High-Mixed-Frequency Forecasting Models for GDP and Inflation

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Abstract

This paper analyzes the technical and practical issues involved in the use of data at mixed frequencies (quarterly and monthly and, possibly, weekly and daily) to forecast monthly and quarterly economic activity in a country. In particular, it considers alternative high-frequency forecasting models for GDP growth and inflation in the Philippines s, utilizing indicators that are observable at different frequencies and with particular focus on dynamic time-series models that involve latent factors. The study compares the forecasting performance of this approach with more commonly used data-intensive methods that have been developed in applications in the U.S. and Europe. These alternative approaches include Mixed Data Sampling (MIDAS) Regression and Current Quarter Modeling (CQM) with Bridge Equations. While these alternatives are mostly data-intensive, the dynamic latent factor modeling with mixed frequencies presents a 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.

Regarding high-frequency forecasting of GDP growth and inflation in the Philippines, our preliminary results based on static simulations and turning point analysis indicate that the mixed dynamic latent factor model (MDLFM) performs better than MIDAS regression, bridge equations with and without principal components, and the benchmark autoregressive models. Further comparison analysis and empirical applications are needed to settle this issue more definitively – especially in the direction of introducing more elaborate error structures, multiple latent common factors, and other exogenous indicators in the high-frequency models for Philippine GDP growth. Future work also will cover dynamic multi-period simulations of the estimated models as well as extensions to other selected countries in Southeast Asia.

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1. Introduction

Building on earlier results reported in Mariano and Ozmucur (2015a, 2015b), 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 was a research area of extreme interest to Lawrence Klein. In the context of macroeconometric models, his works on this topic started over twenty five years ago – e.g., as reported in his presentations in international meetings in the 1980s, Klein and Sojo (1987, 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 Quarter Model (CQM) 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.*
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> *"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 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 monitors of financial market developments, who would be interested in timely utilization of high-frequency indicators to update their market assessments and forecasts.

The mixed-frequency models of the type we consider 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 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).

Earlier published references dealing with dynamic factor modeling for construction of business conditions indices (BCI) 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 rely on filtering algorithms that can be set up within software packages that are commercially available, such as EVIEWS, MATLAB, or OX.

Regarding high-frequency forecasting of GDP growth in the Philippines, the preliminary results reported in the paper, which are based on static simulations of the estimated models, indicate that the dynamic latent factor model performs better than the unrestricted MIDAS regression, the bridge equations with and without principal components, and the benchmark autoregressive models. Further analysis and empirical applications are needed to settle this issue more definitively – especially in the direction of introducing more elaborate error structures, multiple latent common factors, and other exogenous indicators in the high-frequency models for Philippine GDP growth. Future work also will cover out-of-sample and dynamic simulations and turning point analysis of the estimated models as well as extensions to other selected countries in Southeast Asia.

2. METHODOLOGY FOR DYNAMIC LATENT FACTOR MODELS WITH MIXED FREQUENCIES (MDLFM)

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. A related 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.

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 – e.g., see Kalman, 1960; Kalman & Busy, 1961; Cuthbertson, Hall, and Taylor, 1992; Durbin & Koopman, 2012; Hamilton, 1994; Harvey, 1989; Kim & Nelson, 1999; Tanizaki, 1996) 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.

In terms of dynamic factor modeling with mixed frequencies 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: Liu and Hall, 2001; Mariano and Murasawa, 2003 and 2010; ADS, 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 in this paper to the Philippines and other selected Southeast Asian countries.

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, $y^{\sim}{}^{i}_t$ 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. It should be pointed out that specific expressions for the variables and parameters in the measurement and state equations depend on the mixed frequencies appearing in the model. The formulas get more complex and numerical treatment of the model gets more computer intensive as higher and higher frequencies are introduced into the model.

3. ALTERNATIVE MODELING APPROACHES

3.1. BENCHMARK – AR (p) and VAR (p)

For this paper, we use univariate and vector autoregressive processes as benchmark models for the target variables under discussion. For quarterly observable target variables, alternative models could be used: unrestricted quarterly AR(p) or VAR(p) or multi-frequency monthly AR(p) or monthly VAR(p) with missing observations – see Zadrozny (1988), Abeysinghe (1998, 1999), and Mariano and Murasawa (2010). In the monthly models with missing observations, the model can be re-cast with a state-space representation and Kalman filtering technology can then be applied to the state-space formulation to estimate the model.

3.2. Current Quarter Model (CQM): Bridge Equations and Principal Components

In an effort to develop an alternative full-blown structural modeling of the economy which at the same time harnesses key information available at different frequencies, Klein and Sojo (1989) proposed a high-frequency macro-econometric or current quarter model (CQM) for the U.S. This concept and modeling approach has been applied to other countries and studied in various subsequent publications – e.g., Klein and Park (1993, 1995), Klein and Ozmucur (2004, 2008), Baffigi, Golinelli and Parigi (2004), and Ozmucur (2009). Now, CQM models have been developed for updating quarterly forecasts in China, Hong Kong, Japan, Mexico, Russia and Turkey. CQMs are now under construction for Malaysia, the Philippines, and Thailand.

The main objective is to forecast in a timely fashion the national income components – typically available quarterly – utilizing quarterly and higher-frequency data as they become available. For the U.S., real GDP components are considered from the production, expenditure and income sides.

To establish statistical relationships, CQM uses “bridge equations” relating GDP components to quarterly and monthly “indicator” variables. Indicator variables are observable, with sufficient correlation to the GDP component; and with enough lead time relative to the GDP components. For monthly indicators, averages are used over the quarter – averages (or estimates of them) are updated as more monthly observations become available. For purposes of forecasting the monthly and quarterly indicators, ARIMA models are used as well. If no indicators are available, an ARIMA model would be estimated for the GDP component itself.

Since data for the production side are released with a longer lag in the United States (about 3 months), the method of principal components is used as the third way of estimating GDP. Monthly indicators are used to extract principal components. Quarterly average of the first principal component is used as the first determinant of real GDP, and GDP deflator. The remaining principal components (quarterly averages since they are available monthly) enter the equation in a stepwise fashion provided they are significant at the five percent level.

More details for the U.S. CQM are provided in Klein and Park (1993, 1995) and Klein and Ozmucur (2004, 2008).

3.3. MIDAS (Mixed Data Sampling) Regressions

A typical bridge equation relates a quarterly variable to three month averages of monthly variables. This implicitly imposes a restriction on parameters for the months of the quarter, which introduces asymptotic biases and inefficiencies (Ghysels, 2013). In contrast, MIDAS estimates a monthly regression of GDP on monthly (and possibly quarterly) indicators using parsimonious distributed lags to represent missing observations. The initial reference is Ghysels, Santa-Clara, and Valkanov (2004). One typical lag structure that is used is the exponential Almon lag structure. Alternative lag structures that have been used in empirical work include Beta, Linear, Hyperbolic, and Geometric lag coefficients. The model is estimated by nonlinear least squares using actual observed data at mixed frequencies.

The approach also has been extended to Unrestricted (Truncated) MIDAS; Autoregressive MIDAS, which adds a lagged y to the regressors; Factor-MIDAS – which includes latent factors, thus combining MIDAS with MF-DLFM; and Markov-Switching MIDAS.

