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High-Mixed-Frequency Dynamic Latent Factor Forecasting Models for GDP in the Philippines*

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ABSTRACT

The paper considers constructing high-frequency forecasting models for GDP growth in the Philippines, in the form of dynamic time-series models that combine latent factors with a parsimonious set of indicators that are observable at different frequencies. The forecast performances of the estimated models also are compared with other alternative current modeling approaches - e.g., Mixed Data Sampling Regression (MIDAS), Factor Analytic Models, and Current Quarterly Modeling (CQM) with Bridge Equations.

Keywords: Latent Factor Models, Mixed-Frequency Data, High-Frequency Forecasting, Business Condition Indexes, Leading Economic Indicator Systems, Financial Econometrics, Asian GDP Growth and Inflation.

Modelos de factores dinámicos latentes con datos mixtos de alta frecuencia aplicados a la predicción del PIB en Filipinas

RESUMEN

El objetivo principal es la presentación de la metodología de elaboración y los primeros resultados de la estimación de un modelo de predicción de crecimiento del PIB en Filipinas construido sobre la base de un modelo dinámico de series temporales que combina un conjunto de factores latentes, o inobservables, con un grupo reducido de indicadores observados en distintas frecuencias. Para analizar la capacidad predictiva del modelo desarrollado se comparan sus resultados con los obtenidos mediante otras alternativas metodológicas como los modelos frecuencia mixta (MIDAS), modelos de análisis factorial y componentes principales y modelos del trimestre corriente con ecuaciones puente.

Palabras clave: Modelos de factores latentes, modelos de frecuencia mixta, predicción de alta frecuencia, indicadores cíclicos, sistemas de indicadores adelantados, econometría financiera, Crecimiento del PIB e inflación en Asia.

JEL Classification: C53, C58

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1. INTRODUCTION

This paper analyzes the technical and practical issues involved in the use of data at mixed and high frequencies to forecast monthly economic activity in the Philippines. In particular, it considers constructing high-frequency forecasting models for GDP growth in the Philippines, in the form of dynamic time-series models that combine latent factors with a parsimonious set of indicators that are observable at different frequencies.

The econometric issue of combining mixed high-frequency data for short-term forecasting is a research area of extreme interest and continuing investígation to Lawrence Klein. In the context of macroeconometric models, his published works on this topic started over twenty five years ago - e.g., Klein and Sojo (1989), Klein and Park (1993, 1995), Klein and Ozmucur (2002, 2004, 2008), and Mariano and Tse (2008) -and continued to his dying days- through his weekly reports on updated forecasts from his Current Quarterly Model of the U.S. economy. To quote from Klein and Ozmucur (2008),

> *"Our long-standing conviction stands intact that detailed structural model building is the best kind of system for understanding the macroeconomy through its causal dynamic relationships, specified by received economic analysis. There are, however some related approaches, based on indicator analysis that are complementary for use in high frequency analysis. For most economies, the necessary data base for structural model building, guided by consistent social accounting systems (national income and product accounts, input-output accounts, national balance sheets) are, at best, available only at annual frequencies. Many advanced industrial countries can provide the accounts at quarterly frequencies, but few, if any, can provide them at monthly frequencies.*
>
> *"A more complete understanding of cyclical and other turbulent dynamic movements might need even higher frequency observation, i.e. weekly, daily, or real time. It would not be impossible to construct a structural model from monthly data, but a great deal of interpolation and use of short cut procedures would have to be used; so we have turned to a specific kind of indicator method to construct econometric models at this high frequency. …*
>
> *"In step with new technological developments in the information sector of modern economies, attention has been paid to the use of newly available computer power, data resources, telecommunication facilities and other technical changes that made higher frequency analysis of economic statistics available."*

This topic also has generated considerable interest and attention currently, especially in financial econometrics, as more observable data have become available at different and higher frequencies. This is especially so for government policy planners as well as watchers of financial market developments, who would be interested in timely utilization of high-frequency indicators.

