Automatic Leading Indicators (ALIs) versus Macro Econometric Structural Models (MESMs): Comparison of Inflation and GDP growth Forecasting

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Abstract

This paper compares forecast performance of the ALI method and the MESMs and seeks ways of improving the ALI forecasts. Inflation and GDP growth form the forecast objects for comparison, using data from China, Indonesia and the Philippines. The ALI method is found to produce better short-term forecasts than those by MESMs in general, but the method is found to involve greater uncertainty in choosing indicators, mixing data frequencies and utilizing unrestricted VARs. Two possible improvements are found helpful to reduce the uncertainty: (i) give theory priority in choosing indicators and include theory-based disequilibrium shocks in the indicator sets; and (ii) reduce the VARs by means of the general → specific model reduction procedure.

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1. Introduction

Conventionally, macro econometric structural models (MESMs) serve as one of the most widely used means of forecasting macroeconomic variables. However, the MESMs are constrained to use data of the same frequency – either quarterly or annual - and at the same aggregative level, which is determined by *a priori* theories. As more and more micro and financial data become available at higher frequencies, alternative procedures have been explored that can better utilize various kinds of available data to extract the key signals timely and efficiently. This is best reflected in the recently mounting interest in dynamic factor models (DFMs).

Although economic leading indicators were developed nearly a century ago and factor analysis was used in economics as early as the 1940s,[1] these methods were marginalized in econometric research for decades. The recent revival of leading indicator models is largely due to the work of Stock and Watson, who proposed to extract, by means of dynamic factor analysis, from a large pool of variables a latent 'leading indicator', or an 'index of coincident indicators' as they call it, for the US economy, e.g. see (Stock and Watson, 1989; 1991).[2]

The 'automatic leading indicator' (ALI) model proposed by Camba-Mendez *et al* (2001) makes use of very similar techniques as in (Stock and Watson, 1989).[3] However, the angle of application has been re-oriented. Camba-Mendez *et al* (2001) focus their attention on short-term forecasts of certain officially released variables of interest, e.g. real GDP growth of selected European countries.[4] These variables are excluded from the pool of variables from which a few dynamic factors are extracted. These factors are then used as forcing variables in

[1] W.M. Persons is known as the pioneer of leading indicators; F.V. Waugh and J.R.N. Stone are among the first to apply factor analysis to economic data, see (Gilbert and Qin, 2006) for the history of these econometric methods.
[2] For a recent survey of dynamic factor models, see (Stock and Watson, 2005).
[3] According to the authors, the model derives its name from the fact that the information is selected automatically from the set of indicators.
[4] Another example is to forecast UK inflation by Kapetanios (2002).

forecasting the variables of interest by means of a VAR (Vector Auto-Regression) model, instead of producing one unobserved core index of the economy.

Various applications of the ALI method show that its forecasting performance can be significantly better than that of traditional VAR models, e.g. (Banerjee e*t al*, 2003). However, the performance of VAR models is known to be highly sensitive to the choice of variables, which are limited frequently to fewer than ten in number due mainly to finite sample sizes. As such, VAR models are often not well specified in terms of economic structure. Neither are they as popularly used as MESMs among applied economists outside the academic circle.

In this paper, we compare the forecasting performance of the ALI method with that of the MESMs and experiment with ways to improve the ALI with reference to the MESM method. The comparison is experimented on forecasting two key macro variables – inflation and GDP growth – of three countries, China, Indonesia and the Philippines, as quarterly econometric models for these countries have recently been built at ADB. The main comparison is based on short-run forecasts, as the ALI was developed for this in particular. But in addition, we hope to address the following issues. How does the forecasting performance of each type of models progress as the forecasting horizon is extended? How do variables which are included in the ALI, but not in the MESM, affect the ALI forecasts? How much does the use of higher frequency data of ALI (monthly) improve the forecasts as compared to those by quarterly-data-based MESMs?

Through the comparison experiments, we also seek possible ways of improving the ALI method with respect to the MESM method, as the former is relatively new. One key feature of MESMs is the presence of a long-run, theory-based equilibrium-correction mechanism (ECM) in all the behavioral equations, whereas ALI models only consider common movement among short-run changes of a pool of variables. Hence, we try to see whether the performance of ALI will improve if shocks representing deviations from the long-run cotrending movement, as embodied by the ECM terms in the MESMs, are added into the ALI models. Another feature of MESMs is that every fitted equation is obtained through a parsimonious-specification reduction process, e.g. see (Hendry, 1995) and (Hendry and Krolzig, 2001). In contrast, the VAR used in the ALI suffers from over-parameterization in general. Hence, we try to see whether the parsimonious-specification reduction process will help sharpen the performance of the VAR by pruning out the over-parameterized part.

The rest of the paper is organized as follows. The next section will describe briefly the ALI method, the choice of variable sets and related data, the basic structure of the MESMs, and the design of the comparison experiments. Empirical results for these experiments are discussed in Section 3. The following section discusses possible ways of reducing the uncertainty in the ALI method by adopting two key features from the MESM method. The last section summarizes the results and gives some concluding remarks.

2. The models, choice of ALI indicators, forecast variables and scenarios for comparison

2.1. ALI

The ALI method used here is adopted from (Camba-Mendez *et al*, 2001). The method consists of two steps: factor extraction using a DFM and forecasting using a VAR. Let $\mathcal{Y}_t$ be the variable of forecasting interest and $\mathcal{Z}_t$ a set of *n* variables, often referred to as 'indicator variables'. Economically, there are no set theories to restrict the choice of indicator variables. Statistically, all the variables used in the ALI are required to be stationary. Hence, $\mathcal{Y}_t$ and $\mathcal{Z}_t$ are normally transformed by taking their growth rates, denoted by y_t, and z_t, the latter are also standardized. The first step is to extract *m* factors, f_t, using the following DFM in the form of the state space representation:

$$(1) \qquad \begin{aligned} z_t &= Bf_t + e_t \\ f_t &= Af_{t-1} + u_t \end{aligned}$$

where A and B are parameter matrices to be estimated, and e_t and u_t are error terms. The Kalman filter algorithm is used for the estimation and factor extraction, with the initial parameter estimates obtained via principal component analysis, see (Camba-Mendez *et al*, 2001) for the technical details. One of the advantages of the algorithm is that it allows z_t to contain series observed at different frequencies and also with different sample lengths.

As for determining the number of factors, m, two types of consistent estimators are used, one by Bai and Ng (2005) and the other by Onatski (2005).[5] Note that the latter procedure is computationally easier and more flexible than the former. The Bai-Ng procedure requires that the panel data set is balanced and contains large enough n to enable a comparative judgment of m against a max $m_{(max)}$. As our full data sets are mostly unbalanced and contain relatively small numbers of indicator variables, we are often constrained by the restriction of $(n-m)^2 > (n+m)$ for the identification of the residual covariance matrix of e_t, see e.g. (Steiger, 1994), a matrix that the Bai-Ng procedure is based upon. Nevertheless, both types of estimators are calculated and the larger number is normally adopted as m when the two results differ.