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 and Polistico, 2010; Zhang and Zhuang, 2002; and OECD, 2011) are tapped to jump-start the empirical component of the paper.

The Leading Economic Indicator 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.

Initially, sixteen monthly indicators are considered 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. Furthermore, before estimating equations, these variables were standardized to have zero means and unit variances. These variables are listed below:

Monthly indicators for real GDP (Figure 1)

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--- World trade volume 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 (Figure 2)

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 target variables (Figure 3)

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)

Figure1. Standardized Monthly Indicators for Real GDP Growth (2000M01-2015M12)

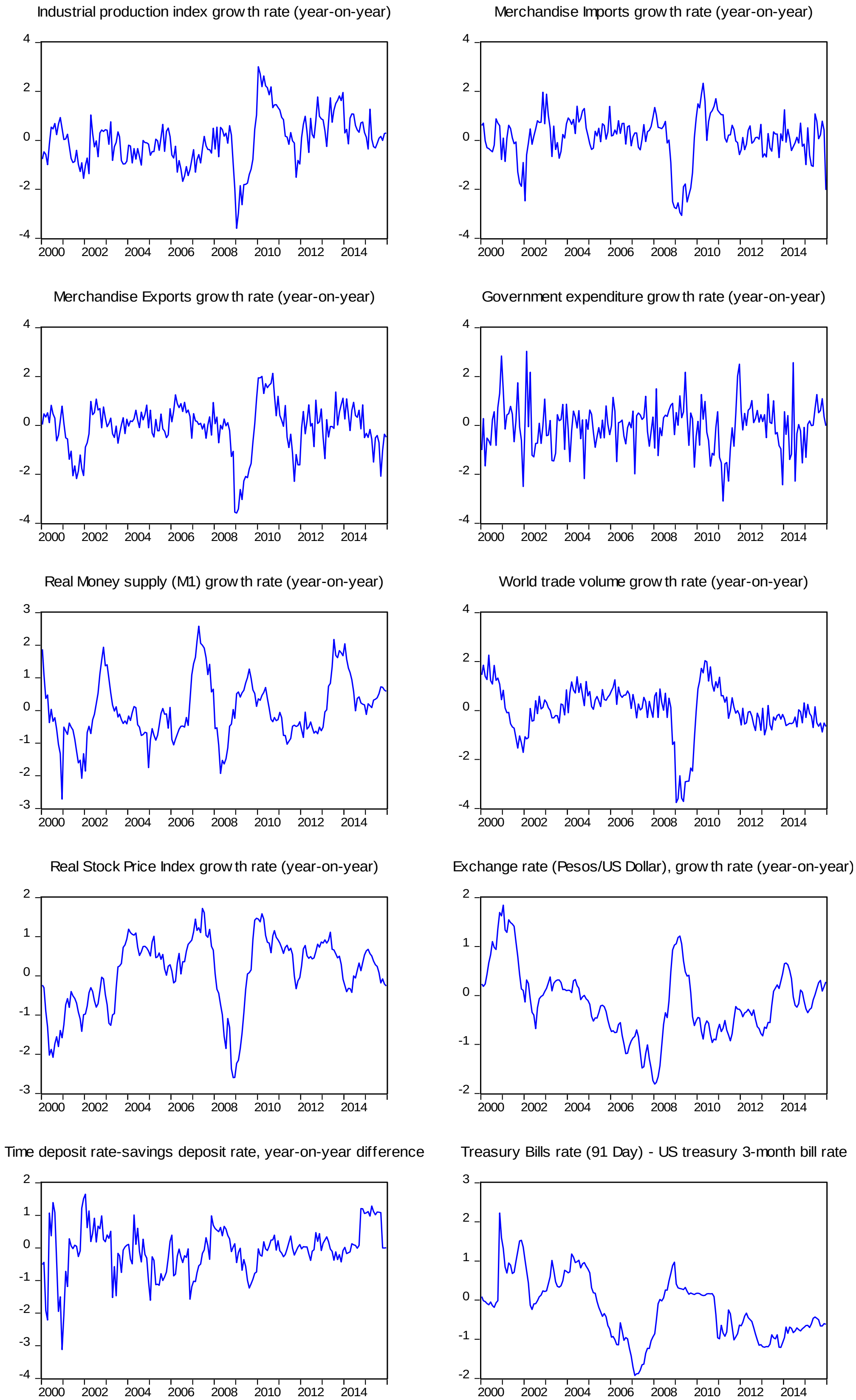


Figure 2. Standardized Monthly Indicators for GDP Deflator (2000M01-2015M12)

