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RESEARCH ARTICLE

Forecasting models for the Chinese macroeconomy in a data-rich environment: Evidence from large dimensional approximate factor models with mixed-frequency data

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Abstract

Our paper contributes to the nascent literature on forecasting the Chinese macroeconomy in a data-rich environment. We perform a horse race among a large set of traditional models and two classes of factor models with 251 monthly and 34 quarterly macroeconomic variables over the period from January 2002 to June 2018. We find evidence that mixed-frequency factor models provide superior forecasts of the CPI, RPI, investment, and consumption when compared to the simple benchmark. During the Global Financial Crisis period, we find little evidence of superiority of factor models over the simple benchmark AR(p) model.

KEYWORDS

China, factor models, forecasting, inflation, mixed-frequency data, real activity

JEL CLASSIFICATION

C52, C53, C55

1 | INTRODUCTION

As China has become the world's second-largest economy, rigorous and systematic research in the evaluation of out-of-sample forecasts of China's macroeconomy is urgently required. Macroeconomic policymaking often faces the problem of forecasting the state of an economy with incomplete statistical information. Important economic variables are released at different frequencies with considerable time lags. In addition, due to the significant effects of the Chinese New Year on the seasonal pattern of the data, the National Bureau of Statistics of China (NBSC) does not release some variables (such as industrial production) for both January and February. The break in the data dissemination pattern largely affects other variables and, therefore, complicates the task of producing an accurate forecast due to the scarcity of information available over that specific time window. Another challenging issue could be the quality of official economic data. The degree of data contamination has made traditional forecasting models less feasible; a high level of care must be taken regarding the selection of inputs of a specific model (Fernald et al., 2014; Higgins et al., 2016; Holz, 2014). Scepticism regarding the contamination of China's official data stems from several factors, among which technical difficulties, outdated reporting systems, incomplete sample surveys and political interference are common concerns (Holz, 2008, 2014).[1]

In this paper, we contribute to the literature by undertaking the task of forecasting Chinese macroeconomic variables in a data-rich environment using large-dimensional approximate factor models with mixed frequency and missing observation components. As suggested by Stock and Watson (2002b), Bernanke and Boivin (2003), Bernanke et al. (2005), and Fernald et al. (2014), the large-dimensional approximate factor model can overcome the concerns regarding such potential contamination of Chinese official economic data and the issue of mixed-frequency sampling with missing observations during Chinese New Year.[2] Moreover, as the number of time observations is small relative to the number of economic indicators in China, pooling information from a large set of predictors can provide substantial benefits compared to standard time series forecasting models.

Factor models provide a sensible way to exploit the information from a very large number of predictors. The underlying assumption is that a small number of unobservable and latent factors are the driving forces behind the state of an economy. The use of a few common factors driving all economic variables is in line with the real business cycle and dynamic stochastic general equilibrium models. This is an appealing feature for forecasting purposes since it allows researchers to concentrate on a few common factors instead of overfitting models with a potentially large number of explanatory variables. In addition, factor models ameliorate omitted variable bias, require minimal conditions on the idiosyncratic disturbances, deal with measurement errors and are relatively easy to implement.

The initial works on factor models were presented by Geweke (1977) and Sargent and Sims (1977). Geweke (1977) applies dynamic factor models to macroeconomic data and analysed these models in the frequency domain for a small number of variables. Sargent and Sims (1977) examine a large-scale macroeconometric model and conclude that two dynamic factors could explain 80 percent or more of the variance of major economic variables, including unemployment rate, industrial production growth, employment growth and wholesale price inflation. However, they impose orthogonality on the idiosyncratic components, and such assumptions are too restrictive for the economic data.

[1]Political economy literature often argues that data manipulation can occur at both the central government and local government levels. At the central government level, it is likely that only the cell members of Communist Party of the NBSC know the choices leading to the final economic data that are presented, possibly with influences from the leaders of the state council and the Communist Party (Holz, 2014; Xiong, 2019). At the local government level, officials compete with each other for career advancement. Since economic performance is an important measure in cadres' evaluation, local officials have a strong incentive to over-report key output statistics (Holz, 2008; Xiong, 2019).

[2]The large dimensional approximate factor model provides robustness in the presence of structural breaks and a small amount of data contamination, see Stock and Watson (2002a, 2002b, 2016) and Bai and Ng (2008b) for references. Not all Chinese official statistics are unreliable-only a few important variables such as GDP and industrial production are considered unreliable. Therefore, the large dimensional approximate factor model is particularly suitable in the context of macroeconomic forecasting for China.

Factor models have been improved through advances in estimation techniques proposed by Forni et al. (2000), Stock and Watson (2002a, 2002b), Bai and Ng (2006) and Kapetanios and Marcellino (2009).[3] To select the number of common factors, Bai and Ng (2002) and Hallin and Liška (2007) develop information criteria for the static factor model and the generalised dynamic factor model. Following these statistical advances, factor models have become popular in the economic literature under the name of the large-dimensional approximate factor model. 'Large' means that the sample size in both dimensions T and N tends to infinity in the asymptotic theory. 'Approximate' means that the idiosyncratic errors are allowed to be weakly correlated across T and N. In empirical macroeconomics, the estimated factors are useful for performing structural analysis. They can be modelled as dynamic structural factor models to identify structural shocks and their dynamic impact on a large set of economic and financial indicators (Aspinall et al., 2021; Bernanke et al., 2005; Bernanke & Boivin, 2003; Boudt et al., 2015; He et al., 2013; Lütkepohl, 2014; Van Nieuwenhuyze, 2005; Wang et al., 2019). They can also be used to improve nowcasting and forecasting accuracy, possibly in combination with autoregressive (AR) terms and/or other selected variables (Artis et al., 2005; Banerjee et al., 2005; Cristadoro et al., 2005; Forni et al., 2003; Giannone & Matheson, 2007; Giannone et al., 2008; Graff & Matheson, 2004; Gupta & Kabundi, 2011; Moser et al., 2007; Schumacher, 2007; Schumacher & Breitung, 2008; Stock & Watson, 2002b).

To motivate this paper, we consider the following two questions: (1) do large-dimensional approximate factor models that are well established for forecasting Western macroeconomies also work well for China? and (2) do factor models based on mixed-frequency data with missing observations provide more accurate forecasts than factor models based on targeted predictors?[4] While evaluation of new forecasting models that have recently been proposed by other research is of considerable interest for governments, academic research, business and many other parties, assessing the performance of large-dimensional approximate factor models with mixed-frequency and missing observations dataset is equally important for a broad programme of research on Chinese macroeconomic forecasting. This is particularly relevant in light of the limited range of existing academic literature in the field.

Scholarly journals have published a small number of papers on forecasting Chinese macroeconomic variables, among which mixed-frequency datasets with missing observations are infrequently considered. Several studies use traditional models such as univariate time series and multivariate vector autoregression (VAR) models to forecast the Chinese real economic activity and inflation and find that the growth rate of industrial value-added goods, the term structure of credit spread and the money supply are useful indicators for predicting China's macroeconomy (He & Fan, 2015; Higgins et al., 2016; Kamal, 2013; Zhou et al., 2013). One possible shortcoming is that these studies typically only employ a handful of predictors. Zhou et al. (2013) only incorporate the term structure of credit spreads into VAR models. Kamal (2013) considers only money supply and output indicators. He and Fan (2015) select 14 money and credit indicators to forecast China's inflation, and Higgins et al. (2016) used only M2, inter-bank repurchase rate and deposit rate; therefore, the potentially useful information from rich sets of macroeconomic predictors is not fully utilised. The literature has extended to areas of big data, but the lack of economic theory and the quality of data are two major concerns. Li et al. (2015) use the mixed-data sampling (MIDAS) method with Google

[3]Stock and Watson (2002a) prove consistency of the principal component estimator of the static factors under the condition which the estimated factors can be treated as observed in subsequent forecasting regressions. Bai and Ng (2006) further provided improved rates for consistency of the estimator for which the factor estimated by principal component can be treated as data (that is, the error in the estimation of the factors can be ignored when they are used as regressors).

[4]We preselect variables from our mixed-frequency dataset according to Bai and Ng (2008a) and name them targeted predictors.

search data to forecast China's inflation. They find that Google search data are strongly correlated with CPI and that the MIDAS model can outperform the benchmark autoregressive integrated moving average (ARIMA) model, with an average reduction of RMSE of 32.9 percent. However, there is currently underutilisation of economic theory when using data from Internet companies to predict the macroeconomy, and the quality and accessibility of Google data are questionable. Jiang et al. (2017) extract a few dynamic factors from 44 monthly variables and 54 daily variables and used them in a mixed-frequency data sampling framework to forecast China's quarterly GDP growth rate. However, they only cover a forecast horizon of one-quarter-ahead. In this case, forecasting the real GDP growth rate at one-quarter-ahead makes limited economic sense, as China is the only major economy that sets a rigid target for annual GDP growth.

This paper also considers a larger number of forecasts than other existing studies forecasting China's macroeconomy. Mehrotra and Sánchez-Fung (2008), Lin and Wang (2013), Kamal (2013), Zhou et al. (2013) and He and Fan (2015) all perform comparisons of alternative forecasting models for China's economic indicators, but these studies only consider a small number of forecasts. Mehrotra and Sánchez-Fung (2008) and Lin and Wang (2013) only conduct 12 forecasts. Kamal (2013) produces nine annual out-of-sample forecasts, whereas Zhou et al. (2013) only consider six out-of-sample forecasts. He and Fan (2015) produce forecasts for five quarters. In comparison, our paper constructs at least 88 forecasts.

This study conducts a horse race among a large set of traditional forecasting models and large-dimensional approximate factor models. We predict two measures of inflation and three measures of real economic activity. Our measures of inflation are the Consumer Price Index (CPI) and the Retail Price Index (RPI), and we measure real activity using data on nominal investment, nominal consumption and railway freight traffic.[5] We use seven different forecasting models, each of which has proved useful for forecasting macroeconomic variables in Western economies. The forecasting results are presented in an out-of-sample forecasting simulation framework. In addition, we assess the performance of comparable models during the Global Financial Crisis (GFC) period.

The set of univariate models covers the AR(p) forecast, the AR(2) forecast, the ARMA(p,q) forecast and the ARMA(2,2) forecast, while the set of multivariate forecasts consists of specifications of the VAR model and multivariate leading indicators. Our set of factor models includes the diffusion index (DI) by Stock and Watson (2002b), factor-augmented autoregressive (FA-AR) models and factor-augmented vector autoregressive (FA-VAR) models. We collect our data over the period January 2002 to June 2018 and construct a 50:50 percent split between in-sample and out-of-sample periods. To estimate factors, we use the principal component analysis for balanced panel data and the expectation-maximisation (EM) algorithm for the mixed-frequency data with missing observations. The parameter estimation for each forecasting model is based on a rolling window of 100 observations to minimise the effect of changing sample size and model instability.[6] Then, we construct 1-month, 3-month, 6-month, 9-month and 12-month-ahead forecasts and compare the forecasting performances by the relative root mean squared error (RMSE) and Giacomini and White's (2006) test of conditional predictive.

[5]We use X-13ARIMA-SEATS in *R* platform to seasonally adjust the measures of inflation and real activity since the non-seasonal components of variables are generally of most interest in macroeconomic analysis.

[6]The issue of model instability, which refers to the situation in which the data-generating process varies over time (Elliott & Timmermann, 2016), is common in emerging countries like China. This could result from constant changes in the makeup of the economy, changes in regulations, and technological evolution. The obvious problem arising from model instability is that forecasting models might be good on average over the long data sample, but not at the time we make forecasts. Elliott and Timmermann (2016) suggest forecasters should consider robust methods that do not rely on estimating the number of breaks, such as the use of a rolling window estimator.

Overall, our results show that mixed-frequency factor models, especially mixed-frequency FAVAR models, provide more accurate forecasts than the benchmark model for inflation price series, nominal investment and nominal consumption at horizons longer than 1 month, but not for railway cargo. Therefore, our paper provides solid support for the conclusions found by a body of existing literature for Western economies (see, for example, Clements, 2016; Gupta & Kabundi, 2011; Stock & Watson, 2002b). Of further interest is that the forecasting results for the GFC period are markedly different. In most cases, the ARp model provides the most accurate forecasts for real economic activity. For inflation, only the mixed-frequency FA-VAR(p) model provides accurate forecasts for the CPI at 1-month-ahead and for the RPI at 1-month, 3-months and 6-months ahead. The results for the GFC are consistent with An et al. (2018) and Plagborg-Møller et al. (2020) where they argue that forecasting the macroeconomy can be problematic during times of crisis because the realisation of the variables are far away from their average values, while the traditional econometric models (in particular the linear models) are typically better at forecasting close to the average.

Our paper joins the growing body of empirical applications evaluating the relative success of using big data econometric models to forecast important macroeconomic variables for China. To the best of our knowledge, ours is a rare attempt to consider forecasting China's macroeconomy using hundreds of macroeconomic variables. The main contributions to the literature can be summarised twofold. First, the factor models we considered are based on a very large number of predictors with mixed-frequency and missing observation components, as well as factor models based on pre-selected targeted variables. The number of predictors used in other studies for China is relatively smaller, usually around 40 variables or less. Second, we run a sufficiently large number of training sets and validation sets, whereas other studies normally have 5–60 observations for the validation set.[7]

The rest of this paper is organised as follows. Section 2 describes the large-dimensional approximate factor model and its estimation. Section 3 presents the forecasting methodologies of each model. Section 4 describes the data. Section 5 presents empirical results. In Section 6, we discuss our findings, and in Section 7, we make some concluding comments.

2 | THE FACTOR MODELS AND ESTIMATION

Factor models arise naturally in economics. For example, x_{it} is the GDP growth rate for country i in period t, F_t is a vector of common shocks, λ_i is the heterogeneous impact of the shocks and e_{it} is the country-specific growth rate (Bernanke et al., 2005). In finance, x_{it} is the return for asset i in period t, F_t is a vector of systematic risks (or factor returns), λ_i is the exposure to the factor risks and e_{it} is the idiosyncratic returns (Bornholt, 2007; Elliot et al., 2018).

To motivate the representation of factor models, we can assume that the state of an economy can be represented as the sum of two mutually orthogonal components: the common component and the idiosyncratic component. The common component of each variable is a linear combination of a small number of common factors, whereas the idiosyncratic components are variable specific. Theoretically, the premise of factor models is that there exist a small number of latent and unobservable factors driving the co-movements of the high-dimensional vector of macroeconomic variables.[8] We now address the representation of factor models.

[7]Mehrotra and Sánchez-Fung (2008), Lin and Wang (2013), He and Fan (2015) and Jiang et al. (2017) conduct comparisons of alternative forecasting models for Chinese macroeconomic variables, covering a broad range of forecasting models. However, these studies consider only a very small number of out-of-sample forecasts. For example, Lin and Wang (2013) provide forecasts for a maximum of 12 months only, and Jiang et al. (2017) only consider a total of eight out-of-sample forecasts. It is arguably suspect that short periods of out-of-sample forecast would not be robust to changes in the sampling periods considered.

[8]This is also affected by a vector of zero mean uncorrelated idiosyncratic disturbances.

2.1 | Factor models representation

The classical factor model has been widely used in psychology and other disciplines of social science but less so in economics and finance, perhaps because the assumption that factors and idiosyncratic errors are serially and cross-sectionally independent does not align with economic data. The dynamic factor model explicitly recognises serial dependence across T and N, where N is the number of variables and T is the number of time observations. Let y_{t+h} denote the scalar series to be forecast at h-step-ahead and let x_{it} be a predictor variable observed for $t = 1, \ldots, T$ and $i = 1, \ldots N$. Following the work of Stock and Watson (2016), we suppose that (x_{it}, y_{t+h}) admits a dynamic factor model representation with $\bar{r}$ common dynamic factors f_t:

$$y_{t+h} = \beta(L)f_t + \gamma(L)y_t + \epsilon_{t+1}, \tag{1a}$$

$$x_{it} = \lambda_i(L)f_t + e_{it}, \tag{1b}$$

where $\lambda_i(L)$, $\gamma(L)$ and $\beta(L)$ are lag polynomials in non-negative powers of L.[9] Although knowledge of the dynamic factor model is useful in the structural identification of the number of primitive shocks in the economy, the estimation of factors and factor loading requires the use of tools of frequency domain analysis, and the proper choice of the auxiliary parameters is relatively difficult. For the purpose of multi-step forecasts, Stock and Watson (2016) impose two important modifications to (1a) and (1b). First, the lag polynomials $\lambda_i(L)$, $\gamma(L)$ and $\beta(L)$ are restricted to have finite orders of maximum q so that $\lambda_i(L) = \sum_{j=0}^{q} \lambda_{ij} L^j$ and $\beta(L) = \sum_{j=0}^{q} \beta_j L^j$. The finite lag assumption allows the dynamic factor model (1a) and (1b) to be written as a static factor model:

$$y_{t+h} = \beta' F_t + \gamma(L)y_t + \epsilon_{t+1}, \tag{2a}$$

$$X_t = \Lambda F_t + e_t, \tag{2b}$$

where $X_t = (x_{1t},\ldots,x_{Nt})'$ is the $N \times 1$ vector of stationary variables, $F_t = (f_{1t},\ldots,f_{rt})$ is the $r \times 1$ vector of unobservable factors (with $r \leq (q+1)\bar{r}$), $\Lambda = (\lambda_1',\ldots,\lambda_N')'$ is known as $N \times r$ matrix of factor loadings and $e_t = (e_{1t},\ldots,e_{Nt})'$ is the $N \times 1$ vector of idiosyncratic disturbances.[10] Second, instead of developing a vector time series model for F_t and rolling the forecasts $y_{t|Ft}$ forward, which entails estimating a large number of parameters that could erode forecasting results, the construction of the h-month-ahead forecast can be achieved by linear combination of F_t and y_t (with or without its lags) (Marcellino et al., 2006). The resulting adopted multi-step-ahead forecasting equation is:

$$y_{t+h} = \alpha_h + \beta_h(L)F_t + \gamma_h(L)y_t, \tag{3}$$

where y_{t+h} is the h-month-ahead variable to be forecast, the constant term is introduced explicitly, and the subscripts reflect the dependence of the projection on the horizon.

