An Adaptive Approach to Forecasting Three Key Macroeconomic Variables for Transitional China *

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Abstract

The macroeconomic forecasts for emerging economies often suffer from the constraints of instability and limited data. In light of these constraints, we propose the use of a local autoregressive (LAR) model with a data-driven estimation window, i.e., a local homogenous interval, that is adaptively identified to strike a balance between information efficiency and stability. When applied to three key macroeconomic variables of China, the LAR model substantially outperforms the alternative models for various forecast horizons of 3 to 12 months, with forecast error reductions of between 4% and 64% for the IP growth, and between 1% and 68% for the inflation rate. The one-quarter ahead performance of the LAR model matches that of a well-known survey forecast. The patterns of the identified local intervals also coincide with the characteristic evolution of the gradual reforms and monetary policy shifts in China. In short, the LAR model is suitable for not only forecasting, but also the real-time monitoring of the effects of regime and policy changes in emerging economies.

Keywords: Emerging economy, China, Local parametric model, Out-of-sample forecasting, Instability, Data limitation

JEL Classification: E43, E47

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*The authors gratefully acknowledge the many useful comments and suggestions received from the anonymous referees and the editor of this journal. The authors take responsibility for any errors.

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1 Introduction

Compared with the forecasts for developed economies, the macroeconomic forecasts for emerging markets and transition economies face greater challenges in two key areas: first, the structural changes due to policy and regime shifts occur more frequently (Balcilar et al., 2015); and second, the available data tend to be far more limited (Jusczak et al., 1993; Liu et al., 2012). In this paper, we examine these features by using a local autoregressive (LAR) model to estimate and forecast three key macroeconomic variables of China. We find that the LAR model is able to deliver robust predictive performance under the constraints of instability and limited data.

The accurate prediction of macroeconomic variables is a crucial factor in policy decisions. However, economists and policymakers face difficulties in predicting these variables, even for developed economies, which suffer less from the aforementioned problems (De Gooijer and Hyndman, 2006; Clements and Hendry, 2008; Manganelli, 2009). In general, the problem of instability increases the parameter uncertainty in parameterised models (Stock and Watson, 1999, 2007; Hendry and Clements, 2003; D'Agostino et al., 2013; Cross and Poon, 2016). This problem is more severe in emerging markets (Jusczak et al., 1993). Thus, given the increasing importance of emerging markets in the world economy, there is an urgent need to develop accurate economic forecasts for developing countries. Kaya (2013) examines the yield curve forecasting performance in Turkey. Gupta and Steinbach (2013) forecast key macroeconomic variables for South Africa using a DSGE-VAR model. Pourazarm and Cooray (2013) examine and forecast the electricity demand in Iran. Liu et al. (2012) evaluate the GDP nowcasts for Latin American economies. In a study on the Chinese economy, Maier (2011) compares the out-of-sample performance of three mixed-frequency forecasting models, and finds that the factor model fares best. Mikosch and Zhang (2014) use a mixed sampling model to forecast Chinese GDP growth, and extensively evaluate the predictive power of various indicators. However, the research on systematic forecasting in the context of transition economies has largely overlooked the transition effects. Although some studies recognise the data limitation and instability problems (Jusczak et al., 1993; Liu et al., 2012; Balcilar et al., 2015), the tools for conducting accurate forecasting are still lacking.

There are numerous fruitful studies on forecasting macroeconomic variables in the literature, including time series models, macro-theoretical based models such as the Philips curve model, structural VAR models and factor-augmented VAR models (Forni et al., 2000, 2003; Stock and Watson, 2002a,b; Bai and Ng, 2002, 2008; Moser et al., 2007). To address the issue of parameter instability, many models include features such as a long memory and structural breaks (Banerjee et al., 2008; Stock and Watson, 2009; Clark and McCracken, 2010; Geweke and Jiang, 2011; Bekiros, 2014). However, complex econometric models often fail to outperform simple time series models or ad-hoc forecasts based on surveys (Ang et al., 2007; Stock and Watson, 2008; Belmonte and Koop, 2014), especially for emerging markets with limited data (Liu et al., 2012). The factor-augmented VAR model, for example, hinges on the effective selection of factors and tends to perform poorly in out-of-sample forecasting due to the potential structural changes in the factors. Predicting local shifts in the factors can also present computationally non-trivial challenges (Castle et al., 2013).

In terms of the modeling and forecasting for emerging economies, a desirable model is required to appropriately strike a balance between efficiency and parameter stability under the constraint of limited information. We consider the recently developed LAR model to be a particularly suitable candidate. The model is based on the local parametric approach (LPA) proposed by Spokoiny (1998, 2009), which is predicated on the idea that a parametric framework can be used to locally approximate sophisticated stochastic processes within data-driven intervals of homogeneity at each time point. Chen et al. (2010) propose an LAR model to forecast the realised volatilities with long-memory patterns prevalent in financial time series. The empirical out-of-sample forecast of the LAR model outperforms the popular alternative models. Chen and Niu (2014) further apply the local adaptive approach to forecast the US yield curve. Their method substantially outperforms the alternative term-structure models at 3- to 12-month forecast horizons. The approach is shown to capture structural changes in the time series quite well, and the detected interval endings are in line with major policy changes and economic recessions. Recent successful applications of the adaptive approach include Härdle et al. (2014), Härdle et al. (2015), Xu et al. (2015), Chen and Li (2016) in forecasting the order flows, trading volumes, tail events and energy prices in financial markets.

To verify the effectiveness of the LAR model in the context of emerging markets and economies in transition, we take China as a representative context for our empirical study. China has undergone notable reforms since 1978, gradually changing from a planned economy to its current socialist market model, and has actively adopted modern technologies and management practices (Naughton, 2007; Lin, 2013; Chow, 2015). The transition has been accompanied by several decades of rapid economic growth and remarkable economic achievements. China's GDP growth averaged 9.8% per year from 1978 to 2013, and in 2009, China surpassed Japan as the world's second largest economy. Given this structural instability and the data limitations, we use the LAR model to forecast three key macroeconomic variables of China: the growth rate of industrial production (IP growth) as a proxy for real output growth, the CPI inflation rate as representative of the nominal variables, and the seven-day China Interbank Offered Rate (Chibor, i.e., National Interbank Offered Rate) as a money market indicator.

For model comparison, we choose as alternatives popular forecast models with predetermined estimation windows, including a time series model, a real activity augmented model and a factor model. We also make comparisons with Bayesian model averaging (BMA) and a well-recognised survey, the China Macroeconomic Research Center (CMRC) Langrun[1] survey forecast, denoted as the CMRC survey in this paper. We find that the LAR model substantially outperforms the alternative models for 3- to 12-month ahead forecasts, with error reductions of between 4% and 64% for the IP growth and between 1% and 68% for the inflation rate. The model also outperforms the alternatives for 4- to 24-week ahead forecasts of the interest rates, with error reductions of between 1% and 25%. In addition, the identified homogenous intervals from the LAR model provide useful information for monitoring and understanding China's economic dynamics in real time. The average sample length of the identified homogenous intervals is 22 months for the IP growth, 41 months for the inflation rate and 46 weeks for interest rates, which are much shorter than the estimation

[1] The Langrun survey was initiated in July 2005 by the Peking University China Center for Economic Research (CCER). Following the release of the official data for the previous quarter, the CMRC invites about two dozen institutions to predict the major macroeconomic variables for the next quarter, including the GDP growth, CPI, industrial production growth, interest rates and exchange rates. The involved financial institutions include JP Morgan, HSBC, Goldman Sachs, UBS and the Industrial and Commercial Bank of China.

sample lengths traditionally used in rolling and recursive window forecasts.

The rest of the paper is organised as follows. Section 2 presents the statistical properties of the three macroeconomic variables of interest and the motivations for using LAR modeling. Section 3 describes the adaptive model. Section 4 presents all of the related data, the forecast procedure, and the alternative models used for comparison. Section 5 presents the forecast results and a detailed discussion of the comparisons with the alternatives. Section 6 concludes the paper.

2 Data

We consider three macroeconomic variables from the China Economic and Industry Database (CEIC) and use their longest available samples: the CPI inflation rate (1992:1–2015:12) and the year-on-year growth rate of industrial production (IP growth) (1995:1–2015:12), which are sampled monthly; and the weighted average of the seven-day Chibor[2], which is taken from the closing rate of the weekly final trading day from January 2001 to December 2015, a total of 773 data points.

[Figure 1. Plot of the three macroeconomic variables]

Table 1 presents the descriptive statistics for the three time series. The graphs of the autocorrelation functions in Figure 2 show that all three series exhibit high persistence, with the autocorrelations slowly decaying up to lag 30. This feature indicates either a long memory or structural changes. The interest rate series presents a clustering feature of volatility, and jumps that imply changing volatility in innovations. This evidence provides the justification for applying an adaptive approach that features a globally changing, yet locally stationary data-generating process.

[2]It is worth mentioning that there are other interest rate candidates, such as the Shanghai Interbank Offered Rate (Shibor), which was officially launched in January 2007, much later than the Chibor. These two rates follow each other very closely in the common sample period and jointly play crucial roles as the basic interest rates in China.

[Table 1. Statistics of the three macroeconomic variables]

[Figure 2. Autocorrelation functions of the three variables]

3 LAR-based adaptive modeling and forecasting

In this section, we introduce the model set-up and estimation procedure of the LAR model. Each of the macroeconomic time series is modelled as an LAR(1) process, which is also elaborated in detail in Chen et al. (2010).

3.1 The LAR model

3.1.1 The LAR model and estimator

Each macroeconomic variable is modelled using a simple LAR(1) model that defines the data-generating process as an autoregressive process with one lag. Unlike the traditional AR(1) model, the parameter set is allowed to be time varying and thus is indexed to the local time t when the model is estimated with data up to t. Denoting the parameter set as $\theta_t = (\theta_{0t}, \theta_{1t}, \sigma_t)^\top$, the model is,

$$y_t = \theta_{0t} + \theta_{1t} y_{t-1} + \mu_t, \quad \mu_t \sim N(0, \sigma_t^2). \tag{1}$$

The time-varying parameter set indicates that the model recognises possible parameter changes in the data-generating process. In addition, the model estimation relies on the existence and identification of a local interval of length m_t, $[t - m_t + 1, t]$, over which the parameter θ_t stays approximately constant, i.e., locally homogenous, so that the process can be reasonably described by a traditional AR model.