The second step is to run a standard VAR model to forecast y_t and f_t in combination:

$$(2) \qquad \begin{pmatrix} y \\ f \end{pmatrix}_t = \Pi_1 \begin{pmatrix} y \\ f \end{pmatrix}_{t-1} + \cdots + \Pi_p \begin{pmatrix} y \\ f \end{pmatrix}_{t-p} + \varepsilon_t$$

where the minimum lag order p should be such as to entail the residuals ε_t to satisfy the classical assumptions.

2.2. Indicators

A wide range of economic factors is believed to be correlated with inflation and GDP growth, e.g. monetary and finance variables, variables from the real sector such as industrial

[5] The Onatski's procedure exploits ideas from random matrix theory, similar to the approach explored by Kapetanios (2004).

production, not to disregard all those micro factors which affect prices of individual commodities, which comprise the consumer price index (CPI), the indicator from which inflation is measured.

In the present exercise, the indicators are chosen mainly at the macro level, such as the index of industrial production, monetary aggregates, unemployment, average labor wage rate, and short-run interest rate. Consumer confidence index or business confidence index is also used when such survey data are available. Monthly series of the indicators are used whenever possible. A detailed list of the indicators and data sources for all the three countries, i.e. China, Indonesia and the Philippines is given in the appendix. All the indicator variables are processed into standardized stationary series.

2.3. Modeling CPI and GDP in MESMs

The MESM of each of the three countries is comprised of about 70-80 variables, covering private consumption, investment, government, foreign trade, the three production sectors of the economy, labour, prices, and monetary blocks.[6] The models are built following the general→specific model reduction approach and estimated using quarterly data starting from the early 1990s. The ECM form is used for all the behavioral equations.

In these models, CPI is modeled essentially as a simple mark-up of producer/wholesale prices in the long run. Import price may also play a part. The producer prices are explained by factor prices and/or labor productivity. In the case of China and Indonesia, an indicator called 'the GDP gap' is found to impact on inflation. The GDP gap is defined as the ratio of a long-run GDP trend, generated by a simple production function, to GDP.

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[6] For more detailed description of the China model, see (Qin *et al*., 2006) and the Philippine model, see (Cagas *et al*., 2006). Detailed equation lists with essential diagnostic test statistics of these models can be found from: http://www.adb.org/Documents/ERD/Working_Papers/WP081.pdf and http://www.adb.org/Documents/ERD/Working_Papers/WP062.pdf
These two models are relatively mature whereas the ADB Indonesia model is the latest being developed. The Indonesia model is structurally similar to the Philippine model.

The real GDP is modeled via its three sectors – primary, secondary and tertiary sectors. The secondary sector output follows a simple production function in the long run. The tertiary sector output is demand driven, i.e. explained by income and relative prices. The primary sector output in the China model is also demand driven, and follows basically an autoregressive process in the other two models. Various short-run demand factors, e.g. cross-section demand factors, sometimes also impact on these output equations.

2.4. Forecast variables and comparison statistics

We choose inflation (measured by CPI growth) and GDP growth as the forecast variables of interest mainly because these two are the most frequently quoted and the most monitored macroeconomic indicators of an economy and are the objects of investigation in most of the literature on leading indicators modeling methods. Moreover, they present us with very different experimental setting. While CPI data are available at a monthly frequency, GDP data is only available at a quarterly frequency. In the quarterly MESMs, inflation is endogenously determined by an equation in the price block, whereas GDP is derived as the sum of the outputs of the three sectors, each endogenously determined by an equation in the output block.

However, certain features of the data samples may pose a challenge to the ALI method. Specifically, both Indonesia and the Philippines suffered from the East Asian financial crisis in the late 1990s. As a result, the related inflation series and many of the indicator series are more volatile than what are expected of normally distributed series, see Figure 1. Another data feature is the pronounced seasonal pattern in the GDP data, as well as in some of the associated indicators, of all the three countries (see Figure 1 as well as Figure 2). As the MESMs are built to forecast the published GDP series as they are, seasonal adjustment of the raw data is not an option for ALI forecasts here.

Standard RMSE (root mean square error) statistics are used for the evaluation of model forecast performance and are calculated for the out-of-sample forecasts, which cover the period of 2002Q1-2005Q1.[7] This forecast horizon is admittedly short as it is limited by the relatively small quarterly samples that are required to estimate the MESMs. The RMSE statistics are supplemented by graphs of forecast series and errors. In order to find answers to the questions raised in the previous section, the following four scenarios are designed for the comparison exercise:

1. Scenario A: the indicator set includes all the indicator variables listed in the Appendix;
2. Scenario B: the indicator set only includes those variables which are used in the MESMs;
3. Scenario C: the indicator set only includes those variables having monthly observations;
4. Scenario D: the indicator set is the same as in Scenario C but the monthly frequency is integrated into quarterly frequency.

3. Comparison of forecast results

Note that the ALI indicator sets finally presented here differ from country to country due mainly to data availability, see Table 1 as well as the Appendix. These differences may contribute to the different results in model comparison.[8] Another issue to note is that the ALI method can provide monthly forecasts whereas the MESMs only give quarterly forecasts. To compare their results, we integrate those monthly ALI forecasts into quarterly forecasts.

[7] In the case of the MESMs, this also involves revising data on exogenous variables from actual to what would have been reasonable forecasts at the time they are to be made. In other words, the values of the exogenous variables during the forecasting period are also forecasted.

[8] One factor which might have caused the China results to differ from those of the other two countries is the unique way that the monthly CPI data are released. It is based on the current year, rather than having a set base year, thus making it impossible to convert monthly series into quarterly series without imposing extra assumptions.

Table 2 reports the estimated number of factors, *m*, by the Bai-Ng and the Onatski procedures respectively. Table 3 reports the numbers of lags, *p*, used in the VARs based on residual mis-specification tests. As for the lag lengths of the factors in (1), we have chosen one lag from a number of experiments with two lags. The information criteria suggest that one lag is adequate in these experiments. These test statistics are not reported here to keep the paper short.

3.1 Short-term forecast comparison

It is easily discernible from Table 4, as well as Figure 2, that ALI models can generate more accurate short-run forecasts (i.e., in terms of smaller RMSEs) than the MESMs on the whole.[9] The only exception is in the case of Philippine GDP growth forecasts.

However, the main factor that has improved the forecasts turns out not to be those additional indicators which are not included in the MESMs. If we compare the RMSEs of scenario A with those of scenario B, we see that exclusion of the additional indicators (i.e. scenario B) actually reduces the forecast errors in most of the cases, especially in the case of China. This suggests that MESMs are not mis-specified in regard to the exclusion of these indicators in the first place, that an expansion of the indicator set does not necessarily lead to forecast improvement, and that priority should be given to indicator variables with *a priori* theory underpinning when it comes to choosing indicators.