[9]It is assumed that $E(\epsilon_{t+1}|f_t,y_t,X_t,f_{t-1},X_{t-1},\ldots) = 0$. Therefore, in the case that f_t, $\beta(L)$ and $\gamma(L)$ were known, the minimum mean squared error forecast of y_{t+1} would be $\beta(L)f_t + \gamma(L)y_t$.

[10]In factor model literature, r is known as the true number of factors whereas k refers to the estimated number of factors. Typically, r is much smaller than N, and r does not necessarily equal k.

When the dataset contains no missing observations, we use asymptotic principal component analysis to estimate factors and factor loadings, subject to the PC1 restriction by Bai and Ng (2013).[11] The number of static factors is determined by Bai and Ng (2002)'s $g_2(N,T)$ information criteria.[12]

2.2 | The expectation–maximisation algorithm for unbalanced data

Macroeconomic forecasting often encounters a situation in which a dataset may be highly unbalanced, possibly due to missing observations and different sampling frequencies. In practice, economic information is released with different sampling frequencies and publication lags. When data are unbalanced, the standard principal component estimator cannot be applied in such circumstances; instead, we consider using the EM algorithm, which is an iterative method for an efficient and consistent estimate of Λ and F when data irregularities are present.[13]

With the EM algorithm, the least squares estimators of factors and factor loadings are achieved by solving the following minimisation problem:

$$V(k) = (NT)^{-1} \sum_{i=1}^{N} \sum_{t=1}^{T} I_{it} \left(x_{it} - \lambda_i' F_t \right)^2, \tag{4}$$

where $I_{it} = 1$ if x_{it} is observed and $I_{it} = 0$ if x_{it} is unobserved. Minimising (4) requires the use of iterations and sometimes may be difficult to solve analytically (Stock & Watson, 2016). Stock and Watson (2002b) propose a simple EM algorithm to estimate the space spanned by factors.[14] Let $\hat{F}^{(j-1)}$ and $\hat{\Lambda}^{(j-1)}$ denote the estimated factors and factor loadings at the $(j-1)$th iteration of the EM algorithm. Then, the estimates of factors and factor loadings at the j^{th} iteration solve the following minimisation problem:

$$Q\left(X^{obs}, \hat{\Lambda}^{(j-1)}, \hat{F}^{(j-1)}, F, \Lambda\right) = \sum_{i=1}^{N} \sum_{t=1}^{T} \left\{ E_{\hat{F}^{(j-1)}, \hat{\Lambda}^{(j-1)}} \left(x_{it}^2 | X^{obs} \right) + \left(\lambda_i^{k\prime} F_t^k \right)^2 - 2\hat{x}_{it} \left(\lambda_i^{k\prime} F_t^k \right) \right\}, \tag{5}$$

where X^{obs} is the full set of observed data and $\hat{x}_{it} = E_{\hat{F},\hat{\Lambda}}\left(x_{it} | X^{obs}\right)$. The first term on the right side of (5) does not depend on either factors or factor loadings. This implies that the minimiser of (5) is proportional to the minimiser of:

[11] Bai and Ng (2008b) suggest normalisation of $T^{-1}FF' = I_r$ and $\Lambda\Lambda'$ being diagonal or, alternatively, $N^{-1}\Lambda\Lambda' = I_r$ and FF' being diagonal. Since the method of principal components estimates space spanned by latent factors instead of factors themselves, further restrictions are required for F and Λ. Following the methods of Bai and Ng (2013), $\Lambda\Lambda'$ is restricted, being a diagonal matrix whose diagonal elements are distinct entries, positive and arranged in decreasing order. Such a restriction is referred to as a PC1 restriction by Bai and Ng (2013). Under PC1 conditions, the normalisation of factors provides $r \times (r+1)/2$ restrictions, whereas the diagonal matrix $\Lambda\Lambda'$ gives $r \times (r - 1)/2$.

[12] Traditional information criteria such as the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC), which are functions of N or T alone, provide inconsistent estimations of the number of static factors when both N and T diverge. Bai and Ng (2002) argued that the penalty function for overfitting must include both N and T. They pioneered the literature by proposing information criteria to take into account both dimensions of the dataset as arguments of the function penalising over-parametrisation. Their information criteria can consistently estimate the true number of statics factors; hence, they should be given priority over the AIC or BIC (Stock & Watson, 2016)

[13] The EM algorithm is also used by McCracken and Ng (2016) to build the balanced FRED-MD dataset. The FRED-MD is a large macroeconomic database designed for the empirical analysis of 'big data' and has been widely used by macroeconomists.

[14] For the purpose of macroeconomic forecasting, one only needs to estimate the space spanned by factors as long as estimated factors are subject to the PC1 condition of Bai and Ng (2013). For the purpose of structural analysis, factor identification schemes such as name identification should be further considered.

$$\hat{V}(F,\Lambda)=\sum_{i=1}^{N}\sum_{t=1}^{T}\left(\hat{x}_{it}-\lambda\prime_i F_t\right)^2. \tag{6}$$

At the j^{th} step of convergence, this reduces to the usual principal component analysis wherein the missing data are replaced by their expectation, conditional on the observed data and using the parameter values from the previous iteration. Following the work of Stock and Watson (2002b), we proceed with the EM algorithm as follows:

1. Initial step: Provide an initial estimate of missing observations. In our application, observations that are missing are initialised to the unconditional mean based on the non-missing values (which is zero since the data are demeaned and standardised). Then, we use standard principal component analysis to estimate factors and factor loadings.
2. E-step: For the j^{th} iteration, given the estimated factors and loadings from the previous $(j-1)$th iteration, compute the updated estimate of missing monthly series and monthly estimate of quarterly series by the expectation of X_i ($T\times 1$ vector), conditional on the observed data X_i^{obs} and the previous iteration factors and loadings for variable i according to:

$$\begin{aligned}\hat{X}_i^j &= E\left(X_i \mid X_i^{obs}, \hat{F}^{(j-1)}, \hat{\lambda}_i^{(j-1)}\right)\\ &= \hat{F}^{(j-1)}\hat{\Lambda}_i^{(j-1)} + A_i'\left(A_iA_i\prime\right)^{-1}\left(X_i^{obs}-A_i\hat{F}^{(j-1)}\hat{\Lambda}^{(j-1)}\right),\end{aligned} \tag{7}$$

where $\hat{F}^{(j-1)}$ is the $T\times r$ matrix of factors estimated from the previous $(j-1)$th iteration, $\hat{\lambda}_i^{(j-1)}$ is the i^{th} row of $\hat{\Lambda}^{(j-1)}$ and A_i is a time aggregation matrix. In (7), part $\hat{F}^{(j-1)}\hat{\Lambda}_i^{(j-1)}$ is the common component from the previous iteration and the term $\left(X_i^{obs}-A_i\hat{F}^{(j-1)}\hat{\lambda}^{(j-1)}\right)$ is the low-frequency idiosyncratic component, distributed by the projection coefficient $A_i'\left(A_iA_i\prime\right)^{-1}$. If X_i contains no missing values, A_i is the identity matrix and (7) simply becomes $\hat{X}_i=\hat{F}\hat{\Lambda}_i+\left(X_i^{obs}-\hat{F}\hat{\Lambda}_i\right)=X_i^{obs}$. Therefore, for variables without data irregularities, no EM iteration is required.

3. M-step: Repeat the E-step for each variable i. The estimated monthly observations for quarterly series, the estimated monthly missing observations and the monthly series without data irregularities are combined into a new $T\times N$ dataset. Re-estimate factors and factor loadings by principal component analysis. Go back to the E-step until convergence. In our application, we stop the algorithm if the change in the objective function (5) is smaller than 10^{-5}.

2.3 | Time aggregation matrices

Correctly specifying A_i in (7) is key to the EM algorithm. When dealing with mixed-frequency datasets, transformation of quarterly observations into monthly estimates must be performed properly. If missing observations occur (e.g., at the end of the sample period), further transformation is required. This transformation procedure is called *mapping* by Schumacher and Breitung (2008). We distinguish X^{obs} to be the $T^{obs}\times 1$ vector of available observations and X_i to be the $T\times 1$ vector of all observations (including available and missing) for the i^{th} variables. Then, the function of mapping can be written as a linear relationship as below:

$$X_i^{obs} = A_i X_i, \tag{8}$$

where A_i is a $T^{obs} \times T$ matrix that tackles missing values or different sampling frequencies. Next, we provide three examples to demonstrate the specifications of A_i for different variables.

2.4 | Example 1: Missing observations at the end of the sample

If missing observations occur, rows of the identifying matrix corresponding to the missing values of X_i should be removed. For instance, if the last observation in X_i is not available, the last row of the identity matrix A_i corresponding to the missing value of X_i should be removed. The mapping matrix A_i becomes:

$$A_i = \begin{pmatrix} 1 & \cdots & 0 & 0 \\ \vdots & \ddots & \vdots & \vdots \\ 0 & \cdots & 1 & 0 \end{pmatrix} \tag{9}$$

2.5 | Example 2: Gross domestic product as a monthly flow variable

The key output indicator GDP is usually a quarterly flow variable, and we let the natural log of GDP be denoted as y_t^q. If we assume that the observable quarterly data are averages of unobservable monthly series, the underlying relationship between the observed natural log of quarterly GDP y_t^q and the unobserved monthly GDP in the natural log can be written as:

$$y_t^q = (1/3)\left(y_t^m + y_{t-1}^m + y_{t-2}^m\right), \tag{10}$$

where t is the monthly time index, and (10) holds for $t = 3, 6, 9, \ldots T$, assuming that quarterly observations are available in the last month of the quarter. If time index T is not a multiple of three, then the last row (or last two rows) are missing observations. The theory outlined in Section 2.1 requires stationary time series; therefore, it may be useful to convert quarterly GDP in the natural log to the growth rate of GDP and rewrite (10) as:

$$\Delta^q y_t^q = (1/3)\left(y_t^m + y_{t-1}^m + y_{t-2}^m\right) - (1/3)\left(y_{t-3}^m + y_{t-4}^m + y_{t-5}^m\right) \tag{11}$$

$$= (1/3)\left(\Delta y_t^m + 2\Delta y_{t-1}^m + 3\Delta y_{t-2}^m + 2\Delta y_{t-3}^m + \Delta y_{t-4}^m\right), \tag{12}$$

Rewriting (10) and (11) is a standard approach and is often referred to as GDP interpolation in the literature (see, for example, Marcellino et al., 2003; Schumacher and Breitung, 2008). This yields the relationship between the quarterly GDP growth rate and the monthly GDP growth rate of $\Delta^q Y^q = A_y \Delta Y^m$ and implicitly defines the rows of A_y as

$$A_y = \frac{1}{3}\begin{pmatrix} \ddots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ \cdots & 3 & 2 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ \cdots & 0 & 1 & 2 & 3 & 2 & 1 & 0 & 0 & 0 \\ \cdots & 0 & 0 & 0 & 0 & 1 & 2 & 3 & 2 & 1 \end{pmatrix}, \tag{13}$$

where $\Delta^q Y^q = \left(\cdots, \Delta^q y_{T-6}^q, \Delta^q y_{T-3}^q, \Delta^q y_T^q\right)'$ and the corresponding monthly GDP growth rates $\Delta Y^m = \left(\cdots, \Delta y_{T-2}^m, \Delta y_{T-1}^m, \Delta y_T^m\right)'$. If more timely monthly observations are available at the end of the sample than quarterly GDP series, the rows of mapping matrix A_y corresponding to missing values of the quarterly GDP must be removed, and the final three columns of A_y will become zero vectors.

2.6 | Example 3: Business survey index as quarterly $I(0)$ stock variable

The quarterly business survey index is a stock variable as it is a point-in-time figure at the end of each quarter, measuring how confident business managers are given current economic conditions. The range of the quarterly business survey index is relatively small – usually between 45 and 55 in our study. It is an $I(0)$ process as verified by unit root tests.[15] If the quarterly series is a stock variable in the $I(0)$ process, it can be treated as a monthly series with missing observations occurring in the first and second months of each quarter. The corresponding mapping matrix A_i is then:

$$A_i = \begin{pmatrix} 0 & 0 & 1 & 0 & 0 & 0 & \cdots \\ 0 & 0 & 0 & 0 & 0 & 1 & \cdots \\ \vdots & \ddots & \ddots & \ddots & \ddots & \vdots & \vdots \\ 0 & \cdots & \cdots & \cdots & 0 & 0 & 1 \end{pmatrix} \tag{14}$$

3 | FORECASTING METHODOLOGY

Our choice of forecasting models is guided by two considerations. First, our interest is to assess whether large-dimensional factor models with ragged-edge and mixed-frequency datasets that work well for Western countries can also improve forecasts of China's macroeconomy. Second, we aim to investigate whether univariate and multivariate models can perform as well as factor models. We settled on the following set of models.

3.1 | AR

The second univariate model is the AR model.[16] The number of AR lags can be determined using the sequential downward t-test or information criteria such as the AIC and the BIC. The h-month-ahead AR forecasting model is:

$$\hat{y}_{t+h} = \hat{\alpha}_h + \sum_{j=1}^{p} \hat{\gamma}_{jh} y_{t-j+h}. \tag{15}$$

We propose two variants of the AR model. For the first, AR(p), we use the AICc to determine the number of lags with maximum allowed orders of 12.[17] For the second, (AR(2)), the lag order of the AR term is (arbitrarily) set equal to 2.[18]

[15]The unit root test is performed using the adf.test function in R.

[16]Detailed discussion of the AR model can be found in many textbooks (e.g., Stock & Watson, 2003).

[17]AIC is commonly known to over-parameterise the model and choose long lags, which would, in general, lead to inferior forecasting performance (Findley & Wei, 2002; Konishi & Kitagawa, 2008). This is particularly problematic when the sample size is small. AICc can be used to correct the bias lag selection of small sample sizes. Robustness checks using AIC, AICc, BIC, the Hannan-Quin criterion and the Schwarz information criterion show similar forecasting results.

[18]The AR(p) model is the most commonly used univariate model for macroeconomic forecasting; see, for example, Stock and Watson (1998, 2002b), Artis et al. (2005), Schumacher (2007) and Gupta and Kabundi (2011). A specific lag (i.e. lag = 2) is often used for robustness checks.

3.2 | Autoregressive moving average (ARMA)

Extending the AR model to an ARMA model that considers the autocorrelation in error terms is relatively straightforward. The h-month-ahead ARMA forecast is:

$$\hat{y}_{t+h} = \hat{\alpha}_h + \sum_{j=1}^{p} \hat{\gamma}_j y_{t-j+h} + \sum_{i=1}^{q} \hat{\delta}_j \varepsilon_{t-i+h} \tag{16}$$

We fit two types of ARMA models. For the first type, we select the order of p and q based on the AICc with maximum allowed orders of 12, denoting this as ARMA(p,q). For the second type, we arbitrarily set the value of p and q equal to 2 and denote it as ARMA(2,2).

