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(with Application to Philippine Inflation and GDP Growth)

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Abstract

This paper studies the comparative predictive accuracy of forecasting methods using mixed-frequency data, as applied to nowcasting Philippine inflation, real GDP growth, and other related macroeconomic variables. It focuses on variations of mixed-frequency dynamic latent factor models (DFM for short) and Mixed Data Sampling (MIDAS) Regression. DFM is parsimonious and dependent on a much smaller data set that needs to be updated regularly but technically and computationally more complicated, especially when there are mixed-frequency data. On the other hand, MIDAS is data-intensive but computationally more tractable. The analysis is done through comparison of forecast performance measures (such as mean squared prediction error) and application of statistical tests of comparative predictive accuracy and tests of forecast encompassing. Results obtained so far indicate that just about every method in the pool of forecasting methods studied performs best in some cases and worst in other cases. Thus, there is no clear winner. Under the circumstances, one viable approach in applications is to combine the forecasts from these powerful techniques to improve predictive accuracy. In most cases, least squares weights perform better for purposes of forecast averaging.

Keywords: N*owcasting, Mixed-Frequency Forecasting, Dynamic Factor Model, MIDAS, Principal Components, Factor Analysis, ARDL, VAR, Elastic Net, Combining Forecasts*

JEL Classification: C22, *C32, C51, C52, C53, C55*

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1. Introduction

Combining mixed high-frequency data – e.g., quarterly, monthly, weekly, even daily, for short-term forecasting has generated considerable renewed interest. The timely and statistically efficient use of "breaking news" is critical in a wide range of disciplines, where harnessing high-frequency indicators for more up-to-date forecasts and assessment is particularly important. Several fields to note are statistics, data sciences, financial econometrics and macro-econometric forecasting, as data information in these fields have become richer, more diversified, non-standard, and available at different and higher frequencies. This is especially so for government policy planners who need to monitor the state of the economy in real time, as well as financial managers and analysts.

This paper studies the comparative predictive accuracy of forecasting methods using mixed-frequency data, as applied to nowcasting Philippine inflation, real GDP growth, and other related macroeconomic variables. By now, all these methods are commonly used in current econometric forecasting environments (some examples include Castle, Hendry & Kitov, 2017; Doz, Giannone & Reichlin, 2011; Geweke, 1977; Ghysels, 2016; Ghysels & Marcellino, 2018; Ghysels, Santa-Clara & Valkanov, 2002; Foroni & Marcellino, 2017; Klein & Ozmucur, 2001, 2008, 2009; Klein & Park, 1993,1995; Klein & Sojo, 1987, 1989; Mariano & Murasawa, 2003, 2010; Mariano & Ozmucur, 2015, 2018, 2020a, 2020b). At the same time, additional variations of these techniques continue to be developed as new needs arise and new data become available.

The paper focuses on variations of mixed-frequency dynamic latent factor models (DFM for short) and Mixed Data Sampling (MIDAS) Regression. DFM is parsimonious and dependent on a much smaller data set that needs to be updated regularly but technically and computationally more complicated, especially when data come in mixed frequencies. On the other hand, MIDAS is data-intensive but computationally more tractable. In all these models, the fact that the data set is of mixed frequencies raises technical issues in the estimation and forecasting phases of the exercise. In the case of DFM, the additional feature of unobserved common factors introduces additional complications in implementing the estimation and simulation strategy based on the derived observable state-space formulation of the model.

In terms of comparative forecasting performance, our recent earlier studies (Mariano & Ozmucur, 2015, 2018, 2020a) send mixed signals: suggesting superior performance of DFM for forecasting GDP growth, while for forecasting inflation, the performance of DFM is not significantly better than MIDAS.

Section 2 provides a brief description of the summary measures of prediction performance and various predictive accuracy tests of forecasting models that are utilized in the analysis – the Diebold-Mariano (DM) test for pairwise comparisons, Mariano-Preve (MP) test for multivariate comparisons, and encompassing tests of forecasting methods. Section 3 then provides the forecasting methods and combinations covered in this study. Section 4 goes into findings and practical implications of the study. Results obtained so far indicate that just about every method in this study's pool of forecasting methods performs best in some cases and worst in other cases. Thus, there is no clear winner. Under the circumstances, one viable approach in applications is to combine the forecasts from these powerful techniques to improve predictive accuracy. Several combination methods are used. In most cases, least squares weights perform better for purposes of forecast averaging.

2. Forecast Evaluation Criteria Utilized in this Study

2.1 Summary Measures of Prediction Performance

In this paper we shall rely mostly on the mean absolute error (MAE) mean square error (MSE)[1] of calculated one-period forecasts over the sample (see Theil, 1958, 1961 for alternative measures): MAE $=\sum \mid P_t - A_t \mid /T$, MSE $=\sum (P_t - A_t)^2/ T$, where A_t and P_t represent actual and predicted values at time t, t ranging from 1 to T.

2.2 Comparing Predictive Accuracy

For pairwise comparison of two methods, we utilize the Diebold-Mariano (DM, 1995) Test for equal forecast accuracy. This is a very general and model-free test of forecast accuracy. It is applicable to nonquadratic loss functions, multi-period forecasts, and forecast errors that are non-Gaussian, non-zero mean, serially correlated, and contemporaneously correlated (Diebold and Mariano, 1995; for a small sample modification, see Harvey, Leybourne and Newbold, 1997). The DM test with the HLN modification is in the diagnostic tools in (IHS Markit, 2019), the econometrics software which we use in this study. They are also available in other standard software packages.

The test statistic for the DM test is based on the sample mean of the observed loss differentials:

$$d_t = [g(e_{1t})-g(e_{2t})],\ t=1,2,\ \ldots\ n,\ \ n \text{ - number of forecasts}$$

where, $g(e_{1t})$ - is the function of error in the first model, typically squares or absolute value of errors $g(e_{1t})=(P_{1t} - A_{1t})^2$ or $g(e_{1t})=|P_{1t} - A_{1t}|$

and similarly, $g(e_{2t})$ - is the loss in the second model.

The mean of loss differences (m):

$$m= \Sigma\, d_t /n = \Sigma\, [g(e_{1t})-g(e_{2t})]/n$$

and the Diebold-Mariano statistic is

$$DM = m/[2\pi\, \hat{S}(0)/n]^{(1/2)}$$

where, $\hat{S}(0)$ is a consistent estimate of the spectral density of the loss differential d_t at zero displacement. In canonical form, this test can be thought of as an analogue of the standard classical test for equality of two populations with heteroskedastic and autocorrelated observations in a time-series context.

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[1] Square error loss is the standard approach in classical statistics; in many applications, more general loss functions (asymmetric, etc) – e.g., gambling, financial investment analysis, weather forecasting, epidemiological issues ("death" much more serious consequence) may be more relevant. The methodology for comparing forecasts that we apply here can be modified to accommodate alternative loss functions.

If there are more than two forecasts, it would be of interest to test the accuracy of these as a group rather than two at a time. For testing equal accuracy in this multivariate setting, we utilize the extension of the DM test as developed in Mariano and Preve (MP, 2012) – we shall refer to this extension as the MP test. Recently, Drachal (2020) introduced a package (multDM) as part of R software, which provides the MP tests, in addition to the regular DM tests. As one would expect, the MP test is the analogue of the classical multivariate test for the equality of k means, considering heteroscedasticity and serial correlation. More details are available in numerous publications – including Diebold & Mariano (1995), Mariano (2002), Mariano and Preve (2012), Drachal (2020), and IHS Markit (2019).