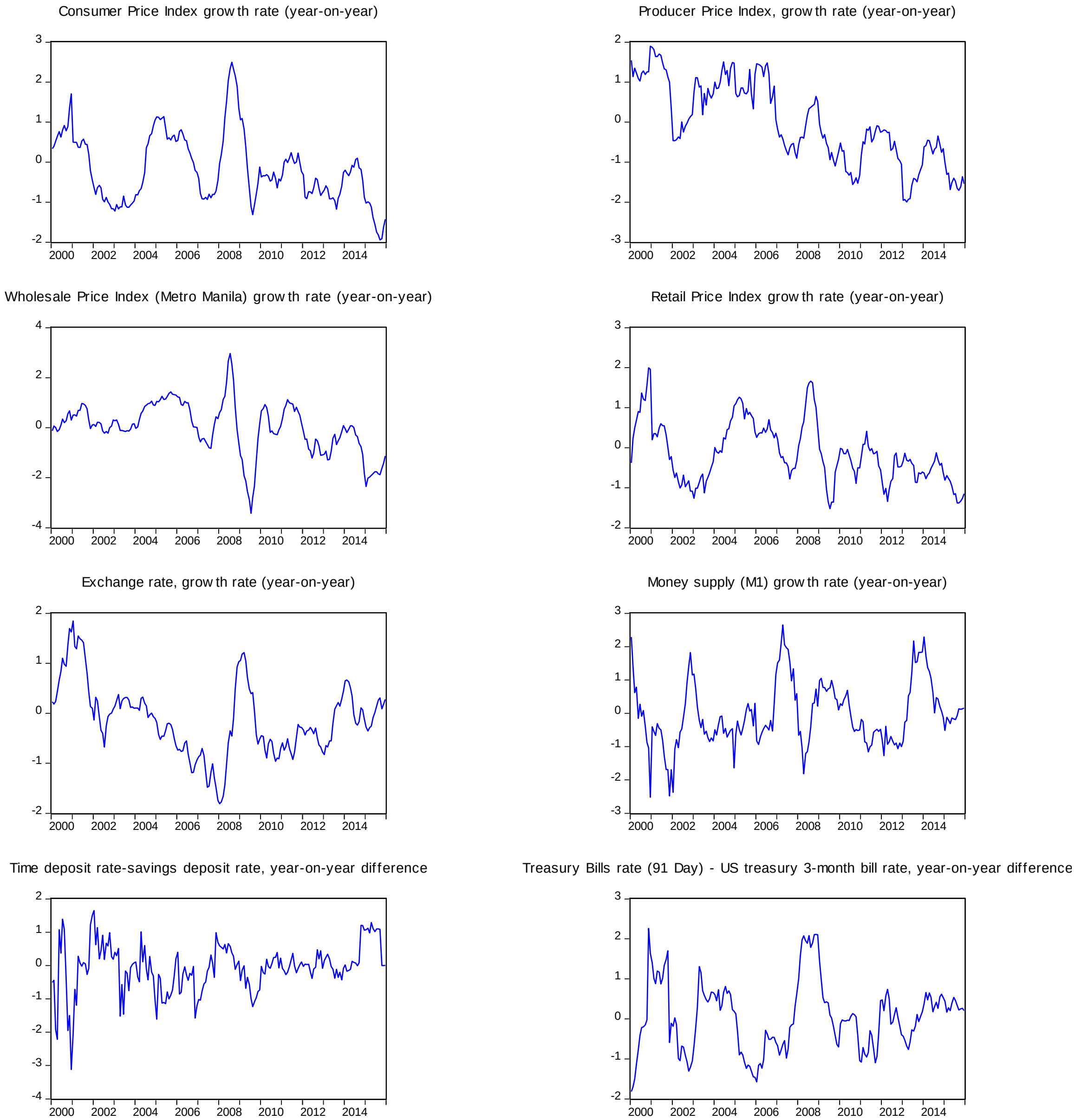
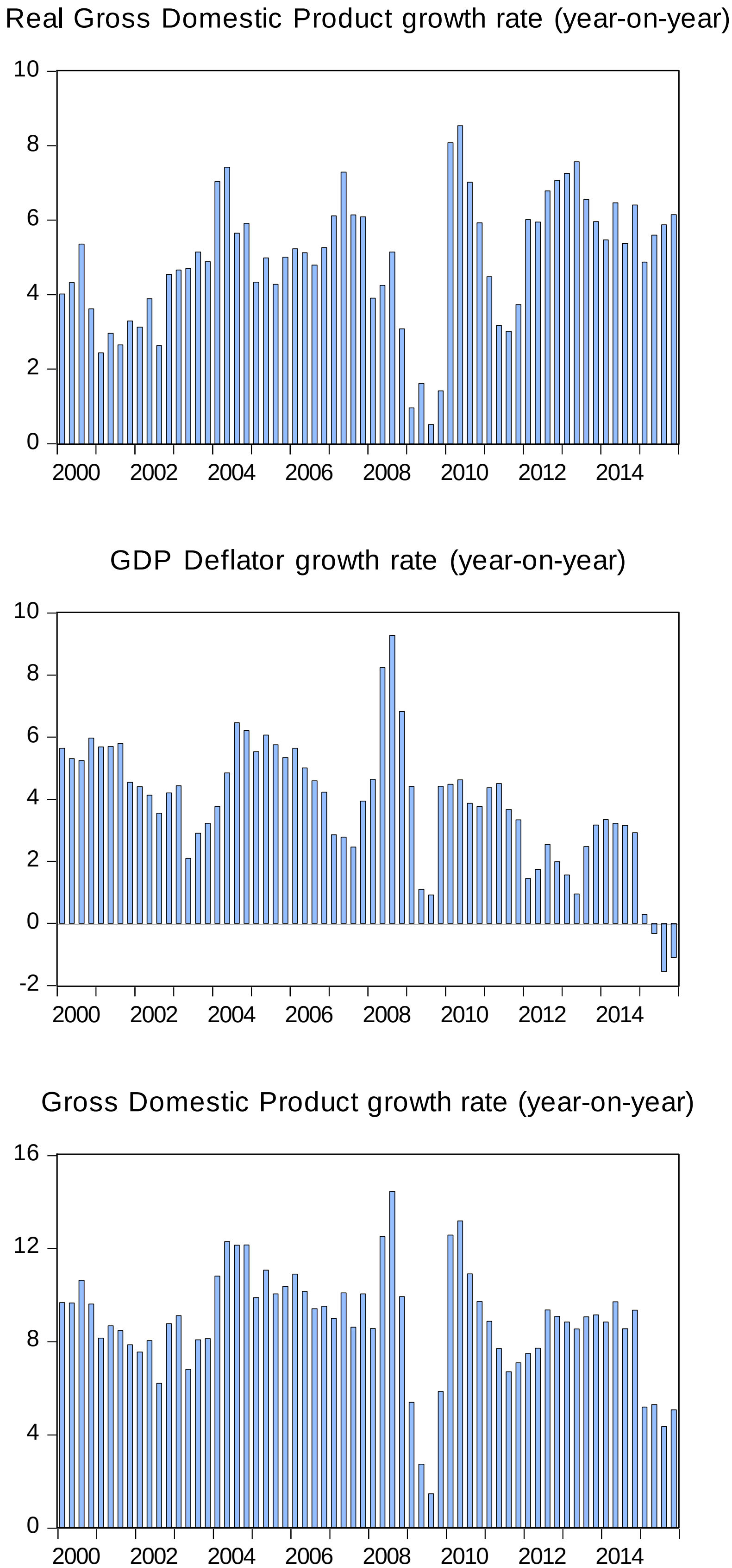


Figure 3. Real GDP Growth and GDP Deflator Growth (2000Q1-2015Q4)



Data for the 2000 to 2015 period are used in all estimations. In addition to the mixed-frequency dynamic latent factor model, four other modeling approaches are included – the benchmark Autoregressive Process, Bridge Equations, Principal Components, and MIDAS.

Specifically, the following nine models are estimated in this empirical exercise (listed in Table 1 below). The model variations in the categories of benchmark autoregressive process, bridge equations, and principal components – models 1 – 6 in the list below - are based on quarterly observations (actual or aggregated from monthly data) while variations of MIDAS and MF-DLFM – models 7 – 9 - are monthly models using mixed actual monthly and quarterly data.

1. AR - The selected model for real GDP growth (Y52) is an AR (1) – based on Box-Jenkins methodology. For the GDP deflator growth rate (Y53), the estimated model is an AR (2). All coefficients are significant at the five percent level. Determination coefficients are 0.49 for real GDP, and 0.67 for the GDP deflator (Appendix A1).
2. VAR - The estimated bivariate model for Y52 and Y53 keeps lags 1 and 2 (Appendix A2). Likelihood ratio test, final prediction error, Akaike information criterion, Schwarz information criterion, Hannan-Quinn information criterion all select lag order of 2.
3. LEI - This includes the Leading Economic Indicator Index for the Philippines in separate autoregressive distributed lag (ARDL) models for Y52 and Y53 (Appendix A3). Schwarz criterion is used to select the model with a possible maximum lag of 8 quarters. Selected models are ARDL(1, 1) for real GDP growth, and ARDL (2, 0) for GDP deflator. Determination coefficients are 0.58 for real GDP growth, and 0.67 for GDP deflator growth.
4. Bridge - Separate regressions are done for Y52 and Y53 on the indicator variables described earlier, with correction for error serial correlation. The monthly data for the indicators are converted to quarterly figures by averaging, which are then used in estimating the bridge equations. Monthly indicators entering into the equations are selected using forward stepwise method with stopping criterion of a

p-value of 0.1 (Appendix A4). Real GDP equation includes Y01 (industrial production), Y03 (exports), Y04 (government expenditures), Y07 (real stock prices), and Y09 (time deposit rate-savings deposit rate), in addition to lagged real GDP and a constant term. On the other hand, in addition to lagged GDP deflator and a constant term, Y21 (consumer price index) and Y23 (wholesale price index) are selected in the equation for GDP deflator. Determination coefficients are 0.74 for real GDP growth, and 0.89 for GDP deflator growth.