3.3 | VAR

The VAR model is one of the most successful, flexible and easy-to-use models for the analysis of multivariate time series. It has proved especially useful for describing the dynamic behaviour of economic time series and for undertaking macroeconomic forecasting (Lütkepohl, 2014; Stock & Watson, 2017). We follow the recommendations of Stock and Watson (2002b) by specifying the vector to contain an indicator for inflation, an indicator for real economic activity and an indicator for monetary policy instruments. We use the growth rate of money supply M2, rather than the interest rate, in our VAR model. Such a choice regarding the monetary policy instrument is based on findings by Higgins et al. (2016), He et al. (2013) and Chen et al. (2016). Chen et al. (2016) and Higgins et al. (2016) find that the Chinese government is effective at controlling bank credit via M2 growth to influence investment and, therefore, GDP growth. He et al. (2013) find that the repurchase rate, the benchmark lending rate and a market-based monetary stance have little effect on the Chinese economy, but that non-market-based measures such as growth rates of total loans and money supply are effective in adjusting the real economy and price level. Therefore, to forecast an inflation variable, the vector Y_t consists of the variable to be forecast, the industrial production index and the growth rate of M2. To forecast a real economic variable, the vector Y_t includes the variable to be predicted, CPI and the growth rate of M2. Multi-step forecasts are computed by iterating the VAR forwards. The general formula for the h-month-ahead point forecast is:

$$\hat{z}_{t+h} = \hat{\phi}_0 + \hat{\Phi}_1 z_t \ \dots \ + \hat{\Phi}_p z_{t-p} \tag{17}$$

where $\hat{z}_{t+h}$ is the vector of k variables (in our study $k = 3$) for h-month-ahead forecasts, p is the lag order of the VAR, $\hat{\phi}_0$ is a $(k \times 1)$ vector of constants, $\hat{\Phi}$ are $(k \times k)$ coefficient matrices. We consider two implementations of the VAR model. For the first implementation, the order of the VAR model is set equal to 2. For the second implementation, the order is chosen by an AICc with a maximum allowed order of 4.[19]

3.4 | Multivariate leading indicator

Leading indicators are useful for predicting future economic conditions and have been used widely to predict output and inflation in the economic forecasting literature

[19]We use AICc rather than AIC to avoid the issue of overfitting the VAR model. A robustness analysis is done using AIC, AICc, BIC, the Hannan-Quin criterion and the Schwarz information criterion. These information criteria show similar forecasting results.

(Granger et al., 2006; Stock & Watson, 1989, 2002b, 2008). The multivariate leading indicator forecasts have the form:

$$\hat{y}_{t+h} = \hat{\delta}_0 + \sum_{j=1}^{m} \hat{\delta}\prime_i W_{t-j+1} + \sum_{j=1}^{p} \hat{\gamma}_j y_{t-j+h}, \tag{18}$$

where W is a vector of leading indicators that have been featured in our forecasting applications and $\hat{\delta}_j$ for $j = 0, \ldots, m$ are ordinary least squares (OLS) coefficient estimates.

For the real activity forecasts, the vector of leading indicators W consists of the Organisation for Economic Co-operation and Development (OECD) composite leading indicator, the change of railway freight turnover, the growth rate of fixed asset investment and the growth rate of imports. For the inflation forecasts, the W includes the change in outstanding loans, the OECD composite leading indicators, the change in retail sales of consumer goods and the one-year benchmark deposit rate set by the People's Bank of China. In all cases, the leading indicators are transformed such that W is $I(0)$ and screened for potential outliers. We propose two variants of multivariate leading indicator forecasts. For the first variant, MLD(2), the lag orders are arbitrarily set to 2. For the second variant, MLD(p), the lag orders in each variable to be forecast are determined by a recursive AICc with maximum allowed orders of 6.

3.5 | FA-AR

The factor models we use are based on the diffusion index developed by Stock and Watson (2002b). The distinctive feature of this index is that it adds latent factors to a standard AR model. The general formula for the h-month-ahead point forecast model is:

$$\hat{y}_{t+h} = \hat{\alpha}_h + \sum_{j=1}^{m} \hat{\beta}_j{}' \hat{F}_{t-j+1} + \sum_{j=1}^{p} \hat{\gamma}_j y_{t-j+h}, \tag{19}$$

where $\hat{y}_{t+h|t}$ is the h-month-ahead variable to be forecast, the constant term is introduced explicitly, $\hat{F}_t$ are factors, y_{t-j+1} is a lag of y_t, $\hat{\gamma}$ and $\hat{\beta}$ are the coefficients associated with the lags and the subscript t reflects the time horizon of the variable. The number of factors is determined using information criteria developed by Bai and Ng (2002), with the maximum allowed number of factors set to 6. We consider three variants of (19). The first and the second, denoted as models FA-AR(p) and FA-AR(2), include contemporaneous $\hat{F}_t$ and a lag of $\hat{y}_t$ (i.e., $m = 1$). The lag order p in the first variant FA-AR(p) is chosen by the AICc with the maximum order of 6, whereas in the second variant FA-AR(2), it is arbitrarily set to be 2. The third, denoted as DI, includes only contemporaneous $\hat{F}_t$ (so $m = 1$ and $p = 0$).[20]

3.6 | FA-VAR

Our study proposes a stochastic process to capture linear interdependencies among variables to be predicted and latent factors. Bernanke et al. (2005) suggest a VAR framework for factors and factor loadings wherein the vector contains only a single observable variable plus

[20]Bai and Ng (2002) estimate the number of factor to be 1.

unobservable and latent factors. Letting r denote the number of static factors and q denote the number of dynamic factors, we represent the FA-VAR model as in Stock and Watson (2016) so that the factors and factor loadings can be estimated by least squares and all the restrictions can been seen clearly as follows:

$$X_t = \Lambda \begin{pmatrix} Y_t \\ F_t \end{pmatrix} + u_t,$$
$$F_t^{+} = \Phi(L) F_{t-1}^{+} + G\eta_t, \quad \text{where} \quad F_t^{+} = \begin{pmatrix} Y_t \\ F_t \end{pmatrix}, \eta_t = H\varepsilon_t. \tag{20}$$

where $\Phi(L)$ is the lag operator, $\overset{r\times q}{G}$ and $\overset{r\times r}{H}$ are restriction matrices, $\overset{q\times 1}{\varepsilon_t}$ is the vector of structural shock, and $\overset{q\times 1}{\eta_t}$ is the vector of innovations to factors. The h-month-ahead FA-VAR forecasting model we fit the FA-VAR model with only is then:

$$\hat{z}_{t+h} = \hat{\phi}_0 + \hat{\Phi}_1 z_t \ldots + \hat{\Phi}_p z_{t-p} \tag{21}$$

where $\hat{z}_t$ is the vector containing variables to be forecasted and latent factors, p is the lag order of the FA-VAR, $\hat{\phi}_0$ is a vector of constants, and $\hat{\Phi}_i$ are coefficient matrices. We fit the FA-VAR model with only four factors for two reasons. First, the information criteria developed by Bai and Ng (2002) suggests that $k = 4$ (four factors) minimises the penalty function.[21] Second, we tend to avoid the problem of overfitting the VAR model. Since most VAR models are estimated using symmetric lags (i.e., the same lag length is used for all variables in all equations of the model), a large number of variables would result in a significantly large number of parameters to be estimated. Jolliffe (1993) indicated that overfitting the VAR model causes an increase in the RMSE. Therefore, we use only four factors and also restrict the maximum number of p to 4. Two variants of the FA-VAR are considered: FA(4)-VAR(2), wherein the lag orders p and q are arbitrarily set equal to 2, and FA(4)-VAR(p), wherein the lag orders p and q are selected using an AICc with a maximum allowable lag of 4.

We generate FA-VAR forecasts directly rather than forecasts of the common and idiosyncratic components separately. As Boivin and Ng (2005) suggest, when data-generating processes and their dynamic structures are known, no single method stands out to be systematically superior. However, when they are unknown, direct and unrestricted factor forecasts that impose fewer constraints and estimate a smaller number of auxiliary parameters appear to be less vulnerable to misspecification compared to indirect and restricted factor forecasts, leading to improved forecasts.

3.7 | Targeted FA-AR and FA-VAR

A critique of factor models is that not all series in X_t are relevant for predicting y_{t+h}. Instead of estimating factor space based on hundreds of predictors, Bai and Ng (2008a) suggest that a preselected subset of X_t that are relevant for forecasting y_{t+h} yield a better forecasting performance. Bai and Ng (2008a) propose two ways to construct the subset X_t^*:

[21]Selection of the number of factors for FAVAR models could be problematic, especially in the presence of structural instability. Mao Takongmo and Stevanovic (2015) documented that, in the presence of structural instability, many selection methods typically overestimate the number of factors.

1. Hard threshold (OLS):

$$y_t = \alpha + \sum_{j=0}^{m} p_j y_{t-j} + \beta_i X_{i,t} + \epsilon_t, \tag{22}$$

$$X_t^* = \{X_i \in X_t | \, t_{Xi} > t_c\}. \tag{23}$$

2. Soft threshold (LASSO):

$$\beta^{LASSO} = argmin_\beta \left[RSS + \lambda \sum_{i=1}^{N} |\beta_i| \right], \tag{24}$$

$$X_t^* = X_i \in X_t \,|\, \beta_i^{LASSO} \neq 0. \tag{25}$$

where the *RSS* refers to the sum of squared residual from a regression of y_t on all available regressors X_t. In hard thresholding, a regression is conducted for each predictor X_t. Then, the subset X_t^* is obtained by gathering those series whose coefficients have *t*-statistic larger than the critical value. In soft thresholding, the least absolute shrinkage and selection operator (*LASSO*) technique is used to select X_t^* by regressing y_t on all elements of X_t and discarding uninformative predictors (this process is also known as variable selection).

We follow the precedent of Bai and Ng (2008a) to pre-screen and select (judgementally) our targeted predictors. First, we remove variables with missing observations from our full-panel dataset, reducing the number of variables from 285 to 140. Then, we combine hard thresholds, soft thresholds and judgements to obtain 41 monthly variables from January 2002 to June 2018. These series represent 12 main categories of macroeconomic variables: industrial output and manufacturing production, retail and private consumption, international trade, investment, financial market, exchange rates, interest rates, money supply and loan, price indexes, government expenditure and revenue, business and consumer confidence index, and transportation sector. The description of data for targeted predictors is presented in Table A1 in Appendix 3. Finally, we denote forecasts of factor models from selected predictors as targeted DI, targeted FA-AR and targeted FA-VAR.

In Appendix 2, we present the stability of predictor selection for the targeted FA-AR and the FA-VAR in Figure A1. It shows the type of series that is selected by hard thresholding, with the critical value being 1.67 over the whole out-of-sample period. We find that hard thresholding can consistently select predictors over the whole out-of-sample period for price series, whereas the selection for investment and consumption varies over time.

4 | CHINA'S DATA

4.1 | Composition of China's data

Chinese official economic data are characterised by two critical features. First, the available data from the NBSC in a particular period may differ substantially from the data released in the previous month due to regular benchmark revisions. The size of revisions tends to be relatively large compared to that in Western economies, and the reasons for revisions are not always clear (Holz, 2014). Second, some particular data are not available in January and February due to the Chinese New Year. One typical example is that of industrial production. The NBSC used to publish the industrial production series for January and February; however, due to the significant effect of the Chinese New Year on the seasonal pattern of the data, the NBSC discontinued the release of industrial production data for both January and February in 2007. Therefore, every year, the first-hand information on Chinese industrial production becomes available to the public in mid-March in the form of a growth rate of production measuring accumulated production in January and February compared with the previous year. Thus, we do not consider forecasting industrial production as a measure of real economic activity.

The full dataset used to estimate the factors includes 251 important monthly macroeconomic variables and 34 quarterly variables for China, spanning from January 2002 to June 2018.[22] Due to the rapid institutional and structural change in China's economy, data from the 1990s might (arguably) be of limited informative value regarding the current state of the Chinese economy (Fernald et al., 2014; He et al., 2013; Lin & Wang, 2013). Our sample period covers the sharp downturn during the Global Financial Crisis as well as China's rapid subsequent recovery, which reflects the most important information about China's macroeconomy to date. The data include the following categories of macroeconomic variables: taxes and government expenditure, industrial sales and industrial production, energy production and consumption, exchange rates and stock indexes, interest rates and money supply, commodity price index and agricultural price index, exports and imports, business and consumer confidence indexes, and various survey data. We source our Chinese data from CEIC Data Manager. All data are also freely available to download at the NBSC website. We report the description of data for the full-panel dataset in Table A2 in Appendix 3.

The theory outlined in Section 2 states that stationarity of x_{it} is a moment condition for factor models (Bai & Ng, 2008b). All monthly and quarterly variables are subjected to four preliminary steps: possible deseasonalisation, possible transformation by taking either the difference or the percentage change, screening for possible outliers and standardisation. The deseasonalisation process removes the seasonal patterns of China's macroeconomic data, especially the effect of the Chinese New Year on many industrial sector-related series. We use *X-13ARIMA-SEATS* in *R* to perform the deseasonalisation.[23] The decision to take the difference or the percentage change is made judgementally, mainly based on inspection of time series plots and unit root tests. Generally, the difference is taken for those series that are already in the index or percentage terms, and the percentage change is implemented to series with actual quantities. We then clean the data by removing outliers for which the first difference deviates from the median of the first difference by more than five times the interquartile range and replacing them with missing data. Finally, all series are standardised to mean zero and unit variance according to Stock and Watson (2002a, 2002b).

4.2 | The five variables of interest

We consider two categories of monthly economic indicators: the measures of inflation and the measures of real economic activity. The measures of inflation that we forecast are the CPI

[22]Studies using mixed-frequency methods to estimate factors for forecasting the Chinese macroeconomy are limited compared to studies into the macroeconomy of Western countries. Quarterly variables provide additional information over monthly variables and may lead to improved forecasts.

[23]Developed by the United States Census Bureau, the *X-13* supports user-defined holiday variables such as Chinese New Year or Indian Diwali. It returns deseasonalised series if seasonality is detected and returns original series if seasonality is not detected.

and the RPI, while the measures of real economic activity are nominal investment, nominal consumption and the railway traffic freight. The CPI and the RPI are two common indicators for measuring inflation and are standard in economic forecasting literature. Nominal investment and consumption account for more than 80 percent of total GDP according to the aggregated expenditure approach. Using the railway traffic freight as a real economic indicator has two benefits. First, it is not on the government target list; that is, the statistical authorities do not have incentives to purposefully falsify the railway freight data to meet certain growth rate targets or to please the media and public (Holz, 2014). Second, the information about the actual cargo volume is relatively easier to collect than the GDP. This means that the margin of collection error is relatively small.

4.2.1 CPI and RPI

The data for the two price indexes are available from January 2002 to June 2018. Since the CPI and the RPI variables are collected in index terms, with the index value of the same month in the previous year being 100, subtracting 100 provides a proxy for the inflation rate. The CPI and the RPI are annualised year-on-year rates. After deseasonalisation and screening for outliers, the transformation equations for the CPI and the RPI are:

$$\begin{aligned} y_{t|CPI} &= \mathrm{CPI}_t - 100, \\ y_{t|RPI} &= \mathrm{RPI}_t - 100. \end{aligned} \tag{26}$$

4.2.2 Investment, consumption and railway traffic freight

Nominal investment, nominal consumption and railway traffic freight are expressed in nominal terms in billions of yuan and billions of tonnes and are available from January 2002 to June 2018. Similarly to the CPI and the RPI, we seasonally adjust them and screen for outliers. Since there exists a unit root for all three real variables, as shown in Table 1, we model these as the first difference of logarithms. Since we treat all three real variables identically, consider investment, which we transform as:

$$y_t = 1200^{*}\ln\left(\mathrm{Investment}_t / \mathrm{Investment}_{t-1}\right). \tag{27}$$

The results of augmented Dickey-Fuller tests for unit roots are presented for each variable in Table 1. In each case, we set the maximum lag order to 6. For untransformed variables in Panel A, we find evidence against a unit root existing for the CPI and the RPI, but not for nominal investment, consumption and railway freight. Once transformed, the unit root hypothesis is rejected for all variables, as shown in Panel B of Table 1. In addition, we display time series plots of the raw and transformed CPI, RPI, investment, consumption and railway freight in Figure 1.

4.3 | Forecasting design

Our study forecasts five Chinese monthly economic indicators h-month-ahead, and we set h equal to 1, 3, 6, 9 and 12 months. All forecasts are performed in a simulated out-of-sample framework wherein all statistical calculations are conducted using a fully recursive

TABLE 1 Augmented Dickey–Fuller test statistics with trend and drift

	CPI	RPI	Investment	Consumption	Railway freight
Panel A: Raw variables					
Lag order	6.00	6.00	6.00	6.00	6.00
Test statistics	−4.09	−3.81	−2.40	−2.40	−1.56
p-value	0.01	0.02	0.41	0.41	0.76
Panel B: Transformed variables					
Lag order	6.00	6.00	6.00	6.00	6.00
Test statistics	−4.07	−3.73	−3.61	−5.37	−5.38
p-value	0.01	0.02	0.03	0.01	0.01

Note: For the raw variable outliers have been removed and seasonal adjustment has been applied.

methodology. To ensure a sufficient number of within-sample and out-of-sample forecasting periods, we consider the total sample size in a 50:50 percent split between in-sample and out-of-sample periods.[24]

We apply the fixed rolling window method, in which we use a fixed number of observations to estimate model parameters in every within-sample period. The first h-month-ahead forecast is made for May 2010. To construct this forecast, we take the first 100 observations from the raw dataset – that is, observations from January 2002 to April 2010 – and remove outliers, seasonally adjust, standardise, estimate factors, select the model orders and run forecasting models using only the data in this subsample. After constructing forecasts from all models at each horizon, we drop the first observation from the previous subsample and add an extra observation of raw data to the end of the previous subsample. Then, we repeat the same steps for the second subsample – that is, take observations from February 2002 to May 2010 and construct the second h-month-ahead forecast for June 2010. We continue this process – dropping the first observation, adding an extra observation to the end of subsample, screening for outliers, standardising data, adjusting seasonality, estimating factors and running forecasting models using the data in the subsample, and computing forecasts – until the final forecast is made for June 2018.