2.3 Forecast Encompassing Tests

If a single forecast contains all information in the other individual forecasts, that forecast will be just as good as a combination of all the forecasts. To address this issue through a statistical significance test, so-called forecast encompassing tests (Chong and Hendry, 1986; Timmermann, 2006) are developed in the econometrics literature. Basically, the encompassing test is the significance test for the null hypothesis:

$$H_0: \beta_j = 0 \ \forall\ (j \neq i) \ \text{ vs. } \ H_1: \beta_j \neq 0 \ \forall\ (j \neq i).$$

in the synthetic linear regression relationship

$$A_{t+h} - P_{t+h,i} = \beta_0 + \Sigma\, \beta_j\, P_{t+h,j} \ \ , j=1,2,..k, \ \ i \neq j,$$

where A_{t+h} –actual values for period (t+h) , $P_{t+h,I}$ -forecast value for period (t+h) by model i.

If the difference between the true values and the forecasted values from the model (model i) is not related to forecast from all other models (fail to reject H_0: $\beta_j=0\ \forall\ (j\neq i)$), then one can say "forecast i contains all information in the other forecasts and, therefore, in this sense, "encompasses" them. Thus, model i can be used by itself. If the differences are affected by the other models (i.e., reject H_0: $\beta_j=0\ \forall\ (j\neq i)$), then other models should also be included in the formation of a combination forecast because they have some explanatory power to add.

3. Alternative Forecasting Models in This Study

In general, the data analyst may encounter situations with data set with mixed frequencies, where variables (for both target and indicator variables), may include quarterly, monthly, weekly, and daily observations. This is the case with the Philippine database that we use in this paper. We should note at the outset that the algorithms and model set-up that we use in our subsequent experiments are designed for situations involving only a combination of monthly and quarterly observations. Variables in the database that are available daily (e.g., stock market data, etc.) are still used in our analysis here, but are aggregated to monthly prior to use in the analysis.

In this paper, we deal with the following ***six target variables to be forecasted***, all measured in terms of year-on-year growth rates:

1. Real GDP (observable quarterly),
2. GDP implicit price deflator (quarterly),
3. Consumer Price Index, CPI (monthly),
4. Industrial Production Index (monthly),
5. Merchandise Exports (monthly),
6. Producer Price Index (monthly).

Indicator variables used in this study consist of pertinent information, available at different frequencies (daily, monthly, quarterly) over the period 1999 - 2019, regarding the Philippines and its major trading partners. Numbering close to sixty, they are all available to the public, coming from the following sources: Philippine Statistics Authority (PSA), Philippine Central Bank or Bangko Sentral ng Pilipinas (BSP), International Monetary Fund (IMF), US Federal Reserve Board (Fed), US Bureau of Labor Statistics (BLS), Federal Reserve Bank of St. Louis FRED database, and Organization for Economic Cooperation and Development (OECD). All these variables, together with their sources, are listed in the Data Appendix of this paper, Roughly speaking, they can be grouped as follows:

1. Real sector – Philippine economy, e.g., merchandise imports growth, government expenditures, volume of business activity indexes, capacity utilization in manufacturing
2. Financial / monetary sector – Philippine economy, e.g., money supply, interest rates, exchange rates
3. Prices in the Philippines – e.g., wholesale price, rice retail price, stock market price.
4. Labor sector – unemployment and underemployment rates, labor force participation rate
5. Expectation survey data in the Philippines – e.g., from BSP surveys of consumers and businesses about confidence, inflation and income
6. External price data – e.g., US and world CPI, Dubai oil import price
7. Other external data – e.g., world trade volume, world uncertainty index for Philippines and global, OECD leading indicators

We focus on the following nowcasting and forecasting models:

1. Dynamic Factor Models (DFM) with small number of variables,
2. Dynamic Factor Models with large number of variables,
3. Mixed Data Sampling (MIDAS) Regressions,
4. Factor MIDAS,
5. Vector Autoregressive –MIDAS,
6. Principal Components and Stepwise Regressions,
7. Autoregressive Distributed Lags (ARDL) Models,
8. Elastic Net and LASSO,
9. Bridge Equations,
10. Combination of Forecasts.

3.1 Dynamic (Latent) Factor Models (with small number of variables)

Additional details are provided here on the specific features of the estimated models covered in the forecast comparison exercise. Start with the dynamic factor model with a small number of variables.

The underlying philosophy is that macroeconomic fluctuations are driven by a small number of common shocks or factors and an idiosyncratic component peculiar to each economic time series. The seminal papers are Sargent and Sims (1977) and Stock and Watson (1989). Earlier works (e.g., Stock and Watson) develop single factor models to construct composite indices of economic activity based on a handful of coincident indicators. More recent studies use the model to extract unobserved common factors from a large collection of observable indicator variables. More recently, the approach was revived for forecasting purposes in the U.S. and larger European countries – Foroni & Marcellino (2012, 2017).

In brief, the underlying model consists of two parts. The first explains the dynamics of the target variables depending on own lags, unobservable common factor(s), and possibly, observable indicator (or exogenous) variables. The second part explains the behavior of the latent common factor(s) in terms of their own joint dynamics and possibly, interactions with observable indicators. The system also may have other observable exogenous varibles that serve as additional explanatory variables for the latent common factors.

The model is in the spirit of the one built by Mariano & Murasawa (2003) but with one common factor. All variables are standardized. Each quarterly variable is synchronized with the monthly ones by placing the observed value at the last month of the quarter. Therefore, weights 1/3, 2/3, 1, 2/3, and 1/3 are used for lags 0,1,2,3, and 4, respectively. This increases the number of state equations.

The model may be summarized with six measurement equations. Using the above notation, Y has 6 variables. There are also six ε's, one for each of the observed variables in Y. Since all the variables are standardized, intercepts from those equations are not needed. As a standard procedure, the state vector (common factor) is assumed to have a variance of one (normalized, as in Stock & Watson (1989)). The model consists of two sets of equations:

Measurement Equations $\quad Y_t = AF_t + GW_t + \varepsilon_t,$

Each measurement equation (there are 6 of them) has the following variables: Y_t is an nx1 vector of a target variable (n-number of observations), F_t is the kx1 vector of k factors, W_t is the n x r matrix of explanatory variables, and r denotes the number of explanatory variables. A and G are associated coefficient matrices.

State Equations $\quad F_t = B(L)F_{t-1} + \nu_t,$

B(L) is polynomial lag operator in a typical VAR model. In principle, the state equations can be extended to include explicitly effects of observable indicators on the latent common factor.

For the forecast model in our comparison pool, only one common factor is used for all six equations for the target variables; and it is assumed to behave as an autoregressive process of order 2, AR(2). Furthermore, specific factors are assumed to be all AR(1), mutually independent. Thus, in this special case, F_t is (an n x 1 vector) and the state equation can be written as: $F_t = \beta_1 F_{t-1} + \beta_2 F_{t-2} + \nu_t$, while for the specific factors, the equation for each component simplifies to $\varepsilon_t = \rho\, \varepsilon_{t-1} + \phi_t$.

The operational counterpart of the theoretical model (state space representation) is described below, for a quarterly variable (data are available for the third month of the quarter, and unavailable for the first and second months of each quarter) and a monthly variable (data available for all the months from 1999M01 to 2019M12). When working with data with missing values, Kalman filtering applied to the "operational" state-space model derived from the starting theoretical model is a convenient, established way of estimating the model parameters and simulating the model for forecasting (Stock & Watson, 1989; Mariano & Murasawa, 2003; Aruoba, Diebold, and Scotti, 2009).