For a specified interval $I_t = [t - m_t + 1, t]$, the (quasi) maximum likelihood estimation can be implemented to obtain the local maximum likelihood estimator $\tilde{\theta}_t$, which is defined as,

$$\begin{aligned}\tilde{\theta}_t &= \arg\max_{\theta_t \in \Theta} L(y; I_t, \theta_t) \\ &= \arg\max_{\theta_t \in \Theta} \left\{ -(m_t - 1)\log \sigma_t - \frac{1}{2\sigma_t^2} \sum_{s=t-m_t+2}^{t} (y_s - \theta_{0t} - \theta_{1t} y_{s-1})^2 \right\}.\end{aligned}$$

where Θ is the parameter space and $L(y; I_t, \theta_t)$ is the local log-likelihood function.

3.1.2 Testing procedure for homogenous intervals

In practice, although the interval of local homogeneity is unknown, it can be automatically identified through a backward testing procedure in the LAR model. Specifically, the longest possible homogenous interval is selected from various interval candidates containing information up to time t. To reduce the computational burden, at any particular t, we divide the local sample with discrete increments of M periods ($M > 1$) between any two adjacent subsamples to obtain K_t candidate subsamples,

$$I_t^{(1)}, \cdots, I_t^{(K)} \text{ with } I_t^{(1)} \subset \cdots \subset I_t^{(K)}.$$

where $I_t^{(1)}$ is the shortest subsample that can cover a sufficient sample period such that an AR(1) model is reasonably fitted with approximately constant parameters.

The idea of the testing procedure is to use the shortest candidate interval as a benchmark and sequentially evaluate the next longer candidate interval with more information to decide whether to replace the previously accepted candidate with a longer one for higher estimation efficiency, or terminate the screening when a significant break is identified. For a specific interval $I_t^{(k)}$, the maximum likelihood (ML) estimator is denoted as $\tilde{\theta}_t^{(k)}$ and the local homogenous estimator is denoted as $\hat{\theta}_t^{(k)}$. Given that $I_t^{(1)}$ is locally homogenous, we have $\hat{\theta}_s^{(1)} = \tilde{\theta}_s^{(1)}$ by default. For subsequent intervals, we obtain $\tilde{\theta}_t^{(k)}$ from the maximum likelihood estimation. Under the null hypothesis that $I_t^{(k)}$ is locally homogenous, we compute the test statistic

$$T_t^{(k)} = \left| L(I_t^{(k)}, \tilde{\theta}_t^{(k)}) - L(I_t^{(k)}, \hat{\theta}_t^{(k-1)}) \right|^{1/2}, \quad k = 2, \cdots, K \tag{2}$$

to measure the divergence of fitness between the interval candidate under hypothetical homogeneity and the previously accepted local homogenous interval. Here, $L(I_t^{(k)}, \tilde{\theta}_t^{(k)}) = \max_{\theta_t \in \Theta} L(y; I_t^{(k)}, \theta_t)$ denotes the fitted likelihood under *hypothetical* homogeneity and $L(I_t^{(k)}, \hat{\theta}_t^{(k-1)}) = L(y; I_t^{(k)}, \hat{\theta}_t^{(k-1)})$ refers to the likelihood of the current testing subsample assuming the parameter estimate from the previously *accepted* local homogenous interval. If $I_t^{(k)}$ is homogenous, the difference measured by the test statistics is due to the sampling randomness and is thus insignificant. Otherwise, if parameter changes occur between $I_t^{(k-1)}$ and $I_t^{(k)}$, then the difference becomes significant. A set of critical values $\zeta_1, \cdots, \zeta_K$ is calibrated with Monte Carlo (MC) simulations and used to test the significance. If $T_s^{(k)} \leq \zeta_k$, we accept that the current subsample $I_t^{(k)}$ is homogenous and update the adaptive estimator $\hat{\theta}_t^{(k)} = \tilde{\theta}_t^{(k)}$ for improved information efficiency with an extended sample length. If $T_t^{(k)} > \zeta_k$, it indicates that the model significantly changes, and the testing procedure ends with the latest accepted subsample $I_t^{(k-1)}$ being selected, such that $\hat{\theta}_t^{(k)} = \hat{\theta}_t^{(k-1)} = \tilde{\theta}_t^{(k-1)}$. For $\ell \geq k$, we have $\hat{\theta}_s^{(\ell)} = \tilde{\theta}_s^{(k-1)}$, so that the adaptive estimator for an even longer subsample at time t is the ML estimator over the identified longest subsample of local homogeneity. The procedure ends if a significant change is found or the longest subsample, $I_t^{(K)}$, is reached under local homogeneity.

3.1.3 Critical values

The critical values are calibrated empirically with MC experiments using an initial training sample of the data. The homogenous intervals are sequentially determined by the likelihood ratio test procedure in section 3.1.2. Suppose that the true parameter set in (1) under homogeneity is θ_t^* at time t, then the accuracy of the model estimation can be measured by the log-likelihood ratio (LR) as,

$$LR_t = L(I_t, \tilde{\theta}_t) - L(I_t, \theta_t^*). \tag{3}$$

Polzehl and Spokoiny (2006) derive a theoretical risk bound for LR when the innovations of the model specification follow i.i.d. Gaussian distributions,

$$E_{\theta_t^*} |LR_t(I_t, \tilde{\theta}_t, \theta_t^*)|^{1/2} \leq \xi. \tag{4}$$

The critical values are selected so that the estimator can fulfill the risk bound Equation (4) under homogeneity for each interval. We calculate the critical values with MC simulations and generate 10,000 AR(1) processes with the parameter set, $\theta^* = (\theta_0^*, \theta_1^*, \sigma^*)$. θ^* is estimated using a 10-year sample before the forecast exercise, assuming that 10 years is the longest possible homogenous interval for China,

$$y_t = \theta_0^* + \theta_1^* y_{t-1} + \mu_t, \quad \mu_t \sim N(0, \sigma^{*2}) \tag{5}$$

with the initial value $y_0 = \theta_0^*/(1 - \theta_1^*)$. The sample size for each simulation is also equal to the largest homogenous interval, 120 observations, i.e., 10 years for the IP growth and the inflation rate. If the largest interval I_t^K is homogenous, then the largest interval ML estimator is the optimal estimator $\hat{\theta}_t = \hat{\theta}_t^K$, which should then fulfill the risk bound in Equation (4) as,

$$E_{\theta^*} |LR_t(I_t^K, \tilde{\theta}_t^K, \hat{\theta}_t^K)|^{1/2} \leq \xi, \tag{6}$$

where $\hat{\theta}_t^K$ depends on the critical values obtained in the testing procedure as described in 3.1.2.

Using the so-called propagation conditions (Polzehl and Spokoiny, 2006; Spokoiny, 2009) in Equation (7), we sequentially calculate the critical values by substituting the unknown true parameter θ^* with the optimal ML estimator $\hat{\theta}_t^k$ at each sequential testing step k. As the first interval I_t^1 is set as homogenous, when $\zeta_1, \cdots, \zeta_{k-1}$ is fixed, ζ_k is selected as the minimal value that fulfills the following condition,

$$E_{\theta^*} |LR_t(I_t^k, \tilde{\theta}_t^k, \hat{\theta}_t^k)|^{1/2} \leq \frac{k-1}{K-1}\xi, k = 2, \cdots, K. \tag{7}$$

3.2 Real-time estimation and forecast

Following the test and estimation procedure described in section 3.1, we estimate the LAR(1) model for each variable from a selected starting point, and then forecast the variable h-steps ahead assuming that the parameters remain homogenous over the forecast horizons. The estimation and forecast move forward one period at a time until the end of the entire sample.

For a specific forecast horizon h, we follow a direct forecast approach that is simple to implement and robust for possibly misspecified models. The LAR(1) model for horizon h is specified as,

$$y_t = \theta_{0t} + \theta_{1t} y_{t-h} + \mu_t, \quad \mu_t \sim N(0, \sigma_t^2). \tag{8}$$

Hence, at time t, the LAR(1) model for the different forecast horizons may have different sets of parameter estimates and correspondingly identified homogenous intervals.

4 Out-of-sample forecast

This section introduces the forecast procedure, alternative models, and measures of the forecast accuracy for model comparison.

4.1 The LAR forecast procedure

For the time t estimation and its h-step ahead out-of-sample forecast, we choose the same maximum length of interval $I_t^{(K)}$ as $120 + h$ periods for all of the variables. To reduce the computational burden when identifying the homogenous interval at time t, we use a universal set of $K = 20$ subsamples with $M = 6$ at each time point, where M is the number of steps between two adjacent subsamples (between k and $k+1$). Starting from the shortest subsample ($k = 1$) covering the most recent $6 + h$ lag periods, the next subsample ($k + 1$) has a six-period increment backward, and the longest subsample (k capped at $K = 20$) includes $120 + h$ periods. Once an optimal subsample is selected against the next longer subsample, the parameter change is understood to have taken place within the six-period increment in between. In so doing, we trade off precision in break identification for computational efficiency. After all, precise identification of the breaking point may not be a major concern. Moreover, as changes may occur gradually in transition economies, precise point identification of the breaks may not be necessary.

The resulting initial samples for estimation and the forecast comparison periods are summarised in Panel A of Table 2. Due to the limited data availability, the intervals of the data vary, which occasionally binds our choices of alternative window lengths in the forecast comparison. For the monthly inflation and IP growth data, we make out-of-sample forecasts for 1-, 3-, 6-, 9- and 12-month horizons. For the interest rate, the first sample for estimation uses data up to the end of 2005 for 1-, 4-, 12- and 24-week ahead forecasts. Starting from the initial period, we move forward one period at a time to forecast at the respective horizons until we reach the end of the full sample.

[Table 2. Summary of data]

4.2 Alternative models for comparison

For comparison, we choose a comprehensive set of popular forecast models for each macroeconomic variable, denoted as y_t in the following elaboration. These models fall into three different categories: (1) univariate time series models that rely only on the past information of the predicted variable, such as the AR model and the random walk (RW) model; (2) models that explore additional macroeconomic regressors, as motivated by Ang et al. (2007), including the real activity augmented models (RA) for the IP growth, the Phillips curve model (PC) for inflation and the term structure models (TS) for both variables; and (3) models based on large information sets, such as the factor model and BMA. In addition, the well-recognised CMRC survey is selected as the comparison model. As it is weekly and thus has a higher frequency than the other macroeconomic data, the only alternative models for the Chibor are univariate time series models.