As for the contribution of higher-frequency data (i.e. comparison of scenarios C and D), the results are mixed. The inflation forecasts of Indonesia and the Philippines clearly show that short-term forecasts are more accurate when based on monthly data than on quarterly data. However for GDP forecasts, this observation is only true for the Philippines. In the other two cases, the change in data frequency hardly shows any effects, due probably to the data features of GDP series being low frequency (quarterly) and highly seasonal (see Figure 1).

Relatively, the case of inflation forecast of China shows clearly that higher frequency data might exacerbate forecast errors by bringing too much unwanted data volatility.[10] This serves as a warning against the common belief that utilization of higher frequency information (e.g. monthly data) will generate more accurate short-run forecasts.

In summary, the better short-run accuracy of the ALI forecasts compared to those by the MESMs appear to derive from the greater capacity of the ALI method itself to capture short-run dynamics. This capacity, however, can be subdued by false inclusion of irrelevant indicators or false exclusion of relevant indicators. Careless variable selection is indeed one of the most important factors to induce forecast failure, e.g. see (Clements and Hendry, 2002).

3.2 Longer-term forecast comparison

The main results are summarized in the RMSEs of the 8-step ahead forecasts in Tables 5 and 6, as well as Figure 3. To keep the paper short, only two scenarios of the ALI are reported here: scenario A and the best scenario selected for each case.

From the inflation results in Table 5, we can see that the superior forecasting record of the ALI models fades away rapidly as the forecast horizon widens, roughly within two quarters or six months when compared with the forecasting record of the MESMs. On the other hand, GDP forecasts in Table 6 show mixed results. For the Philippines, the forecast performance of the MESM remains the best. The ALI forecasts outperform those of the MESMs in the cases of China and Indonesia, quite independent of the extension of the forecast horizon. In comparison with the inflation series, one factor which has very probably contributed to the persistence of good ALI forecasts over multiple steps is the dominant seasonality in the GDP growth rates, as shown in Figure 1.

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[9] The RMSEs for GDP forecasts by the MESMs are calculated on the basis of the sum of forecast errors of the three sector output.

[10] It is possible that the inferior result of scenario C to that of scenario D in the China case is due partly to the undesirable volatility brought in by those monthly indicators in scenario A but not in scenario B. But it is

On the other hand, there is one important difference between the ALI forecasts and the MESM forecasts. The MESMs produce forecasts on GDP levels and price indices whereas the ALI only forecasts growth rates. In other words, the MESMs operate largely in a non-stationary world where many non-stationary variables could randomly drift away from the forecasted stochastic trend, known as 'unanticipated location shifts',[11] whereas the ALI is largely immune from the location-shift problem by operating mainly within the stationary world as the stochastic trends in the data series have already been filtered out. This means that the ALI forecasts could outperform the MESM forecasts over multi-period horizon when the latter suffer from location shifts. To check whether the MESM forecasts suffer from location shifts, *h*-step forecast errors on the GDP levels and CPI series are plotted in Figure 4. It is evident from the figure that the GDP level forecasts drift apart from their actual values more than the CPI forecasts and that the drifts are most severe in the case of Indonesia and mildest in the case of the Philippines. These help explain why the ALI multi-step forecasts can outperform those of the MESMs in the cases of GDP growth forecasts in China and Indonesia.

3.3 Comparison of forecast methods

The ALI forecasts presented here are actually chosen from a huge amount of modeling experiments with different indicator variable sets, different *m* and *p* as well. This is mainly because of the high flexibility of the method and the relatively low computational costs. However, flexibility also implies uncertainty. As seen, the forecasting performance of the ALI is sensitive to the choice of indicators and frequency mix, and there are no *a priori* rules to narrow down the choice. Furthermore, it is difficult to judge how robust the forecasting

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difficult to verify this postulate here as exclusion of those monthly indicators from scenario C would result in too small an indicator set (5 indicators) to carry out the ALI properly.

[11] The location shifts form a common type of forecast failures in structural econometric modeling. They are due frequently to historically specific events, or institutional changes, which are excluded from theories and which are totally unanticipated *ex ante*, e.g. see (Hendry, 2004; 2005).

capacity of each factor is in the VAR. In fact, forecasts by the existing MESMs have actually served as a benchmark for the selection of the ALI trials.

4. Modified ALI method

Two key features of the MESM method emerge as potentially beneficial to the ALI method during the comparison experiments. The first is the ECM specification; the second is the general→simple model reduction procedure.

Let us first consider the ECM representation from the perspective of a VAR model of (y_t, z_t). The ECM representation of an individual equation in the VAR should be:

$$(3)\qquad y_t = \sum_{i=0}^{p} \Gamma_i Z_{t-i} + \sum_{j=1}^{p} \Phi_j y_{t-j} + \phi \underbrace{\left(y - \beta Z\right)_{t-1}}_{ECM} + v_t$$

The above equation explains the endogenous variable by three types of dynamic variables: exogenous short-run variables, own lagged short-run variables, and an ECM term, known also as error of 'cointegration', and often explained as disequilibrium from a theory-based long-run relation. If we compare (3) with an ALI model, we may regard the factors, *f*, in (1) as a summary representation of exogenous short-run shocks, i.e. type one shocks, and the own lags of the forecast variable in (2) as covering own lagged short-run shocks, i.e. type two shocks. However, type three shocks are not explicitly included in the ALI. It seems that the ALI method only summarizes co-movement in the form of covariance of a pool of variables, whereas, according to many equilibrium economic theories, co-movement in the form of co-trend among certain variables plays an important role in driving the dynamics of endogenous variables.[12]

Therefore, a new scenario, designated as Scenario E, is proposed to see if the ALI results can be improved when deviations from such co-trend, i.e. the third type of shocks, are added to the indicator set of Scenario A. The third type of shocks is adopted from the ECM terms embedded in certain relevant equations in the MESMs.[13] Notice that the extension can be executed in two ways. One is to add the ECM terms as indicator variables in the first step; the other is to extend the VAR model by the ECM terms during the second step. However, experiments show that the latter way is undesirable due to the data-frequency problem. Since all the ECM terms are at quarterly frequency, extension of VARs by these terms forces us to reduce the VARs from monthly to quarterly models, making the forecasts significantly worse than those by the former way. Hence, Scenario E is carried out by treating the ECM terms as indicators.

In terms of short-run forecasts, the addition of the ECM terms is shown to improve the forecast accuracy in most cases, especially in comparison with Scenario A, albeit sometimes marginally (Table 4).[14] The improvement is more discernible in the inflation forecasts, as the inflation series are more random and less seasonal than the GDP growth series.

When it comes to multiple-step forecasts (see Tables 5 and 6), the addition of the ECM terms generates mixed results. The addition help significantly in delaying the deterioration of ALI forecasts in the cases of inflation forecasts of the Philippines and GDP growth forecasts of Indonesia; but it can also make the forecasts worse, as in the case of inflation forecasts in China; it has not made significant differences for the rest of the cases. On balance, it seems worthwhile to take into consideration in the ALI indicator sets, disequilibrium shocks guided by economic theories. Albeit, caution should be exercised in choosing which disequilibrium shocks are the most relevant to include.