5. <u>PCA with Two Groups</u> - Principal components are calculated separately from the two groups of monthly indicators for real GDP growth and the GDP deflator growth, as in Klein & Park (1993,1995), Klein & Ozmucur (2002,2004,2008), and Mariano & Ozmucur (2015a, 2015b). Separate regressions are then performed for Y52 and Y53 on the corresponding group of principal components. The first principal component explains 31% of the variation in 10 indicators for real GDP growth. First seven principal components can explain over 90% of the variation in those ten indicators. Factor loadings indicate that the first principal component stands for international trade, exports (Y02) and imports (Y03), the second principal component for real exchange rate (Y08), the third principal component for the difference between time deposit rate and savings deposit rate (Y09), the fourth component for real government expenditures (Y04), the fifth component for real money supply (Y05), the sixth component for gross international reserves (Y06), and the seventh component for industrial production (Y01).

   On the other hand, the first principal component explains 40% of the variation in the 8 indicators for GDP deflator growth and the first five principal components can explain over 90% of the variation in those indicators. Factor loadings indicate that the first principal component stands for consumer prices (Y21), producer prices (Y22), wholesale prices (Y23), and retail prices (Y24), the second component for the exchange rate (Y25), the fourth component for the difference between time deposit rate and savings deposit rate (Y29), and the fifth component for money supply (Y26). The third principal component stands for three indicators, namely money supply (Y26), the difference between time deposit rate and savings deposit rate (Y29) and the difference between the Treasury bill rate and the US Treasury bill rate (Y30).

The relationship between real GDP growth and the principal components was established with the stepwise least squares (Appendix A5). The first principal component and the first lag of the dependent variable are included in the equation. Other principal components and the dependent variable with lags 2 to 4 lags are selected using forward selection method. Those indicators which are significant at the ten percent level are kept in the equation. It should be noted that those who did not make the first cut (those who account for 90% of the variation in indicators) may turn out to be significant in these bridge equations. For example, real GDP growth equation includes Z09 (ninth principal component), in addition to Z01, Z03 and Z04. This equation, which also includes the first and third lags of Y52, has a determination coefficient of 0.75. GDP deflator growth equation includes sixth and seventh principal components (Z26 and z29), in addition to first and second principal components (Z21, Z22). The equation, which also includes the first and fourth lags of Y53, has a determination coefficient of 0.90.

6. Bridge with PCA - This is a variation of #5, using as regressors the principal components of all indicator variables grouped together (Appendix A6). Real GDP growth equation, now, includes Z30, in addition to Z01, Z03, Z04, Z09 and Y52 (-1). There is a little change in the determination coefficient compared with the one in equation with two groups (0.7595 and 0.7549). However, GDP deflator growth equation is slightly improved with similar additions. This equation, which includes eight principal components and 2 lagged values of the dependent variable, has a determination coefficient of 0.94. Adjusted determination coefficient is 0.92, compared with 0.89 in the equation with two groups.

7. MIDAS – MIDAS regressions are estimated separately for Y52 and Y53, using actual monthly data for the indicator variables (Appendix A7). Eviews,version 9.5, software (IHS, 2016) allows one to use Almon, exponential Almon, Beta, and step options. Almon lags (polynomial distributed lags) are used in this paper. This

option had several advantages for the particular data set at hand. It yielded higher determination coefficients, and also required less computation time. Somewhat more common options, exponential Almon lags and beta functions, may lead to highly nonlinear equations with convergence and computation time issues. Almon lag (Almon, 1965, 1968) with a polynomial degree of 3 is used, and a maximum of 6 lags are allowed (IHS, 2016). Both real GDP and GDP deflator equations has eight monthly indicators. For all eight variables a lag of 3 or more is chosen. This is an improvement on our earlier papers (Mariano & Ozmucur, 2015a, 2015b), which used unrestricted MIDAS with 2 lags. Almon type of restrictions enable the use of more lags without increasing the number of right hand variables hence reducing the number of degrees of freedom. Determination coefficients are 0.90 for real GDP growth and 0.95 for GDP deflator growth. It should be noted that, in both equations, there are quite few coefficients which are insignificant. However, alternative equations with fewer variables (omitting variables which are not significant) gave forecast results which were inferior to the ones provided from these equations. Therefore, these equations with better forecasting power were kept as the final set of equations.

8. <u>MIDAS_PCA</u> - Variation of #7, with principal components of the indicator variables as regressors (Appendix A8). Results are not very different than the previous model (MIDAS) in terms of determination coefficients, but there are some differences in forecasting performance.

9. <u>DLFM</u> - A bivariate mixed-frequency dynamic latent factor model is estimated for Y52 and Y53, with two unobserved common factors. As the first step of dynamic factor modeling, all monthly variables are grouped into one. Real exchange rate and real money supply are deleted from the first since nominal magnitudes of these variables are already in the second group. There were also two interest rate differential variables, which appear in both groups. This reduces the total number of indicators from 18 in two groups to 14 variables in a single group. Real government expenditures (Y04), and time deposit rate and savings rate difference (Y09) are also excluded from the original list because of data issues. The final list contains the two quarterly variables of interest (Y52 and

Y53) and twelve monthly indicator variables: Y01, Y02, Y03, Y06, Y07, Y10, Y21, Y22, Y23, Y24, Y25, and Y26.

The system closely follows Mariano & Murasawa (2003), and extends it by including variables related to the general price level. There are 14 target variables (12 monthly, 2 quarterly, listed above), and two unobserved common factors (S1 and S6), and two specific factors (S11 and S16). Common factors are included in all fourteen measurement or observation equations, while specific factors (idiosyncratic components) are included in the related equation. For example, specific factor S11 appears in real GDP equation, while specific factor S16 appears in GDP deflator equation. Derivation of the form of the lags in equations with quarterly and monthly target variables are given in Mariano & Murasawa (2003). All variables are standardized before estimating the model. This has the advantage of reducing the number of parameters to be estimated, and determining the initial values of some of the variables as zeros (average for the period). Here, exact maximum likelihood estimators are computed, despite the longer time required compared with some short-cut methods such as the EM algorithm. BFGS (Broyden-Fletcher-Goldfarb-Shannon) algorithm with Marquart steps are utilized to maximize the likelihood function. Convergence was achieved after 82 iterations. Estimated equations using standardized variables are given below (details are in Appendix A9):

Real GDP growth equation:

Y52 =-0.3069-0.0431*((1/3)*S1+(2/3)*S1(-1))+ S1(-2)+(2/3)*S1(-3)+(1/3)*S1(-4))-0.000967*((1/3)*S6+(2/3)*S6(-1)+S6(-2)+(2/3)*S6(-3)+(1/3)*S6(-4))+((1/3)*S11+(2/3)*S11(-1)+S11(-2)+(2/3)*S11(-3)+(1/3)*S11(-4))+[RES. VAR.= EXP(-3.083)]

GDP deflator growth equation:

Y53 =-0.3908+0.54379*((1/3)*S1+(2/3)*S1(-1))+ S1(-2)+(2/3)*S1(-3)+(1/3)*S1(-4))+0.000255*((1/3)*S6+(2/3)*S6(-1)+S6(-2)+(2/3)*S6(-3)+(1/3)*S6(-4))+((1/3)*S16+(2/3)*S16(-1)+S16(-2)+(2/3)*S16(-3)+(1/3)*S16(-4))+[RES. VAR.= EXP(-3.2547)]

Equations for monthly indicators also include exogenous variables (lagged dependent variables), in addition to common factors S1 and S6. The number of lags are determined with the help of autoregressive equations prior to building the state space model. For example, Y01 (industrial production) includes lags 1 and 2, and Y02 (merchandise imports) include lags 1, 4, and 5.