The mixed-frequency models of the type we propose for forecasting purposes in this paper have been used in the construction of business condition indices in the econometrics literature. From a methodological perspective, the combination of mixed-frequency data and latent factors in the dynamic model introduces complexities in the estimation of the model. Algorithms have been developed to address these complexities and applied in BCI construction for the U.S. and Europe.

This paper investigates the potential gains in applying this approach to high-frequency forecasting of GDP growth in the Philippines. Extensions of the approach, introducing richer error structures in the model and use of multiple factors, are also investigated. For purposes of application to the Philippines, we take “high-frequency” forecasting to refer to either month or quarter, with updates on the forecast as information becomes available within the forecasting period.

Compared to other forecasting approaches that have been applied in the literature, which are mostly data-intensive, the dynamic factor modeling procedure in BCI construction presents an interesting and parsimonious approach which depends on a much smaller data set that needs to be updated regularly. But it also faces additional complications in methodology and calculations as mixed-frequency data are included in the analysis.

The forecast performance of the estimated models also are compared with other alternative current modeling approaches - e.g., Mixed Data Sampling Regression (MIDAS), Factor Analytic Models, and Current Quarterly Modeling (CQM) with Bridge Equations.

Earlier published references dealing with dynamic factor modeling for BCI construction in the U.S. and Europe provide the starting point for the application to the Philippines that is presented in the paper. The current efforts towards constructing and maintaining economic index indicators in the Philippines are tapped to jump-start the specifications for the empirical component of the project. Estimation and validation of the empirical models presented in the paper for the Philippines relies on filtering algorithms that can be set up within software packages that are commercially available, such as EVIEWS, MATLAB, or OX.

2. METHODOLOGY

This paper uses mixed-frequency data to estimate dynamic latent factor models for high-frequency forecasting of GDP growth in the Philippines. The approach is intertwined with analyzing the business cycles in an economy. The basic philosophy that drives the approach 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 on this are Sargent and Sims (1977) and Stock and Watson(1989). We also introduce another feature - use of mixed-frequency data. This further complicates the analysis, but also enhances the potential for further gains in forecast performance. More recently the approach has received renewed interest for forecasting purposes in the U.S. and larger European countries (e.g., see Foroni & Marcellino, 2012 and 2013). The earlier works (e.g., Stock and Watson, 1989) develop single factor models to construct composite indices of economic activity based on a handful of coincident indicators. An alternative approach (e.g., Chow & Choy, 2009) uses the model to extract unobserved common factors from a large collection of observable indicator variables. Furthermore, the estimated factor model, properly validated, also may be used to forecast macroeconomic variables of interest. Application to the Philippine case is the main focus of this paper.

The common factors are latent, explained by their joint dynamics and, possibly, interactions with observable indicators. The dynamics of the target variable output depends on own lags, the unobservable common factors, and, possibly, exogenous factors. The system may also have other observable variables that serve as indicators for the latent common factors.

A similar modeling approach is used in:

- Mariano and Murasawa (2003, 2010) in constructing an improved coincident economic index indicator for the U.S. using mixed frequencies. Here, quarterly GDP is included in the standard list of monthly coincident indicators, namely
  - Employees on non-agricultural payrolls.
  - Personal income less transfer payments.
  - Index of industrial production.
  - Manufacturing and trade sales.
- Aruoba, Diebold & Scotti (2009), ADS for short, in constructing a “real-time” (daily) BCI for the US, using four indicators
  - GDP - Quarterly.
  - Employment - Monthly.
  - Initial jobless claims - Weekly.
  - Yield curve premium rate - Daily.

Here the business economic condition of a country is treated as a latent (unobservable) entity for which there are observable variables or indicators. As ADS remarked, “Latency of business conditions is consistent with economic theory, …which emphasizes that the business cycle is not about any single variable, whether GDP, industrial production, sales, employment, or anything else. Rather, the business cycle is about the dynamics and interactions (“co-movements”) of many variables.”