For two quarterly variables (Real GDP growth, and GDP deflator growth), equations are in the following form. In these equations, Y is the observed dependent variable, F is the unobserved common factor, ε is the unobserved specific (idiosyncratic) factor, W's are observed exogenous variables (given below).

$$Y_t = \alpha_1 [(1/3)*F_t + (2/3)*F_{t-1} + F_{t-2} + (2/3)*F_{t-3} + (1/3)*F_{t-4}] + \gamma_1 W_{1,t-1} + \gamma_2 W_{2,t-1}$$

$$+ \gamma_3 W_{3,,t-1} + [(1/3)*\varepsilon_t + (2/3)*\varepsilon_{t-1} + \varepsilon_{t-2} + (2/3)*\varepsilon_{t-3} + (1/3)*\varepsilon_{t-4}]$$

$$F_t = \beta_1 F_{t-1} + \beta_2 F_{t-2} + \nu_t, \quad \nu_t \sim iid(0,1)$$

$$\varepsilon_t = \rho\, \varepsilon_{t-1} + \phi_t, \quad \phi_t \sim iid(0,\sigma^2)$$

For four monthly variables (industrial production growth, exports, growth, consumer price index growth, and producer price index growth), equations are in the following form:

$$Y_t = \alpha_1 F_t + \gamma_1 W_{1,t-1} + \gamma_2 W_{2,t-1} + \gamma_3 W_{3,t-1} + \varepsilon_t$$

$$F_t = \beta_1 F_{t-1} + \beta_2 F_{t-2} + \nu_t, \quad \nu_t \sim iid(0,1)$$

$$\varepsilon_t = \rho\, \varepsilon_{t-1} + \phi_t, \quad \phi_t \sim iid(0,\sigma^2)$$

There are three explanatory variables for the real sector target variables: World trade volume growth rate, Leading Indicators for OECD counties, OECD Leading Indicators for trading partners of the Philippines. There are also three exogenous variables for the target price variables: Dubai oil import price growth rate, world consumer price index growth rate, and regular milled rice retail price growth rate.[2]

[2] One possible motivation for including the three external variables as additional indicators is that the unobserved common factor has low correlation with these indicators and have significant coefficients in the estimated model. It may be possible to improve forecasting performance in a couple of directions. a. add a second unknown common factor, but initial calculations based on this show no significant improvement, b. add more explanatory (exogenous) variables that might help - like the financial conditions index, the labor market conditions index, and overseas remittances c. introduce lagged Y to capture own-time-dynamics.

3.2 Dynamic Factor Models with large number of indicator variables

The standard dynamic factor models are very powerful tools for models with small number of variables. If the number of variables is large, it may be difficult to get convergence in a state space framework. Stock & Watson (2002a, 2002b), and Doz, C., D. Giannone, and L. Reichlin (2011) introduce methods dealing with large data sets. In general, the first step is to use factor analysis to reduce the number of indicators. The second step is to use these factors in a VAR framework. In the third step, predicted values of factors from the VAR model are used to forecast the target variables. The third step would involve state-space modeling if one introduces time-varying coefficients. The method of least squares also yields consistent estimators in the second and third steps. We use this latter approach to estimate the DFM-Large model in this study.

1. $X_t = A\ F_t + \varepsilon_t$ -- > first 8 factors of 43 original indicators
2. $F_t = D(L)\ F_{t-1} + \varpi_t$ ---- > $Fhat_t$, estimate of F_t from fitted VAR(12)
3. $Y_t = B(L)\ Fhat_{t-1} + \upsilon_t$ ---- > estimate of DFM-Large

In step 1, eight factors were extracted from 43 daily, monthly and quarterly indicators using method of principal factors. These indicators are (all variables are transformed and then standardized, see Mariano & Ozmucur, 2020b for data sources, descriptions, and transformations):

1. Industrial production,
2. Merchandise Imports,
3. Merchandise Exports,
4. Government expenditures ,
5. World trade volume,
6. Deposit rate less than 360 days-savings deposit rate,
7. Treasury Bills rate (91 Day) - US treasury 3-month bill rate,
8. 182-day Treasury bill rate - 91-day Treasury bill rate,
9. Deposit rate more than 360 days - Savings rate,
10. Lending rate - Deposit rate less than 360 days ,
11. Average lending rate - overnight rate,
12. Consumer Price Index,
13. Producer Price Index,
14. Wholesale Price Index (Metro Manila),
15. Retail Price Index,
16. Exchange rate,
17. Money supply (M1),
18. Import Price Index,
19. World consumer price index,
20. US consumer price index,
21. Stock Price Index,
22. Deposit rate more than 360 days ,
23. Average Lending rate ,
24. Overnight rate ,
25. Deposit rate less than 360 days ,
26. Current account balance
27. Global Economic Policy Uncertainty Index: Current Price Adjusted GDP,
28. Gold Price in U.S. Dollars,
29. Leading Indicators OECD - Total,

30. OECD Leading indicators - weighted average of countries, weights by shares in exports of the Philippines,
31. Rice Regular Milled Retail Price,
32. Capacity Utilization in Manufacturing,
33. Employment,
34. Export Price Index,
35. World Uncertainty Index for Philippines,
36. World Uncertainty Index: Global - GDP weighted average ,
37. World Uncertainty Index: Global - Simple average,
38. Business Confidence Index - Current Quarter,
39. Business Confidence Index- Next-Quarter,
40. Business Expectations Index on Inflation Rate,
41. Unemployment Rate,
42. Underemployment Rate,
43. Labor Force Participation Rate.

The method of principal factors is generally used when the number of variables is large. The method of maximum likelihood was also used. Although, there are alternative methods of determining the number of factors, these factors are selected to explain two thirds of the variance in 43 indicators. In most studies, 60% to 65% of variance is the common figure used in economic analysis. It was possible to include many more indicators because of richness of data in the Philippines, including many sectors, and regions. However, data for sub-sectors, say for industrial production, do not have the same number of observations, or the correlation with the headline figure may be so high that inclusion may not add too much to the explanatory power. Obviously, keeping the number at 43, makes some calculations much easier. Based on various lag order selection criteria (likelihood ratio test, Akaike information criterion, Chow's final prediction error, Schwarz or Bayesian information criterion, Hannan-Quinn information criterion), a VAR model with 12 lags was selected in Step 2.

3.3 Bridge Equations and MIDAS Regressions

Typical bridge equation modeling relates a quarterly variable to three-month averages of monthly variables (Klein & Sojo, 1987, 1989; Klein & Park, 1993, 1995; Klein & Ozmucur, 2008). This implicitly imposes a restriction on coefficients for the months of the quarter and consequently introduces asymptotic biases and inefficiencies (Ghysels, Santa-Clara, Valkanov, 2002). In contrast, MIDAS estimates a regression of quarterly GDP on monthly (and possibly quarterly) indicators using parsimonious distributed lags to represent missing observations. Since its introduction, this modeling approach has been used extensively in the mixed-frequency forecasting literature and has been enhanced with numerous variations. Ghysels & Marcellino (2018) provides a good review.

For implementation, MIDAS applies a more parsimonious parametrization of distributed lag structures to model the relation of GDP to current and lagged indicators at the monthly frequency, so that the basic model can be expressed as

$$Y_{tq} \sim \ DL(Z_{tm}) + \text{error}$$

The estimation method is nonlinear least squares using actual observed data at mixed frequencies. Early examples of lag structures used in MIDAS include Unrestricted (but truncated), Step

Function (equal weights for months of same quarter, truncated) (this is also the bridge equation), Polynomial Almon Lag (Almon, 1965), Exponential Almon, and Beta Distribution.