4.2.1 Alternative models

In the following models, we denote the lag length by p, and determine the optimal lag length using the Schwarz criterion (BIC).

1. Time series (AR(p)) model. Using a direct forecast approach as in the h-step ahead forecast of the LAR(1) model in Equation (8), the AR(p) model for the h-step ahead forecast is,

$$y_t = \theta_0 + \theta_1 y_{t-h} + \theta_2 y_{t-h-1} + \cdots + \theta_p y_{t-h-p+1} + \varepsilon_t, \varepsilon_t \sim N(0, \sigma_t^2). \tag{9}$$

The corresponding time-t forecast is,

$$\widehat{y}_{t+h|t} = \widehat{\theta}_0 + \widehat{\theta}_1 y_t + \widehat{\theta}_2 y_{t-1} + \cdots + \widehat{\theta}_p y_{t-p+1}. \tag{10}$$

2. Random walk (RW) model.

$$y_t = y_{t-h} + \varepsilon_t,\ \ \varepsilon_t \sim N(0, \sigma_t^2). \tag{11}$$

$$\hat{y}_{t+h|t} = \hat{y}_t. \tag{12}$$

3. AR model augmented with the real activity (RA) variable. We denote the model of IP growth directly as the RA model, and denote that of inflation as the Phillips curve (PC) model. As Shiu and Lam (2004); Chen et al. (2007); Narayan et al. (2008) note, there is a strong correlation between real economic growth and real activity variables such as electricity consumption growth. Inflation is also closely related to real activities in the Phillips curve models. Denoting the real activity as X_t, the model can be represented as

$$y_t = \theta_0 + \sum_{i=1}^{p_1} \theta_{1,i} y_{t-h-i+1} + \sum_{i=1}^{p_2} \theta_{2,i} X_{t-h-i+1} + \varepsilon_t,\ \ \varepsilon_t \sim N(0, \sigma_t^2). \tag{13}$$

   The parameters in lag term i are denoted as $\theta_{j,i}, j = 1, 2$. To predict the IP growth, we choose two alternatives for X_t, i.e., either electricity consumption or a leading economic indicator constructed by the National Bureau of Statistics of China, both of which are retrieved from the CEIC database. We denote these two RA models as RA1 and RA2, respectively. To predict inflation, we choose two alternatives for X_t, i.e., either IP growth or a leading economic indicator constructed by the National Bureau of Statistics of China. We denote these two PC model versions as PC1 and PC2, respectively.

4. Interest rate term-structure (TS) model. We expand the RA model and the PC model to include the nominal risk-free rate, r_t, which is represented by the one-month weighted average national interbank rate offered by the People's Bank of China

(PBoC). This short-term interest rate is an important monetary policy instrument because it is closely linked to the business cycle and carries useful information for forecasting the performance of the real economy in the short to medium run. Although it would be useful to consider the term spread (the difference between long- and short-term interest rates), as it may be more effective in predicting business cycles, we limit our term-structure information to the short-term rate due to the data limitations. China has only had an active treasury bond market producing a meaningful yield curve since 2006. The TS model is thus written as

$$y_t = \theta_0 + \sum_{i=1}^{p_1} \theta_{1,i} y_{t-h-i+1} + \sum_{i=1}^{p_2} \theta_{2,i} X_{t-h-i+1} + \sum_{i=1}^{p_3} \theta_{3,i} r_{t-h-i+1} + \varepsilon_t,\ \ \varepsilon_t \sim N(0, \sigma_t^2). \quad (14)$$

The corresponding parameters in lag term i are denoted as $\theta_{j,i}, j = 1, 2, 3$. For the IP growth, the real activity X_{t-h} can be either the electricity consumption growth (denoted as TS1) or a leading indicator (TS2) or both variables (TS3). For inflation, X_{t-h} can be either IP growth (TS1) or a leading indicator (TS2) or both (TS3).

5. Factor model. For N-dimensional time series X_t, a factor model states that X_t can be sufficiently represented by J number of components, where $J \ll N$,

$$X_t = \Lambda F_t + e_t, \quad (15)$$

where F_t is the J-dimensional factors or principle components, which are derived from the first J eigenvectors of the variance-covariance matrix of X_t. Then, h-step ahead y_t is

$$y_t = \theta_0 + \alpha^\top F_{t-h} + \sum_{i=1}^{p} \theta_i y_{t-h-i+1} + \varepsilon_t,\ \ \varepsilon_t \sim N(0, \sigma_t^2). \quad (16)$$

Based on the variables listed in Table 2, we select the factors that explain at least 90% of the variance of the whole sample. There must be at least three factors.

6. Bayesian model averaging (BMA). Consider R numbers of models, $M_r, r = 1, 2, \cdots, R$, with different model specifications. If at time t, the h-period ahead forecast of y_t with

model M_r is $\hat{y}_{t+h,r}$, then the average forecast with posterior model probabilities is

$$\hat{y}_{t+h|t} = \sum_{r=1}^{R} \hat{y}_{t+h,r} p(M_r \mid y), \tag{17}$$

where $p(M_r \mid y)$ denotes the posterior model probability for model M_r, which can be implied from the prior model probability with Bayesian law.

It is noteworthy that BMA actually incorporates the aforementioned alternative models. If there are Z explanatory variables in the linear regression (in our case, $Z = 27$), then the potential candidate models are $R = 2^Z$. BMA provides a framework of averaging over all possible combinations of forecasts with the weights implied from the posterior model probability (see Equation (17)). The MC3 approach of Madigan et al. (1995) is applied to derive the posterior model distribution. The calculation details can be found in Koop et al. (2007). The BMA approach has been used in various empirical applications (Raftery et al., 1997; Horvath, 2011; Próchniak and Witkowski, 2013; Man, 2015) and has outstanding performance in out-of-sample forecasting because it combines all of the optimal information in the regressors and decreases the risk of model uncertainty. In our estimation, for each round of the MCMC computation, we repeat the simulation 1,100 times, omit the first 100 draws and keep the remaining 1,000 simulation results.

7. CMRC Langrun survey forecast.

   The CMRC survey is a quarterly forecast of the year-on-year growth rate that dates from the third quarter of 2005. In contrast, our IP growth and inflation data are for the monthly year-on-year growth rates. Thus, we transform our three-months ahead monthly forecasts into the one-quarter ahead quarterly counterparts of the year-on-year growth data with Equation (18) (Mariano and Murasawa, 2003),

$$y_t = \frac{1}{3}\left(y^*_{t-2} + y^*_{t-1} + y^*_t\right), \tag{18}$$

   where y_t denotes the transformed quarterly data, and y^*_t represents the corresponding monthly data. For the same underlying realisation y_t, we compare the one-quarter ahead LAR(1) model forecasts with the one-quarter ahead CMRC survey forecasts.

The variables used in the alternative models are listed in Panel B of Table 2. All of the variables are log differences from their original levels, except for the economic indicators and interest rate. For the factor model and BMA model, we uniformly choose the monthly data sample of 1996:1–2015:12.

4.2.2 Forecast procedure for the alternative models

For the alternative models, the choice of regression window follows a rule of thumb: a rolling window of 60 periods (for sufficiently long samples, we also try with 120 periods) and a recursive window expanding sample observations as the forecast progresses. The recursive window approach is preferred when the sample has no changing parameters and the extended sample length increases the information efficiency. The rolling window approach addresses the balance of information efficiency versus possible breaks and the resulting parameter uncertainty. In both cases, however, the choice of window length is predetermined and not selected in a systematic and data-driven manner. Using the direct forecast approach used for the h-step ahead forecast of the LAR(1) model in Equation (8), we also specify alternative models for the h-step ahead forecast as a generalised one-step ahead forecast by lagging the predetermined dependent variables h-step backward.

In addition to the model comparison, we use the CMRC survey as an alternative. The predictive power of the CMRC survey is reputed to be unbeatable because it combines the outlooks of forecast institutions in possession of rich information and sophisticated forecast methods. The resulting CMRC survey forecast provides two measures: a simple average of the institutional forecasts and a weighted average based on the historical forecast accuracy of each participating institution. As the values in both measures are similar, we select the simple average with a longer sample as our comparison candidate.

4.3 Measures of the forecast comparison

We use the measures of the forecast RMSE and mean absolute error (MAE) as indicators of the forecast precision. To compare the out-of-sample forecast performance of the various models, we report the results of a forecast comparison regression and the ratio of the RMSEs relative to the proposed LAR(1) model. As such, we have

$$RMSE = \sqrt{\frac{1}{T}\sum_{t=1}^{T}\left(y_t - \widehat{y}_t\right)^2} \tag{19}$$

and

$$MAE = \frac{1}{T}\sum_{t=1}^{T}\left|y_t - \widehat{y}_t\right|, \tag{20}$$

where T is the forecasting interval, y_t is the actual data for time t, and $\widehat{y}_t$ is the forecast estimator.

Following Stock and Watson (1999); Ang et al. (2007), we regress the observed actual data on the forecast of our benchmark LAR(1) model, $\hat{y}_{t,LAR}$, and the counterparts of the other models, $\hat{y}_{t,i}$,

$$y_t = \lambda\hat{y}_{t,LAR} + (1-\lambda)\hat{y}_{t,i} + \varepsilon_t. \tag{21}$$

If $\lambda = 0$, i.e., $1-\lambda = 1$, then the LAR(1) model counts for nothing in the variable forecasts, indicating that model i outperforms the benchmark model. If $\lambda = 1$, i.e., $1-\lambda = 0$, then model i has no effect on the forecasts compared with the LAR model. We compute the Hansen and Hodrick (1980) standard errors and the West (1996) standard errors of parameter $1-\lambda$, which we denote as HH SE and West SE, respectively.

5 Empirical results

In this section, we compare the performance of the forecasts under the different measures, and then discuss the real-time monitoring function of the LAR approach in distinguishing structural shifts from economic transitions[3] .