In total, we produce a sequence of 99 1-month-ahead forecasts from April 2010 to June 2018, a sequence of 97 3-month-ahead forecasts from June 2010 to June 2018, a sequence of 94 6-month-ahead forecasts from September 2010 to June 2018, a sequence of 91 9-month-ahead forecasts from December 2010 to June 2018, and a sequence of 88 12-month-ahead forecasts from March 2011 to June 2018.

5 | ASSESSING FORECAST RESULTS

In this section, we assess the forecasting performance of competing models. We evaluate the forecasts' performance using the relative root mean squared error (RMSE). Evaluation of the relative RMSE in out-of-sample forecasting exercises is commonly used in the economic forecasting literature. Let y_t be the variable to be forecast at time t. Let $\hat{y}_{t+h|m}$ denote the h-month-ahead forecasts for variable by model m and define y_{t+h} as the actual value of the variable at

[24]When the number of time observations is large, the literature tends to split the estimation sample and forecast sample evenly to ensure a sufficient number of within-sample and out-of-sample periods; see, for example, Stock and Watson (2002b), Kotchoni et al. (2019), and Coulombe et al. (2019).

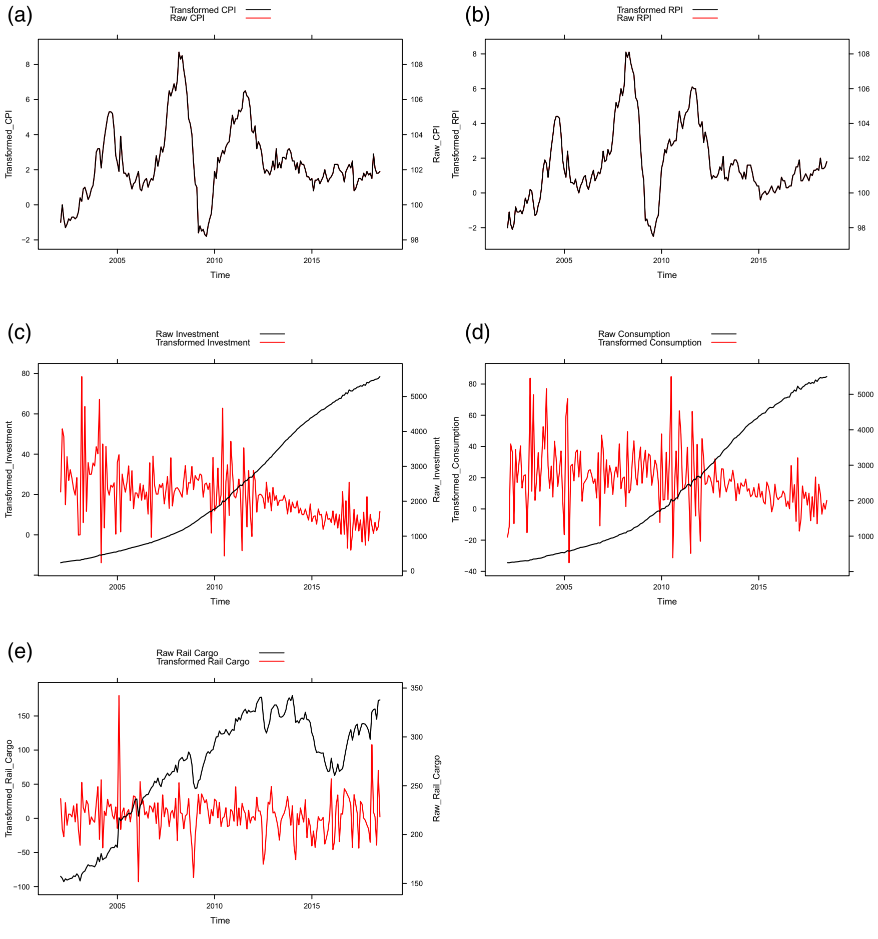

FIGURE 1 Time series plot of forecasted variables: (a) raw and transformed CPI, (b) raw and transformed RPI, (c) raw and transformed investment, (d) raw and transformed consumption, (e) raw and transformed railway cargo. For CPI and RPI, we transform with regard to Equation (26). For investment, consumption and railway traffic freight, we transform according to Equation (27). Note that plots for raw series are of the data after outliers have been removed and seasonal adjustment has been applied using *X-13-ARIMA*.

time $t+h$. The forecasting error at time $t+h$ for model m is computed as $\Delta_h y_{t+h|m} = \hat{y}_{t+h|m} - y_{t+h}$. The RMSE by model m for each variable is then calculated as:

$$\sqrt{\frac{\sum_1^{T-P} \left(\Delta_h y_{t+h|m}\right)^2}{T-P}} \tag{28}$$

where in T refers to the total number of time observations, and P refers to the number of within-sample periods. The relative RMSE is computed by setting the RMSE of the benchmark AR(p) model to be 1.[25] For example, to calculate the relative RMSE for the FA-VAR model, we divide the

[25]Dufour and Stevanović (2013) advised caution when choosing either the AR model or the ARMA model as a benchmark. As the AR model uses a finite order and only approximates to the process of x_{it}, a long AR model is needed if the MA polynomial has roots close to the non-invertibility region. This could cause overfitting of the AR model. However, the AR model has been widely used as the benchmark in the context of large datasets and factor models; see, for example, Stock and Watson (1998, 2002b), Artis et al. (2005), Schumacher (2007) and Gupta and Kabundi (2011). Even Dufour and Stevanović (2013) set AR(p) as the benchmark model.

RMSE of the FA-VAR model by the RMSE of the AR(p) model. A relative RMSE greater than 1 means the model performs worse than the benchmark model and vice versa. The choice of the benchmark model is guided by two considerations: (1) a well-defined AR model is commonly used as the benchmark model in the economic forecasting literature (Kotchoni et al., 2019; Li et al., 2015) and (2) Lin and Wang (2013), He and Fan (2015) and Higgins et al. (2016) find that AR models perform relatively well compared to ARMA models, diffusion index models, Bayesian VAR models and Phillips curves for forecasting China's inflation and GDP. If factor models based on mixed-frequency datasets with missing observations can outperform the AR(p), this indicates strong predictability.

In addition to the relative RMSE, we employ the conditional predictive test described by Giacomini and White (2006) to test null hypotheses of RMSE equality between mixed-frequency factor models and corresponding targeted factor models. Giacomini and White's (2006) test had a null of equal expected loss evaluated at the current parameter estimates as in (29) and, therefore, is conditional on the information set available at time t. Giacomini and White (2006) also claimed that the conditional test can capture the effect of estimation uncertainty on relative forecast performance when forecasting models may be mis-specified.

$$H_0: E\left[L\left(f_{1t+1|t}\left(\hat{\beta}_{1t}\right), y_{t+1}\right)\right] = E\left[L\left(f_{2t+1|t}\left(\hat{\beta}_{2t}\right), y_{t+1}\right)\right]. \tag{29}$$

5.1 | In-sample performance

Tables 2 and 3 report the in-sample rRMSE and p-value for the F-test of each forecasting model we proposed in Section 3. For inflation, the results show that, among all these models, FA-AR and FA-VAR can generate superior forecasts to the benchmark AR(p) model at all horizons, regardless of whether factors are estimated using preselected predictors or the mixed-frequency dataset. These gains in forecast accuracy are statistically significant according to a simple F-test statistic.[26] Regarding real variables, the results are less clear cut. For consumption and railway cargo, only DI and FA-AR can statistically outperform the benchmark AR(p) model, whereas for investment, the benchmark AR(p) model is hard to beat at all horizons.

5.2 | Out-of-sample forecasting results

We now address the results for inflation in Table 4. For the CPI inflation rate, the benchmark AR(p) model produces the best 1-month-ahead forecasts out of sample. For all other forecast horizons, VAR models, targeted FA-AR(2) models and mixed-frequency FA-AR(2) models generate superior forecasts to the benchmark AR(p) model and other competing models. The relative improvements are more modest at horizons of 3 and 6 months compared to 9 and 12 months. In some cases, the improvements over the benchmark forecasts are substantial; for example, the FA-AR(2) model with factors estimated using mixed-frequency data with missing observations has a forecast error variance that is 61 percent that of the AR(p) model. Other factor models perform poorly at horizons of 3 and 6 months, but perform well at horizons of 9 and 12 months.

The results for the RPI inflation rate are similar to those for the CPI inflation rate. The VAR forecasts, multivariate leading indicator forecasts, FA-VAR forecasts and FA-AR forecasts

[26]We describe how the simple F-test statistics are calculated in Appendix 1.

TABLE 2 Inflation: In-sample standardised root mean squared forecast by horizon

	CPI					RPI				
	$h = 1$	$h = 3$	$h = 6$	$h = 9$	$h = 12$	$h = 1$	$h = 3$	$h = 6$	$h = 9$	$h = 12$
Univariate forecasts										
AR(p)	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
AR(2)	1.09	1.10	1.10	1.10	1.10	1.06	1.06	1.07	1.07	1.07
ARIMA(p,q)	0.97	0.99	0.98	0.98	0.96	0.99	0.99	0.99	0.98	0.98
ARIMA(2)	0.96	0.96	0.96*	0.96	0.95	0.99	0.99	0.99	0.98	0.98
Multivariate forecasts										
MLD(p)	0.99	1.00	1.00	1.00	1.00	1.02	1.03	1.03	1.03	1.03
MLD(2)	0.99	1.00	1.00	1.00	1.00	1.00	1.01	1.01	1.01	1.02
VAR(p)	1.01	1.03	1.04	1.04	1.04	0.99	1.02	1.03	1.03	1.03
VAR(2)	1.07	1.08	1.09	1.09	1.09	1.04	1.05	1.06	1.06	1.07
Balanced-panel factor forecasts										
Targeted DI	10.18	9.89	9.50	9.23	8.86	12.55	12.15	11.94	11.80	11.63
Targeted FA-AR(p)	0.49***	0.50***	0.50***	0.50***	0.50***	0.52***	0.53***	0.53***	0.52***	0.52***
Targeted FA-AR(2)	0.48***	0.50***	0.50****	0.50***	0.50***	0.52***	0.53***	0.52***	0.52***	0.52***
Targeted FA-VAR(p)	0.71**	0.72*	0.72*	0.72*	0.71*	0.72*	0.73*	0.74*	0.74*	0.74
Targeted FA-VAR(2)	0.83	0.84	0.85	0.84	0.84	0.81	0.82	0.84	0.83	0.84
Mixed-frequency factor forecasts										
Mixed-frequency DI	11.31	11.34	10.87	10.42	9.82	13.90	13.86	13.58	13.25	12.86
Mixed-frequency FA-AR(p)	0.61***	0.63***	0.63***	0.63***	0.63***	0.69***	0.73***	0.72***	0.72***	0.70***
Mixed-frequency FA-AR(2)	0.62***	0.63***	0.63***	0.63***	0.63***	0.72***	0.72***	0.71***	0.71***	0.69***
Mixed-frequency FA-VAR(p)	0.64**	0.65**	0.65**	0.65**	0.64**	0.68**	0.68*	0.69*	0.68*	0.68*
Mixed-frequency FA-VAR(2)	0.74*	0.76	0.77	0.76	0.77	0.76*	0.77	0.78	0.77	0.76

Note: The rows are the forecasting models described in Section 3. The columns are forecast horizons. The table elements are the point forecasts of the relative RMSE expressed as a ratio of the RMSE of the benchmark model for the same forecast horizon. The benchmark model is the AR(p) model. ***, ** and *Significance at the 1%, 5% and 10% levels, respectively, for the F-test.

TABLE 3 Real variables: Simulated in-sample standardised root mean squared forecast by horizon

	Investment					Consumption					Railway cargo				
	$h=1$	$h=3$	$h=6$	$h=9$	$h=12$	$h=1$	$h=3$	$h=6$	$h=9$	$h=12$	$h=1$	$h=3$	$h=6$	$h=9$	$h=12$
Univariate forecasts															
AR(p)	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
AR(2)	1.38	1.38	1.37	1.40	1.43	1.21	1.22	1.22	1.22	1.22	1.01	1.01	1.01	1.01	1.01
ARIMA(p)	1.01	1.01	1.00	1.00	0.99	1.08	1.08	1.08	1.07	1.08	1.04	1.04	1.01	1.04	1.04
ARIMA(2)	0.99	0.98	0.98	1.00	0.99	1.03	1.11	1.11	1.11	1.11	0.96	0.98	0.95	0.96	0.93
Multivariate forecasts															
MLD(p)	1.05	1.05	1.05	1.03	1.02	0.64**	0.62**	0.66**	0.63**	0.62**	0.96	0.96	0.96	0.96	0.96
MLD(2)	1.35	1.36	1.36	1.39	1.41	0.69**	0.71**	0.72**	0.72**	0.72**	0.95	0.95	0.95	0.95	0.95
VAR(p)	1.00	1.04	1.05	1.08	0.91	0.97	0.99	1.00	1.00	0.99	0.97	0.97	0.98	0.98	0.96
VAR(2)	1.28	1.28	1.29	1.32	1.31	1.07	1.10	1.11	1.11	1.09	0.98	0.98	0.99	0.99	0.97
Balanced-panel factor forecasts															
Targeted DI	1.62	1.65	1.62	1.66	1.71	1.15	1.17	1.17	1.17	1.17	0.74***	0.74***	0.73***	0.73***	0.73***
Targeted FA-AR(p)	1.05	1.05	1.06	1.03	1.05	1.03	1.04	1.04	1.04	1.00	0.74***	0.74***	0.73***	0.73***	0.73***
Targeted FA-AR(2)	1.34	1.35	1.35	1.37	1.39	1.12	1.13	1.14	1.14	1.14	0.73***	0.73***	0.72***	0.72***	0.72***
Targeted FA-VAR(p)	0.94	0.98	0.99	1.00	0.85	0.95	0.99	1.00	1.01	0.94	0.89	0.89	0.90	0.89	0.87
Targeted FA-VAR(2)	1.22	1.24	1.26	1.30	1.29	1.10	1.14	1.15	1.15	1.13	0.90	0.90	0.91	0.91	0.88
Mixed-frequency factor forecasts															
Mixed-frequency DI	1.63	1.66	1.64	1.67	1.71	1.20	1.22	1.22	1.22	1.22	0.77***	0.77***	0.77***	0.77***	0.77***
Mixed-frequency FA-AR(p)	1.03	1.06	1.06	1.03	1.06	1.06	1.08	1.07	1.08	1.03	0.77***	0.77***	0.77***	0.77***	0.77***
Mixed-frequency FA-AR(2)	1.35	1.34	1.34	1.37	1.39	1.19	1.21	1.21	1.22	1.21	0.77***	0.77***	0.77***	0.77***	0.77***
FA-VAR(p)	0.98	1.01	1.03	1.04	0.87	0.97	1.00	1.01	1.02	0.93	0.88	0.88	0.89	0.88	0.87
FA-VAR(2)	1.31	1.33	1.34	1.38	1.39	1.13	1.17	1.16	1.16	1.16	0.90	0.91	0.91	0.91	0.90

Note: The rows are the forecasting models described in Section 3. The columns are forecast horizons. The table elements are the point forecasts of the relative RMSE expressed as a ratio of the RMSE of the benchmark model for the same forecast horizon. The benchmark model is the AR(p) model. ***, ** and *Significance at the 1%, 5% and 10% levels, respectively, for the F-test we proposed above.