3.4 Factor MIDAS

For Factor MIDAS, we used factors that are extracted from indicators as regressors in the forecasting model in a two-step procedure. First, factor analysis is used, in our case with the 43 monthly indicators introduced in the previous sub-section. Then, MIDAS regressions with explanatory variables in the form of these eight factors are estimated. MIDAS is used because two of the six target variables are quarterly; all the factors are available monthly, by construction. Initially, ten MIDAS regression models are estimated, using alternative weights: Almon, exponential Almon, and beta distribution, step function and unrestricted MIDAS (each with lags of 6-months, and 12-months). In general, U_Midas, Almon or step give better results.

3.5 Mixed Frequency Vector Autoregressive – VAR-MIDAS

Ghysels (2016) introduces a mixed-frequency VAR representation, in which high and low frequency data are stacked as skip-sampled processes. This observation-driven approach, called VAR-MIDAS, includes all six target variables. Since there are 4 monthly variables, there will be a total of 14 variables in the VAR system (4*3, one for each month, and two quarterly variables) Standard VAR techniques can be applied to this model with fourteen variables (Ghysels & Marcellino,2018).

In addition, lagged values (1, 2, and 3 lags) of eight monthly factors are also incorporated into the system. Those factors which are not statistically significant are later excluded from the system. A VAR with 6 lags is considered, but joint significance tests suggested the exclusion of lags 3, 5, and 6. The final model includes lags 1,2, and 4, and 4 factors with lags 1 and/or 3). A Bayesian option for VAR-MIDAS was also estimated; Unrestricted MIDAS gave better results. Also, see Schorfheide and Song (2013) for a state-space approach to mixed-frequency VARs.

3.6 Principal Components (PC) and Stepwise Regressions

Instead of using hundreds of indicators, the method of principal components is used to construct a weighted average of these indicators. There are two groups of indicators, one for the real sector and the other one for prices (some indicators appear in both groups), as in Klein & Park (1993, 1995), and Klein & Ozmucur (2008).[3]

[3] If the method of principal factors is used, the first step in factor analysis and principal components analysis is the same, but there is a very fundamental difference between the two methods. In factor analysis Y=AX+ε, where Y is observed, and X is unobserved. In principal components, there is not such a formal model, and X is observed, and Y is unobserved and constructed based on the proportion of total variance of the group explained by X variables. In Principal Components, parallel to Klein's US CQM, there are two groups, one for the real sector, another one for prices (there may be some common variables in both groups). There is only one group in Factor analysis (includes all 43 variables). Relative to MIDAS-VAR, PC-Stepwise focuses on economizing on the

Indicators for the real sector (all variables are transformed and then standardized):

1. Industrial production,
2. Merchandise Imports,
3. Merchandise Exports,
4. Government expenditures,
5. Real Money supply (M1),
6. World trade volume,
7. Real Stock Price Index,
8. Real exchange rate (Pesos/US Dollar),
9. Deposit rate less than 360 days-savings deposit rate,
10. Treasury Bills rate (91 Day) - US treasury 3-month bill rate, Employment,
11. 182-day Treasury bill rate - 91-day Treasury bill rate,
12. Deposit rate more than 360 days - Savings rate,
13. Lending rate - Deposit rate less than 360 days,
14. Average lending rate - overnight rate,
15. Current account balance,
16. Global Economic Policy Uncertainty Index: Current Price Adjusted GDP,
17. OECD Leading indicators - Total,
18. OECD Leading indicators - weighted average of countries, weights by shares in exports of the Philippines,
19. Capacity Utilization in Manufacturing ,
20. World Uncertainty Index for Philippines,
21. World Uncertainty Index: Global - GDP weighted average,
22. Business Confidence Index-Current Quarter,
23. Business Confidence Index-Next-Quarter,
24. Unemployment Rate,
25. Underemployment Rate,
26. Labor Force Participation Rate .

In the real GDP group, the first principal component explains 20.8% of the variance in 27 indicators. This is a rather low number, but this is expected in cases of where variables are not very highly correlated. The second principal component contributes 11.6%, and the third one contributes 8.7%. The first five principal components explain 55.6% of the variance, and the first 10 components explain 78.2% of the variance.

Ideally, a single principal component should be used as a summary measure for all the variables. However, a component which explains a smaller proportion of the variance may contribute more to the forecasting power of the equation. This is a common occurrence because a measure of the forecasting power does not appear in the objective function, but just the proportion of the variance explained by the variable is maximized. A relatively recently introduced method, three-pass regression filter, addresses this issue and provides some promising results (Kelly & Pruitt, 2015; Ghysels and Marcellino, 2018). Here, stepwise, forward selection, regressions are used to get the

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dimensionality of the information content of the multitude of indicator variables, does not pay attention to the own time-dynamics of the target variables, which, on the other hand, is a major focus in MIDAS-VAR.

best equation in the forecasting of target variable. There are 81 variables in the starting group (27 principal components each with 1, 2 and 3 lags). The p-value of 0.05 is used, and the number of variables selected is limited to 15 to avoid overfitting. The selected equation for real GDP growth, which has 14 variables, has a relatively good in-sample fit, with adjusted R^2 of 0.83. It includes the first principal component, and components 20, 23, and 27 with 3 lags among others. This is an example where other principal components besides the first one may be statistically significant contributor in the forecasting equation.

There are 22 indicators used to extract principal components for prices. Indicators for prices are (all variables are transformed and then standardized):

1. Deposit rate less than 360 days-savings deposit rate,
2. Treasury Bills rate (91 Day) - US treasury 3-month bill rate,
3. 182-day Treasury bill rate - 91-day Treasury bill rate,
4. Deposit rate more than 360 days - Savings rate,
5. Lending rate - Deposit rate less than 360 days,
6. Average lending rate - overnight rate,
7. Consumer Price Index,
8. Producer Price Index,
9. Wholesale Price Index (Metro Manila),
10. Retail Price Index,
11. Import Price Index,
12. World consumer price index,
13. US consumer price index,
14. Global Economic Policy Uncertainty Index: Current Price Adjusted GDP,
15. Gold Prices in U.S. Dollars,
16. Rice Regular Milled Retail Price,
17. Export Price Index,
18. World Uncertainty Index for Philippines
19. World Uncertainty Index: Global - GDP weighted average,
20. Business Confidence Index-Current Quarter,
21. Business Confidence Index - Next-Quarter,
22. Business Index on Inflation Rate-Current Quarter

The first principal component explains 28.3% of the variance in 22 indicators. The second principal contributes 12.5%, and the third one contributes 8.7%. The first five principal components explain 64.5% of the variance, and the first 10 components explain 85.5% of the variance. As in the real sector, stepwise, forward selection, regressions are used to get the best equation in the forecasting of target variable. Since the first principal component with 1 lag is included in the equation, there are 65 variables in the starting group (22 principal components each with 1, 2 and 3 lags). The p-value of 0.05 is used, and the number of variables selected is limited to 20 to avoid overfitting. The selected equation for GDP deflator, which has 11 variables, has a relatively good in-sample fit, with adjusted R^2 of 0.89. It includes the first principal component, and components 16, 17, and 18 and 20.

3.7 Autoregressive Distributed Lags (ARDL)

Autoregressive distributed lags (ARDL) or dynamic models represent a very common form in econometrics. The dependent and explanatory variables are related not only at the current period, but accross lagged values also. Here, the selection is done in a more systematic way. Schwarz information criterion is used in model selection to keep the number of variables in the equation rather small. The maximum number of lags of the dependent variable is restricted with one, and the maximum number of lags for explanatory variables is set to be 12.