5.1 LAR model performance compared with the alternatives

Tables 3 and 4 compare the LAR model with the alternative models of the first six categories, as stated in section 4.2.1. The survey forecast has only a one-quarter ahead prediction, and

[3]The additional empirical results on the stability and robustness of the LAR forecast performance are available upon request.

is compared at the end of the section.

Table 3 reports the forecast RMSE and MAE for the macroeconomic variables with the selected forecast horizons. The best forecast in each column is indicated in boldface across the forecast measure and horizon, and the second best forecast is underlined. Table 3 shows that the LAR model substantially outperforms the alternative models in 3- to 12-month ahead forecasts, with error reductions of between 4% and 64% for the IP growth and between 1% and 68% for the inflation rate. The LAR model also outperforms the alternatives in 4- to 24-week ahead forecasts for the interest rate, with an error reduction of between 1% and 25%. The improvement increases as the forecast horizon lengthens. Not surprisingly, the BMA is usually the second best due to its efficient combination of cross-section information. However, the success of the LAR model based on a small information set indicates the importance of dealing with the time-varying parameters of the data.

[Table 3. Forecast comparison of the three macroeconomic variables: RMSE and MAE]

To visualise the performance of the LAR model, we take the IP growth and the inflation rate as examples. Figure 3 plots a forecast comparison between the LAR model and BMA with a rolling window of 60 months for 1-, 6- and 12-month ahead forecasts. The realised data are displayed with solid lines, the LAR model forecasts with dashed lines and the alternative model forecasts with dot-dashed lines. As they are so close, it is difficult to distinguish between the three series for the one-period ahead forecast. Nevertheless, as the forecast horizon increases, it is clear that the dashed line of the LAR forecast tracks the actual data more closely. In particular, the LAR 6- and 12-month ahead forecasts promptly capture the sharp falls in the IP growth and inflation during the 2007-2010 recession.

[Figure 3. Plots of the realised data with forecasts of the LAR and the representative comparison models]

Table 4 reports the out-of-sample forecasting comparison based on the other measures. Here, we list the relative RMSE between the LAR model and the alternative models, the estimated parameter $1 - \lambda$ and the corresponding standard errors (the significance levels are marked by asterisks). Although the advantage of the LAR model is insignificant for the one-month ahead forecast for the IP growth and inflation, it outperforms all of the alternative models for the 3- to 12-month ahead forecasts. Similar patterns hold for the interest rate forecast across horizons.

[Table 4. Forecast comparison between the LAR and alternative models]

Table 5 compares the forecast performance of the LAR model against that of the CMRC survey. For the comparison with the quarterly survey forecast, we transform our three-month ahead forecast data into a one-quarter ahead year-on-year forecast according to Equation (18). To match the same forecast period of inflation and IP growth, and in view of the potential incompleteness of the involved forecast institutions at the initial stage of the CMRC survey, we discard the first two forecasts of the CMRC survey and conduct a forecast comparison for both variables over the period 2006:Q1–2015:Q4. We report the RMSE and MAE, together with the other comparative measures. In Panel A, the LAR model outperforms the CMRC survey for IP growth with smaller RMSE and MAE, presenting a 12% forecast improvement in the relative RMSE. In Panel B, the performance of the LAR model is mixed, with lower MAE values but higher RMSE values. The LAR model, however, produces more overall satisfactory results compared with the CMRC survey forecast. Furthermore, the LAR model can deliver predictions more frequently at a lower cost than the CMRC survey.

[Table 5. Forecast comparison between the LAR model and the CMRC survey]

Figure 4 plots the one-quarter ahead forecasts of the LAR model and the CMRC survey for IP growth and inflation. The actual data are indicated with solid lines, the LAR model forecast with dashed lines and the CMRC survey with dot-dashed lines. The figure shows that although both the LAR model and CMRC survey forecasts match the actual data very well, the LAR model better forecasts the economic downturn in 2008.

[Figure 4. Plots of the realised data with the LAR and CMRC forecasts]

5.2 Lengths of homogenous intervals

Table 6 summarises the average lengths of the detected homogenous intervals for the three variables at each forecast horizon. The average sample length is relatively low with a mean value of 22 months for the IP growth. The average range of the homogenous interval is 27–76 months for the inflation and 34–64 weeks for the interest rates. These stable average lengths are much shorter than the sample lengths of, for example, 5 years, 10 years and even longer, traditionally used in rolling and recursive window forecasts.

[Table 6. Average lengths of the homogenous intervals detected by the LAR model]

Figure 5 presents the parameter evolution in the LAR model for a one-period ahead forecast for the three variables. Here, we can observe that the estimated parameters change over time with abrupt breaks and gradual changes, indicating different types of regime shifts. The financial crisis dramatically drags down the persistence of inflation and the interest rate, and pushes up the standard deviations of all of the variables to historical highs.

[Figure 5. Parameter evolution in the LAR model]

5.3 Patterns of implied breaks and revealed policy changes

Understanding the time-varying features of state dynamics in real time could be valuable for not only forecasting, but also the real-time diagnosis of the macro-economy and policy-making. Figure 6 plots the detected stable subsamples and breaks for the one-step ahead forecast of the LAR(1) model. The vertical axis denotes the time when the forecast is made. At each time point, an optimal homogenous interval is detected, which is shown as a light solid line along the horizontal time axis. At the end of the line, a dotted line indicates the period, in this case six months for the IP growth and the inflation rate and six weeks for the interest rate, during which time the most recent break happens such that the hypothesis concerning the homogenous interval no longer holds. When the blue dotted lines are stacked along the forecast time, common areas of detected breaks become evident.

[Figure 6. Detected subsamples of homogeneity]

Figure 6 shows that the real variable, IP growth, has fewer clear-cut breaks with shorter homogenous intervals than the nominal variable, the inflation rate. This is supported by the statistics of the average interval lengths reported in Table 6. This finding echoes the gradual transition strategy of China and the diffusion of growth factors such as technological innovation, human capital development and the implementation of gradual institutional reforms.

In contrast, the nominal variables, inflation and the interest rate, exhibit several commonly identified ending periods of the homogenous intervals, such as an abrupt break in late 1994 for inflation. The breaks in the interest rate (early 2004 and early 2008) tend to lead those in inflation (early 2005 and early 2009), suggesting that monetary policy shifts were directly manifested in the interest rate dynamics and then transmitted to inflation due to price stickiness. In fact, all of these abrupt breaks in the nominal variables coincide with important monetary policy shifts:

1) In 1994, the government officially responded to the economic overheating that began in 1992, with the PBoC embracing monetary policies that have since kept inflation below 10 %.

2) On January 1, 2004, the marketisation of interest rates was launched. The PBoC allowed commercial bank lending rates to float between 0.9 and 2 times the official lending rate. As a result, interest rates became partly determined by the market and bank interest rates began to vary in response to supply and demand. Preparations were also made for a change in the exchange rate regime from a fixed to a managed float in July 2005. A period of stable inflation ended as inflationary pressure began to build in mid-2005 in anticipation of the appreciation of the yuan and large inflows of international capital.

3) During early 2008, there was a sudden tightening of the monetary policy stance, with the PBoC increasing the bank reserve requirements four times, eventually reaching 16.5%,

the highest level since 1985. The reserve ratio averaged about 10% between 1985 and 2007. This tightened monetary policy helped end the overheating of the credit markets and altered the interest rate dynamics. However, with the global financial crisis depressing Chinese exports and economic growth, the drop in inflationary pressure turned into a deflation concern in 2009 and ended another period of stable inflation.

6 Conclusion

In this paper, we address an important issue relating to the economic forecasting of emerging economies under the constraints of instability and limited data. We focus on the case of China because China has experienced notable policy shifts and vast structural reforms since the launch of the reforms in 1978. Our findings demonstrate how an adaptive model can be used to forecast the key macroeconomic variables for China in a way that automatically captures the features of the transition economy. The proposed method is shown to outperform other popular models and window selection methods in out-of-sample predictions of real and nominal variables. The LAR model is also useful for monitoring the structural breaks of the economic process in real time, showing gradual and smooth transitions in the real economic variables and abrupt changes in the nominal variables, which are largely in line with major monetary policy shifts. An ability to make timely and precise predictions can help market participants and policymakers better assess and monitor the economic dynamics and policy effects, which is particularly useful for forecasting and monitoring in the context of a transition economy.

The extension of the proposed LAR model to the forecasting of other economic variables should be fairly straightforward. Future studies could also extend the LAR model with exogenous variables and consider Bayesian model-averaging based on an adaptive method.

Acknowledgements

Linlin Niu acknowledges the support of the Natural Science Foundation of China (Grant No. 70903053 and Grant No. 71273007), and wishes to thank the BOFIT Visiting Researcher Program for its hospitality during her research stay at BOFIT.

Xiu Xu acknowledges the support of the Deutsche Forschungsgemeinschaft through the International Research Training Group IRTG 1792 - High Dimensional Non Stationary Time Series and the SFB 649 Economic Risk.

Ying Chen acknowledges the support of the Natural Science Foundation of China (Grant No. 71528008), and the FRC grant at the National University of Singapore.

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Table 1: Statistics of the Three Macroeconomic Variables

Variables	Sample periods	Mean (%)	Std (%)	Skewness	Kurtosis
IP growth	252	12.428	3.551	-0.020	2.013
Inflation rate	288	4.467	6.222	1.934	6.415
Interest rate	773	2.745	1.149	1.775	8.511

Notes: The first row is the monthly growth rate of industrial production from 1995:M1 to 2015:M12; the second row is the monthly CPI inflation rate from 1992:M1 to 2015:M12; and the third row is the weekly seven-day Chibor (China Interbank Offered Rate), taken from the weighted average closing rate of the last trading day of each week, from January 2001 to December 2015. All of the data are from the CEIC China Economic and Industry database.