In view of the finding that results of scenario B are better than those of scenario A in the cases of China and Indonesia, another scenario (Eb) is setup that adds ECM terms to scenario B. This scenario is carried out only for the relevant two countries. Comparison of the results

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[12] See (Forni *et al*, 2004) for a detailed discussion between DFMs and structural VARs.

[13] The ECM terms derive from long-run relationships postulated by economic theory. On many occasions, the long-run coefficients are imposed.

(see Tables 4, 5 and 6) reveals the dominance of scenario Eb over scenario E, especially in the case of inflation forecasts in China, where both the number of factors and the VAR lag number are smaller in scenario Eb as compared to scenario E.[15] This experiment suggests that it is desirable to augment an indicator set by the ECM terms embodying the relevant long-run theories when the set is chosen under *a priori* theoretical guidance and this is shown to produce relatively good forecasts.

Let us now look at how the general→simple model reduction procedure can help reduce the uncertainty in the ALI forecasts. Although the DFMs have the power of significantly reducing a large number of indicators into a few common factors, a VAR model used in the second step can still easily run up to over a hundred parameters when there are more than three factors involved, making it difficult to decide how robust the VAR is in producing the forecasts. To combat the curse of dimensionality of VARs, the general→simple modeling procedure is adopted here to reduce unrestricted VARs into parsimoniously reduced VARs. Specifically, the computer-automated approach of PcGets is utilized to carry out the reduction efficiently, see (Hendry and Krolzig, 2001).[16]

The advantages of this modification are immediately noticeable from the drastic reduction of the number of parameters reported in Table 7. As the parameter number in each equation of a VAR shrinks to a manageable size, it becomes possible for us to examine how much and in what manner each factor contributes to the forecasts and how robust the VAR is by means of various model specification tests. In particular, parameter constancy can be checked via recursive estimation and parameter instability tests in view of the forecasting requirement.[17]

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[14] For the details of the ECM terms added, see the Appendix.

[15] The only exceptional case here not showing better results is inflation forecasts of Indonesia. However, it should be noted that the VAR of scenario E contains six factors whereas the VAR of scenario Eb only four factors in this case.

[16] The default ‘conservative’ strategy is used during the model reduction in PcGets.

[17] PcGive is used for detailed parameter analyses. None of these model specification and reduction statistics are reported here in order to keep the paper short.

The results reveal that some of the VAR equations in certain scenarios suffer significantly from structural shifts, mostly due to the East Asian financial crisis, and that some factors are largely unpredictable in the VARs. Such information enables us to assess the reliability of the VAR in generating the forecasts.

The advantages of the VAR reduction are also noticeable from various RMSEs reported in Tables 4, 5 and 6. In view of the one-step ahead forecasts (Table 4), the VAR reduction has brought down the RMSEs in about half of the cases. The improvement is more marked in several cases in the eight-step ahead forecasts (Tables 5 and 6), e.g. the inflation forecasts of China and the Philippines, and the GDP growth forecasts of Indonesia. The improvement seems due to the fact that model reduction has significantly reduced unwanted noises in the unrestricted VAR from getting into the forecasts. It is also found that the cases where model reduction has not helped improve forecasts tend to suffer from parameter shifts in the reduced VAR as well as from low forecastability of one or more of the factors in the related VAR.

5. Conclusion

This paper investigates the comparative forecast performance of the ALI method versus the MESMs. Inflation and GDP growth are used as the objects of the forecast comparison. China, Indonesia and the Philippines are used as the cases of the investigation. The following key results can be summarized from a huge amount of ALI experiments that have been carried out.

1. The ALI method can generally outperform MESMs in short-run forecasts provided that the indicator variable sets, the number of factors and the VAR lag orders are carefully selected. However, its forecasting advantage tends to fade away as the forecast horizon increases. MESMs can be more robust for longer-run forecasts in comparison.

2. Freer inclusion of data information into the ALI indicator variable sets, as compared with the more theory-guided variable selection in the MESMs, may help improve forecast

accuracy, but may also spoil it by bringing in unwanted noise. On balance, both theory and good economic sense are required in choosing indicator variables and the tendency of including whatever data is available should be avoided.

3. Use of monthly frequency data can help improve forecast accuracy of quarterly indicators, but it also carries the risk of bringing in unwanted noise. To avoid such risk, it is advisable to consider carefully the data features of the forecast target when choosing indicator variables. The common belief that higher frequency information will always help improve forecasts is unwarranted.

4. Inclusion of long-run disequilibrium indicators as an additional type of indicator variables in the ALI may help improve the forecast accuracy, especially for multi-step forecasts. This finding suggests that the common practice of de-trending indicator variables in DFMs may result in loss of long-run disequilibrium information and can be tested or remedied by inclusion of the theory-based equilibrium-correction variables.

5. The ALI method involves greater uncertainty than MESMs in the use of unrestricted VARs. One way of reducing the uncertainty is to adopt the general→simple model reduction procedure from the MESMs. The procedure not only helps to trim out unwanted noise from entering the ALI forecasts but also enables modelers to assess closely the robustness of the VAR model specification.

6. As the specification uncertainty of econometric models is known to be hard to evaluate as far as forecasting an evolving economic reality is concerned, it is more desirable to compare and utilize forecasts from both modeling sources than settle on a single method.

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Appendix: Variables and Data Sources

" ✔ " indicates that the variable is used as an indicator for Inflation or GDP growth.

Variables	Frequency	Inflation	GDP growth	Source
China				
Average Repo Rate	Monthly	✔		PBC
Balance of Trade	Monthly		✔	Computed from IMF
Base Money (million yuan, M0 plus RSV)	Monthly	✔	✔	QB
Base Money Supply (million yuan, net foreign assets plus net government claims and borrowed reserve by financial institutions at PBC)	Monthly	✔	✔	QB
Brent Crude - Current Month,FOB U$/BBL	Monthly	✔	✔	Datastream
Chinese Renminbi to US$ (GTIS)	Monthly	✔		CMEI
Consumer Confidence Index	Monthly	✔	✔	NBS
Consumer Price Index (1992Q1=1)	Monthly		✔	NBS
Consumer Price Index (1992Q1=1) ECM term	Quarterly	✔		PRC Model
Government Expenditure	Monthly		✔	CMEI
Gross Domestic Product (in 1992Q1 price)	Quarterly	✔		CMEI
Investments	Monthly		✔	CMEI
Loans	Monthly		✔	CMEI
M1	Monthly	✔	✔	QB
M1 ECM term	Quarterly	✔		
Net Industrial Production (Value Added) Current Price	Monthly	✔	✔	CMEI & NBS
Real Effective Exchange Rate Index - CPI Based	Monthly	✔		IMF
Real Estate Climate Index	Monthly	✔		Datastream
Secondary Sector Value Added (in 1992Q1 price) ECM term	Quarterly	✔	✔	PRC Model
Shanghai Composite Stock Index	Monthly	✔		NBS
Tertiary Sector Value Added (in 1992Q1 price) ECM term	Quarterly		✔	PRC Model
Total Retail Sales Current Price	Monthly	✔	✔	CMEI
Unemployment Rate	Quarterly	✔	✔	Computed from CSY

Note: National Bureau of Statistics is abbreviated as NBS; China Monthly Economic Indicators is abbreviated as CMEI; Quarterly Banking is abbreviated as QB; China Statistics Yearbook is abbreviated as CSY; International Monetary Fund is abbreviated as IMF.