From this perspective, it becomes natural to use a state-space formulation for the latent factor model. Kalman filtering procedures (linear and nonlinear) are then applied to estimate unknown model parameters and perform signal extraction for the calculation of the latent factors.

The Kalman filtering approach needs to be adapted to special complicating features of the problem. In particular, using mixed frequency data for the indicators introduces inherent nonlinearities and missing data in the "measured" variables. Also, additional attention is needed and further complications in calculations arise when dealing with indicators that are flow variables. All these are accounted for in the specific way in which the state-space representation is set up for the analysis.

3. MODEL FRAMEWORK

The model structure for the analysis is as follows. Let

x_t = latent business condition at time t.

y_t^i = ith business / economic indicator at time t.

w_t^k = kth exogenous variable at time t.

$y^{\sim}{}_t^i$ = ith observable business / economic indicator at time t.

Note that y_t^i may not be observable at all values of t when observations are available at lower frequency (e.g., quarterly or semester or annual, instead of monthly). In this case, there would be missing data for $y^{\sim}{}_t^i$. When available, $y^{\sim}{}_t^i$ would equal y_t^i if it is a stock variable, but would equal the intra-period sum of corresponding monthly values if it is a flow variable.

For the dynamic latent factor model for x_t and its interaction with y_t^i , we assume that x_t follows an autoregressive process of order p, AR(p):

$$\rho(L)\, x_t = \varepsilon_t,\ \ \varepsilon_t \sim \text{iid } N(O,1)\ ,\ \rho\,(L) = 1 + \ \rho\, L + \rho^2 L^2 + \ldots + \rho^p\, L^p$$

In turn, the indicators y_t^i are linearly related to their own lags (internal dynamics), to x_t, as well as to some exogenous variables w_t^k :

$$y_t^i = \chi_i + \beta_i\, x_t + \ \Sigma\, (\delta_{ik}\, w_t^k\ + \gamma(L)\, y_t^i + u_t^i$$

where, u_t^i are contemporaneously uncorrelated (for different i) and iid N(0,1) and uncorrelated with ε_t. γ (L) is a polynomial lag operator of some finite degree, with an additional idiosyncratic structure due to the time-spacing of available observable indicators (see ADS, p. 418).

This model can be recast in the standard state-space form (e.g., see ADS (2009), p. 419 or Mariano and Murasawa (2003, 2010)):

$$y_t = Z_t\, \alpha_t + \Gamma\, w_t + \varepsilon_t$$

$$\alpha_{t+1} = T_t + R\nu_t$$

$$\varepsilon_t \sim (0, H_t)$$

$\nu_t \sim (0, Q)$

where

y_t = vector of observed variables.

α_t = vector of state variables.

Z_t = matrix of parameters for state variables.

w_t = vector of predetermined variables such as constant term, trends, and lagged dependent variables.

Γ = matrix of parameters for predetermined variables.

ε_t = measurement shocks.

ν_t = transition shocks.

Kalman filtering procedures can then be applied to estimate unknown parameters in this state-space formulation and perform signal extraction to calculate estimates of the latent factor. This Kalman filtering approach needs to be adapted to special complicating features of the problem. In particular, using mixed frequency data for the indicators introduces missing data in the "measured" variables y_t. Details for formulating the state space model to accommodate this are in Mariano and Murasawa (2003, 2010). Also, additional attention is needed and further complications in calculations arise when dealing with indicators that are flow variables (see Harvey, 1989, and ADS, 2009). All these are accounted for in the specific way in which the state-space representation is set up for the analysis.