The general form for ARDL is: $A(L)\ Y_t = B(L)\ X_t + \varepsilon_t$, where Y is the dependent variable, X are explanatory variables, A(L) and B(L) are matrices of polynomial lag operators.

Individual indicators and principal components enter the equation one by one as X variables.

3.8 Ridge Estimators, Least Absolute Shrinkage Selection Operator (Lasso), and Elastic Net

Ridge Regression (or biased estimators for enhanced performance) shrinks the regression coefficient by imposing a penalty (James & Stein, 1961; Hoerl & Kennard, 1970). The ridge coefficients minimize a penalized residual sum of squares: $\min \{\Sigma\ (Y_i-\beta_0-\Sigma\beta_j X_{ij})^2+ \lambda\ \Sigma\ \beta_j^2\}$, $\lambda\geq0$ is a complexity parameter; the larger the value of λ, the greater the amount of shrinkage. This is equivalent to minimizing $\min \{\Sigma\ (Y_i-\beta_0-\Sigma\beta_j X_{ij})^2$ subject to $\Sigma\ \beta_j^2 \leq v$. There is a one-to-one correspondence between parameters λ and v (Hastie, Tibshirani, and Friedman, 2008, pp. 63). It should be noted that shrinkage is not applied to the intercept term. It should also be noted that standardized variables should be used so that penalties applied are equivalent. Ridge estimator is biased. The bias increases as λ increases. On the other hand, variances of estimators decrease as λ increases. This is the trade-off, which was the motivation for introducing biased estimators.

The Least absolute shrinkage and selection operator (lasso) estimate is defined by minimizing $\min \{\Sigma\ (Y_i-\beta_0-\Sigma\beta_j X_{ij})^2$ subject to $\Sigma\ |\beta_j| \leq v$, which is equivalent to

$$\min \{(1/2)\Sigma\ (Y_i-\beta_0-\Sigma\beta_j X_{ij})^2+ \lambda\ \Sigma\ |\beta_j|\ \},\ \lambda\geq0$$

The penalty is in absolute values and not squares. This makes the solutions nonlinear and can be solved numerically. An advantage of Lasso is that some coefficients shrink to zero, and may be excluded from the equation (Tibshirani, 1996).

Elastic net combines ridge and lasso (Zou & Hastie (2005). The penalty is $\lambda\ \Sigma\ (\alpha\beta_j^2+(1-\alpha)|\beta_j|)$. The penalty in Eviews is written as:

$$\lambda[((1-\alpha)/2)\Sigma\ \beta_j^2+\alpha\Sigma|\beta_j|].$$

The minimization problem in elastic net, which combines ridge regression with lasso, is written as (Zou & Hastie, 2005; Hastie, Tibshirani, and J. Friedman, 2008):

$$\min \{(1/2)\Sigma\ (Y_i-\beta_0-\Sigma\beta_j X_{ij})^2+ \lambda[((1-\alpha)/2)\Sigma\ \beta_j^2 +\alpha\Sigma|\beta_j|]\ \},\ \lambda\geq0$$

The penalty is a combination of the L1 and L2 penalties. If α=0, it becomes a ridge regression. If α =1, it becomes a lasso model. It selects variables like the lasso (pushes some of them to zero) and shrinks the coefficients like the ridge regression (Hastie, Tibshirani, and J. Friedman, 2008, pp. 73).

3.9 Combination of Forecasts

Rather than selecting the best model, researchers may combine forecasts from competing models. Combining forecasts may improve the accuracy (Bates and Granger, 1969; Diebold and Pauly, 1987, 1990; Figlewski and Urich,1983; Makridakis and Hibon, 2000; Marcellino, 2004; Newbold and Granger, 1974; Stock and Watson, 22004; Timmermann, 2006).

$$P_{tc}= \Sigma\, w_{it} P_{ti},\ \ i=1,2,\ldots k,\ t=1,2,\ldots n,$$

P is the forecast, w is the weight, n- number of forecast periods, k- number of models. In general, the weight is assumed to be the same for all the periods (instead of w_{it}, just the same w_i is used for all t)

Although analytical approaches for an optimal weighting leads to an expression with covariances, empirical studies show that just using variances is the common approach.

For least squares weights, a regression equation is estimated to obtain the weights using data in the training sample. Several versions of the regression are available. A regression with a constant term and weights not constrained to add to one is suggested by Granger and Ramanathan (1984).

$$A_{ti} = w_{0i} +\Sigma\, w_i P_{ti} +\varepsilon_{ti}\ \ ,\ i=1,2,\ldots k,\ t=1,2,\ldots n,$$

P is the forecast, estimated value of w_i is the weight, n- number of forecast periods, k- number of models. Since, there are no restrictions on coefficients of this version, estimated weights may be negative or bigger than one, i.e. $w<0$, or $w>1$). There are regression versions with restrictions on coefficients ($0\leq w\leq 1$).

The alternative weighting schemes tabulated in our EVIEWS printout for encompassing tests and forecast combinations are the following (for each target variable)

- Mean of individual forecasts
- Median of individual forecasts
- Mean Square Errors (MSE) of individual forecastsas weights
- MSE ranks as weights
- Weights from ***Least Squares regression of actual observations on individual forecasts***

4 Empirical Findings

For the pool of forecasting methods covered in this study, the one-period-ahead forecast errors over the period 1999Q1 – 2019Q4 are calculated and used as the basic "data" for analysis. Tables 1-6 and Graph 1 provide a summary of results.

In the first two tables, the focus of attention is the dynamic factor model (DFM) and its encompassing tests and DM tests versus the benchmark AR model in Table 1; and in Table 2, versus each alternative forecasting method taken one at a time. Note that the null hypothesis in the DM test is equal forecast accuracy for the two methods under study.

Table 3 highlights the conclusions based on the joint encompassing tests for the six target variables, applied to the whole comparison pool of forecasting methods. Here, results of six encompassing tests are reported, one for each target variable, to test the null hypothesis that forecast "j" includes all the information in the other forecasts under study. Here, the joint encompassing tests summarized in the table point to a variety of forecasting methods that encompass the rest as we consider the various target variables:

1. For real GDP growth, Factor MIDAS encompasses the other methods,
2. For the GDP deflator percentage change, both Factor MIDAS and VAR-MIDAS encompass the rest
3. For CPI inflation, both DFM and DFM-Large encompass the rest
4. For industrial production growth, none encompasses the rest,
5. For merchandise exports growth – none encompasses the rest, and
6. For producer price Index percentage change, both PC-Stepwise and Bridge equations encompass the rest.

Table 4 details the ranks of the forecasting methods based on the predictive abilities of the multivariate forecast comparison MP tests run through Drachal's R package (2020). Once again, we see for each forecasting method a variation in relative performance across target variables. DFM is 3rd best for CPI and 4th for GDP but only 7th for the producer price. Factor MIDAS is rated #2 for GDP and #8 for CPI; ARDL ARDL-PC and Elastic Net are in the best three for CPI and PPI but among the worst in GDP and P. Bridge does well for real GDP and Industrial Production but badly for CPI and PPI. One exception: VAR invariably lands in the relatively high MSE end.

Similarly, Table 5 and Table 6, showing MAE values and rankings for alternative forecasting methods, show a divergence in relative values across target variables. In this metric, however, DFM-Large shows uniformly bad performance with high MSE, while VAR-MIDAS turns out to have the lowest or near lowest MSE for GDP, IP, Exports, and GDP deflator but near highest MSE for CPI and PPI.