Variables	Frequency	Inflation	GDP growth	Source
Indonesia				
Brent Crude - Current Month, FOB U$/BBL	Monthly	✔	✔	Datastream
Consumer Price Index	Monthly		✔	BI
Consumer Price Index ECM term	Quarterly	✔		INO Model
EOP Consumer Confidence Index	Monthly	✔	✔	CEIC
EOP Interbank Call Rate	Monthly	✔	✔	BI
Interest rate differential (domestic rate net of US prime lending rate)	Monthly	✔		Datastream
EOP Jakarta Stock Exchange Composite Index	Monthly	✔	✔	BI
Exchange Rate-Indonesian Rupiah To US $ (GTIS)	Monthly	✔	✔	BI
Total exports	Monthly		✔	Datastream
Total Imports	Monthly	✔	✔	Datastream
Imports of consumer goods	Monthly	✔		Datastream
Gross Domestic Product, constant price	Quarterly	✔		BI
Industrial Labor Wage Index	Quarterly	✔	✔	CEIC
Volume of Production Index in Manufacturing	Monthly	✔	✔	CEIC
M1	Monthly	✔	✔	BI
M1 ECM term	Quarterly	✔		INO Model
Commercial Bank Total Outstanding Credits net of credits to individuals	Monthly	✔	✔	Datastream
Primary Sector Value Added, constant price	Quarterly		✔	BI
Secondary Sector Value Added ECM term	Quarterly		✔	INO Model
Tertiary Sector Value Added ECM term	Quarterly		✔	INO Model
Unemployment rate	Quarterly	✔	✔	Computed from CEIC

Note: Bank Indonesia is abbreviated as BI.

Variables	Frequency	Inflation	GDP growth	Source
Philippines				
91-day Treasury Bill Rate	Monthly	✔	✔	Datastream
Brent Crude - Current Month,FOB U$/BBL	Monthly	✔	✔	Datastream
Consumer Price Index (1994=100)	Monthly		✔	SPEI
Consumer Price Index (1994=100) ECM term	Quarterly	✔		PHI Model
Domestic Credit	Monthly	✔	✔	BSP
Domestic Credit CB & DMB ECM terms	Quarterly	✔		PHI Model
Exports (PhP, FOB)	Monthly		✔	FTS
Foreign Exchange Rate	Monthly	✔	✔	SPEI
Government Expenditure (PhP Mn)	Monthly		✔	SPEI
Gross Domestic Product (in 1994 constant price)	Quarterly	✔		NAP
Imports (PhP, CIF)	Monthly	✔	✔	FTS
Imports ECM term	Quarterly	✔		PHI Model
Imports of Consumer Goods (PhP, CIF)	Monthly	✔		FTS
Interest rate differential (domestic rate net of US prime lending rate)	Monthly	✔		Datastream
Job Vacancies	Monthly	✔	✔	SPEI
M1 (PhP Mn)	Monthly	✔	✔	SPEI
M1 ECM term	Quarterly	✔		PHI Model
Overseas Workers Remittances	Monthly	✔		BSP
Prime Lending Rate	Monthly	✔	✔	SPEI
Rainfall Index	Quarterly	✔	✔	PAGASA
Savings Deposit Rate	Monthly	✔	✔	SPEI
Secondary Sector Valued Added (in 1994 constant price) ECM term	Quarterly	✔	✔	PHI Model
Stock Composite Index	Monthly	✔	✔	PSE
Tertiary Sector Value Added (in 1994 constant price)	Quarterly		✔	NAP
Tertiary Sector Value Added ECM term	Quarterly	✔	✔	PHI Model
Unemployment Rate	Quarterly	✔	✔	LFS
Value of Production Index in Manufacturing (1994=100)	Monthly	✔	✔	Datastream

Note: Selected Philippine Economic Indicators is abbreviated as SPEI; Philippine Stock Exchange is abbreviated as PSE; Survey of Selected Industries is abbreviated as SSI; Bangko Sentral ng Pilipinas is abbreviated as BSP; National Account of the Philippines is abbreviated as NAP; Labor Force Survey is abbreviated as LFS; Foreign Trade Statistics is abbreviated as FTS.

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Table 1. ALI information: Number of indicators used

	China		The Philippines		Indonesia	
	inflation	GDP growth	inflation	GDP growth	inflation	GDP growth
Scenario A	13	12	16	17	14	13
Scenario B	8	8	11	14	8	8
Scenario C or D	10	10	13	14	11	10
Scenario E	16	14	23	19	16	15
Scenario Eb	11	10	—	—	10	10

Table 2. ALI: Consistent Estimates of the Number of Factors

(Bai & Ng procedure / Onatski procedure)

Inflation	China	The Philippines	Indonesia
ALI scenario A	1 / 4	1 / 5	2 / 4
ALI scenario B	4 / 3	4 / 4	4 / 3
ALI scenario C	1 / 4	1 / 4	2 / 4
ALI scenario D	1 / 4	4 / 4	4 / 4
ALI scenario E	1 / 5	1 / 4	6 / 5
ALI scenario Eb	4 / 4	—	4 / 4
GDP growth			
ALI scenario A	4 / 4	3 / 5	5 / 4
ALI scenario B	3 / 4	4 / 4	3 / 3
ALI scenario C	4 / 4	3 / 4	2 / 4
ALI scenario D	2 / 4	3 / 4	1 / 4
ALI scenario E	4 / 4	3 / 5	5 / 4
ALI scenario Eb	4 / 4	—	4 / 5

Table 3. ALI: Number of Lags used in the VAR

Inflation			
	China	The Philippines	Indonesia
ALI scenario A	12	5	6
ALI scenario B	10	5	6
ALI scenario C	12	5	6
ALI scenario D	4	2	4
ALI scenario E	12	6	5
ALI scenario Eb	10	—	6
GDP growth			
	China	The Philippines	Indonesia
ALI scenario A	9	7	6
ALI scenario B	9	7	9
ALI scenario C	9	7	9
ALI scenario D	4	3	4
ALI scenario E	9	7	6
ALI scenario Eb	9	—	6