Table 2: Summary of the Data

Panel A Data Sample and Estimation Periods for the Three Target Variables

Variables	Frequency	Sample interval	Initial estimation samples	Out-of-sample forecast periods
IP growth	monthly	1995:M1-2015:M12	1995:M1-2004:M12	2005:M1-2015:M12
Inflation rate	monthly	1992:M1-2015:M12	1992:M1-2001:M12	2002:M1-2015:M12
Interest rate	weekly	2001:W1-2015:W52	2001:W1-2005:W52	2006:W1-2015:W52

Panel B Data used in the Alternative Models

Number	Variables
1-4	Inflation rate (with lags 1-4)
5-8	IP growth (with lags 1-4)
9	Leading economic indicator
10	Electricity consumption growth
11	Seven-day Chibor rate (monthly weighted average)
12	Coincident economic indicator
13	Lagging economic indicator
14	Exports
15	Imports
16	Retail price index
17	Producer price index
18	Producer price index: consumer goods
19	Money supply M0
21	Money supply M1
22	Money supply M2
23	Shanghai stock exchange index: A Share
24	Shenzhen stock exchange index: A Share
25	Foreign exchange
26	Fixed asset investment
27	Real estate investment
28	CMRC survey data

Notes:

- In Panel A,
  - The longest available sample period until the end of 2015 is selected for each of the three target variables.
  - The interest rate is represented by the seven-day Chibor rate (weekly weighted average) with weekly frequency.
  - For IP growth and the inflation rate, the forecast horizons are 1, 3, 6, 9 and 12 months. For the direct forecast approach, the corresponding forecast periods are 132, 130, 127, 124 and 121 months for IP growth and 168, 166, 163, 160 and 157 months for the inflation rate.
  - For the interest rate, the forecast horizons are 1, 4, 12, and 24 weeks, and the corresponding forecast periods are 517, 514, 506 and 494 weeks.
- In Panel B,
  - All of the variables are in difference of logs, except 9 and 11-13.
  - Variables 9-11 are used in the models with additional macroeconomic variables, including the real activity models for IP growth, Phillips curve models for inflation and term structure models for both.
  - Variables 1-27 are used in the Bayesian model averaging and factor models for IP growth and the inflation rate. The sample periods are uniformly 1996:M1-2015:M12.
  - Variables 1-4 are excluded in the factor model of the inflation rate, and variables 5-8 are excluded in the factor model of IP growth.
  - The sample period of the CMRC survey data (variable 28) is 2006:Q1-2015:Q4, with quarterly-frequency.

Table 3: Forecast Comparison of the Three Macroeconomic Variables: RMSE and MAE

Panel A IP Growth

	$h=1m$		$h=3m$		$h=6m$		$h=9m$		$h=12m$	
	RMSE	MAE	RMSE	MAE	RMSE	MAE	RMSE	MAE	RMSE	MAE
LAR(1)	1.136	0.819	**1.553**	1.192	1.630	**1.208**	**1.656**	**1.175**	**1.556**	**1.091**
AR Rolling 60m	1.131	0.833	2.081	1.480	2.862	2.108	3.351	2.619	3.429	2.679
AR Recursive	1.067	0.780	1.949	1.394	2.922	2.235	3.500	2.761	3.807	3.046
Random Walk	1.057	0.782	1.977	1.342	3.090	2.178	3.861	2.738	4.336	3.071
RA1 Rolling 60m	1.150	0.881	2.101	1.492	2.877	2.106	3.272	2.568	3.452	2.690
RA1 Recursive	1.063	0.788	1.956	1.386	2.930	2.244	3.520	2.772	3.826	3.055
RA2 Rolling 60m	1.018	0.763	1.736	1.206	2.534	1.875	3.077	2.390	3.376	2.816
RA2 Recursive	0.961	0.717	1.711	1.212	2.744	2.121	3.489	2.764	3.896	3.078
TS1 Rolling 60m	1.103	0.818	1.947	1.327	2.629	1.896	2.752	2.060	2.738	2.235
TS1 Recursive	1.058	0.782	1.921	1.350	2.806	2.132	3.270	2.613	3.488	2.861
TS2 Rolling 60m	1.059	0.769	1.929	1.385	2.731	1.969	2.720	2.072	2.413	1.970
TS2 Recursive	0.992	0.734	1.810	1.274	2.752	2.084	3.287	2.648	3.526	2.871
TS3 Rolling 60m	1.008	0.768	1.803	1.299	2.517	1.861	2.725	2.015	2.552	2.063
TS3 Recursive	**0.945**	**0.712**	1.683	1.178	2.580	1.943	3.174	2.535	3.471	2.810
Factor Rolling 60m	1.630	1.229	2.051	1.502	2.631	2.071	2.996	2.355	3.331	2.582
Factor Recursive	1.669	1.230	2.436	1.758	3.444	2.625	3.841	3.023	3.859	3.192
BMA Rolling 60m	1.246	0.947	1.617	1.218	**1.597**	1.260	1.835	1.463	2.068	1.493
BMA Recursive	1.228	0.931	1.622	**1.160**	1.952	1.490	2.179	1.630	2.214	1.644

Panel B Inflation Rate

	$h=1m$		$h=3m$		$h=6m$		$h=9m$		$h=12m$	
	RMSE	MAE	RMSE	MAE	RMSE	MAE	RMSE	MAE	RMSE	MAE
LAR(1)	0.661	0.505	0.942	**0.718**	**1.019**	**0.745**	**1.037**	**0.765**	**1.046**	**0.795**
AR Rolling 60m	0.646	0.492	1.163	0.879	1.625	1.262	1.811	1.419	2.110	1.638
AR Recursive	0.652	0.493	1.180	0.917	1.805	1.347	2.423	1.766	3.050	2.284
Random Walk	0.633	0.478	1.219	0.921	2.013	1.506	2.720	2.056	3.319	2.539
PC1 Rolling 60m	0.582	0.452	1.048	0.845	1.526	1.204	1.631	1.266	1.877	1.386
PC1 Recursive	0.581	0.446	1.078	0.867	1.695	1.334	2.142	1.659	2.449	1.916
PC2 Rolling 60m	0.596	0.464	0.980	0.795	1.397	1.086	1.671	1.313	1.923	1.450
PC2 Recursive	0.635	0.480	1.117	0.858	1.911	1.399	2.577	1.850	3.217	2.333
TS1 Rolling 60m	0.590	0.451	1.158	0.935	1.786	1.409	2.114	1.626	2.076	1.555
TS1 Recursive	0.585	0.446	1.099	0.867	1.716	1.351	2.086	1.616	2.232	1.710
TS2 Rolling 60m	0.603	0.468	0.964	0.782	1.476	1.191	1.831	1.417	2.005	1.464
TS2 Recursive	0.602	0.467	1.048	0.843	1.602	1.276	1.955	1.530	2.200	1.668
TS3 Rolling 60m	**0.571**	**0.441**	0.959	0.766	1.494	1.176	1.850	1.410	2.022	1.513
TS3 Recursive	0.587	0.453	1.037	0.850	1.604	1.300	1.965	1.555	2.180	1.690
Factor Rolling 60m	0.787	0.597	1.031	0.798	1.191	0.916	1.485	1.157	1.599	1.319
Factor Recursive	0.809	0.621	1.158	0.884	1.613	1.256	2.084	1.531	2.427	1.784
BMA Rolling 60m	0.658	0.506	**0.922**	0.740	1.083	0.818	1.108	0.852	1.056	0.850
BMA Recursive	0.688	0.530	0.968	0.764	1.138	0.895	1.378	1.102	1.515	1.182

Panel C Interest Rate

	$h=1w$		$h=4w$		$h=12w$		$h=24w$	
	RMSE	MAE	RMSE	MAE	RMSE	MAE	RMSE	MAE
LAR(1)	**0.857**	**0.486**	**1.015**	**0.603**	**1.033**	**0.645**	**1.070**	**0.680**
AR Rolling 60m	0.920	0.541	1.069	0.675	1.179	0.780	1.235	0.861
AR Rolling 120m	0.871	0.523	1.037	0.668	1.198	0.796	1.198	0.829
AR Recursive	**0.857**	0.508	1.027	0.647	1.195	0.765	1.216	0.828
Random Walk	0.930	0.499	1.118	0.691	1.382	0.877	1.397	0.996

Notes:

- h denotes the forecast horizon.
- RMSE denotes the root mean squared error, and MAE denotes the mean absolute error.
- For each column, the best forecast, i.e., the smallest RMSE or MAE, is marked in bold; the second best is underlined. When the first and second best are the same, both are marked in bold, and no second best is further indicated. When the second and third best are the same, both are underlined.
- RA, PC and TS denote models with additional macroeconomic variables, including the real activity model (RA1, RA2) for IP growth, the Phillips curve model (PC1, PC2) for the inflation rate and models incorporating the interest rate term structure (TS1, TS2, TS3) for both.
- BMA denotes the Bayesian modeling average model with $Z = 27$ variables, while Factor denotes the factor models for IP growth and the inflation rate.