The absence of any uniformly dominant method is illustrated further in Graph 1. Here, each line pertains to a specific forecasting method connecting the MAE values for each of the six target variables. For example, the purple line corresponds to Factor MIDAS, red for DFM, etc. Except for the big blue line, each line refers to a specific forecasting model. The big blue line corresponds to the MAEs obtained when the individual forecasts are averaged using the least squares regression weights ***obtained from the regression of actual values of a particular target variable on the individual forecasts as regressors***.

The criss-crossing lines in Graph 1 for the individual forecasts illustrate that there is no individual method with uniformly lowest MAE. Just about every method considered performs better in some cases, worse in other cases. These results, together with the encompassing results described earlier, point to forecast combination for improvement in forecast accuracy.

In considering alternative weighting schemes, we find that forecast averaging using the least squares weights improves on the forecast accuracy of the individual methods – and this applies in all six target variables. Graph 1 shows that least squares MAE (the thick blue line) for each target variable is uniformly lower than any of the individual forecast in the comparison pool.
How about other averaging schemes? Though not shown in Graph 1, four other weighting schemes are included in the comparison pool:

1. simple mean of individual forecasts
2. median of individual forecasts
3. MSE of individual forecasts as weights, and
4. MSE ranks of individual forecasts as weights.

The numerical MAE values for these alternative schemes are provided in Table 6. They show that least squares weights deliver the lowest MAE for five of the six target variables, and second lowest MAE (by a small margin) for Producers' Price index.

Concluding Remarks (for now):

1. Thus, among the competing forecasts, there is no clear winner. In terms of forecast accuracy and forecast encompassing, there is no one method that uniformly dominates the rest when applied to all six target variables.

2. Under the circumstances, one viable approach in applications is to combine the forecasts from these powerful techniques to improve predictive accuracy. For each target variable, the forecast may be improved by a combination of these powerful techniques.

3. In most cases, based on what we have obtained so far, least squares weights perform better for purposes of forecast averaging.

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Table 1. Encompassing and DM Tests

DFM Vs. AR

Target Variable (Growth)	**Encompassing**		**DM Test**
	DFM	**AR**	**DFM vs AR**
Real GDP	~	**	** (negative)
Industrial Production	~	**	** (negative)
Merchandise Exports	**	**	** (negative)
GDP Deflator	**	**	** (negative)
Consumer Price Index	~	**	** (negative)
Producer Price Index	**	**	** (negative)

1. In the encompassing test, Ho is "forecast j" includes all info contained in others"- ***so insignificant coefficient Indicates encompassing,*** 2. In column 1, " ~ " means insignif***ic***ant at 5% level, " ** " significant at 1 % level, 3. In column 3, ***negative means DFM has better forecasting*** accuracy than AR

Table 2.1-2.9. Pairwise Encompassing and Diebold-Mariano Tests, DFM vs. Alternatives

2.1 DFM vs DFM-Large — **Target Variables**

	GDP	**IP**	**X**	**PGDP**	**CPI**	**PPI**
Encompassing Test						
Accept DFM	R	R	A	A	A	A
Accept Alternative	R	R	R	R	A	A
DM Test						
Accept DFM~Alt	A	R	R	R	R	R
Sign of DM Stat	neg	neg	neg	neg	neg	neg

2.2 DFM Vs Factor MIDAS — **Target Variables**

	GDP	**IP**	**X**	**PGDP**	**CPI**	**PPI**
Encompassing Test						
Accept DFM	R	R	R	A	A	R
Accept Alternative	A	R	R	A	R	R
DM Test						
Accept DFM~Alt	R	R	A	R	R	R
Sign of DM Stat	pos	neg	pos	pos	neg	neg

2.3 DFM Vs BRIDGE Stepwise — **Target Variables**

	GDP	**IP**	**X**	**PGDP**	**CPI**	**PPI**
Encompassing Test						
Accept DFM	R	A	A	A	A	A
Accept Alternative	A	A	A	A	A	A
DM Test						
Accept DFM~Alt	R	R	R	R	R	R
Sign of DM Stat	pos	pos	pos	pos	pos	pos

2.4 DFM Vs PC Stepwise

	Target Variables					
	GDP	**IP**	**X**	**PGDP**	**CPI**	**PPI**
Encompassing Test						
Accept DFM	R	R	R	A	A	R
Accept Alternative	A	A	A	A	A	A
DM Test						
Accept DFM~Alt	A	A	R	A	R	R
Sign of DM Stat	pos	Pos	pos	neg	neg	neg

2.5 DFM Vs Elastic Net

	Target Variables					
	GDP	**IP**	**X**	**PGDP**	**CPI**	**PPI**
Encompassing Test						
Accept DFM	R	A	A	A	A	A
Accept Alternative	R	R	A	R	R	R
DM Test						
Accept DFM~Alt	A	A	R	A	A	R
Sign of DM Stat	pos	Neg	pos	neg	neg	pos

2.6 DFM Vs BRIDGE

	Target Variables					
	GDP	**IP**	**X**	**PGDP**	**CPI**	**PPI**
Encompassing Test						
Accept DFM	A	A	R	A	A	A
Accept Alternative	R	R	R	R	R	R~
DM Test						
Accept DFM~Alt	R	A	A	R	R	R
Sign of DM Stat	neg	neg	po/neg	neg	neg	neg

2.7 DFM Vs MIDAS

	Target Variables					
	GDP	**IP**	**X**	**PGDP**	**CPI**	**PPI**
Encompassing Test						
Accept DFM	R	A	R	A	A	A
Accept Alternative	R	A	R	A	A	A
DM Test						
Accept DFM~Alt	R~	A	A	R	A	A
Sign of DM Stat	neg	pos	pos	neg	neg	neg

2.8 DFM Vs ARDL-MIDAS

	Target Variables					
	GDP	**IP**	**X**	**PGDP**	**CPI**	**PPI**
Encompassing Test						
Accept DFM	A	A	A	A	A	A
Accept Alternative	A	R	A	A	A	A
DM Test						
Accept DFM~Alt	A	A	R	R	A	A
Sign of DM Stat	neg	neg~	neg	neg	pos~	pos~

2.9 DFM Vs MF-VAR	Target Variables					
	GDP	IP	X	PGDP	CPI	PPI
Encompassing Test						
Accept DFM	R	R	R	A	A	R
Accept Alternative	A	R	A	A	A	A
DM Test						
Accept DFM~Alt	R	A	R	R	R	A
Sign of DM Stat	pos		pos	pos	neg	neg

Notes for Summary Tables 2.1-2.9: 1. A/R means "accept/reject the null hypothesis", 2. For encompassing, the null hypothesis is the forecast "j" includes all the information in the other methods under study, 3. For the DM test, null hypothesis is equal forecast accuracy, in this case, comparing DFM with one alternative in each test, 4. A wiggle, "~" after 'neg" or "pos" means "near zero"; after "R" means near critical boundary, 5. Positive DM statistic indicates mean loss for DFM is **bigger** than that of the alternative forecast – hence DFM is **less accurate** than the alternative forecast, 6. Note the correspondence in the sign of the DM test statistic and the difference in MAE (DFM minus alternative).