TABLE 4 Inflation: Simulated out-of-sample standardised root mean squared forecast by horizon

	CPI					RPI				
	$h=1$	$h=3$	$h=6$	$h=9$	$h=12$	$h=1$	$h=3$	$h=6$	$h=9$	$h=12$
Univariate forecasts										
AR(p)	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
AR(2)	1.24	1.06	1.12	1.01	0.94	1.07	1.01	1.01	0.94	0.84
ARMA(p,q)	1.23	1.11	0.98	0.80	0.77	0.99	0.98	0.98	0.94	0.89
ARMA(2,2)	1.16	1.02	0.93	0.87	0.82	1.05	1.20	1.39	1.39	1.29
Multivariate forecasts										
MLD(p)	1.25	1.20	1.17	0.99	0.89	0.97	0.95	0.90	0.74	0.68
MLD(2)	1.14	1.03	1.00	0.84	0.71	0.92	0.84	0.74	0.63	0.57
VAR(p)	1.28	1.01	0.90	0.75	0.68	0.97	0.80	0.65	0.55	0.54
VAR(2)	1.44	1.23	1.04	0.79	0.67	1.11	1.04	0.84	0.63	0.55
Balanced-panel factor forecasts										
Targeted DI	9.41	3.57	1.82	1.07	0.72	11.97	3.71	1.65	1.00	0.69
Targeted FA-AR(p)	1.30	1.22	1.10	0.82	0.74	1.00	1.01	0.93	0.77	0.71
Targeted FA-AR(2)	1.32	1.06	0.92	0.71	0.63	0.98	0.87	0.71	0.55	0.50
Targeted FA-VAR(p)	1.42	1.10	1.12	0.80	0.67	1.07	0.86	0.76	0.57	0.57
Targeted FA-VAR(2)	1.20	1.05	1.00	0.71	0.59	0.91	0.80	0.70	0.55	0.54
Mixed-frequency factor forecasts										
Mixed-frequency DI	7.68	3.02	1.62	1.02	0.70	8.76	2.77	1.27	0.80	0.61
Mixed-frequency FA-AR(p)	1.21	1.14	1.10	0.86	0.77	0.95	0.95	0.92	0.77	0.71
Mixed-frequency FA-AR(2)	1.20	0.95	0.89	0.71	0.61	0.95	0.79	0.67	0.53	0.47
Mixed-frequency FA-VAR(p)	1.16	0.96	0.92	0.75	0.67	0.92	0.78	0.65	0.51	0.48
Mixed-frequency FA-VAR(2)	1.29	0.97	0.87	0.68	0.59	0.98	0.80	0.65	0.51	0.48

Note: The rows are the forecasting models described in Section 3. The columns are forecast horizons. The table elements are the point forecasts of the relative RMSE expressed as a ratio of the RMSE of the benchmark model for the same forecast horizon. The benchmark model is the AR(p) model.

generally outperform the benchmark AR(p) forecasts at any horizon, regardless of whether lag is predetermined at 2 or is selected by AICc and whether factors are estimated using mixed-frequency datasets or targeted predictors. The relative performance improves substantially as the forecast horizon grows. Among all competing models, VAR(2) and mixed-frequency FA-AR(2) are the two best performing models for horizons of 3, 6, 9 and 12 months. Therefore, judged solely on point forecasts, there appears to be a gain in using factors estimated from mixed-frequency datasets and the M2 growth rate to forecast Chinese CPI and RPI inflation at horizons longer than 1 month.

When the differences between targeted and full-panel factor forecasts are considered, the use of mixed-frequency datasets with missing observations yields substantial improvements for FA-VAR(p) forecasts and FA-VAR(2) forecasts while yielding marginal or no improvements for DI forecasts, FA-AR(p) forecasts and FA-AR(2) forecasts for the CPI inflation rate at all horizons. In some cases, improvements are noticeable. For example, the mixed-frequency FA-VAR(p) model produces 49 percent less forecast error variance than the targeted FA-VAR(p) model. For the RPI inflation rate, the use of mixed-frequency datasets can only improve DI forecasts at horizons of 1, 3, 6 and 9 months and FA-VAR(p) forecasts at horizons of 1, 3 and 6 months. For sampling variability, the results of pairwise conditional predictive tests between mixed-frequency factor models and targeted factor models are presented in Table 6. Only p-values of the DI model for the RPI inflation rate are smaller than 5 percent at $h = 1$, $h = 3$, $h = 6$ and $h = 9$, indicating that DI models based on mixed-frequency datasets generally have better predictive performance than corresponding DI models based on targeted predictors at the 5 percent levels of significance. For other factor models, mixed-frequency datasets with missing observations could not yield better predictive performance at any horizons.

The forecasting results for the real variables are presented in Table 5. For nominal investment, the performance of mixed-frequency FA-VAR(p) models, targeted FA-VAR(p) models and ARMA(p,q) models is usually better than that of the benchmark model across all horizons, except for targeted FA-VAR(p) models at 1-month-ahead. The relative improvements are more modest at $h = 6$, $h = 9$ and $h = 12$ than at $h = 1$ and $h = 3$. In contrast, VAR models, targeted DI models and mixed-frequency DI models perform poorly compared to the benchmark AR(p) model.

For nominal consumption at a forecasting horizon of 1 month, all models considered are inferior to the benchmark AR(p) model. For a forecasting horizon of 3-months-ahead, only mixed-frequency FA-VAR(p) models provide smaller RMSE than the benchmark model. At longer horizons, the relative performance of the FA-VAR(p) model improves, regardless of whether factors are estimated based on mixed-frequency datasets or preselected targeted predictors. The multivariate models and FA-VAR(2) model perform significantly worse than the benchmark model, whereas the univariate models, DI models and FA-AR model produce forecasts that are similar to or slightly worse than the benchmark model.

As with the railway freight, the results are less clear. Overall, competing models can barely outperform the benchmark model at any horizon. The level of relative improvement is marginal, with maximum error reduction being 11 percent for targeted DI models at $h = 1$ and minimum error reduction being 1 percent for the mixed-frequency FA-VAR(2) model at $h = 6$. Of all competing models, FA-VAR models and VAR models perform relatively well, regardless whether lag orders are predetermined at $p = 2$ or selected by AICc and whether factors are estimated on mixed-frequency datasets or targeted predictors. Multivariate leading indicators perform poorly at all horizons, with these forecasts resulting in, on average, 51.8 percent more forecasting error than the benchmark forecasts.

For the real variables, forecasting performance is usually not improved when the empirical factors from the mixed-frequency dataset are used compared to those from the targeted predictors. We report results of pairwise conditional predictive tests between mixed-frequency factor forecasts and targeted factor forecasts in Table 7. Overall, we find no strong evidence that the use of the mixed-frequency dataset yields statistical improvements over the targeted predictors when a 5 percent level of significance is considered. Occasionally, the conditional test finds evidence in favour of mixed-frequency factor models. For example, the p-values of the FA-AR(2) model for investment yield less than a 5 percent level of significance at $h = 1$, $h = 3$ and $h = 6$. Therefore, we do not consider that using mixed-frequency datasets with missing observations can provide evidence of superior forecasting power for real variables as the relative improvements are very small.

TABLE 5 Real variables: Simulated out-of-sample standardised root mean squared forecast by horizon

	Investment					Consumption					Railway cargo				
	$h = 1$	$h = 3$	$h = 6$	$h = 9$	$h = 12$	$h = 1$	$h = 3$	$h = 6$	$h = 9$	$h = 12$	$h = 1$	$h = 3$	$h = 6$	$h = 9$	$h = 12$
Univariate forecasts															
AR(p)	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
AR(2)	1.01	1.04	0.96	0.96	0.95	1.06	1.00	0.97	0.94	0.91	1.00	1.00	1.00	1.00	1.00
ARMA(p,q)	0.97	0.98	0.87	0.86	0.80	1.05	1.05	1.04	1.09	1.04	1.01	0.97	0.99	1.01	1.02
ARMA(2,2)	1.05	1.03	0.95	0.95	0.94	1.22	1.07	1.06	1.15	1.02	1.12	1.02	0.99	0.98	1.00
Multivariate forecasts															
MLD(p)	1.12	1.14	1.02	1.02	0.96	1.68	1.28	1.12	1.23	1.32	1.46	1.59	1.54	1.39	1.52
MLD(2)	1.80	1.62	1.54	1.46	1.28	1.65	1.30	1.12	1.23	1.30	1.39	1.54	1.53	1.42	1.50
VAR(p)	3.39	2.90	2.81	2.29	1.82	1.92	1.86	1.83	1.58	1.34	0.93	0.93	0.97	0.97	0.94
VAR(2)	3.38	2.90	2.81	2.29	1.82	1.92	1.86	1.83	1.58	1.34	0.93	0.93	0.97	0.97	0.94
Balanced-panel factor forecasts															
Targeted DI	1.71	1.58	1.56	1.44	1.27	1.29	1.24	1.21	1.15	1.07	0.89	0.93	1.08	0.99	1.05
Targeted FA-AR(p)	1.08	1.11	1.02	1.00	0.96	1.20	1.02	1.10	1.10	1.05	0.92	0.95	1.07	1.00	1.05
Targeted FA-AR(2)	1.70	1.63	1.60	1.48	1.30	1.43	1.13	1.21	1.16	1.08	0.95	0.93	1.08	1.00	1.05
Targeted FA-VAR(p)	1.15	0.85	0.74	0.62	0.63	1.27	1.10	0.86	0.87	0.93	0.99	0.93	0.98	0.96	0.94
Targeted FA-VAR(2)	1.68	1.09	0.95	0.93	0.99	1.68	1.28	1.39	1.40	1.30	0.95	0.91	0.97	0.97	0.94
Mixed-frequency factor forecasts															
Mixed-frequency DI	1.60	1.50	1.46	1.38	1.21	1.29	1.23	1.18	1.15	1.06	0.91	0.96	0.96	0.99	1.06
Mixed-frequency FA-AR(p)	1.06	1.11	1.02	1.02	0.97	1.16	1.02	1.07	1.10	1.05	0.94	0.97	0.97	0.98	1.04
Mixed-frequency FA-AR(2)	1.66	1.58	1.45	1.37	1.20	1.41	1.12	1.16	1.14	1.05	0.95	0.95	0.97	0.98	1.05
Mixed-frequency FA-VAR(p)	0.90	0.85	0.71	0.60	0.64	1.08	0.98	0.88	0.88	0.96	1.01	1.02	0.99	0.97	0.94
Mixed-frequency FA-VAR(2)	1.67	1.09	0.97	0.95	1.02	1.73	1.27	1.43	1.43	1.32	0.95	0.93	0.97	0.97	0.94

Note: The rows are the forecasting models described in Section 3. The columns are forecast horizons. The table elements are the point forecasts of the relative RMSE expressed as a ratio of the RMSE of the benchmark model for the same forecast horizon. The benchmark model is the AR(p) model.

TABLE 6 Inflation: Pairwise conditional predictive test results by horizon

	CPI					RPI				
	$h = 1$	$h = 3$	$h = 6$	$h = 9$	$h = 12$	$h = 1$	$h = 3$	$h = 6$	$h = 9$	$h = 12$
Diffusion Index	**0.03**	0.17	0.38	0.65	0.80	**0.00**	**0.02**	**0.05**	**0.05**	0.24
FA-AR(p)	0.30	0.11	0.97	0.08	0.26	0.48	0.09	0.77	0.94	0.88
FA-AR(2)	0.12	**0.05**	0.39	0.88	0.33	0.49	**0.02**	0.12	0.42	0.22
FA-VAR(p)	0.37	0.28	0.17	0.12	0.15	0.77	1.00	0.50	0.25	0.17
FA-VAR(2)	0.54	0.33	0.09	0.26	0.27	0.43	0.92	0.44	0.75	0.62

Note: The rows are the forecasting models described in Section 3. The columns are forecast horizons. The table elements are the p-values of the pairwise conditional predictive test between mixed-frequency factor models and corresponding targeted factor models (i.e., mixed-frequency FA-AR(p) model vs. targeted FA-AR(p) model). p-Values displayed with a bold font mean that we reject the null hypotheses of equal expected loss at a 5% level of significance and conclude that the mixed-frequency factor model has better expected loss than the targeted factor models.

5.3 | The effects of the Global Financial Crisis

In response to the Global Financial Crisis, the Chinese government injected an unprecedented four trillion yuan to stimulate the economy in 2009. These investments aimed to promote household consumption, increase job opportunities and stabilise economic growth until the end of 2011. This undoubtedly helped stabilise the double-digit real GDP growth in the aftermath of the financial crisis. Fears of the GFC and follow-up investments by the Chinese government have had persistent effects on inflation and output expectations. Several existing studies have argued that AR models and random walk, which are gold-standard models for forecasting US inflation and output, might be less effective during economic recessions with unstable financial conditions (Alessandri & Mumtaz, 2017; Berge, 2015; Faust & Wright, 2013; Gilchrist & Zakrajšek, 2012; Liu & Moench, 2016; Pain et al., 2014). Contrastingly, Kotchoni et al. (2019) and Coulombe et al. (2019) find that factor structure-based models perform well in National Bureau of Economic Research recession periods; this may be explained by the fact that these models are flexible enough to accommodate the faster-than-usual changes in economic variables during recessions. In this regard, this paper also considers assessing the performance of the factor models during the GFC.

In our study, the GFC is defined as the period from November 2008 to December 2011.[27] The process of forecast construction is the same as in the out-of-sample period. All forecasts are made based on a simulated framework whereby all calculations are conducted using a fully recursive methodology. The first h-month-ahead forecast in the GFC period is made for November 2008 using the raw dataset from January 2002 to October 2008. To compute this forecast, we remove outliers; seasonally adjust, standardise and estimate factors; select the model orders; and run forecasting models using only the data in the January 2002–October 2008 sub-sample period. To compute the next h-month-ahead forecast for December 2008, we delete the first observation from the previous sample, add an extra observation to the end of the previous sample and repeat the same steps for the second subsample period. We continue this process – at each subsample period, we screen for outliers, perform seasonal adjustments, estimate factors and run forecasting models – until the final forecast is made for December 2011.

[27]The National Bureau of Economic Research defines the GFC recession period as lasting from December 2007 to June 2009, but this definition applies to the United States. We define the recession period for China based on how the State Council responded to the GFC. At the end of 2008, the Chinese government announced a series of investment plans (about 4 trillion CNY) to promote consumption, increase job opportunities and stabilise economic growth until the end of 2011. Therefore, our definition of the GFC period is from November 2008 to December 2011.

TABLE 7 Real variables: Pairwise conditional predictive test results by horizon

	Investment					**Consumption**					**Railway cargo**				
	***h* = 1**	***h* = 3**	***h* = 6**	***h* = 9**	***h* = 12**	***h* = 1**	***h* = 3**	***h* = 6**	***h* = 9**	***h* = 12**	***h* = 1**	***h* = 3**	***h* = 6**	***h* = 9**	***h* = 12**
Diffusion Index	**0.01**	0.07	0.07	0.23	0.23	0.93	0.60	0.17	0.93	0.67	0.54	0.54	**0.01**	0.91	0.89
FA-AR(*p*)	0.75	0.83	0.82	0.45	0.64	0.18	0.94	0.19	0.84	0.68	0.53	0.62	**0.01**	0.72	0.96
FA-AR(2)	0.47	0.18	**0.00**	**0.03**	**0.05**	0.67	0.41	0.12	0.41	0.37	0.94	0.64	**0.01**	0.66	0.95
FA-VAR(*p*)	**0.04**	0.98	0.65	0.55	0.33	0.18	0.25	0.55	0.82	0.19	0.85	**0.01**	0.46	0.57	0.59
FA-VAR(2)	0.81	0.73	0.44	0.53	0.31	0.49	0.66	**0.04**	0.11	**0.04**	0.94	0.10	0.72	0.20	0.71

Note: The rows are the forecasting models described in Section 3. The columns are forecast horizons. The table elements are the p-values of the pairwise conditional predictive test between mixed-frequency factor models and corresponding targeted factor models (i.e., mixed-frequency FA-AR(p) model vs. targeted FA-AR(p) model). p-Values displayed with a bold font mean that we reject the null hypotheses of equal expected loss at a 5% level of significance and conclude that the mixed-frequency factor model has better expected loss than the targeted factor models.