Table 4: Forecast Comparison of the LAR and the Alternative Models

Panel A IP Growth

	$h = 1m$				$h = 3m$				$h = 6m$				$h = 9m$				$h = 12m$			
	Relative RMSE	$1-\lambda$	HH SE	West SE	Relative RMSE	$1-\lambda$	HH SE	West SE	Relative RMSE	$1-\lambda$	HH SE	West SE	Relative RMSE	$1-\lambda$	HH SE	West SE	Relative RMSE	$1-\lambda$	HH SE	West SE
AR Rolling 60m	1.005	0.539	0.214	0.318	0.746	0.101	0.127	0.118	0.569	-0.029	0.112	0.093	0.494	-0.029	0.134	0.050	0.454	0.024	0.133	0.053
AR Recursive	1.065	0.876	0.203	0.294	0.797	0.220	0.129	0.120	0.558	-0.060	0.113	0.094	0.473	-0.035	0.119	0.057	0.409	-0.002	0.106	0.040
Random Walk	1.074	0.980	0.215	0.299	0.786	0.171	0.132	0.128	0.528	-0.121	0.106	0.108	0.429	-0.051	0.098	0.056	0.359	-0.004	0.082	0.037
RA1 Rolling 60m	0.988	0.466	0.149	0.175	0.739	0.086	0.126	0.114	0.567	-0.024	0.110	0.092	0.506	-0.003	0.133	0.043	0.451	0.026	0.131	0.052
RA1 Recursive	1.070	0.890	0.201	0.304	0.794	0.214	0.129	0.120	0.556	-0.064	0.113	0.094	0.471	-0.038	0.119	0.058	0.407	-0.004	0.105	0.041
RA2 Rolling 60m	1.116	0.710	0.109*	0.127	0.894	0.344	0.139	0.173	0.643	0.099	0.111	0.155	0.539	0.104	0.119	0.104	0.461	0.014	0.130	0.048
RA2 Recursive	1.183	1.094	0.149*	0.168*	0.907	0.346	0.149	0.159	0.594	-0.101	0.124	0.115	0.475	-0.063	0.120	0.058	0.399	-0.012	0.103	0.044
TS1 Rolling 60m	1.030	0.640	0.179	0.233	0.797	0.208	0.127	0.130	0.620	0.037	0.117	0.131	0.602	0.144	0.122	0.097	0.568	0.166	0.127	0.042
TS1 Recursive	1.074	0.868	0.187	0.290	0.808	0.245	0.127	0.119	0.581	-0.023	0.116	0.095	0.507	0.003	0.125	0.055	0.446	0.034	0.113	0.039
TS2 Rolling 60m	1.073	0.645	0.112	0.146	0.805	0.178	0.143	0.142	0.597	0.010	0.117	0.146	0.609	0.153	0.122	0.098	0.645	0.223	0.123	0.050
TS2 Recursive	1.145	1.091	0.167*	0.223	0.858	0.258	0.148	0.141	0.592	-0.064	0.122	0.108	0.504	-0.006	0.126	0.056	0.441	0.020	0.117	0.043
TS3 Rolling 60m	1.127	0.698	0.099*	0.114	0.861	0.298	0.135	0.137	0.648	0.102	0.112	0.158	0.608	0.138	0.126	0.112	0.610	0.188	0.121	0.047
TS3 Recursive	1.202	1.069	0.138*	0.157*	0.923	0.381	0.143	0.153	0.632	-0.009	0.124	0.126	0.522	-0.002	0.128	0.065	0.448	0.020	0.118	0.044
Factor Rolling 60m	0.697	-0.063	0.090	0.099	0.757	0.227	0.109	0.103	0.620	0.064	0.113	0.084	0.553	0.020	0.142	0.051	0.467	0.010	0.127	0.062
Factor Recursive	0.681	-0.082	0.087	0.104	0.637	0.098	0.100	0.097	0.473	-0.083	0.094	0.079	0.431	-0.028	0.109	0.045	0.403	0.051	0.101	0.039
BMA Rolling 60m	0.912	0.397	0.082	0.094	0.961	0.467	0.112	0.080	1.021	0.534	0.136	0.146	0.903	0.390	0.143	0.139	0.752	0.155	0.160	0.078
BMA Recursive	0.925	0.401	0.088	0.100	0.957	0.455	0.127	0.139	0.835	0.313	0.128	0.101	0.760	0.242	0.145	0.119	0.703	0.191	0.144	0.042

Panel B Inflation Rate

	$h = 1m$				$h = 3m$				$h = 6m$				$h = 9m$				$h = 12m$			
	Relative RMSE	$1-\lambda$	HH SE	West SE	Relative RMSE	$1-\lambda$	HH SE	West SE	Relative RMSE	$1-\lambda$	HH SE	West SE	Relative RMSE	$1-\lambda$	HH SE	West SE	Relative RMSE	$1-\lambda$	HH SE	West SE
AR Rolling 60m	1.022	0.679	0.208	0.191	0.810	0.217	0.110	0.103	0.627	0.099	0.112	0.073	0.572	0.125	0.110	0.076	0.496	0.013	0.119	0.066
AR Recursive	1.013	0.562	0.154	0.190	0.799	0.212	0.086	0.079	0.565	0.012	0.086	0.053	0.428	-0.077	0.074	0.058	0.343	-0.051	0.066	0.040
Random Walk	1.045	1.089	0.273	0.243	0.773	0.131	0.118	0.074	0.506	-0.010	0.099	0.056	0.381	-0.106	0.089	0.048	0.315	-0.075	0.075	0.028
PC1 Rolling 60m	1.135	0.714	0.091*	0.094*	0.899	0.315	0.119	0.107	0.668	0.098	0.120	0.072	0.636	0.193	0.106	0.082	0.557	0.120	0.111	0.058
PC1 Recursive	1.136	0.751	0.099*	0.096*	0.874	0.323	0.116	0.098	0.602	0.069	0.112	0.056	0.484	-0.046	0.111	0.071	0.427	-0.006	0.102	0.050
PC2 Rolling 60m	1.109	0.715	0.103*	0.093*	0.962	0.448	0.114	0.111	0.729	0.208	0.114	0.088	0.620	0.129	0.112	0.077	0.544	0.058	0.107	0.069
PC2 Recursive	1.041	0.641	0.138	0.161	0.844	0.317	0.079	0.090	0.533	0.019	0.083	0.064	0.402	-0.098	0.074	0.057	0.325	-0.006	0.063	0.050
TS1 Rolling 60m	1.120	0.705	0.095*	0.104*	0.814	0.220	0.106	0.085	0.571	0.061	0.094	0.046	0.490	0.018	0.096	0.060	0.504	0.099	0.098	0.052
TS1 Recursive	1.130	0.737	0.098*	0.098*	0.857	0.285	0.121	0.097	0.594	0.092	0.110	0.046	0.497	-0.006	0.114	0.079	0.469	0.047	0.108	0.059
TS2 Rolling 60m	1.095	0.716	0.111*	0.111*	0.978	0.472	0.106	0.105	0.691	0.151	0.111	0.096	0.566	0.076	0.103	0.076	0.522	0.080	0.096	0.062
TS2 Recursive	1.098	0.766	0.121	0.113*	0.899	0.362	0.115	0.105	0.636	0.126	0.115	0.066	0.531	0.033	0.116	0.091	0.476	0.040	0.105	0.072
TS3 Rolling 60m	1.157	0.734	0.088*	0.090*	0.982	0.478	0.106	0.117	0.683	0.148	0.107	0.098	0.561	0.078	0.101	0.071	0.518	0.080	0.100	0.060
TS3 Recursive	1.126	0.699	0.090*	0.090*	0.908	0.380	0.115	0.105	0.636	0.131	0.115	0.066	0.527	0.035	0.117	0.080	0.480	0.062	0.107	0.069
Factor Rolling 60m	0.840	0.303	0.072	0.098	0.913	0.386	0.105	0.112	0.856	0.374	0.112	0.150	0.698	0.263	0.116	0.103	0.654	0.188	0.122	0.058
Factor Recursive	0.817	0.320	0.061	0.080	0.814	0.253	0.103	0.090	0.632	0.117	0.107	0.096	0.498	0.035	0.112	0.082	0.431	0.031	0.107	0.053
BMA Rolling 60m	1.004	0.506	0.070*	0.077*	1.022	0.529	0.106	0.103	0.942	0.455	0.100	0.138	0.935	0.451	0.113	0.110	0.991	0.493	0.108	0.094
BMA Recursive	0.961	0.448	0.081	0.087	0.974	0.470	0.111	0.101	0.896	0.412	0.119	0.136	0.752	0.250	0.141	0.095	0.691	0.176	0.140	0.078

Panel C Interest Rate

	$h = 1w$				$h = 4w$				$h = 12w$				$h = 24w$			
	Relative RMSE	$1-\lambda$	HH SE	West SE	Relative RMSE	$1-\lambda$	HH SE	West SE	Relative RMSE	$1-\lambda$	HH SE	West SE	Relative RMSE	$1-\lambda$	HH SE	West SE
AR Rolling 60m	0.931	0.294	0.071	0.144	0.949	0.313	0.123	0.127	0.876	0.141	0.186	0.140	0.866	0.109	0.278	0.090
AR Rolling 120m	0.984	0.444	0.080	0.154	0.978	0.430	0.117	0.163	0.863	0.127	0.169	0.122	0.893	0.263	0.242	0.073
AR Recursive	1.000	0.502	0.080	0.152	0.988	0.458	0.121	0.170	0.864	0.099	0.169	0.135	0.880	0.256	0.232	0.075
Random Walk	0.921	0.211	0.079	0.164	0.907	0.198	0.099	0.141	0.747	0.076	0.062	0.073	0.766	0.062	0.125	0.066

Notes:

- h denotes the forecast horizon. The forecast periods are the same in Tables 3 and 4.
- Relative RMSE denotes the ratio between the LAR(1) and the alternative models; the lower the value, the more favorable the LAR(1) model. The value of 1 - Relative RMSE presents the reduction in the RMSE of LAR(1) compared with the other models.
- Parameter $1-\lambda$ is the regression coefficient of the alternative models; the lower the value, the better the performance of the LAR(1) benchmark. We perform the regression $y_t = \lambda \hat{y}_{t,LAR} + (1-\lambda)\hat{y}_{t,i} + \varepsilon_t$, where y_t is the actual data, $\hat{y}_{t,LAR}$ is the forecast from the LAR(1) benchmark, and $\hat{y}_{t,i}$ represents the forecasts from the other candidate models i. We compute the standard error of parameter $1-\lambda$ with the Hansen and Hodrick (1980) and West (1996) standard errors, denoted as HH SE and West SE, respectively.
- For the $1-\lambda$ column, $*$ denotes a significance level of 5%, and $**$ denotes a significance level of 1%.