Y01 --- Industrial production index growth rate (year-on-year)
Y01 = -0.0436*S1-0.0016*S6+ 0.5045*Y01(-1)+0.2120*Y01(-2)+[RES. VAR.= EXP(-1.2985)]

Y02 --- Merchandise Imports growth rate (year-on-year)
Y02= 0.13085*S1-0.002149*S6+0.41157*Y02(-1)+0.28401*Y02(-4)-0.16893*Y02(-5)+[RES. VAR.= EXP(-1.410006)]

Y03 --- Merchandise Exports growth rate (year-on-year)
Y03 = 0.12419*S1-0.002313*S6+0.2745*Y03(-1)+ 0.2516*Y03(-2)+ [RES. VAR.= EXP(-1.3862)]

Y06--- World trade volume growth rate (year-on-year)
Y06 = 0.2243*S1-0.0018599*S6+0.25413*Y06(-1)+ 0.2451*Y06(-2)+0.4416*Y06(-3)-0.2333*Y06(-4)+[RES. VAR.= EXP(-2.2223)]

Y07 --- Real Stock Price Index growth rate (year-on-year)
Y07 = -0.19767*S1-0.0002923*S6+1.1261*Y07(-1)- 0.2147*Y07(-2)+[RES. VAR.= EXP(-2.7318)]

Y10 --Treasury Bills rate (91 Day)-US treasury 3-month bill rate, year-on-year difference
Y10 = 0.11053*S1+0.0001563*S6+0.94088*Y10(-1)+[RES. VAR.= EXP(-2.86688)]

Y21 --- Consumer Price Index growth rate (year-on-year)
Y21 = 0.59905*S1+0.00046*S6+0.8159*Y21(-1)- 0.021172*Y21(-2)+ [RES. VAR.= EXP(-4.6344)]

Y22 --- Producer Price Index, growth rate (year-on-year)
Y22 = 0.17209*S1-0.000094331172*S6+0.94388*Y22(-1)+[RES. VAR.= EXP(-2.7506)]

Y23 --- Wholesale Price Index (Metro Manila) growth rate (year-on-year)
Y23 = 0.27944*S1-0.000158559*S6+1.2710*Y23(-1)- 0.4092*Y23(-2)+ [RES. VAR.= EXP(-3.07542)]

Y24 --- Retail Price Index growth rate (year-on-year)
Y24 = 0.60569*S1+0.00027127*S6+0.70901*Y24(-1)+ 0.02889*Y24(-2)+ [RES. VAR.= EXP(-3.5733)]

Y25 --- Exchange rate, growth rate (year-on-year)
Y25 = 0.05251*S1+0.00007894*S6+1.34411*Y25(-1)- 0.3937*Y25(-2)+ [RES. VAR.= EXP(-3.5915)]

Y26 --- Money supply (M1) growth rate (year-on-year)
Y26 = -0.3777*S1-0.000358*S6+0.7227*Y26(-1)+ 0.2614*Y26(-2)-0.18230*Y26(-4)+[RES. VAR.= EXP(-2.0635)]

Common factors S1 and S6 form a first order vector autoregressive system (VAR(1)), and specific factors are represented as random walks.

Transition (or state) equations:

S1 =0.7664*S1(-1)-0.00028*S6(-1)-0.02119+[RES. VAR.= EXP(-2.8259)]
S6 =-8.5390*S1(-1)+0.7895*S6(-1)-0.2046+[RES. VAR.= EXP(9.5671)]
S11 = S11(-1)+[RES. VAR.= EXP(-4.6756)]
S16 =S16(-1)+ [RES. VAR.= EXP(-6.7478)]

Results indicate that common factors with lags and specific factors are significant in the model. Lagged dependent variables also play an important role (Appendix 9A).

The estimated models are used to calculate one-period ahead forecasts over the sample period. For illustrative purposes, the actual values and one-step ahead forecasts for the mixed-frequency dynamic latent factor model are presented in Figures 4a, 4b, and 4c below.

Figure 4a. DLFM One-step-ahead growth forecasts (red-actual,green-predicted, blue-residuals) for Real GDP (Y52) and GDP Deflator (Y53), 2000 - 2015

