation using high frequency data"** with Modugno, Michele; International Journal of Forecasting, 2013 – Elsevier
18. **"Realtime nowcasting with a Bayesian mixed frequency model with stochastic volatility"** with Andrea Carriero, Queen Mary, Todd E. Clark; Journal of the Royal Statistical Society; 27 January 2015