Table 5: Forecast Comparison between the LAR Model and CMRC Survey

Panel A Growth of Industrial Production

	LAR(1)	CMRC
	h=1q	h=1q
RMSE	**1.327**	1.499
MAE	**1.040**	1.061
Relative RMSE	-	0.885
$1-\lambda$	-	0.360
HH SE	-	0.160
West SE	-	0.295

Panel B Inflation Rate

	LAR(1)	CMRC
	h=1q	h=1q
RMSE	0.748	**0.596**
MAE	**0.541**	0.571
Relative RMSE	-	1.255
$1-\lambda$	-	0.726
HH SE	-	0.134
West SE	-	0.168

Notes:

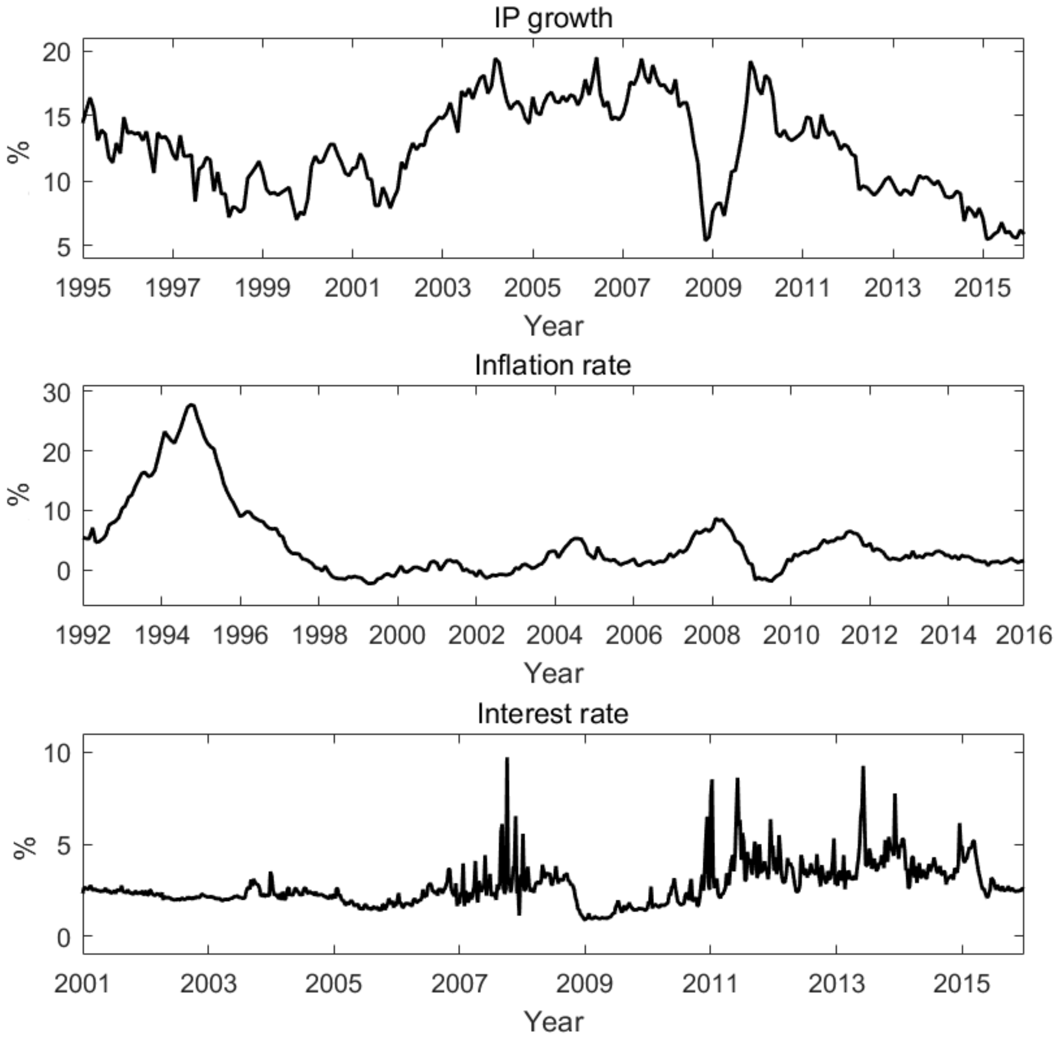
- h denotes the forecast horizon. The column CMRC denotes the one-quarter horizon forecast with the CMRC data. We transform the three-month horizon monthly forecast of the LAR model into the one-quarter horizon quarterly forecast according to Equation (18). The data intervals are from 2006:Q1 to 2015:Q4 for the CMRC survey data, IP growth, and inflation rate, a total of 40 quarters.
- The bolded number indicates the better performer of the LAR forecast and the CMRC survey one-step ahead forecast for RMSE and MAE.
- We perform the regression $y_t = \lambda \hat{y}_{t,LAR} + (1-\lambda)\hat{y}_{t,CMRC} + \varepsilon_t$, where y_t is the actual data, $\hat{y}_{t,LAR}$ is the forecast from the benchmark LAR(1) model and $\hat{y}_{t,CMRC}$ is the CMRC forecast. We compute the standard error of parameter $1-\lambda$ with Hansen and Hodrick (1980) and West (1996) standard errors, denoted as HH SE and West SE, respectively.
- For the $1-\lambda$ row, $*$ denotes a significance level of 5%, and $**$ denotes a significance level of 1%.

Table 6: Average Lengths of the homogenous Intervals Detected by the LAR Model

	$h = 1m$	$h = 3m$	$h = 6m$	$h = 12m$
IP growth	34	21	15	17
Inflation rate	76	32	27	28
	$h = 1w$	$h = 4w$	$h = 12w$	$h = 24w$
Interest rate	64	47	38	34

Notes: h denotes the forecast horizon.

Figure 1: Plot of the Three Macroeconomic Variables



Notes: The first graph is the monthly data of the growth rate of industrial production from 1995:1 to 2015:12; the second graph is the monthly CPI inflation rate from 1992:1 to 2015:12; and the third graph is the weekly seven-day Chibor (China Interbank Offered Rate), taken from the weighted average closing rate of the last trading day of each week, from January 2001 to December 2015. All of the data are from the CEIC China Economic and Industry database.

Figure 2: Autocorrelation Functions of the Three Variables

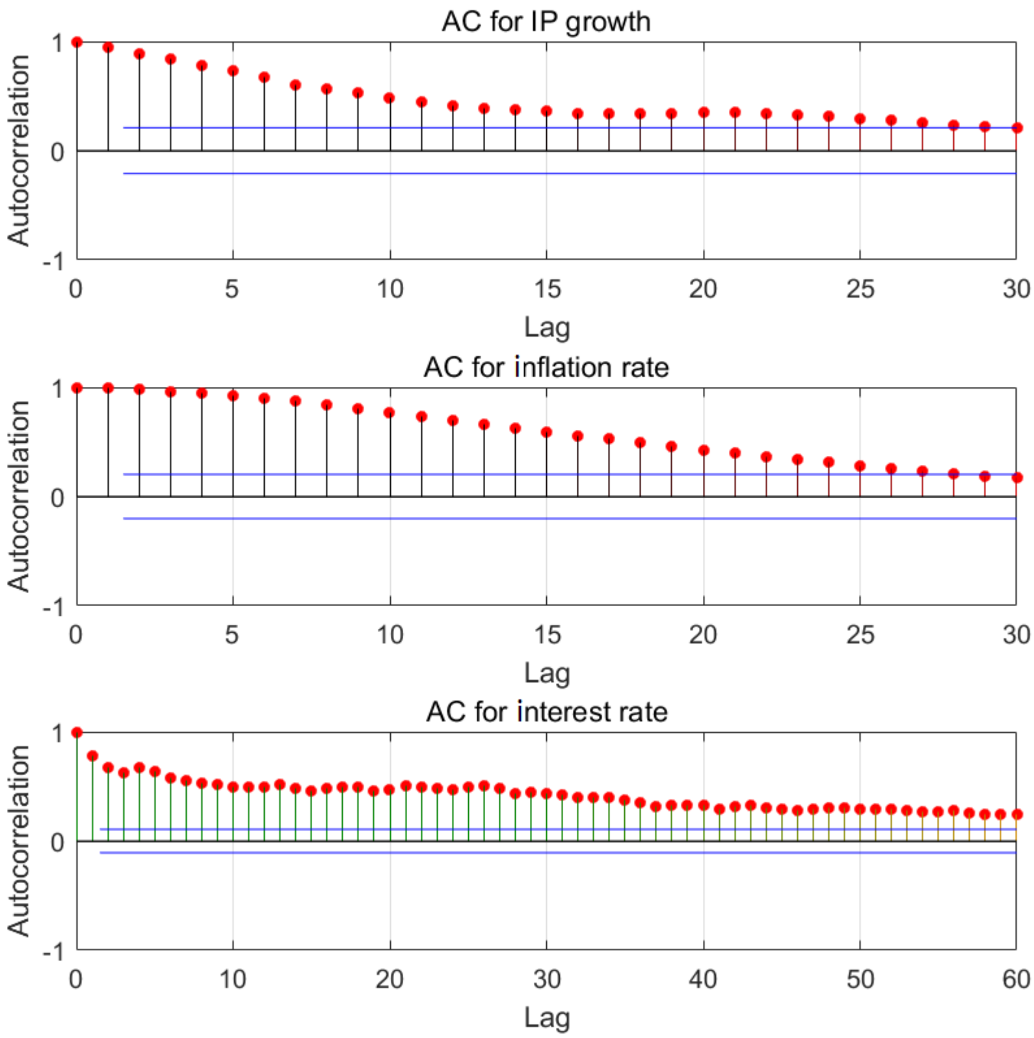
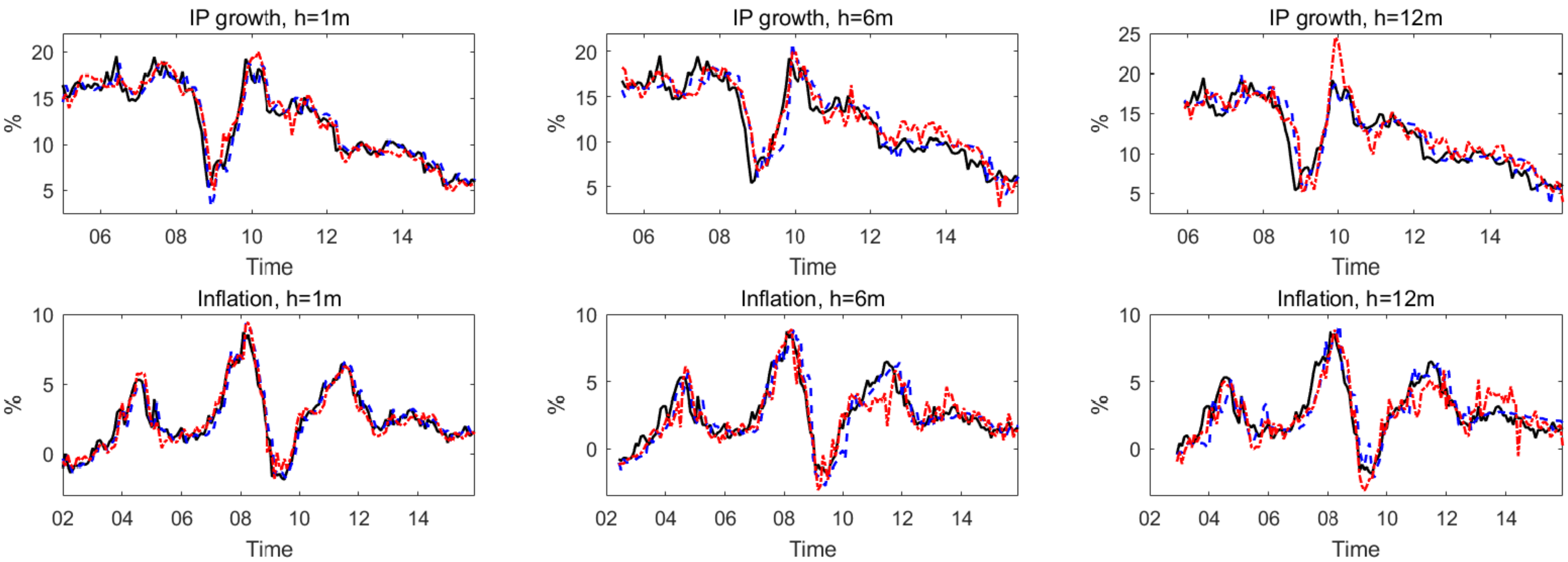
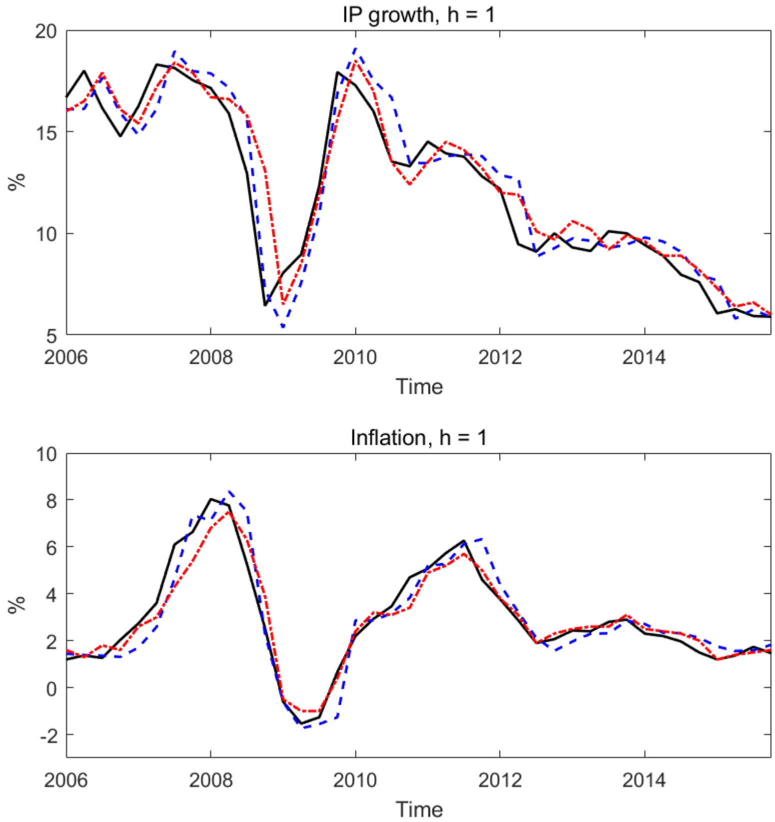