Table 3. Methods that Encompass the Rest (based on Joint encompassing tests)

Target Variable	Method
GDP	Factor MIDAS
Industrial Production	None
Merchandise Exports	None
GDP Deflator	Factor MIDAS and VAR-MIDAS
CPI	DFM and DFM-Large
Producer Price Index	PC-Stepwise and Bridge

Table 4. Rank of Methods Based on Predictive Ability from Multivariate Forecast Comparison (MP) test – One-period Ahead Forecasts; Rank 1 is the best

Forecasting Method	GDP	IP	Exports	PGDP	CPI	PPI	AVE
DFM	4	4	6	5.5	3	7	4.92
FACTOR MIDAS	2	8.5	5	5.5	8	5	5.67
MIDAS	7	2	1	5.5	5	4	4.08
BRIDGE	3	1	7	5.5	9	10	5.92
PC-STEPWISE	1	3	3	5.5	4	2	3.08
STEPWISE-INDIVIDUAL	5	5	4	1	6	8	4.83
ELASTIC NET	6	8.5	2	5.5	1	3	4.33
ARDL-PC	8	6	9	5.5	2	1	5.25
VAR	9	7	8	5.5	7	9	7.58
accept Ho after cut-off	2	3	4 reject	8	3	1	

Ho says all models have equal predictive accuracy

Table 5. Rank of Forecasting Methods Based on Mean Absolute Error (MAE) for Each Target Variable, One-period-Ahead Forecasts; Rank 1 is the lowest MAE

Forecasting Method	GDP	IP	Exports	PGDP	CPI	PPI	AVERAGE
DFM	6	6	8	4	4	4	5.33
DFM-LARGE	10	9	9	8	8	7	8.5
FACTOR MIDAS	1	10	5	3	10	10	6.5
MIDAS	8	2	6	9	5	5	5.83
BRIDGE	9	5	7	10	9	9	8.17
PC-STEPWISE	4	3	1	6	6	6	4.33
STEPWISE-INDIVIDUAL	3	4	4	2	1	1	2.5
ELASTIC NET	5	8	3	5	3	2	4.33
ARDL-PC	7	7	10	7	2	3	6
VAR	2	1	2	1	7	8	3.5

Table 6. Mean Absolute Error (MAE) of Forecasting Methods for Each Target Variable, One-period-ahead Forecasts

Forecasting Method	GDP	IP	Exports	PGDP	CPI	PPI
DFM	0.406	0.429	0.437	0.225	0.153	0.182
DFM-LARGE	0.459	0.5	0.468	0.307	0.217	0.228
FACTOR MIDAS	0.255	0.539	0.415	0.181	0.266	0.283
MIDAS	0.442	0.403	0.426	0.341	0.157	0.185
BRIDGE	0.503	0.427	0.436	0.379	0.232	0.235
PC-STEPWISE	0.39	0.409	0.369	0.244	0.162	0.204
STEPWISE-INDIVIDUAL	0.337	0.411	0.41	0.178	0.132	0.174
ELASTIC NET	0.361	0.432	0.408	0.231	0.149	0.177
ARDL-PC	0.425	0.43	0.471	0.305	0.148	0.181
VAR	0.299	0.368	0.399	0.162	0.169	0.229
Combined Forecasts						
Simple Mean	0.311	0.356	0.437	0.192	0.14	0.164
Simple Median	0.292	0.398	0.389	0.178	0.137	0.174
Least Squares	0.224	0.299	0.361	0.131	0.119	0.171
MSE (Mean Sq Error)	0.275	0.348	0.424	0.163	0.131	0.164
MSE Ranks	0.281	0.338	0.416	0.167	0.129	0.166

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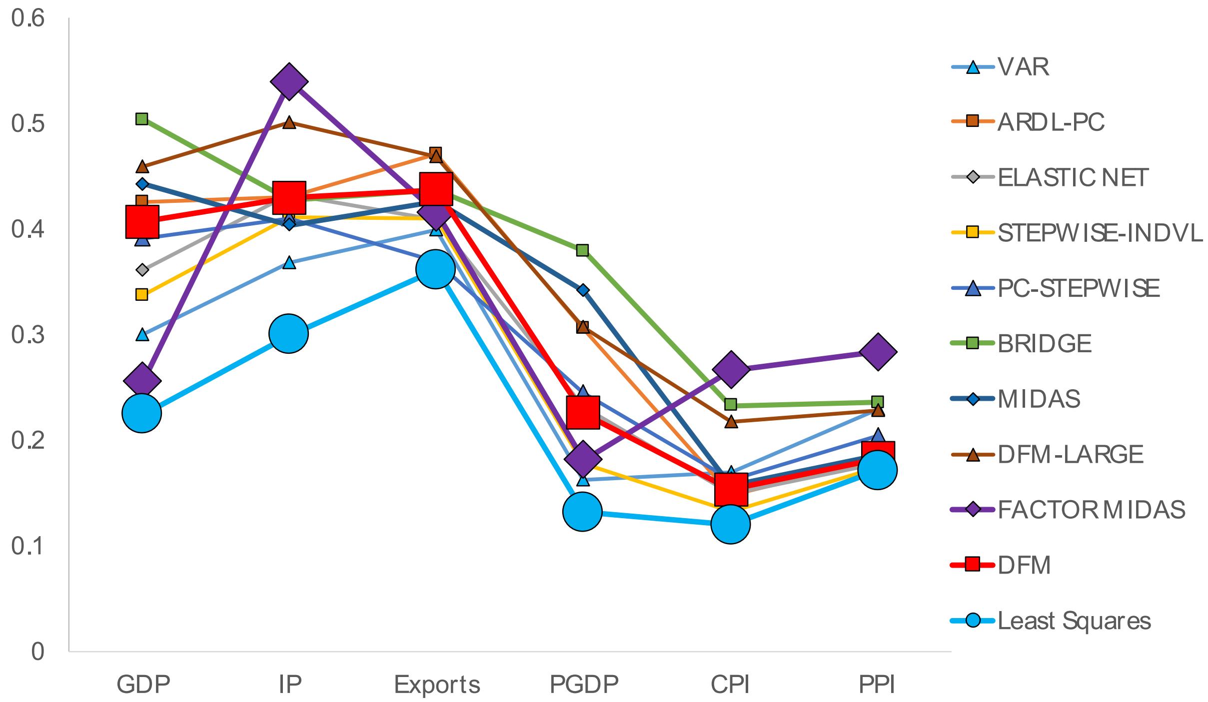
Graph 1. MAE of Forecast Methods for Each Target Variable



DATA APPENDIX

List of Variables

Name	Description	Frequency	Source
yy01	Industrial production index growth rate (year-on-year)	Monthly	Philippines Statistics Authority (PSA)
yy02	Merchandise Imports growth rate (year-on-year)	Monthly	PSA
yy03	Merchandise Exports growth rate (year-on-year)	Monthly	PSA
yy04	Government expenditure growth rate (year-on-year)	Monthly	PSA
yy05	Real Money supply (M1) growth rate (year-on-year)	Monthly	Philippines Central Bank (BSP)
yy06	World trade volume growth rate (year-on-year)	Monthly	International Monetary Fund (IMF)
yy07	Real Stock Price Index growth rate (year-on-year)	Daily and Monthly	BSP
yy08	Real exchange rate (Pesos/US Dollar), growth rate (year-on-year)	Daily and Monthly	BSP
yy09	Deposit rate less than 360 days-savings deposit rate, year-on-year difference	Daily	BSP
yy10	Treasury Bills rate (91 Day) - US treasury 3-month bill rate	Daily	Philippines Central Bank (BSP), US Federal Reserve Board (FED)
yy11	Employment, year-on-year difference	Quarterly	PSA
yy12	182-day Treasury bill rate - 91-day Treasury bill rate	Daily	BSP
yy13	Deposit rate more than 360 days - Deposit rate less than 360 days	Daily	BSP
yy14	Deposit rate more than 360 days - Savings rate	Daily	BSP