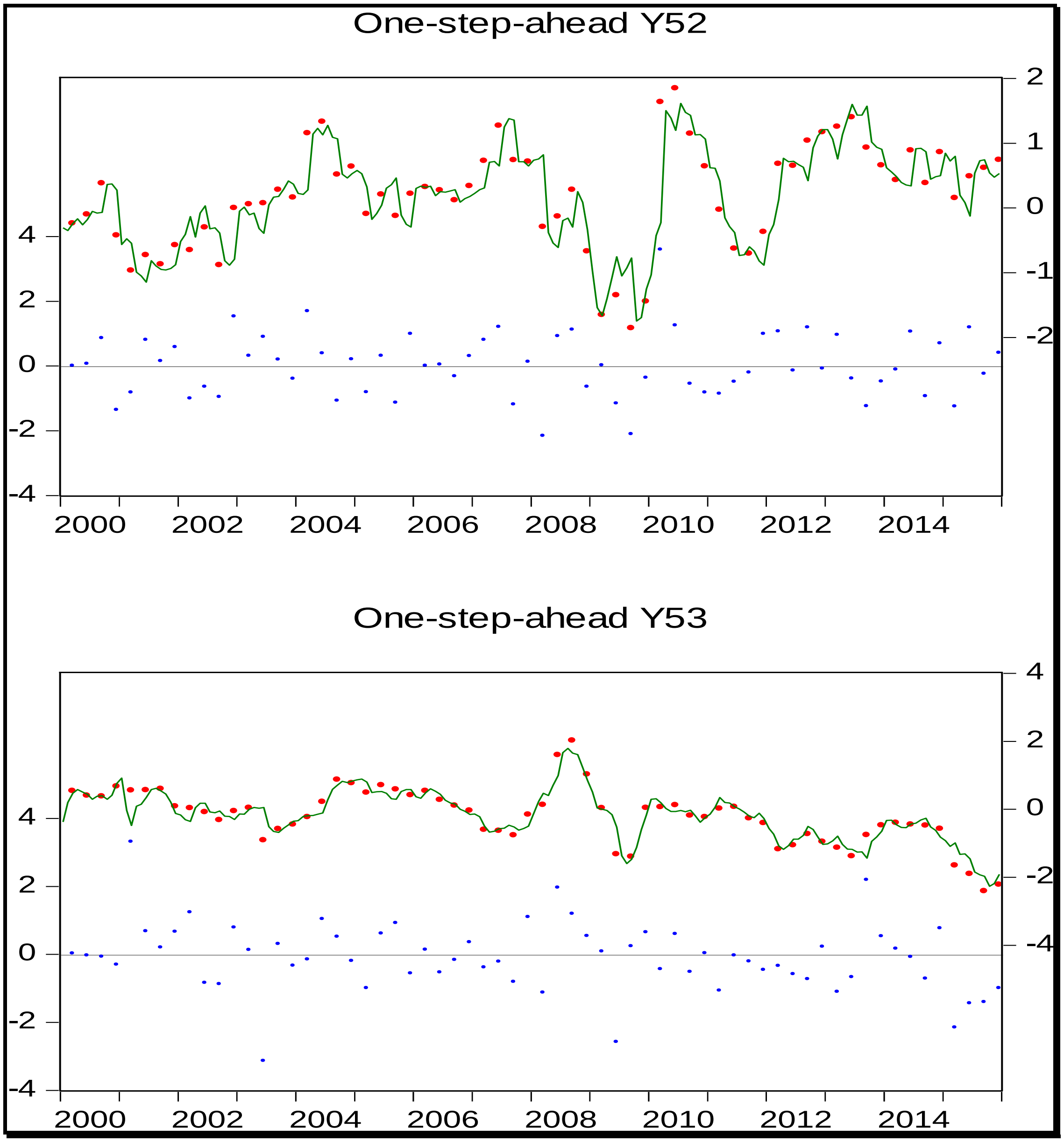


Figure 4b. DLFM One-step-ahead growth forecasts (red-actual,green-predicted, blue-residuals)

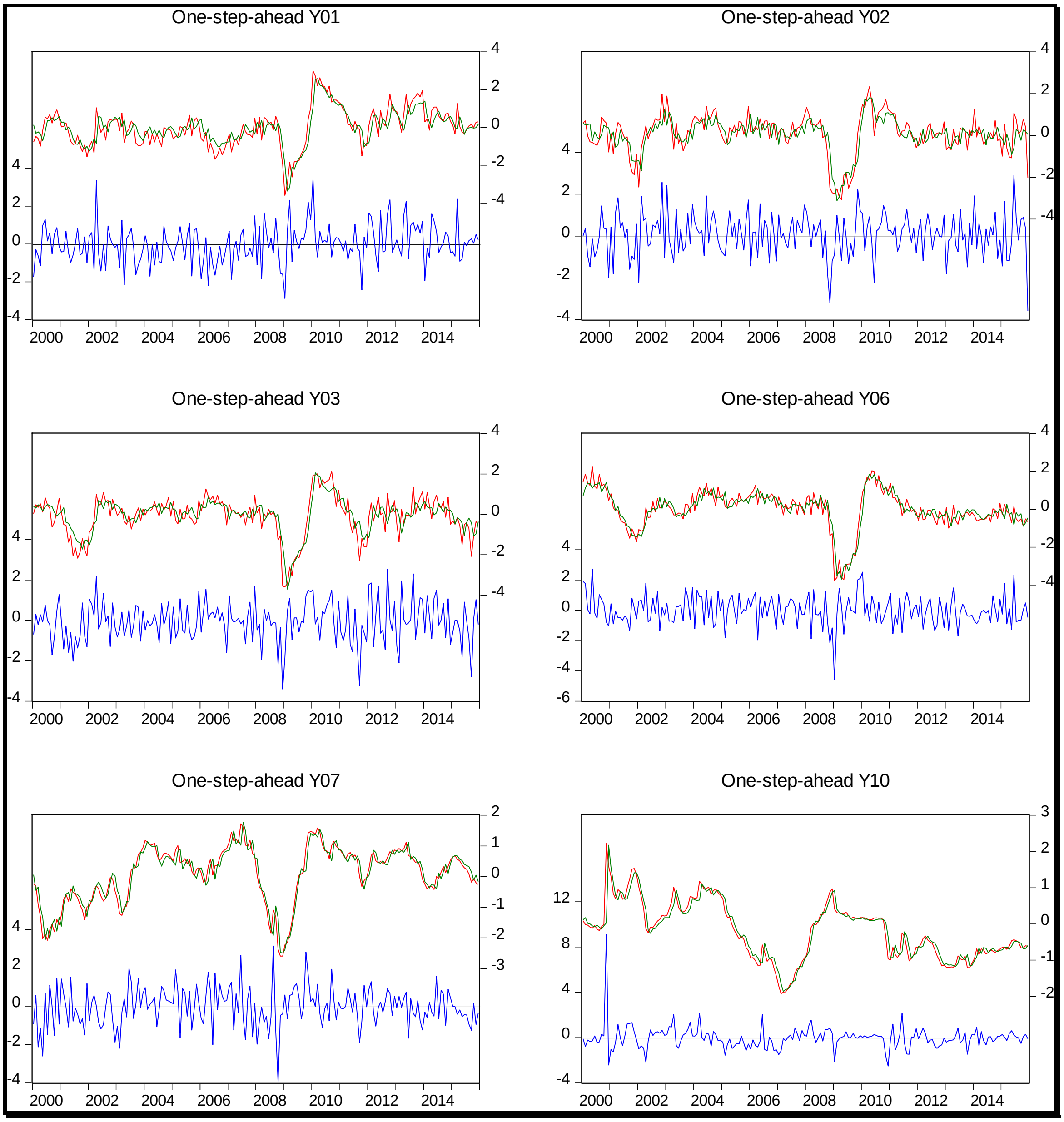


Figure 4c. DLFM One-step-ahead growth forecasts (red-actual,green-predicted, blue-residuals)