The forecast performance of the estimated models are also compared with other alternative current modeling approaches - e.g., Mixed Data Sampling Regression or MIDAS (Ghysels *et al.*, 2004; Ghysels *et al*., 2007; and Ghysels, 2013), Factor Analytic Models (Chow and Choy, 2009), and Current Quarterly Modelling (CQM) with Bridge Equations (Klein and Sojo, 1989; Klein and Ozmucur, 2004 and 2008; and Baffigi, Golinelli and Parigi, 2004).

In terms of dynamic factor modeling for BCI construction, there are earlier published references dealing with the topic and related issues as applied to the U.S. and to Europe (e.g., Stock and Watson (1989), Mariano and Murasawa, 2003 and 2010; Aruoba, Diebold, and Scotti, 2009; and Foroni and Marcellino, 2012 and 2013). These provide the starting point for the analysis of the methodology in the paper and its application to the Philippines.

4. EMPIRICAL RESULTS FOR THE PHILIPPINES

The current efforts towards constructing and maintaining economic index indicators in the Philippines (e.g., Bersales *et al.*, 2004; Virola *et al.*, 2010; Zhang and Zhuang, 2002; and OECD, 2011) are tapped to jump-start the empirical component of the paper.

The Leading Economic Index (Philippine Statistics Authority National Statistical Coordination Board, 2014), which is quarterly, was developed jointly by the Philippine Statistics Authority National Statistical Coordination Board and the National Economic and Development Authority (NEDA). The computation of the composite leading economic indicator involves the use of a reference series (the non-agriculture component of GDP) and eleven leading economic indicators, which reflect the importance of the openness and emerging nature of the economy. These indicators are: consumer price index, electric energy consumption, exchange rate, hotel occupancy rate, money supply, number of new business incorporations, stock price index, terms of trade index, total merchandise imports, visitor arrivals, and wholesale price index. We excluded some variables from the list because of data limitations and included some other variables which proved to be useful in other studies.

There are 16 monthly indicators used in our analysis. As in Klein & Sojo (1989), these indicators are grouped into two. There are ten indicators used in the prediction of real GDP and eight indicators are used in the prediction of GDP deflator. All variables, including quarterly GDP, were tested for unit roots. All variables were transformed to obtain year-on-year growth rates or year-on-year differences. These are indicated below:

Monthly indicators for real GDP:

Y01--- Industrial production index growth rate (year-on-year).

Y02--- Merchandise Imports growth rate (year-on-year).

Y03--- Merchandise Exports growth rate (year-on-year).

Y04--- Real government expenditure growth rate (year-on-year).

Y05--- Real Money supply (M1) growth rate (year-on-year).

Y06--- Gross international reserves growth rate (year-on-year).

Y07--- Real Stock Price Index growth rate (year-on-year).

Y08--- Real exchange rate, growth rate (year-on-year).

Y09--- Time deposit rate-savings deposit rate, year-on-year difference.

Y10--- Treasury Bills rate (91 Day) - US treasury 3-month bill rate, year-on-year difference.

Monthly indicators for GDP Deflator :

Y21--- Consumer Price Index growth rate (year-on-year).

Y22--- Producer Price Index, growth rate (year-on-year).

Y23--- Wholesale Price Index (Metro Manila) growth rate (year-on-year).

Y24--- Retail Price Index growth rate (year-on-year).

Y25--- Exchange rate, growth rate (year-on-year).

Y26--- Money supply (M1) growth rate (year-on-year).

Y29--- Time deposit rate-savings deposit rate, year-on-year difference (same as Y09).

Y30--- Treasury Bills rate (91 Day) - US treasury 3-month bill rate, year-on-year difference (same as Y10).

There are three quarterly indicators:

Y51--- Gross Domestic Product growth rate (year-on-year).

Y52--- Real Gross Domestic Product growth rate (year-on-year).

Y53--- GDP Deflator growth rate (year-on-year).