yy15	Lending rate - Deposit rate less than 360 days	Daily	BSP
yy16	Average lending rate - overnight rate	Daily	BSP
yy21	Consumer Price Index growth rate (year-on-year)	Monthly	PSA
yy22	Producer Price Index, growth rate (year-on-year)	Monthly	PSA
yy23	Wholesale Price Index (Metro Manila) growth rate (year-on-year)	Monthly	PSA
yy24	Retail Price Index growth rate (year-on-year)	Monthly	PSA
yy25	Exchange rate, growth rate (year-on-year)	Monthly	BSP
yy26	Money supply (M1) growth rate (year-on-year)	Monthly	BSP
yy27	Dubai Oil Import Price (in pesos) growth rate (year-on-year)	Daily and Monthly	PSA
yy28	Export Price Index growth rate (year-on-year)	Quarterly	PSA
yy31	World consumer price index, year-on-year growth rate	Monthly	International Monetary Fund (IMF)
yy32	US Consumer Price Index, year-on-year growth rate	Monthly	US Bureau of Labor (BLS)
yy33	Stock Price Index growth rate (year-on-year)	Daily	BSP
yy34	Deposit rate more than 360 days	Daily	BSP
yy35	Average lending rate	Daily	BSP
yy36	Overnight rate	Daily	BSP
yy37	Savings rate	Daily	BSP

yy38	Deposit rate less than 360 days	Daily	BSP
yy39	Current account balance	Monthly	BSP
yy41	World Uncertainty Index for Philippines (year-over-year difference)	Quarterly	Federal Reserve Bank of St. Louis FRED database; Ahir, Bloom, Furceri (2018); Baker, Bloom, Davis (2015)
yy42	Global Economic Policy Uncertainty Index: Current Price Adjusted GDP (year-over-year difference)	Monthly	Federal Reserve Bank of St. Louis FRED database; Ahir, Bloom, Furceri (2018); Baker, Bloom, Davis (2015)
yy43	World Uncertainty Index: Global - GDP weighted average (year-over-year difference)	Quarterly	Federal Reserve Bank of St. Louis FRED database; Ahir, Bloom, Furceri (2018); Baker, Bloom, Davis (2015)
yy44	World Uncertainty Index: Global - Simple average (year-over-year difference)	Quarterly	FRED Federal Reserve Bank of St. Louis FRED database; Ahir, Bloom, Furceri (2018); Baker, Bloom, Davis (2015)
yy45	Gold Fixing Price 3:00 P.M. (London time) in London Bullion Market, based in U.S. Dollars (year-over-year percentage change)	Daily	Federal Reserve Bank of St. Louis FRED database
yy46	Leading Indicators OECD: Leading indicators: CLI: Amplitute adjusted for OECD - Total (year-over-year percentage change)	Monthly	Organization for Economic Co-operation and Development (OECD)
yy47	Leading Indicators OECD: Leading indicators: CLI: Amplitute adjusted for Major Five Asia (year-over-year percentage change)	Monthly	Organization for Economic Co-operation and Development (OECD)
yy48	Leading Indicators OECD: Leading indicators - weighted average of countries, weights by shares in exports of the Philippines (year-over-year percentage change)	Monthly	Organization for Economic Co-operation and Development (OECD)
yy61	Business Confidence Index, Current Quarter	Quarterly	BSP

yy62	Business Confidence Index, Next-Quarter	Quarterly	BSP
yy63	Volume of Business Activity Index, Current Quarter	Quarterly	BSP
yy64	Volume of Total Order Book Index, Current Quarter	Quarterly	BSP
yy65	Volume of Business Activity Index, Next-Quarter	Quarterly	BSP
yy66	Business Expectations Index on Inflation Rate, Current Quarter	Quarterly	BSP
yy67	Business Expectations Index on Inflation Rate, Next-Quarter	Quarterly	BSP
yy70	Unemployment Rate (year-over-year difference)	Quarterly	PSA
yy71	Underemployment Rate (year-over-year difference)	Quarterly	PSA
yy72	Labour Force Participation Rate (year-over-year difference)	Quarterly	PSA
yy73	Rice Regular Milled Retail Price (year-over-year percentage change)	Monthly	PSA
yy74	Capacity Utilisation in Manufacturing (year-over-year difference)	Monthly	PSA
yy75	Consumer Expectations Survey, Economic Condition (year-over-year difference)	Quarterly	BSP
yy76	Consumer Expectations Survey, Financial Situation (year-over-year difference)	Quarterly	BSP
yy77	Consumer Expectations Survey, Family Income (year-over-year difference)	Quarterly	BSP
yy91	Nominal GDP growth (y-o-y)	Quarterly	PSA
yy92	Real GDP growth (y-o-y)	Quarterly	PSA

yy93	GDP Deflator growth (y-o-y)	Quarterly	PSA

Notes on Dealing with Missing Data

Frequency conversion

In this study, daily, monthly and quarterly data are used. Prior to estimating the models, daily data are converted to monthly data by calculating simple averages of daily data. Therefore, at estimation stage, data are either quarterly or monthly. This was somewhat necessary for making some of the models to convergence. Daily data increases the sample size by about 30 for monthly and by about 90 for quarterly data, but it also increases about the same number of "not available" data points.
Some methods also necessitate frequency conversions. For example, to have monthly principal components, some quarterly data must be converted to monthly data. This was done by using the same quarterly figure for all the months of the quarter, hence the average for the monthly numbers give the quarterly figures. Other frequency conversion methods are also utilized. Averaging has the advantage that the functional relationship using quarterly (the original quarterly variable on the left-side of the equation, and after taking the average of monthly data for the quarter on the right-side of the equation) or monthly (fill in all months in a quarter with the original quarterly data on the left-side of the equation, and original monthly data for the variable on the right-side of the equation) data stay the same.

Estimating missing data at the beginning of the period

The Central Bank of the Philippines (BSP) has surveys on business and consumers expectations. These are extremely useful and timely data, but they are available quarterly. Business surveys are available from the second quarter of 2001, and consumer surveys are available from 2007. Backdating these data to 1999 may have advantages. Since it may be a stretch to backdate consumer survey data from 2007, but it may be a worthwhile exercise to backdate business survey data to 1999 from 2001. A variation of the expectation maximization (EM) algorithm is used here (Stock and Watson, 2002a).
The process has several steps:

1. Calculate principal components using a balanced panel for the period with all the variables, 2001M06 – 2019M12 (data for Y61, Y62, Y66 are missing for 1999M01-2001M05).

2. Use factor loadings for Y61, Y62, and Y66 as initial estimates to calculate estimated values of Y61, Y62, and Y66 for the period that data are missing, 1999M01-2001M05.

3. Calculate principal components using a balanced panel for 1999M01-2019M12, with estimated values of Y61, Y62, and Y66 for the 1999M01-2001M05 period.

4. Use factor loadings for Y61, Y62, and Y66 to get new estimated values for Y61, Y62, and Y66.

Repeat steps 3 and 4, until there are no significant changes (value at iteration (i) - value at iteration (i-1) < 0.001) in estimated values. New estimated variables are called Y61_f01, Y62_f01, and Y66_f01.

Estimating missing data at the end of the period (or ragged-edge data as called by Ken Wallis)

At the time of the writing, world uncertainty indexes were not available for the final quarter of 2019. Therefore, 2019 October, November and December figures had to be estimated for variables Y41, Y43, and Y44. Box-Jenkins ARIMA(p,d,q) models are used to predict values for those three months. New variables are called Y41_f01, Y43_f01, and Y44_f01.