Table 4. RMSEs for One-quarter Ahead Forecasts

Inflation

	China	The Philippines	Indonesia
MESM	*1.295*	*0.515*	*1.092*
ALI scenario A (by reduced VAR)	1.273 (1.206)	0.461 (0.551)	1.053 (1.061)
ALI scenario B (by reduced VAR)	0.909 (0.866)	0.430 (0.408)	0.968 (1.037)
ALI scenario C (by reduced VAR)	1.299 (1.233)	0.414 (0.420)	0.967 (1.000)
ALI scenario D (by reduced VAR)	1.176 (0.997)	0.657 (0.877)	2.360 (1.513)
ALI scenario E (by reduced VAR)	1.214 (0.928)	0.308 (0.343)	0.947 (0.872)
ALI scenario Eb (by reduced VAR)	0.879 (0.859)	—	0.960 (1.026)
GDP growth			
	China	The Philippines	Indonesia
MESM	*2.147*	*1.417*	*2.969*
ALI scenario A (by reduced VAR)	1.537 (1.850)	1.897 (2.166)	2.232 (1.980)
ALI scenario B (by reduced VAR)	1.361 (1.474)	1.913 (1.797)	2.115 (2.208)
ALI scenario C (by reduced VAR)	1.528 (1.550)	1.711 (1.837)	1.806 (1.899)
ALI scenario D (by reduced VAR)	1.524 (1.241)	2.487 (2.083)	1.791 (1.870)
ALI scenario E (by reduced VAR)	1.574 (1.441)	1.873 (2.370)	2.173 (2.037)
ALI scenario Eb (by reduced VAR)	1.169 (0.879)	—	2.026 (1.998)

Note: The figures in the upper row are generated by unrestricted VARs using the lag numbers given in Table 3. The figures in brackets are generated by the reduced VARs.

Table 5. RMSEs for H-Quarters Ahead Forecasts: Inflation

Quarters ahead	1	2	3	4	5	6	7	8
China								
MESM	*1.295*	*1.689*	*2.009*	*2.208*	*1.910*	*1.990*	*2.188*	*2.170*
ALI: Scenario A	1.273	2.825	4.450	6.348	3.414	2.442	2.862	3.515
ALI: Scenario B	0.909	1.968	3.199	4.528	3.796	4.563	5.371	6.306
ALI: Scenario E	1.214	2.787	4.534	6.739	5.461	6.437	7.494	8.706
ALI: Scenario Eb	0.879	1.840	3.054	4.177	3.688	4.384	5.143	6.025
Using parsimoniously restricted VAR:								
ALI: Scenario A	1.206	2.226	2.495	3.477	2.808	2.474	2.844	3.125
ALI: Scenario B	0.866	1.089	1.417	2.185	2.502	2.941	3.543	3.787
ALI: Scenario E	0.928	1.338	1.362	2.122	2.120	2.549	3.480	3.304
ALI: Scenario Eb	0.859	1.147	1.423	2.178	2.494	2.856	3.374	3.582
The Philippines								
MESM	*0.515*	*0.912*	*1.319*	*1.507*	*1.604*	*1.643*	*1.634*	*1.615*
ALI: Scenario A	0.461	0.971	2.012	3.025	3.927	4.454	4.532	4.583
ALI: Scenario C	0.414	0.940	1.914	2.943	3.784	4.339	4.483	4.564
ALI: Scenario E	0.308	0.665	1.468	2.421	3.377	3.944	4.086	4.175
Using parsimoniously restricted VAR:								
ALI: Scenario A	0.553	1.259	2.108	2.979	3.652	4.006	4.179	4.325
ALI: Scenario C	0.420	0.891	1.647	2.495	3.189	3.489	3.605	3.651
ALI: Scenario E	0.343	0.745	1.532	2.424	3.438	3.962	4.103	4.203
Indonesia								
MESM	*1.092*	*2.036*	*2.649*	*4.479*	*4.445*	*3.776*	*3.266*	*3.498*
ALI: Scenario A	1.053	2.450	3.152	3.836	4.251	5.294	6.353	7.233
ALI: Scenario C	0.967	2.041	2.426	3.044	3.497	4.298	4.813	5.113
ALI: Scenario E	0.947	2.196	3.537	4.997	6.094	6.762	6.837	6.686
ALI: Scenario Eb	0.960	2.429	3.910	5.767	7.194	7.639	7.457	7.077
Using parsimoniously restricted VAR:								
ALI: Scenario A	1.061	2.406	3.151	3.822	4.547	5.947	7.115	8.014
ALI: Scenario C	1.000	2.279	3.061	4.060	4.996	6.394	7.323	7.767
ALI: Scenario E	0.872	1.836	2.681	3.382	3.732	3.756	3.913	3.659
ALI: Scenario Eb	1.026	2.275	3.111	4.656	6.038	6.699	6.618	6.125

Table 6. RMSEs for H-Quarters Ahead Forecasts: GDP growth

Quarters ahead	1	2	3	4	5	6	7	8
				China				
MESM	*2.147*	*2.181*	*2.070*	*1.605*	*1.326*	*1.379*	*1.299*	*1.393*
ALI: Scenario A	1.537	0.885	1.180	1.020	1.067	0.975	1.072	1.046
ALI: Scenario B	1.361	0.917	1.229	1.039	1.106	0.58	1.036	0.987
ALI: Scenario E	1.574	1.058	1.112	0.980	1.099	1.233	1.174	1.030
ALI: Scenario Eb	1.169	1.034	1.213	1.190	1.127	1.003	1.182	1.101
Using parsimoniously restricted VAR:								
ALI: Scenario A	1.850	2.217	2.352	1.917	1.784	1.419	1.440	1.683
ALI: Scenario B	1.474	0.967	1.239	1.246	1.239	1.482	1.655	1.665
ALI: Scenario E	1.441	1.526	1.907	1.637	1.159	0.997	1.195	1.104
ALI: Scenario Eb	0.879	1.010	1.039	0.917	1.157	1.137	1.297	1.316
				The Philippines				
MESM	*1.417*	*1.228*	*1.028*	*1.249*	*1.324*	*1.255*	*1.411*	*1.381*
ALI: Scenario A	1.897	2.543	2.097	2.077	2.166	2.203	2.167	2.261
ALI: Scenario C	1.711	2.245	2.222	2.158	2.228	2.118	2.128	2.195
ALI: Scenario E	1.873	2.538	2.093	2.084	2.168	2.212	2.172	2.266
Using parsimoniously restricted VAR:								
ALI: Scenario A	2.166	2.512	2.518	2.135	2.000	1.877	1.894	1.964
ALI: Scenario C	1.837	2.453	2.071	2.080	2.244	2.205	2.183	2.212
ALI: Scenario E	2.370	3.088	2.610	2.088	1.928	1.978	2.031	1.969
				Indonesia				
MESM	*2.969*	*3.554*	*5.016*	*4.624*	*3.942*	*4.163*	*4.941*	*3.655*
ALI: Scenario A	2.232	2.106	2.459	1.633	2.334	2.307	2.275	1.964
ALI: Scenario D	1.791	2.780	3.369	3.741	3.976	2.958	2.335	3.362
ALI: Scenario E	2.173	2.281	2.479	1.777	1.643	1.584	1.423	0.951
ALI: Scenario Eb	2.026	2.271	2.096	1.808	2.279	2.250	1.720	1.190
Using parsimoniously restricted VAR:								
ALI: Scenario A	1.980	2.215	2.635	2.129	1.578	1.251	1.363	1.028
ALI: Scenario D	1.870	3.199	3.234	2.472	2.188	1.627	1.721	1.794
ALI: Scenario E	2.037	2.457	2.620	2.316	1.396	1.101	1.038	0.960
ALI: Scenario Eb	1.998	2.486	2.548	2.098	1.804	1.893	1.183	0.974