TABLE 8 Inflation: Standardised root mean squared forecast by horizon during global financial crisis

	CPI					RPI				
	$h = 1$	$h = 3$	$h = 6$	$h = 9$	$h = 12$	$h = 1$	$h = 3$	$h = 6$	$h = 9$	$h = 12$
Univariate forecasts										
AR(p)	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
AR(2)	1.15	0.98	1.01	1.10	1.28	0.95	0.99	0.99	1.07	1.07
ARMA(p,q)	0.95	0.70	0.95	1.66	1.77	1.01	1.05	1.19	1.45	1.46
ARMA(2,2)	0.97	0.74	0.91	1.12	1.17	0.94	0.97	1.03	1.05	0.91
Multivariate forecasts										
MLD(p)	1.13	0.99	1.18	1.75	2.76	0.98	0.97	0.99	1.17	1.34
MLD(2)	1.13	1.02	1.22	1.87	2.89	0.99	1.02	1.13	1.58	1.98
VAR(p)	1.26	1.21	1.38	1.91	2.65	1.16	1.26	1.09	1.79	2.06
VAR(2)	1.23	1.06	1.19	1.58	2.04	0.87	0.91	0.94	1.31	1.40
Balanced-panel factor forecasts										
Targeted DI	13.67	3.57	1.62	1.27	1.20	12.55	3.21	1.54	1.28	1.06
Targeted FA-AR(p)	1.16	0.97	1.19	1.63	2.61	1.02	1.01	1.13	1.60	1.76
Targeted FA-AR(2)	1.19	0.94	1.10	1.54	2.27	0.96	0.90	0.98	1.26	1.50
Targeted FA-VAR(p)	1.44	1.27	1.38	1.82	2.43	1.00	1.03	1.10	1.32	1.40
Targeted FA-VAR(2)	1.32	1.09	1.21	1.53	1.97	0.96	1.00	1.07	1.28	1.36
Mixed-frequency factor forecasts										
Mixed-frequency DI	12.60	3.21	1.44	1.19	1.29	11.40	2.59	1.15	0.99	0.97
Mixed-frequency FA-AR(p)	1.10	0.85	1.05	1.45	2.14	0.85	0.86	1.03	1.36	1.61
Mixed-frequency FA-AR(2)	1.12	0.94	1.14	1.60	2.31	0.86	0.89	1.02	1.32	1.55
Mixed-frequency FA-VAR(p)	1.00	0.62	1.01	1.24	1.66	0.75	0.63	0.86	0.95	1.05
Mixed-frequency FA-VAR(2)	1.01	0.60	1.52	3.45	7.96	0.77	0.58	1.20	2.34	4.16

Note: The rows are the forecasting models described in Section 3. The columns are forecast horizons. The table elements are the point forecasts of the relative RMSE expressed as a ratio of the RMSE of the benchmark model for the same forecast horizon. The benchmark model is the AR(p) model.

The relative RMSEs for inflation are reported in Table 8. For the CPI inflation rate, competing models generally perform less well than the benchmark AR(p) model at horizons of 1, 6, 9 and 12 months. At a horizon of 3 months, mixed-frequency FA-VAR and ARMA models outperform the benchmark model. The relative improvements are substantial, reaching approximately 40 percent for mixed-frequency FA-VAR models and 30 percent for ARMA models. For the RPI inflation rate, the mixed-frequency FA-VAR(p) model generates superior 1-, 3-, 6- and 9-month-ahead forecasts to other competing models. At 12-month-ahead, the ARMA(2,2) model generates the lowest relative RMSE.

For real variables in Table 9, results are less clear cut. For nominal investment and consumption at horizons of 1, 3, 6 and 9 months, competing models can barely outperform the

TABLE 9 Real variables: Standardised root mean squared forecasts by horizon during global financial crisis

	Investment					Consumption					Railway cargo				
	$h = 1$	$h = 3$	$h = 6$	$h = 9$	$h = 12$	$h = 1$	$h = 3$	$h = 6$	$h = 9$	$h = 12$	$h = 1$	$h = 3$	$h = 6$	$h = 9$	$h = 12$
Univariate forecasts															
AR(p)	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
AR(2)	1.06	1.02	0.99	0.98	0.91	1.00	1.00	0.99	1.00	0.95	1.00	1.00	1.00	1.00	1.00
ARMA(p,q)	1.16	1.03	0.98	0.98	0.91	0.93	0.94	0.92	1.01	0.96	1.11	1.01	1.00	1.00	1.00
ARMA(2,2)	1.16	1.04	0.98	1.01	0.93	0.96	0.97	1.00	0.99	0.94	1.11	0.99	0.98	1.01	1.01
Multivariate forecasts															
MLD(p)	1.14	1.02	0.97	0.94	0.87	1.51	1.02	0.89	1.21	1.28	0.94	2.70	2.12	1.83	1.54
MLD(2)	1.25	1.11	0.96	1.01	0.94	1.50	1.01	0.90	1.21	1.26	1.11	2.79	2.27	1.89	1.60
VAR(p)	4.81	3.71	3.35	3.10	2.75	2.43	2.11	1.90	1.80	1.63	0.85	1.32	1.14	0.98	1.01
VAR(2)	4.81	3.71	3.35	3.10	2.75	2.43	2.11	1.90	1.80	1.63	0.85	1.32	1.14	0.98	1.01
Balanced-panel factor forecasts															
Targeted DI	1.33	1.06	1.03	1.03	0.96	1.33	1.09	1.02	1.01	0.97	1.14	2.06	1.65	1.25	1.62
Targeted FA-AR(p)	1.22	1.06	1.00	1.03	0.93	1.05	1.01	0.98	1.01	0.98	1.27	2.02	1.66	1.24	1.61
Targeted FA-AR(2)	1.28	1.12	0.95	1.01	0.93	1.11	1.02	1.03	1.02	0.99	1.32	2.00	1.66	1.25	1.61
Targeted FA-VAR(p)	1.22	1.04	0.98	0.98	0.95	1.07	1.05	1.04	1.01	0.97	1.05	1.36	1.18	1.03	1.04
Targeted FA-VAR(2)	1.30	1.15	0.96	1.02	1.05	1.15	1.03	1.04	1.01	0.98	1.17	1.50	1.43	1.27	1.49
Mixed-frequency factor forecasts															
Mixed-frequency DI	1.39	1.10	1.01	1.04	0.93	1.29	1.10	1.02	1.01	0.96	0.80	1.02	1.02	0.98	1.03
Mixed-frequency FA-AR(p)	1.20	1.07	1.02	1.07	0.94	0.95	1.00	0.98	1.02	0.96	1.02	1.04	1.04	0.97	1.04
Mixed-frequency FA-AR(2)	1.28	1.20	0.96	1.05	0.93	1.05	1.04	1.03	1.01	0.96	1.06	1.05	1.04	0.97	1.04
Mixed-frequency FA-VAR(p)	1.20	1.17	1.01	0.98	0.91	1.12	1.06	1.03	1.01	0.96	1.02	0.98	1.00	0.99	1.00
Mixed-frequency FA-VAR(2)	1.23	1.16	0.97	0.99	0.91	1.05	1.05	1.03	1.01	0.96	1.05	0.99	0.99	0.97	1.01

Note: The rows are the forecasting models described in Section 3. The columns are forecast horizons. The table elements are the point forecasts of the relative RMSE expressed as a ratio of the RMSE of the benchmark model for the same forecast horizon. The benchmark model is the AR(p) model.

TABLE 10 Inflation: Pairwise conditional predictive test results by horizon during global financial crisis

	CPI					RPI				
	$h = 1$	$h = 3$	$h = 6$	$h = 9$	$h = 12$	$h = 1$	$h = 3$	$h = 6$	$h = 9$	$h = 12$
Diffusion Index	0.17	0.16	0.31	0.56	0.18	0.13	0.14	0.21	0.27	0.39
FA-AR(p)	0.32	0.16	0.27	0.55	0.14	**0.03**	0.13	0.40	0.45	0.47
FA-AR(2)	0.16	0.98	0.17	0.14	0.23	**0.04**	0.86	0.07	**0.02**	0.09
FA-VAR(p)	**0.04**	0.12	0.13	0.18	0.25	0.12	0.09	**0.04**	**0.05**	0.21
FA-VAR(2)	**0.05**	0.09	0.59	0.39	0.34	0.15	0.06	0.74	0.43	0.35

Note: The rows are the forecasting models described in Section 3. The columns are forecast horizons. The table elements are the p-values of the pairwise conditional predictive test between mixed-frequency factor models and corresponding targeted factor models (i.e., mixed-frequency FA-AR(p) model vs. targeted FA-AR(p) model). p-Values displayed with a bold font mean that we reject the null hypotheses of equal expected loss at a 5% level of significance and conclude that the mixed-frequency factor model has better expected loss than the targeted factor models.

benchmark AR(p) model. In some cases, such as those of VAR models at all horizons, they even generate considerably worse relative RMSEs than the benchmark. At horizons of 12 months, most competing models perform better than the benchmark, but the relative improvements are very small. For the railway freight at 1-month-ahead, the mixed-frequency DI models provide the lowest RMSE of all competing models. At 3-, 6-, 9- and 12-months-ahead, competing models can hardly generate forecasts that are better than the benchmark forecast.

For sampling variability between mixed-frequency factor models and targeted factor models, we report p-values of conditional predictive tests for inflation in Table 10 and for real variables in Table 11. Overall, we find no strong evidence that the use of mixed-frequency datasets with missing observations yields statistical improvements over the targeted predictors when a 5 percent level of significance is considered for both inflation and real variables. Occasionally, the conditional test finds evidence in favour of the mixed-frequency factor models. For example, the p-values of the FA-VAR(2) model for investment and the p-values of the FA-AR models for RPI have less than a 5 percent level of significance at $h = 6$. Therefore, we do not consider that using mixed-frequency datasets with missing observations can provide evidence of superior forecasting power to preselected targeted predictors during the GFC period.

6 | DISCUSSION

The forecasting models we employ in this paper are all well established for Western economies, and we find two features of the empirical results surprising and intriguing. First, only four factors account for much of the variance of our 251 monthly and 34 quarterly macroeconomic variables for China. One possible interpretation of this finding is that there are only a few important latent and unobservable sources driving China's macroeconomic variability. Second, the most accurate forecasts can be achieved using factors estimated from mixed-frequency and missing observations dataset. This suggests that just a few static factors are necessary for forecasting China's macroeconomic variables.

To demonstrate why the large-dimensional factor models are capable of generating superior forecasts than simple models, we characterise the optimal forecast under the mean squared error loss function:

$$L\left(f\left(z_t\right), y_{t+h}\right) = \left(y_{t+h} - f\left(z_t\right)\right)^2 \tag{30}$$

where L is the loss function, $f\left(z_T\right)$ is a forecasting model using data $z_t = (x_t, y_t)$ observed at time t. Under the mean squared loss, the optimal forecast is the conditional mean of

TABLE 11 Real variables: Pairwise conditional predictive test results by horizon during global financial crisis

	Investment					Consumption					Railway cargo				
	$h = 1$	$h = 3$	$h = 6$	$h = 9$	$h = 12$	$h = 1$	$h = 3$	$h = 6$	$h = 9$	$h = 12$	$h = 1$	$h = 3$	$h = 6$	$h = 9$	$h = 12$
Diffusion Index	0.21	0.37	0.53	0.74	0.66	0.06	0.12	0.78	0.70	0.12	0.07	0.08	0.07	0.20	**0.01**
FA-AR(p)	0.90	0.88	0.47	0.42	0.70	0.10	0.66	0.81	0.73	**0.04**	0.22	0.08	0.06	0.22	**0.01**
FA-AR(2)	0.96	0.18	0.73	0.26	0.94	0.15	0.25	0.83	0.66	**0.02**	0.21	0.08	0.06	0.20	**0.01**
FA-VAR(p)	0.86	0.12	**0.03**	0.96	0.33	0.54	0.72	0.73	0.31	0.11	0.85	0.19	0.26	0.33	0.16
FA-VAR(2)	0.37	0.86	0.64	0.39	0.30	0.17	0.39	0.92	0.51	0.17	0.45	0.23	0.28	0.31	0.27

Note: The rows are the forecasting models described in Section 3. The columns are forecast horizons. The table elements are the p-values of the pairwise conditional predictive test between mixed-frequency factor models and corresponding targeted factor models (i.e., mixed-frequency FA-AR(p) model vs. targeted FA-AR(p) model). p-Values displayed with a bold font mean that we reject the null hypotheses of equal expected loss at a 5% level of significance and conclude that the mixed-frequency factor model has better expected loss than the targeted factor models.

y_{t+h}. Moreover, for any stochastic process of y_t that has a stable ARMA representation, $E(y_{t+h} \mid y_t, y_{t-1}, y_{t-2}, \ldots) - E(y_{t+h}) \to 0$ as h grows large. From a theoretical perspective, we should expect complicated forecasting models to be less likely to outperform simple AR models.

In Section 5, we find evidence that large-dimensional approximate factor models provide substantial improvements over simple forecasting models. There are a number of potential explanations for the relatively good performance of factor models in the Chinese context.

First, given Chinese series have relatively short histories with a large amount of missing data and rapid institutional change, it might simply be that the available macroeconomic variables for China are not sufficiently long for simple models to provide significant results. Our forecasting exercise effectively requires two datasets: one to estimate the model parameters (within-sample period) and another to produce a series of out-of-sample forecasts. Forecasting literature for Western economies generally employs available macroeconomic variables over much longer time spans.[28] In contrast, our data span from January 2002 to June 2018, yielding a maximum of 99 forecasts. We argue that significant results from simple forecasting models might emerge from a larger sample of forecasts, if they were available.

Second, forecasting models in the univariate time series tradition such as the AR model are well suited to variables that are weakly stationary. In the case where the marginal distributions of variables are slowly changing over time or where the marginal distributions change more suddenly, the rationale for the univariate time series forecasting model is less clear. There can be little doubt that non-stationarity exists, especially during the GFC period. How non-stationarity would affect the performance of forecasting models depends on the change in the marginal distribution over time. At present, it is difficult to make specific comments regarding these effects. Further research opportunities might proceed by comparing models that explicitly incorporate parameter drift and structural change to AR and ARMA models.

Finally, it is possible low data quality would render traditional forecasting methods impotent. To understand the potential impact of data quality, consider the following simple model of measurement error: $y_t = y_t^* + e_t$ and $x_{it} = x_{it}^* + e_{it}$, where y_t^* and x_{it}^* are weakly stationary stochastic processes that we intend to forecast and intend to use as a predictor. The e_t are measurement errors that are serially uncorrelated and uncorrelated with y_t and x_{it}. It is simple to demonstrate that the difference between two correlations $Corr(y_t, y_{t-j}) \leq Corr(y^*, y_{t-1}^*)$ and $Corr(x_{it}, y_{it-j}) \leq Corr\left(x^*, x_{it-j}^*\right)$ increases as $Var(e_t)$ increases. Thus, measurement error is a possible cause of the relatively poor performance of forecasting models that exploit correlation structure.

Overall, our findings reaffirm the results of Stock and Watson (2002b) and Bai and Ng (2013), where they prove that under a set of moment conditions for factors and idiosyncratic disturbance and an asymptotic rank condition, the feasible forecast is asymptotically first-order efficient in the sense that the root mean squared forecast error approaches the optimal infeasible forecast as T and N approach infinity. This suggests that the forecasts from the large-dimensional approximate factor models are nearly optimal when T and N are sufficiently large, especially when $N > T$. Moreover, Bernanke and Boivin (2003), Bernanke et al. (2005) and Bai and Ng (2008b) argued that the large-dimensional approximate factor models are robust even if there is some time variation in factor loadings (structural changes), small amount of data contamination and issues emerging from missing observations, which is consistent with our main results.

[28]For example, Kotchoni et al. (2019) use 134 monthly macroeconomic and financial variables that are observed from January 1960 to December 2014 to forecast the US CPI inflation rate, employment growth, industrial production growth and stock market index.

7 | CONCLUSION

The main results of this study provide clear guidance for analysts who are interested in forecasting Chinese macroeconomic variables. An important contribution of our paper is that, to the best of our knowledge, it is one of the first papers to use a large dataset with mixed frequency and missing observations to forecast the Chinese macroeconomy. Our dataset contains 251 monthly variables and 34 quarterly variables, covering all important sectors of the Chinese macroeconomy. The number of predictors that has been used in the previously published literature for China is relatively smaller than that for Western economies, which usually covers 40 variables or less. Also, we run a large number of training sets and validation sets. The range of size of the out-of-sample period in our paper is from 88 (for 12-month-ahead forecasts) to 99 (for 1-month-ahead forecasts), compared with a range from five to 60 observations in the existing literature. Our paper finds evidence that large-dimensional factor models that are well established for forecasting Western macroeconomies also work well for China, especially the mixed-frequency FA-VAR model.

Arguably, there may exist superior models or methods not considered in this paper. Such an argument is inevitable as there is a wide range of econometric models that could deal with a large number of variables. Our work finds evidence that large-dimensional factor models could substantially improve forecasting performance for the CPI, RPI, nominal investment and nominal consumption but not for railway freight. However, this does not imply that other big data-compatible econometric models could not further improve the forecasting performance. Compared to major Western countries, Chinese macroeconomic data are of a short duration with a period of significant structural change, have too many missing values and are of questionable quality. Considering this, researchers might consider econometric forecasting that is more capable of dealing with these stylised facts. Techniques that allow for time variation in the factor loadings might be useful to deal with model instability. Mixed-frequency and state-space VAR models might also be a valuable approach for mixed-frequency and ragged-edge datasets. Recently proposed machine learning algorithms that are compatible with non-stationary and non-parametric features might be useful. Bayesian approaches that allow sample information to be combined with structurally relevant prior information could be an alternative to the frequentist domain. Model combinations across a set of candidate forecasting models could be useful to improve forecasting performance over a single model. Thus, this paper provides considerable scope for future research.