Data for the 1999 to 2014 period are used in all estimations. The method of principal components is used to extract information and to reduce the number of variables (Klein & Sojo, 1989; Klein & Park, 1993, 1995; Klein & Ozmucur, 2002, 2004, 2008, among others). The first three of these principal components are used in the state space model. There are six state variables, and twelve pre-determined variables in two measurement equations. After estimating, the model is used for forecasting real GDP, GDP deflator, and nominal GDP. For the 2000-2014 dynamic solution, mean absolute errors are 1.26% for the real GDP, and 0.83% for GDP deflator (Table 1). These are relatively low errors, but there is room for improvement (Figure 1). An additional advantage of a state space model is a possible by-product. Possible by-products of the state space model include the business conditions index (Mariano & Murasawa, 2003; Aruoba, Diebold, Scotti, 2009), and estimation of monthly GDP (Mariano & Murasawa, 2010).

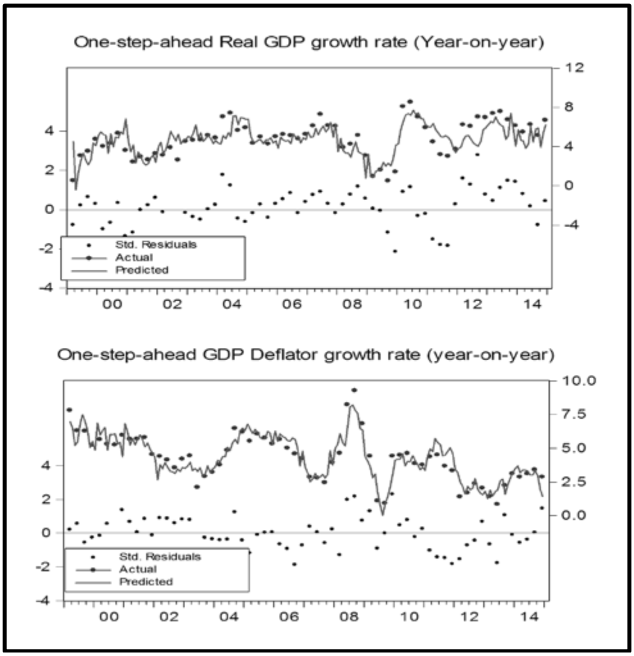
Table 1
Comparison of Model Performance (2000-2014)

	Autoregressive	BRIDGE	MIDAS	Principal Components	State Space
Gross Domestic Product (y-o-y growth)					
RMSE (Root mean square error)	2.36	1.06	0.86	1.03	1.64
Mean absolute error (MAE)	1.72	0.88	0.71	0.83	1.36
Real Gross Domestic Product ((y-o-y growth)					
RMSE (Root mean square error)	1.78	1.16	0.89	1.09	1.67
Mean absolute error (MAE)	1.44	0.89	0.69	0.84	1.26
GDP Deflator (2000=100) (y-o-y growth)					
RMSE (Root mean square error)	2.01	0.63	0.52	0.59	1.03
Mean absolute error (MAE)	1.61	0.49	0.45	0.48	0.83

Source: Own elaboration.

Our very preliminary results, based on mean absolute error and mean square error statistics, indicate that an unrestricted MIDAS (Foroni, Marcellino, Schumacher, 2011, Ghysels, 2013) perform better than the state space model, the principal components model, bridge equations model, and the benchmark model (autoregressive model) (Table 1). MIDAS model has the lowest mean absolute error for the real GDP growth (0.69), and for the GDP deflator growth (0.45) (Table 1). More work is required for a more definite conclusion on this issue.

Figure 1
One-step-ahead growth forecasts



Source: Own elaboration.

5. CONCLUSION

This paper uses mixed-frequency data to estimate dynamic latent factor models for high-frequency forecasting of GDP growth in the Philippines. Kalman filtering procedures can then be applied to estimate unknown parameters in this state-space formulation and perform signal extraction to calculate estimates of the latent factor. Our very preliminary results indicate that an unrestricted MIDAS perform better than the state space model, the principal components model, bridge equations model, and the autoregressive model.

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