Table 7. Numbers of parameters reduced from unrestricted VARs to parsimoniously reduced VARs

	Inflation		
	China	The Philippines	Indonesia
ALI scenario A	300 → 52	180 → 32	150 → 47
ALI scenario B	250 → 38	125→ 25	150 → 46
ALI scenario C	300 → 39	125 → 28	150 → 52
ALI scenario D	100 → 41	50 → 14	100 → 44
ALI scenario E	432 → 73	210 → 27	245 → 61
ALI scenario Eb	250 → 43	—	150 → 46
	GDP growth		
	China	The Philippines	Indonesia
ALI scenario A	225 → 77	252 → 75	216 → 75
ALI scenario B	225 → 52	175 → 55	144 → 41
ALI scenario C	225 → 54	175 → 60	225 → 59
ALI scenario D	100 → 41	75 → 20	100 → 34
ALI scenario E	225 → 61	252 → 70	216 → 76
ALI scenario Eb	225 → 74	—	216 → 81

Note: Unrestricted VARs mean the VARs using the lag numbers given in Table 3.

Figure 1. Variables of forecast interest

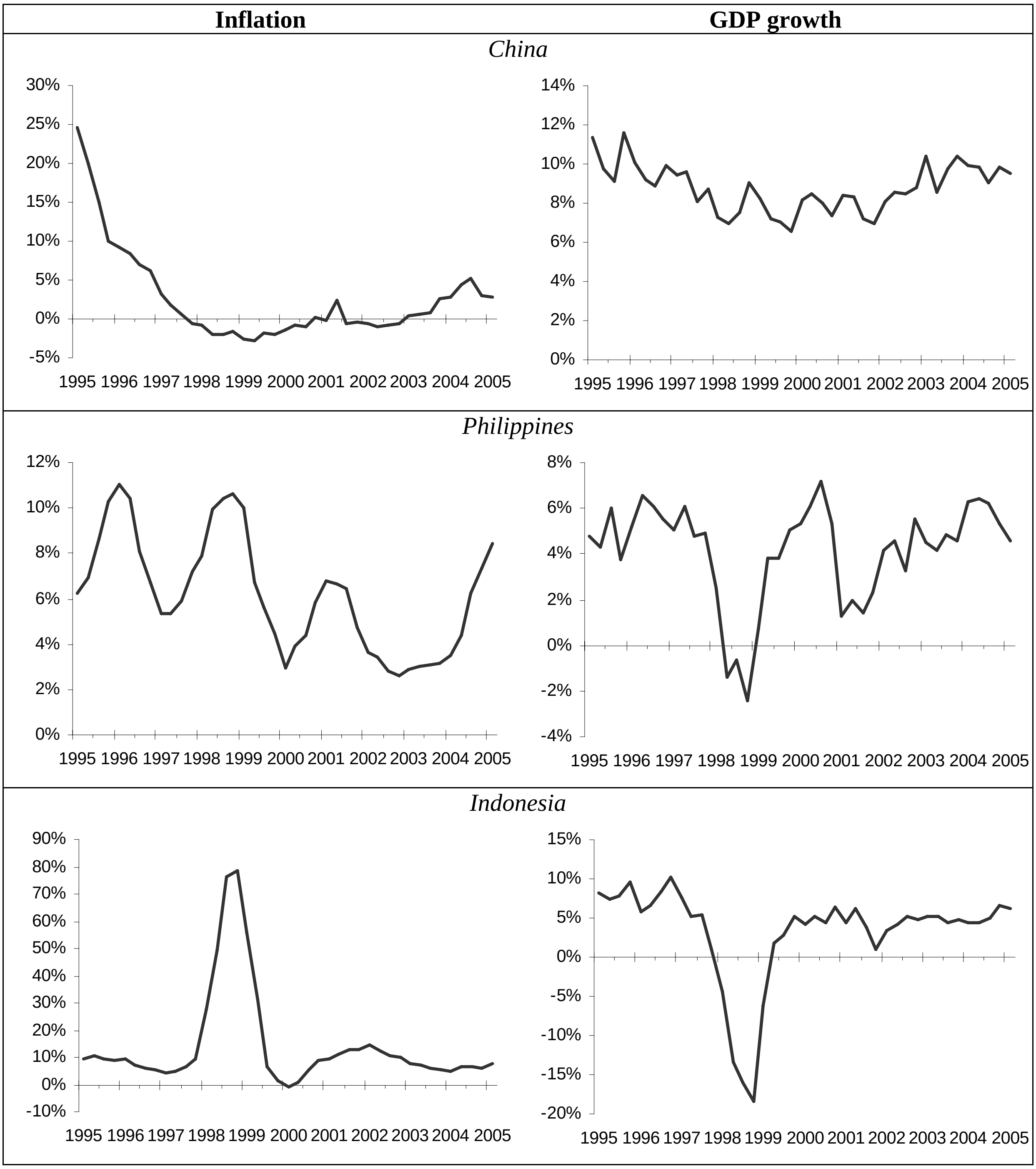
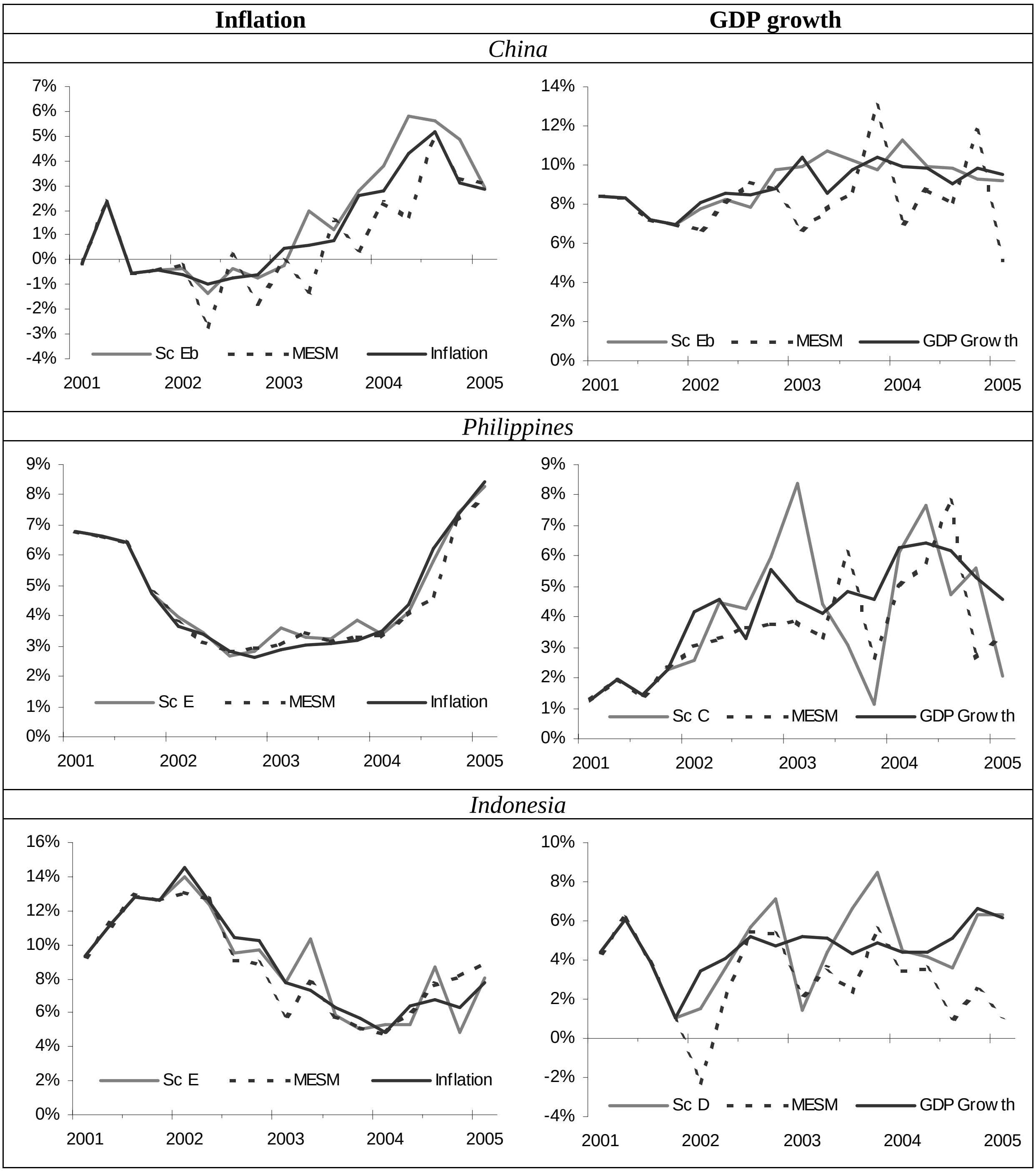
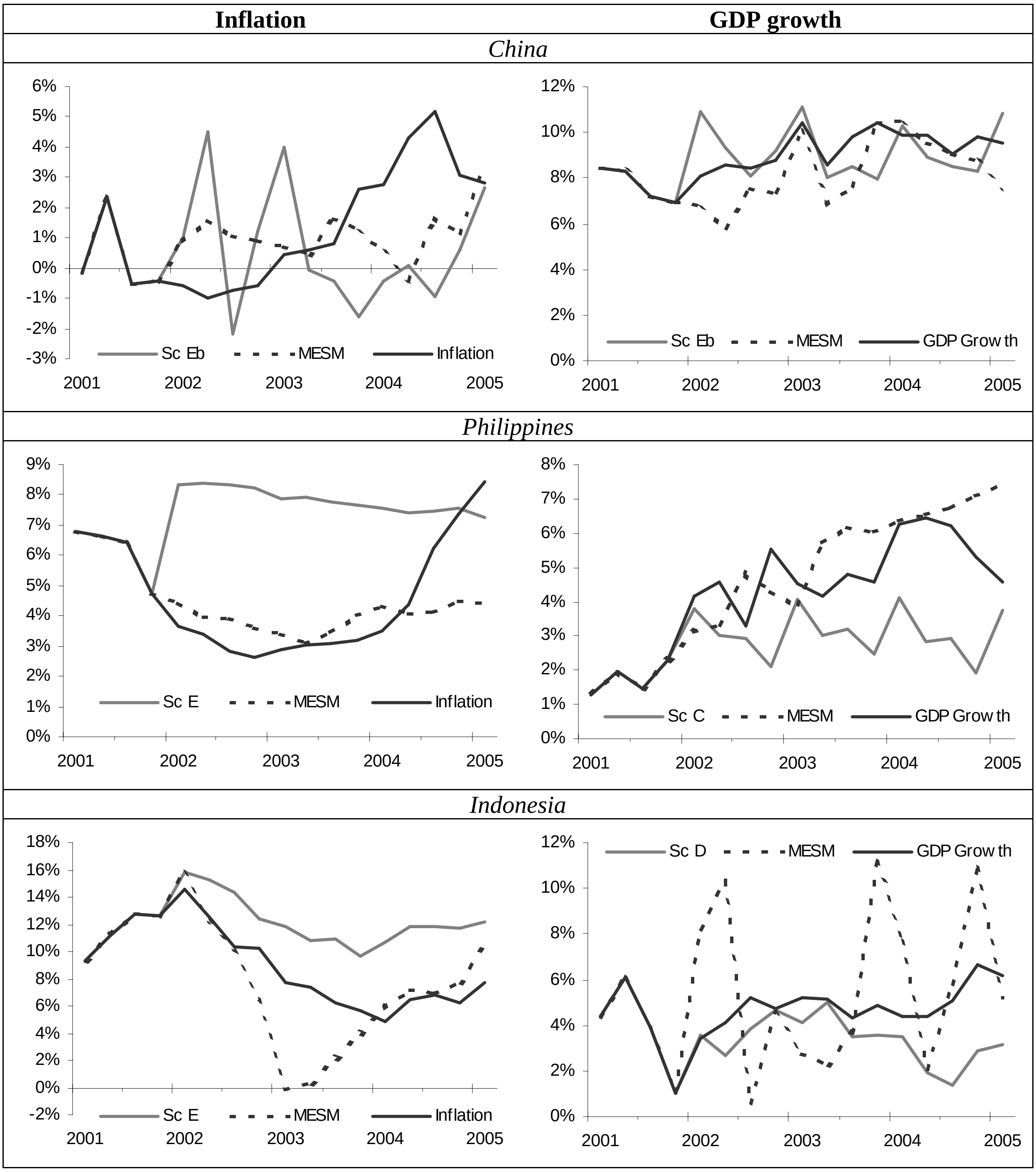


Figure 2. 1-step forecast results



Note: The scenarios (shortened as 'Sc') presented here are the best fitting ALI scenarios by parsimoniously restricted VAR models for the three countries.

Figure 3. 8-steps forecast results



Note: The scenarios (shortened as 'Sc') presented here are the best fitting ALI scenarios by parsimoniously restricted VAR models for the three countries.

Figure 4. MESM *h*-step Forecast Errors (as percentage to the actual values)