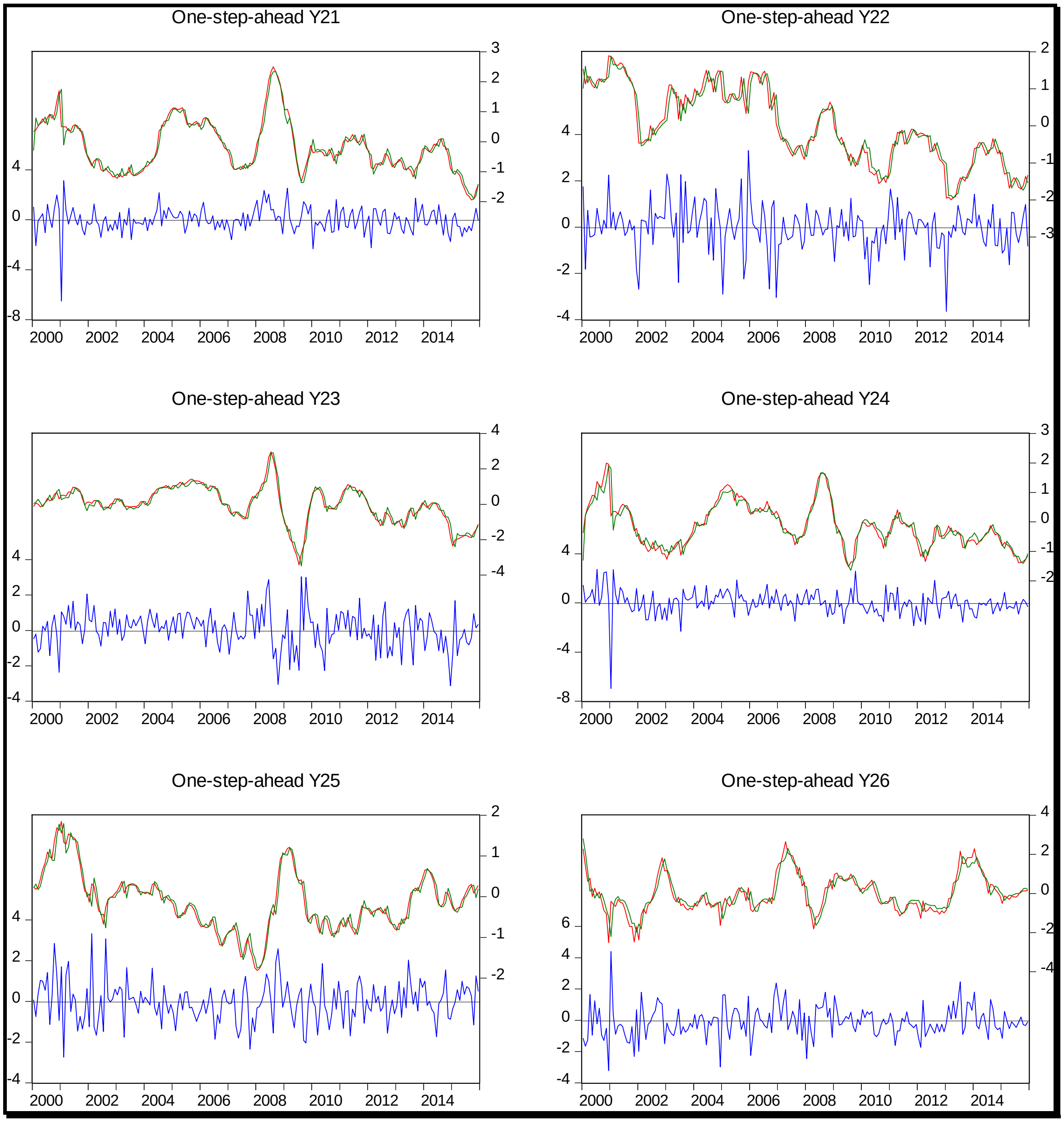


Table 1 summarizes the mean absolute errors and root mean square errors of the alternative estimated models based on one-period-ahead static forecasts. The results indicate that the mixed-frequency dynamic latent factor model has the lowest mean absolute error - .22% for real GDP growth rate, and 0.28% for the GDP deflator growth rate. Corresponding statistics are 0.45%, and 0.37% for MIDAS, which ranks the second. Principal components, and bridge equations follow these two models. The benchmark AR and VAR models show the biggest errors. Note also LEI shows little improvement, in performance relative to the benchmark models.

Table 1. Performance Indicators (mean absolute error and root mean square error)
One-period in-sample simulation, 2000 - 2015

		Real GDP growth	GDP Deflator growth	GDP growth
AR	MAE	0.88	0.76	1.15
AR	RMSE	1.22	1.07	1.55
VAR	MAE	0.84	0.77	1.13
VAR	RMSE	1.04	1.06	1.42
LEI	MAE	0.84	0.75	1.10
LEI	RMSE	1.11	1.05	1.42
Bridge	MAE	0.68	0.53	0.78
Bridge	RMSE	0.87	0.68	0.96
PCA with 2 groups	MAE	0.67	0.51	0.79
PCA with 2 groups	RMSE	0.86	0.64	0.97
Bridge with PCA	MAE	0.66	0.45	0.66
Bridge with PCA	RMSE	0.84	0.56	0.83
MIDAS	MAE	0.45	0.37	0.49
MIDAS	RMSE	0.55	0.44	0.64
MIDAS_PCA	MAE	0.43	0.36	0.49
MIDAS_PCA	RMSE	0.56	0.42	0.61
DLFM	MAE	0.22	0.28	0.36
DLFM	RMSE	0.26	0.35	0.45

To test the statistical significance of the superior forecasting performance of MF-DLFM relative to the other models, we apply the Diebold-Mariano test (1995) to compare the forecast accuracy of MF-DLFM relative to the alternative models, taken one at a time. The test results are indicative of the significantly lower errors (less than -1.96 for a 5% level of significance) for the dynamic factor model (Table 2), with the exception of MIDAS model for the GDP deflator growth rate. Although, errors are lower for DLFM as shown on Table 1, the difference is not significant at the 5% level.

More work is required for a more definite conclusion on this issue. Further analysis and empirical applications are needed to settle this issue more definitively – especially in the direction of introducing more elaborate error structures, multiple latent common factors, and other exogenous indicators in the dynamic latent factor model. Alternative variations of MIDAS will also be explored and the specification of the other modeling strategies can also be refined further for improved forecasting performance.

Table 2. Diebold-Mariano Statistics

Diebold-Mariano Statistics (errors in dynamic factor model compared with errors in an alternative model)

	Absolute value of errors	Squares of errors
Gross Domestic Product Growth (y-o-y)		
DM_Y51_AR	-3.52	-2.55
DM_Y51_BRIDGE	-6.22	-7.24
DM_Y51_BRIDGEPCA	-4.93	-6.01
DM_Y51_LEI	-5.22	-3.93
DM_Y51_MIDAS	-2.83	-4.33
DM_Y51_MIDASPCA	NA	-11.29
DM_Y51_PCA	-6.04	-5.42
DM_Y51_VAR	-6.91	-4.52
Real Gross Domestic Product Growth (y-o-y)		
DM_Y52_AR	-5.75	-2.50
DM_Y52_BRIDGE	-5.46	-3.58
DM_Y52_BRIDGEPCA	-5.48	-4.38
DM_Y52_LEI	-23.08	-5.74
DM_Y52_MIDAS	-3.24	-3.77
DM_Y52_MIDASPCA	-9.05	-6.94
DM_Y52_PCA	-5.44	-4.51
DM_Y52_VAR	-10.73	-5.56
GDP Deflator Growth (y-o-y)		
DM_Y53_AR	-7.28	-4.13
DM_Y53_BRIDGE	-2.91	-2.96
DM_Y53_BRIDGEPCA	-3.36	-3.78
DM_Y53_LEI	-7.80	-4.69
DM_Y53_MIDAS	-1.01	-1.08
DM_Y53_MIDASPCA	-4.38	-3.31
DM_Y53_PCA	-2.86	-2.59
DM_Y53_VAR	-7.73	-4.24

It is also important for a model to predict turning points. Therefore, several statistics are used to see the models' success in predicting turning point points. Changes in model forecast (P(t)-P(t-1)) and the actual A(t)-A(t-1)) are compared to analyze the prediction accuracy. These changes are grouped into four (Theil, 1958; Tsay, 2005), as shown below:

Actual is decreasing, and the model predicts a decrease (correct prediction of a turning point, n11 out of a total number of n predictions),

Actual is decreasing, and the model predicts an increase (false prediction of a turning point, n12 out of a total number of n predictions),

Actual is increasing, and the model predicts a decrease (false prediction of a turning point, n21 out of a total number of n predictions),

Actual is increasing, and the model predicts an increase (correct prediction of a turning point, n22 out of a total number of n predictions).

		predicted Down (-)	predicted Up(+)	
Actual	Down(-)	n11	n12	n1.
Actual	Up (+)	n21	n22	n2.
		n.1	n.2	n

The ratio of total correct prediction of turning points= (n11+n22)/n

The ratio of correct prediction of downturns= n11/n1.