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DATA AVAILABILITY STATEMENT

The authors declared that the datasets generated; during and/or analysed during the current study are available from the corresponding; author on reasonable request.

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APPENDIX 1

A SIMPLE F-STATISTICS FOR IN-SAMPLE TESTS OF PREDICTABILITY

A comparison of the predictive content of two nested forecast models can be conducted based on either the in-sample or out-of-sample fit. The former case employs the full sample in fitting the models of interest, whereas the latter case uses a recursive sequence to mimic the data constraints faced by a real-time forecaster. To make our paper more credible, we consider testing the in-sample performance using relative root mean squared forecast error and a simple *F*-test statistic. The relative rRMSE is calculated relative to the RMSE of the benchmark AR(*p*) model, expressed as a ratio of the RMSE of the benchmark model for the same forecast horizon. For the simple *F*-test, consider

$$y_{t+h} = \gamma' x_t + u_{t+h} = \alpha' v_t + \beta' w_t + u_{t+h}$$

where $x_t = \left(v_t', w_t'\right)'$, v_t and w_t are m, l and k dimensional vectors of regressors, respectively, and $\left\{u_{t+h}\right\}$ is a sequence of martingale differences with respect to the sigma field generated by $\left\{x_t, x_{t-1}, x_{t-2}, \dots\right\}$.

Definition y_{t+h} is said to be predictable based on w_t if and only if $\beta \neq 0$.

We are interested in testing the predicative of two nested models that:

Null Hypothesis Two nested models have equal predictability

Against the one-sided alternative:

Alternative Hypothesis The competing model has the greater predictability than the benchmark.

A simple in-sample test statistic is considered testing H_0 against H_1 as:

$$F = \frac{\sum_{t=1}^{T} \left(\hat{u}_{0t+1}^2 - \hat{u}_{1t+1}^2\right)}{\hat{\sigma}^2}$$

where $\left\{\hat{u}_{1|t+1}\right\}$ are the residuals from the benchmark and $\left\{\hat{u}_{0|t+1}\right\}$ are residuals from the competing model $\hat{\sigma}^2 = (1/T) \sum_{t=1}^{T} \hat{u}_{1|t+h}^2$. The null hypothesis that two nested models have equal predictability is rejected if the p-value is less than the significance level.

APPENDIX 2

STABILITY OF PREDICTOR SELECTION BY HARD THRESHOLDING FOR TARGETED FA-AR AND FA-VAR

Figure A1 shows the type of series selected or not by hard thresholding with critical value being for targeted FA-AR and FA-VAR over the whole out-of-sample period. We group the data into nine categories: exchange rate, household and business savings, housing, interest rate, loan and investment, price and index, trade, transport, and other. The probability that a particular predictor will be consistently selected is higher for some groups and depends on the series being predicted. For instance, indicators in interest rate, household and business savings, housing and load and investment are consistently present when predicting CPI and

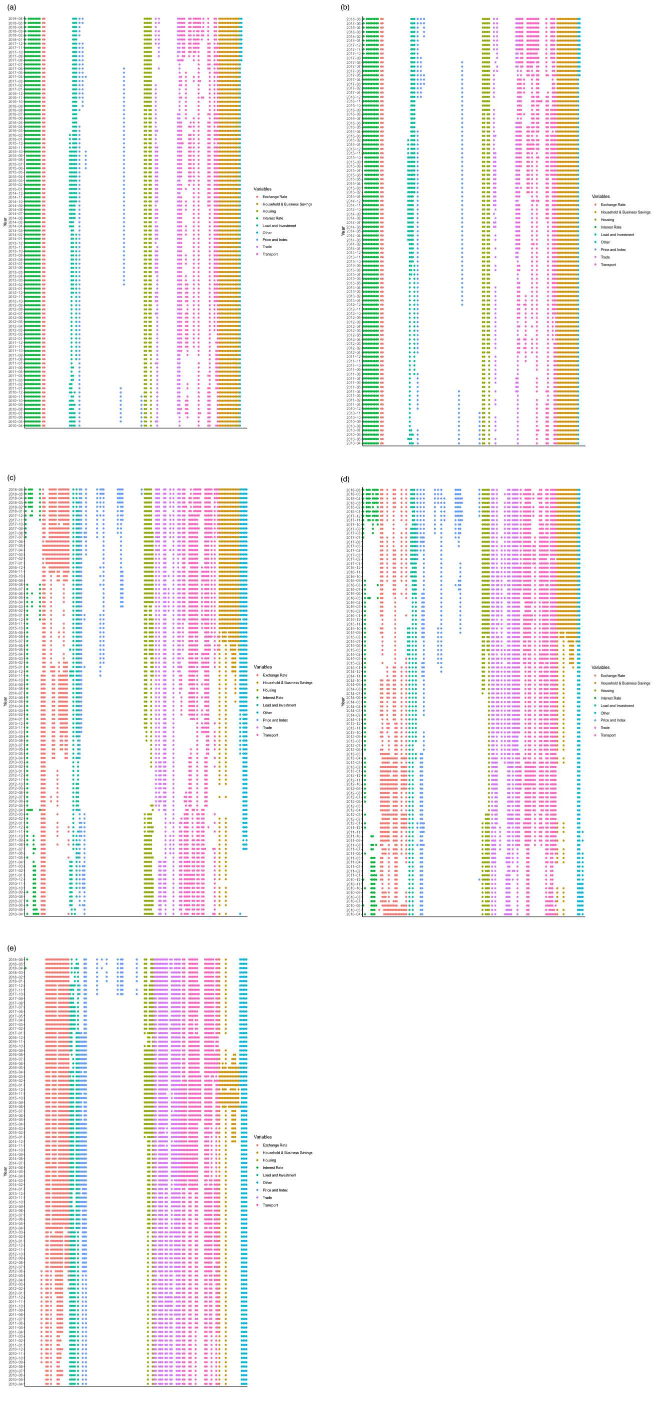

FIGURE A1 Series preselected by hard thresholding with critical value being 1.67 for targeted FA-AR and FA-VAR: (a) CPI, (b) RPI, (c) investment, (d) consumption, (e) railway cargo.

RPI over the whole out-of-sample. A similar pattern is observed in the case of railway freight. Contrastingly, there is vast instability in predictor selection for investment and consumption where the selection criteria change dramatically over time.

APPENDIX 3

DATA DESCRIPTION

This appendix includes the data description used throughout this paper. We report the series name, frequency and transformation technique for our preselected targeted predictors in Table A1, with selection criteria based on hard and soft thresholding and judgements. The format is as follows: series number, series name, transformation technique used. All variables for targeted predictors are observed at monthly frequency. In Table A2, we present the full-panel dataset that we use to construct h-month-ahead forecast. The format is as follows: series number, series name, transformation technique used, frequency, and the number of missing observations. We downloaded these datasets from CEIC Data Manager.

TABLE A1 Data description: Targeted predictors

Series number	Variable name	Transformation
1	Rediscount Rate	None
2	Nominal Lending Rate: Within 1 Year (Including 1 Year)	None
3	Consumer Price Index	First difference
4	Retail Price Index	First difference
5	Retail Price Index: Urban	First difference
6	Retail Price Index: Rural	First difference
7	Producer Price Index: Agricultural Input: Overall	First difference
8	Producer Price Index (PPI)	First difference
9	Household Savings Deposits Rate: Demand	None
10	Interbank Offered Rate: Weighted Avg: Overnight	None
11	Effective Exchange Rate Index: BIS: Real	First difference
12	Effective Exchange Rate Index: BIS: Nominal	First difference
13	Consumer Confidence Index	First difference
14	Consumer Confidence Index: Satisfactory	First difference
15	Consumer Confidence Index: Expectation	First difference
16	Coincident Index	First difference
17	Leading Index	First difference
18	Govt Revenue	Percentage change
19	Govt Expenditure	Percentage change
20	Industrial Production: Crude Oil	Percentage change
21	Industrial Production: Iron Ore	Percentage change
22	Energy Production: Electricity	Percentage change
23	Export FOB	Percentage change
24	Import CIF	Percentage change
25	Money Supply M2	Percentage change
26	Money Supply M1	Percentage change
27	Official Reserve Asset: Foreign Reserve (FR)	Percentage change
28	Loan	Percentage change

TABLE A1 (Continued)

Series number	Variable name	Transformation
29	Index: Shanghai Stock Exchange: Composite	Percentage change
30	Index: Shenzhen Stock Exchange: Composite	Percentage change
31	Official Reserve Asset: Gold: Gold Reserve	Percentage change
32	Money Supply M0	Percentage change
33	Deposit	Percentage change
34	Transport: Freight Traffic	Percentage change
35	Railway: Freight Traffic	Percentage change
36	Highway: Freight Traffic	Percentage change
37	Waterway: Freight Traffic	Percentage change
38	Air: Freight Traffic	Percentage change
39	NomInvestment	Percentage change
40	NomConsumption	Percentage change
41	InvestmentPrice	Percentage change

TABLE A2 Data description: Full-panel dataset

Series number	Variable name	Transformation	Frequency	No. of missing observations
1	Govt Expenditure	Percentage change	Monthly	0
2	Govt Revenue	Percentage change	Monthly	0
3	Industrial Production: Crude Oil	Percentage change	Monthly	0
4	Industrial Production: Natural Gas	Percentage change	Monthly	0
5	Industrial Production: Salt	Percentage change	Monthly	0
6	Industrial Production: Cement	Percentage change	Monthly	0
7	Industrial Production: Crude Steel	Percentage change	Monthly	0
8	Bond Depository: Bond in RMB	Percentage change	Monthly	0
9	Bond Depository: Govt Bond	Percentage change	Monthly	0
10	Bond Depository: Financial Bond	Percentage change	Monthly	0
11	Fixed Asset Investment	Percentage change	Monthly	0
12	FX Rate: PBOC: Month End: RMB to USD	Percentage change	Monthly	0
13	Effective Exchange Rate Index: BIS: Real	Percentage change	Monthly	0
14	Effective Exchange Rate Index: BIS: Nominal	Percentage change	Monthly	0
15	Money Supply M0: sa	Percentage change	Monthly	0
16	Money Supply M1: sa	Percentage change	Monthly	0
17	Money Supply M2: sa	Percentage change	Monthly	0
18	Loan: Short Term	Percentage change	Monthly	0
19	Loan: Medium & Long Term	Percentage change	Monthly	0
20	Loan: sa	Percentage change	Monthly	0
21	Deposit: sa	Percentage change	Monthly	0

(Continues)

TABLE A2 (Continued)

Series number	Variable name	Transformation	Frequency	No. of missing observations
22	Deposit: Saving: sa	Percentage change	Monthly	0
23	Property Price: YTD Avg: Overall	Percentage change	Monthly	0
24	Import Price: Iron Ore & Concentrate	Percentage change	Monthly	0
25	Index: Shanghai Stock Exchange: Composite	Percentage change	Monthly	0
26	Index: Shanghai Stock Exchange: A Share	Percentage change	Monthly	0
27	Index: Shanghai Stock Exchange: B Share	Percentage change	Monthly	0
28	Turnover: Value: Shanghai SE: Total	Percentage change	Monthly	0
29	Index: Shenzhen Stock Exchange: Composite	Percentage change	Monthly	9
30	Index: Shenzhen Stock Exchange: A Share	Percentage change	Monthly	9
31	Index: Shenzhen Stock Exchange: B Share	Percentage change	Monthly	9
32	Turnover: Value: Shenzhen SE: Total	Percentage change	Monthly	9
33	Market Capitalization: Shenzhen SE: Total	Percentage change	Monthly	9
34	Market Capitalization: Shanghai SE: Stock	Percentage change	Monthly	0
35	Market Capitalization: Shanghai SE: A Share	Percentage change	Monthly	0
36	Market Capitalization: Shanghai SE: B Share	Percentage change	Monthly	0
37	Market Capitalization: Shenzhen SE: Stock	Percentage change	Monthly	0
38	Market Capitalization: Shenzhen SE: A Share	Percentage change	Monthly	0
39	Market Capitalization: Shenzhen SE: B Share	Percentage change	Monthly	0
40	Commodity Retail Sales: Above Designated Size Enterprise	Percentage change	Monthly	0
41	Commodity Retail Sales: Food, Beverage, Tobacco & Liquor (FB)	Percentage change	Monthly	0
42	Commodity Retail Sales: FB: Beverage	Percentage change	Monthly	0
43	Commodity Retail Sales: FB: Tobacco & Liquor	Percentage change	Monthly	0
44	Commodity Retail Sales: Clothing, Shoes, Hats & Textile (CT)	Percentage change	Monthly	0
45	Commodity Retail Sales: Cosmetics	Percentage change	Monthly	0
46	Commodity Retail Sales: Gold, Silver and Jewellery	Percentage change	Monthly	0
47	Commodity Retail Sales: Daily Use Goods	Percentage change	Monthly	0
48	Commodity Retail Sales: Other	Percentage change	Monthly	0
49	Commodity Retail Sales: Automobile	Percentage change	Monthly	0
50	Commodity Retail Sales: Petroleum & Related Product	Percentage change	Monthly	0
51	Commodity Retail Sales: Chinese & Western Medicine (CM)	Percentage change	Monthly	0

TABLE A2 (Continued)

Series number	Variable name	Transformation	Frequency	No. of missing observations
52	Commodity Retail Sales: Household Electric & Video Appliance	Percentage change	Monthly	0
53	Commodity Retail Sales: Cultural & Office Goods	Percentage change	Monthly	0
54	Commodity Retail Sales: Furniture	Percentage change	Monthly	0
55	Commodity Retail Sales: Communication Appliance	Percentage change	Monthly	0
56	Energy Production: Crude Oil	Percentage change	Monthly	0
57	Energy Production: Natural Gas	Percentage change	Monthly	0
58	Energy Production: Refined/Processed Crude Oil	Percentage change	Monthly	0
59	Energy Production: Gasoline	Percentage change	Monthly	0
60	Energy Production: Diesel Fuel	Percentage change	Monthly	0
61	Energy Production: Kerosene	Percentage change	Monthly	0
62	Energy Production: Fuel Oil	Percentage change	Monthly	0
63	Energy Production: Liquefied Petroleum Gas (LPG)	Percentage change	Monthly	0
64	Energy Production: Petroleum Pitch	Percentage change	Monthly	0
65	Energy Production: Coke	Percentage change	Monthly	0
66	Energy Production: Coal Gas	Percentage change	Monthly	0
67	Energy Production: Electricity	Percentage change	Monthly	0
68	Energy Production: Electricity: Thermal	Percentage change	Monthly	0
69	Energy Production: Electricity: Hydro	Percentage change	Monthly	0
70	Energy Production: Electricity: Nuclear	Percentage change	Monthly	0
71	Consumer Confidence Index	Percentage change	Monthly	0
72	Consumer Satisfactory Index	Percentage change	Monthly	0
73	Consumer Expectation Index	Percentage change	Monthly	0
74	Import CIF	Percentage change	Monthly	0
75	Export FOB	Percentage change	Monthly	0
76	Export: Live Pig (excl for Breeding)	Percentage change	Monthly	0
77	Export: Live Poultry	Percentage change	Monthly	9
78	Export: Aquatic Product	Percentage change	Monthly	9
79	Export: Grain Food: Cereal & Cereal Flour	Percentage change	Monthly	12
80	Export: Fresh Egg	Percentage change	Monthly	12
81	Export: Vegetable	Percentage change	Monthly	12
82	Export: Edible Oil Seed	Percentage change	Monthly	0
83	Export: Edible Vegetable Oil	Percentage change	Monthly	0
84	Import: Grain Food: Cereal & Cereal Flour: Wheat	Percentage change	Monthly	0
85	Import: Edible Vegetable Oil	Percentage change	Monthly	0
86	Import: Copper Ore & Concentrate	Percentage change	Monthly	0

(Continues)

TABLE A2 (Continued)