Figure 3: Plots of the Realized Data with Forecasts of LAR and the Representative Comparison Models



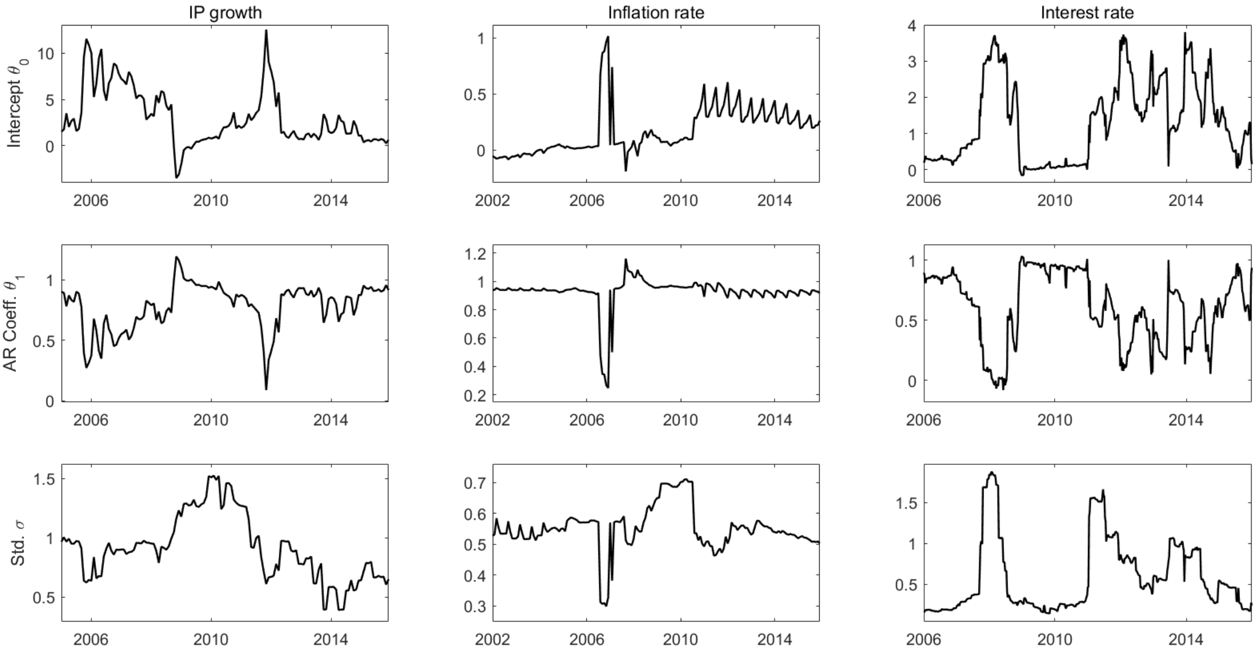
Notes: The solid lines indicate the actual data, the dashed lines are the LAR(1) model forecasts and the dot-dashed lines are the BMA rolling 60 m forecast, for both IP growth and the inflation rate.

Figure 4: Plots of the Realized Data with the LAR and CMRC Forecasts



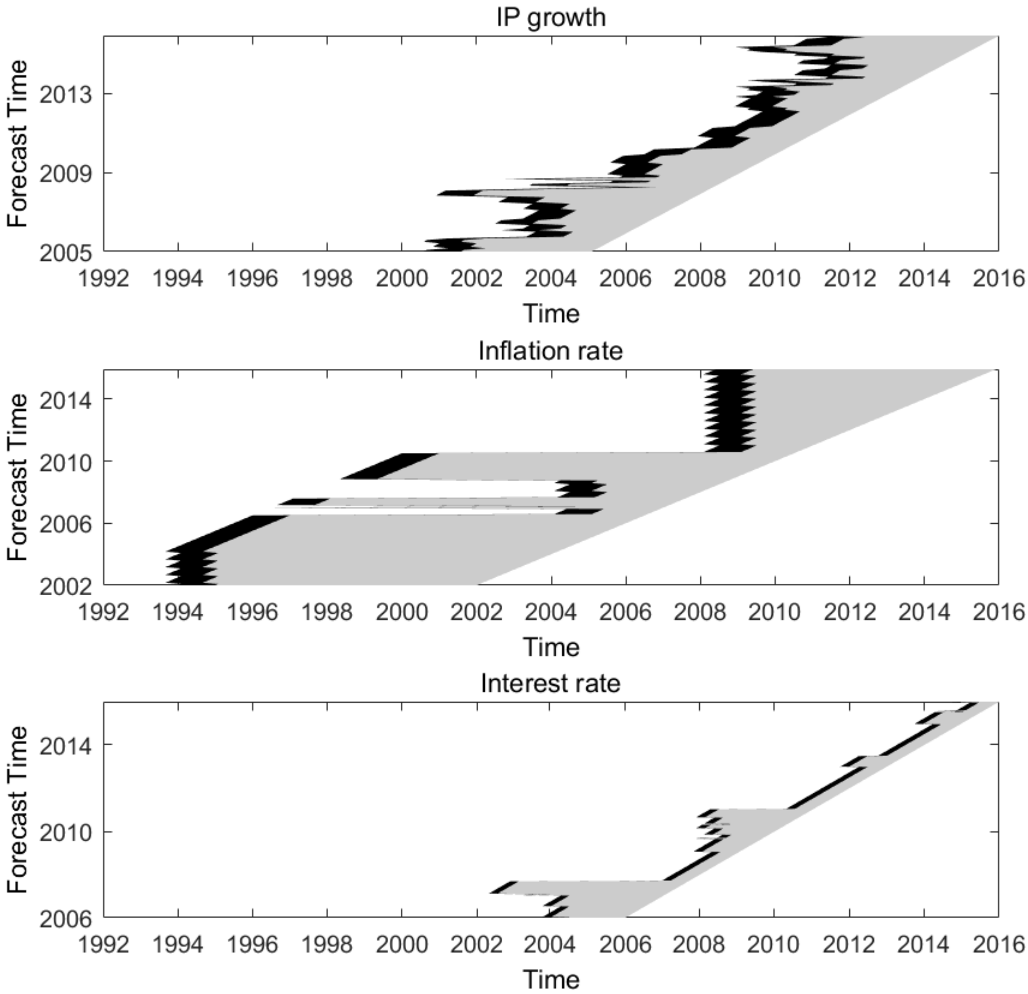
Notes: For both IP growth and the inflation rate, the solid lines indicate the actual data, the dashed lines are the one-quarter horizon LAR model forecasts, and the dot-dashed lines are the CMRC survey forecasts.

Figure 5: Parameter Evolution in the LAR Model



Notes: In each column, we plot the time evolution of the estimated coefficients for the LAR(1) model for h=1 of each variable. The first row displays the intercept, the second row is the autoregressive coefficient on the lagged factor and the bottom row is the standard deviation of the error term.

Figure 6: Detected Subsamples of Homogeneity



Notes: The vertical axis marks the time when the estimation and forecast is made. The selected stable sample interval is marked horizontally as a light solid line, which then stacks together to form the light colored area. The dark line marks the six-month interval during which the most recent break is detected, which then stacks together to outline the boundaries of the homogenous intervals in time.