The ratio of correct prediction of upturns= n22/n2.

All models do relatively well, if the prediction is for the level of GDP, real GDP or the GDP deflator. However, not all of them fare well in predicting the turning point in the growth rate of these indicators (Table 3). For example, DLFM model correctly predicts 87% of turning points in real GDP, while MIDAS predicts 74% of them (Table 3). The ratio is 79% for the bridge equation model, and the PCA model. On the other hand, DLFM correctly predicts 89% of downturns, and 85% of upturns. Corresponding ratios for the MIDAS model are 74% and 68%.

Pearson χ^2, which is a measure of overall independence between changes in "actual" and "prediction" indicate independence for almost all the models (critical value for 95% confidence and 1 degree of freedom, for a 2x2 table, is 3.841). Pearson's Phi coefficient (mean square contingency coefficient), which gives the degree of association between two dichotomous variables, actual and predicted changes here, is higher for the DLFM model. For example, for real GDP growth, Phi coefficient is 0.73 for DLFM, compared with 0.47 for the MIDAS model. Phi coefficient is 0.87 for GDP deflator, compared with 0.42 for the MIDAS model. All in all, DLFM seems to have a bigger edge over other models in predicting turning points.

Table 3. Turning Point Errors

Alternative models	n11	n12	n1.	n21	n22	n.1	n.2	n	correct total	correct downturn	correct upturn	Pearson χ^2	Phi Coefficient
Gross Domestic Product Growth (y-o-y)													
AR	22	10	32	13	16	35	26	61	0.62	0.69	0.62	3.6	0.24
Bridge	26	6	32	6	23	32	29	61	0.80	0.81	0.79	22.4	0.61
Bridge_PCA	22	10	32	6	23	28	33	61	0.74	0.69	0.70	14.2	0.48
LEI	23	9	32	12	17	35	26	61	0.66	0.72	0.65	5.8	0.31
MIDAS	23	9	32	8	21	31	30	61	0.72	0.72	0.70	11.9	0.44
MIDAS_PCA	23	9	32	6	23	29	32	61	0.75	0.72	0.72	16.0	0.51
PCA	25	7	32	6	23	31	30	61	0.79	0.78	0.77	20.1	0.57
VAR	21	11	32	13	16	34	27	61	0.61	0.66	0.59	2.7	0.21
DLFM	29	3	32	3	26	32	29	61	0.90	0.91	0.90	39.3	0.80
GDP Deflator Growth (y-o-y)													
AR	16	12	28	15	18	31	30	61	0.56	0.57	0.60	0.8	0.12
Bridge	18	10	28	16	17	34	27	61	0.57	0.64	0.63	1.5	0.16
Bridge_PCA	21	7	28	14	19	35	26	61	0.66	0.75	0.73	6.6	0.33
LEI	19	9	28	13	20	32	29	61	0.64	0.68	0.69	4.9	0.28
MIDAS	21	7	28	11	22	32	29	61	0.70	0.75	0.76	10.5	0.42
MIDAS_PCA	21	7	28	12	21	33	28	61	0.69	0.75	0.75	9.1	0.39
PCA	20	8	28	12	21	32	29	61	0.67	0.71	0.72	7.5	0.35
VAR	17	11	28	15	18	32	29	61	0.57	0.61	0.62	1.4	0.15
DLFM	27	1	28	3	30	30	31	61	0.93	0.96	0.97	46.2	0.87
Real Gross Domestic Product Growth (y-o-y)													
AR	25	10	35	9	17	34	27	61	0.69	0.71	0.63	8.2	0.37
Bridge	26	9	35	4	22	30	31	61	0.79	0.74	0.71	20.7	0.58
Bridge_PCA	25	10	35	3	23	28	33	61	0.79	0.71	0.70	21.5	0.59
LEI	24	11	35	9	17	33	28	61	0.67	0.69	0.61	6.9	0.34
MIDAS	26	9	35	7	19	33	28	61	0.74	0.74	0.68	13.5	0.47
MIDAS_PCA	27	8	35	5	21	32	29	61	0.79	0.77	0.72	20.1	0.57
PCA	25	10	35	3	23	28	33	61	0.79	0.71	0.70	21.5	0.59
VAR	24	11	35	8	18	32	29	61	0.69	0.69	0.62	8.5	0.37
DLFM	31	4	35	4	22	35	26	61	0.87	0.89	0.85	32.7	0.73

In order to gauge the out-of-sample performance, estimations were done using rolling samples with 44 observations, which gave 20 quarterly and 80 monthly forecasts. A model is first estimated using 2000Q1-2010Q4 period data, and a forecast is obtained for 2011Q1. Then, the same model is estimated using 2000Q2-2011Q1 period, and a forecast for 2011Q2 is obtained. Thess rolling calculations continued to get to the final data point 2015Q4 (using the estimation period 2005Q1-2015Q3). Results are given in Table 4. The dynamic latent factor model has lowest errors in out-of-sample forecasts also.

Table 4. Performance Indicators (out-of-sample, mean absolute error and root mean square error)

		Real GDP growth	GDP Deflator growth	GDP growth
AR	MAE	0.81	1.30	1.00
	RMSE	0.97	1.60	1.41
VAR	MAE	0.78	1.35	1.41
	RMSE	0.90	1.63	1.89
LEI	MAE	1.06	1.33	1.07
	RMSE	1.23	1.62	1.44
Bridge	MAE	1.42	1.59	1.11
	RMSE	1.54	1.78	1.40
PCA with 2 groups	MAE	2.39	0.96	3.35
	RMSE	2.39	0.96	3.35
Bridge with PCA	MAE	2.28	0.70	2.98
	RMSE	2.28	0.70	2.98
MIDAS	MAE	0.41	0.35	0.56
	RMSE	0.56	0.43	0.72
MIDAS_PCA	MAE	0.52	0.54	0.61
	RMSE	0.73	0.64	0.78
DLFM	MAE	0.23	0.29	0.38
	RMSE	0.28	0.36	0.47

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 are then applied to estimate unknown parameters in this state-space formulation and perform signal extraction to calculate estimates of the latent factor. Our results based on static simulations and turning point analysis of estimated models indicate that the mixed dynamic latent factor model performs better than the MIDAS regression, bridge equations with and without principal components, and the benchmark autoregressive models. Further comparison analysis and empirical applications are needed to settle this issue more definitively – especially in the direction of introducing more elaborate error structures, multiple latent common factors, and other exogenous indicators in the high-frequency models for the Philippines. Future work also will cover dynamic multi-period simulations of the estimated models as well as extensions to other selected countries in Southeast Asia.

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