Series number	Variable name	Transformation	Frequency	No. of missing observations
87	Import: Aluminium Oxide	Percentage change	Monthly	0
88	Import: Crude Petroleum Oil	Percentage change	Monthly	0
89	Import: Refined Petroleum Product	Percentage change	Monthly	3
90	Import Price: Crude Oil	Percentage change	Monthly	3
91	Export Price: Crude Oil	Percentage change	Monthly	3
92	Transaction Price: Diesel Oil, No 0: Beijing	Percentage change	Monthly	0
93	Transaction Price: Diesel Oil, No 0: Tianjin	Percentage change	Monthly	0
94	Transaction Price: Diesel Oil, No 0: Shijiazhuang	Percentage change	Monthly	3
95	Transaction Price: Diesel Oil, No 0: Hohhot	Percentage change	Monthly	3
96	Transaction Price: Diesel Oil, No 0: Shenyang	Percentage change	Monthly	3
97	Transaction Price: Diesel Oil, No 0: Dalian	Percentage change	Monthly	0
98	Transaction Price: Diesel Oil, No 0: Shanghai	Percentage change	Monthly	0
99	Transaction Price: Diesel Oil, No 0: Nanjing	Percentage change	Monthly	0
100	Transaction Price: Diesel Oil, No 0: Hangzhou	Percentage change	Monthly	0
101	Transaction Price: Diesel Oil, No 0: Ningbo	Percentage change	Monthly	0
102	Transaction Price: Diesel Oil, No 0: Hefei	Percentage change	Monthly	0
103	Transaction Price: Diesel Oil, No 0: Fuzhou	Percentage change	Monthly	0
104	Transaction Price: Diesel Oil, No 0: Xiamen	Percentage change	Monthly	0
105	Transaction Price: Diesel Oil, No 0: Nanchang	Percentage change	Monthly	0
106	Transaction Price: Diesel Oil, No 0: Jinan	Percentage change	Monthly	0
107	Transaction Price: Diesel Oil, No 0: Qingdao	Percentage change	Monthly	0
108	Transaction Price: Diesel Oil, No 0: Wuhan	Percentage change	Monthly	0
109	Transaction Price: Diesel Oil, No 0: Changsha	Percentage change	Monthly	0
110	Transaction Price: Diesel Oil, No 0: Guangzhou	Percentage change	Monthly	0
111	Transaction Price: Diesel Oil, No 0: Nanning	Percentage change	Monthly	0
112	Transaction Price: Diesel Oil, No 0: Haikou	Percentage change	Monthly	0
113	Transaction Price: Diesel Oil, No 0: Chengdu	Percentage change	Monthly	0

TABLE A2 (Continued)

Series number	Variable name	Transformation	Frequency	No. of missing observations
114	Transaction Price: Diesel Oil, No 0: Guiyang	Percentage change	Monthly	21
115	Transaction Price: Diesel Oil, No 0: Kunming	Percentage change	Monthly	21
116	Transaction Price: Diesel Oil, No 0: Xian	Percentage change	Monthly	21
117	Transaction Price: Diesel Oil, No 0: Lanzhou	Percentage change	Monthly	21
118	Transaction Price: Diesel Oil, No 0: Yinchuan	Percentage change	Monthly	21
119	Transaction Price: Diesel Oil, No 0: Urumqi	Percentage change	Monthly	21
120	Transaction Price: Diesel Oil, No 0: Beijing	Percentage change	Monthly	21
121	Transaction Price: Diesel Oil, No 0: Tianjin	Percentage change	Monthly	21
122	Transaction Price: Diesel Oil, No 0: Shijiazhuang	Percentage change	Monthly	21
123	Transaction Price: Diesel Oil, No 0: Taiyuan	Percentage change	Monthly	21
124	Transaction Price: Diesel Oil, No 0: Hohhot	Percentage change	Monthly	21
125	Transaction Price: Diesel Oil, No 0: Shenyang	Percentage change	Monthly	21
126	Transaction Price: Diesel Oil, No 0: Dalian	Percentage change	Monthly	21
127	Transaction Price: Diesel Oil, No 0: Shanghai	Percentage change	Monthly	21
128	Transaction Price: Diesel Oil, No 0: Nanjing	Percentage change	Monthly	21
129	Transaction Price: Diesel Oil, No 0: Hangzhou	Percentage change	Monthly	21
130	Transaction Price: Diesel Oil, No 0: Ningbo	Percentage change	Monthly	9
131	Transaction Price: Diesel Oil, No 0: Hefei	Percentage change	Monthly	9
132	Transaction Price: Diesel Oil, No 0: Fuzhou	Percentage change	Monthly	9
133	Transaction Price: Diesel Oil, No 0: Xiamen	Percentage change	Monthly	9
134	Transaction Price: Diesel Oil, No 0: Nanchang	Percentage change	Monthly	9
135	Transaction Price: Diesel Oil, No 0: Jinan	Percentage change	Monthly	9
136	Transaction Price: Diesel Oil, No 0: Qingdao	Percentage change	Monthly	9
137	Transaction Price: Diesel Oil, No 0: Wuhan	Percentage change	Monthly	9
138	Transaction Price: Diesel Oil, No 0: Changsha	Percentage change	Monthly	9

(Continues)

TABLE A2 (Continued)

Series number	Variable name	Transformation	Frequency	No. of missing observations
139	Transaction Price: Diesel Oil, No 0: Guangzhou	Percentage change	Monthly	9
140	Transaction Price: Diesel Oil, No 0: Nanning	Percentage change	Monthly	9
141	Transaction Price: Diesel Oil, No 0: Haikou	Percentage change	Monthly	9
142	Transaction Price: Diesel Oil, No 0: Chengdu	Percentage change	Monthly	9
143	Transaction Price: Diesel Oil, No 0: Guiyang	Percentage change	Monthly	9
144	Transaction Price: Diesel Oil, No 0: Kunming	Percentage change	Monthly	9
145	Transaction Price: Diesel Oil, No 0: Xian	Percentage change	Monthly	0
146	Transaction Price: Diesel Oil, No 0: Lanzhou	Percentage change	Monthly	0
147	Transaction Price: Diesel Oil, No 0: Yinchuan	Percentage change	Monthly	0
148	Construction Material Production: Cement	Percentage change	Monthly	0
149	Construction Material Production: Plated Glass	Percentage change	Monthly	0
150	Construction Material Production: Aluminium Product	Percentage change	Monthly	0
151	Transport: Passenger Traffic	Percentage change	Monthly	6
152	Transport: Passenger Turnover	Percentage change	Monthly	0
153	Transport: Freight Traffic	Percentage change	Monthly	0
154	Transport: Freight Turnover	Percentage change	Monthly	0
155	Railway: Passenger Traffic	Percentage change	Monthly	0
156	Railway: Passenger Turnover	Percentage change	Monthly	0
157	Railway: Freight Traffic	Percentage change	Monthly	0
158	Railway: Freight Turnover	Percentage change	Monthly	0
159	Highway: Passenger Traffic	Percentage change	Monthly	0
160	Highway: Passenger Turnover	Percentage change	Monthly	0
161	Highway: Freight Traffic	Percentage change	Monthly	0
162	Highway: Freight Turnover	Percentage change	Monthly	0
163	Waterway: Passenger Traffic	Percentage change	Monthly	0
164	Waterway: Passenger Turnover	Percentage change	Monthly	0
165	Waterway: Freight Traffic	Percentage change	Monthly	20
166	Waterway: Freight Turnover	Percentage change	Monthly	20
167	Air: Passenger Traffic	Percentage change	Monthly	16
168	Air: Passenger Turnover	Percentage change	Monthly	9
169	Air: Freight Traffic	Percentage change	Monthly	10
170	Air: Freight Turnover	Percentage change	Monthly	8

TABLE A2 (Continued)

Series number	Variable name	Transformation	Frequency	No. of missing observations
171	Postal: No of Remittance	Percentage change	Monthly	17
172	Postal: No of Express	Percentage change	Monthly	14
173	Postal: No of Package	Percentage change	Monthly	6
174	Postal: No of Letter	Percentage change	Monthly	8
175	Postal: No of Subscribed Magazine	Percentage change	Monthly	6
176	Postal: No of Subscribed Newspaper	Percentage change	Monthly	13
177	Postal: Business Volume: Express	Percentage change	Monthly	8
178	APPI: Rural Market Fair: Long Grained Nonglutinous Rice: Medium	Percentage change	Monthly	4
179	APPI: Rural Market Fair: Round Grained Rice: Medium	Percentage change	Monthly	12
180	APPI: Rural Market Fair: Wheat: Medium	Percentage change	Monthly	8
181	APPI: Rural Market Fair: Maize: Medium	Percentage change	Monthly	6
182	APPI: Rural Market Fair: Soybean: Medium	Percentage change	Monthly	8
183	Consumer Price Index: MoM	First difference	Monthly	8
184	CPI: MoM: Food, Tobacco & Liquor: Food	First difference	Monthly	15
185	CPI: MoM: Clothing	First difference	Monthly	6
186	CPI: MoM: Transportation and Communication (TC)	First difference	Monthly	14
187	CPI: MoM: Residence	First difference	Monthly	4
188	CPI: Food, Tobacco & Liquor: Food: Vegetable: Fresh Vegetable	First difference	Monthly	4
189	CPI: Food, Tobacco & Liquor: Food: Aquatic Product	First difference	Monthly	6
190	CPI: Food, Tobacco & Liquor: Food: Egg	First difference	Monthly	6
191	CPI: Food, Tobacco & Liquor: Food: Meat of Livestock	First difference	Monthly	11
192	CPI: Food, Tobacco & Liquor: Food: Grain	First difference	Monthly	11
193	CPI: Food, Tobacco & Liquor: Food	First difference	Monthly	32
194	Retail Price Index	First difference	Monthly	20
195	Retail Price Index: Food	First difference	Monthly	16
196	Retail Price Index: Beverage, Tobacco & Liquors	First difference	Monthly	9
197	Retail Price Index: Cosmetics	First difference	Monthly	8
198	Retail Price Index: Daily Sundry Articles	First difference	Monthly	10
199	Retail Price Index: Fuels	First difference	Monthly	8
200	Retail Price Index: Building, Hardware & Electric Materials	First difference	Monthly	17
201	Corporate Goods Price Index: Overall	First difference	Monthly	14
202	Producer Price Index(PPI)	First difference	Monthly	6
203	Producer Price Index: Producer Goods	First difference	Monthly	8

(Continues)

TABLE A2 (Continued)

Series number	Variable name	Transformation	Frequency	No. of missing observations
204	Producer Price Index: Producer Goods: Mining and Quarrying	First difference	Monthly	6
205	Producer Price Index: Producer Goods: Raw Material	First difference	Monthly	13
206	Producer Price Index: Producer Goods: Manufacturing	First difference	Monthly	8
207	Producer Price Index: Consumer Goods	First difference	Monthly	4
208	Producer Price Index: Consumer Goods: Food	First difference	Monthly	12
209	Producer Price Index: Consumer Goods: Clothing	First difference	Monthly	8
210	Producer Price Index: Consumer Goods: Daily Sundry Article	First difference	Monthly	6
211	Producer Price Index: Consumer Goods: Durable	First difference	Monthly	8
212	Purchasing Price Index	First difference	Monthly	8
213	Purchasing Price Index: Fuel and Power	First difference	Monthly	15
214	Purchasing Price Index: Ferrous Metal Material	First difference	Monthly	6
215	Purchasing Price Index: Non Ferrous Metal and Electric Wire	First difference	Monthly	14
216	Purchasing Price Index: Chemical Material	First difference	Monthly	4
217	Purchasing Price Index: Timber and Paper Pulp	First difference	Monthly	4
218	Purchasing Price Index: Building Material	First difference	Monthly	6
219	Purchasing Price Index: Industrial Raw Material and Semi Finished Product	First difference	Monthly	6
220	Purchasing Price Index: Farm and Sideline Product	First difference	Monthly	11
221	Purchasing Price Index: Textile Material	First difference	Monthly	11
222	Retail Price Index: Textiles	First difference	Monthly	12
223	Retail Price Index: Clothing, Shoes and Hats	First difference	Monthly	12
224	Required Reserve Ratio	None	Monthly	12
225	Rediscount Rate	None	Monthly	2
226	Central Bank Benchmark Interest Rate: Loan to FI: 1 Year	None	Monthly	0
227	Central Bank Benchmark Interest Rate: Loan to FI: 6 Month or Less	None	Monthly	0
228	Central Bank Benchmark Interest Rate: Loan to FI: 3 Month or Less	None	Monthly	0
229	Interbank Offered Rate: Weighted Avg: 3 Month	None	Monthly	0
230	Interbank Offered Rate: Weighted Avg: 1 Month	None	Monthly	0

TABLE A2 (Continued)

Series number	Variable name	Transformation	Frequency	No. of missing observations
231	Interbank Offered Rate: Weighted Avg: 21 Day	None	Monthly	0
232	Interbank Offered Rate: Weighted Avg: 2 Month	None	Monthly	0
233	Real Estate Inv: ytd	None	Monthly	0
234	Real Estate Inv: ytd: Residential Building	None	Monthly	0
235	Real Estate Inv: ytd: Office Building	None	Monthly	0
236	Real Estate Inv: ytd: Commercial Building	None	Monthly	0
237	Real Estate Inv: ytd: Other Building	None	Monthly	0
238	Central Bank Benchmark Interest Rate: Loan to FI: Less Than 20 days	None	Monthly	0
239	Household Savings Deposits Rate: Demand	None	Monthly	2
240	Household Savings Deposits Rate: Time: 3 Month	None	Monthly	2
241	Household Savings Deposits Rate: Time: 2 Year	None	Monthly	0
242	Household Savings Deposits Rate: Time: 3 Year	None	Monthly	0
243	Enterprise Deposits Rate: Demand	None	Monthly	0
244	Enterprise Deposits Rate: Time: 3 Month	None	Monthly	0
245	Enterprise Deposits Rate: Time: 6 Month	None	Monthly	0
246	Enterprise Deposits Rate: Time: 1 Year	None	Monthly	0
247	Nominal Lending Rate: Within 1 Year (Including 1 Year)	None	Monthly	0
248	Nominal Lending Rate: 1–5 Year (Including 5 Year)	None	Monthly	0
249	Nominal Lending Rate: Over 5 Year	None	Monthly	0
250	Household Savings Deposits Rate: Time: 6 Month	None	Monthly	0
251	Household Savings Deposits Rate: Time: 1 Year	None	Monthly	0
252	GDP	Percentage change	Quarterly	132
253	GDP: Primary Industry	Percentage change	Quarterly	132
254	GDP: Secondary Industry(SI)	Percentage change	Quarterly	132
255	GDP: SI: Industry	Percentage change	Quarterly	132
256	GDP: SI: Construction	Percentage change	Quarterly	132
257	GDP: TI: Transport, Storage and Post	Percentage change	Quarterly	132
258	GDP: TI: Wholesale and Retail Trade	Percentage change	Quarterly	132
259	GDP: Tertiary Industry(TI)	Percentage change	Quarterly	132
260	GDP: ow: Agriculture, Forestry, Animal Husbandry and Fishery (Incl. Services)	Percentage change	Quarterly	132
261	GDP: TI: Other	Percentage change	Quarterly	132

(Continues)

TABLE A2 (Continued)

Series number	Variable name	Transformation	Frequency	No. of missing observations
262	GDP: TI: Financial Intermediation	Percentage change	Quarterly	132
263	GDP: TI: Real Estate	Percentage change	Quarterly	132
264	GDP: TI: Accommodation and Catering Trade	Percentage change	Quarterly	132
265	Monetary Authority: Asset: Foreign Asset	Percentage change	Quarterly	132
266	Monetary Authority: Asset: Foreign Asset: Gold	Percentage change	Quarterly	132
267	Monetary Authority: Asset: Foreign Asset: Other	Percentage change	Quarterly	132
268	Monetary Authority: Asset: Claims on Government	Percentage change	Quarterly	132
269	Monetary Authority: Asset: Claims on Non Financial Institution	Percentage change	Quarterly	132
270	Finance Company: Asset: Claims on Non Financial Institution	Percentage change	Quarterly	132
271	Finance Company: Asset: Claims on Other Financial Corporation	Percentage change	Quarterly	132
272	Finance Company: Asset: Claims on Government	Percentage change	Quarterly	132
273	Finance Company: Asset: RA: Deposit with Central Bank	Percentage change	Quarterly	132
274	Finance Company: Asset: Reserve Asset (RA)	Percentage change	Quarterly	132
275	Diffusion Index: 5000 Industrial Enterprises Survey: Price Level of Sales	First difference	Quarterly	132
276	Diffusion Index: 5000 Industrial Enterprises Survey: Profitability	First difference	Quarterly	132
277	Diffusion Index: 5000 Industrial Enterprises Survey: Lending Attitude of Bank	First difference	Quarterly	132
278	Diffusion Index: 5000 Industrial Enterprises Survey: Cash Inflow From Sales	First difference	Quarterly	132
279	Diffusion Index: 5000 Industrial Enterprises Survey: Fund Turnover	First difference	Quarterly	132
280	Diffusion Index: 5000 Industrial Enterprises Survey: Overseas Order Level	First difference	Quarterly	132
281	Diffusion Index: 5000 Industrial Enterprises Survey: Domestic Order Level	First difference	Quarterly	132
282	Diffusion Index: 5000 Industrial Enterprises Survey: Inventory Level	First difference	Quarterly	132
283	Diffusion Index: 5000 Industrial Enterprises Survey: Production Capacity Utilisation	First difference	Quarterly	132

TABLE A2 (Continued)

Series number	Variable name	Transformation	Frequency	No. of missing observations
284	Diffusion Index: 5000 Industrial Enterprises Survey: General Business Condition	First difference	Quarterly	132
285	Diffusion Index: 5000 Industrial Enterprises Survey: Fixed Asset Investment	First difference	Quarterly	132