NBER WORKING PAPER SERIES

FORECASTING CHINA'S ECONOMIC GROWTH AND INFLATION

Patrick Higgins
Tao Zha
Karen Zhong

Forecasting China's Economic Growth and Inflation
Patrick Higgins, Tao Zha, and Karen Zhong
NBER Working Paper No. 22402
July 2016
JEL No. C53,E1,E17

ABSTRACT

Although macroeconomic forecasting forms an integral part of the policymaking process, there has been a serious lack of rigorous and systematic research in the evaluation of out-of-sample model-based forecasts of China's real GDP growth and CPI inflation. This paper fills this research gap by providing a replicable forecasting model that beats a host of other competing models when measured by root mean square errors, especially over long-run forecast horizons. The model is shown to be capable of predicting turning points and to be usable for policy analysis under different scenarios. It predicts that China's future GDP growth will be of L-shape rather than U-shape.

Patrick Higgins
Federal Reserve Bank of Atlanta
1000 Peachtree Street, N.E.
Atlanta, GA 30309-4470
patrick.higgins@atl.frb.org

Tao Zha
Emory University
1602 Fishburne Drive
Atlanta, GA 30322-2240
and Federal Reserve Bank of Atlanta
and also NBER
tzha@emory.edu

Karen Zhong
Shanghai Advanced Institute of Finance
Shanghai Jiaotong University
China
wnzhong@saif.sjtu.edu.cn

I. Introduction

China's growth and cyclical fluctuations, especially since the 2008 financial crisis, have largely depended on China's macroeconomic policies. In particular, the government's policies for promoting investment in heavy industries such as real estate and infrastructure constitute a driving force behind both growth and cyclical fluctuations for the past two decades (Chang, Chen, Waggoner, and Zha, 2015). The question of where China's economic growth will be headed in the future (in the Chinese government's language, a L-shape or U-shape growth pattern) has been a hotly contested issue for policymakers and researchers alike.

As China has become the second largest economy in the world, rigorous and systematic research in the evaluation of *out-of-sample* forecasts of China's macroeconomy is urgently needed.[1] For the Federal Reserve System and a number of central banks in other developed countries, macroeconomic forecasting is an integral part of the policymaking process. In this context, monthly macroeconomic time series are very important for *timely policy projections*.

In this paper, we extend the Bayesian vector autoregression (BVAR) methodology to forecasting China's macroeconomy, especially gross domestic product (GDP) growth and consumer price index (CPI) inflation (the two variables exclusively considered by many central banks around the world when taking policy actions). Our proposed benchmark model outperforms a host of other alternatives, including the gold-standard random walk model and other forecasting models studied in the recent literature. The model is close to the one used to provide forecasts for the People's Bank of China and the macro forecasting team at the Shanghai University of Finance and Economics. Our methodology enables one to generate density forecasts in addition to point forecasts. In this paper, we use .68 probability bands as the most commonly used device for communicating density forecasts.

Replicable forecasting models like our benchmark model built in this paper are needed because their forecast performance can be evaluated in a scientific manner on a continual basis. Some models, such as China's Annual Macroeconomic Model developed jointly by the Chinese Academy of Social Science and the National Bureau of Statistics of China (CASS-NBS) and China's Quarterly Macroeconomic Model developed by Xiamen University in 2006 (CQMM), do not have complete information about model structures for independent evaluation. In this paper, we focus on a host of competing models that can be replicated and thus evaluated independently. One exception is the widely used monthly surveys of Blue Chip Economic Indicators (BCEI). Although the BCEI does not have replicable models, it provides a complete set of forecast records that can be used for comparison of forecast accuracy.

---

[1]Another branch of studies concerns the widening distribution of income as well as consumption in China. See Ding and He (2016) and the references therein.

According to the root mean square error (RMSE) criterion, our benchmark model performs remarkably well over the long-run forecast horizon (three and four years ahead). Given the long lag of monetary policy, the long-run forecasting performance is particularly critical for policy analysis. We find that the model is also capable of predicting the turning point for GDP growth and CPI inflation, a task that is challenging for any macroeconomic model. We consider different policy scenarios to show that M2 growth, a tool utilized by the People's Bank of China in conducting its monetary policy, has proven to be very effective in predicting GDP growth in both short and long runs.

For the U.S. economy, forecasting inflation from replicable models is a top priority for policymakers and academic researchers (Stock and Watson, 2007). For China, forecasting GDP growth from replicable models is the most important factor for policy analysis as well as in an analysis of China's impact on the world economy. But model-based forecasts of China's GDP growth have proven to a challenging task. In this paper we demonstrate that while our proposed benchmark model is competitive with other models in predicting CPI inflation, it is this model's superior performance in predicting GDP growth rates that warrants particular attention.

The rest of paper is structured as follows. Section II reviews the methodology for the benchmark model and the related literature on forecasting models. Section III describes the monthly data used in this paper. Section IV compares the forecast accuracy of our benchmark model to the competing models and explore the role of monetary policy using conditional forecasts. Section V uses our benchmark model to forecast future GDP growth to shed light on recent policy debates on whether economic growth in the future will be of L-shape versus U-shape. Section VI concludes the paper.

II. Methodology and the literature review

In this section we review the methodology of our benchmark model and then discuss other methods in the context of the literature. A brief description of this methodology, targeted for our own applications, is self-contained so that the reader does not need to read through the multiple original papers.

II.1. **The benchmark model.** Our benchmark model is a Bayesian vector autoregression (BVAR) based on Waggoner and Zha (1999) with the Sims-Zha prior (Sims and Zha, 1998). It has the following VAR form:

$$\sum_{l=0}^{p} y'_{t-l} A_l = d' + \epsilon'_t \ , \text{ for } t = 1, ..., T, \tag{1}$$

where y_t is an $n \times 1$ vector of endogenous variables for period t, T the sample size, A_l the $n \times n$ coefficient matrix for the lth lag of the VAR, p the number of lags, d an $n \times 1$ vector

of constant terms, and ϵ_t an $n \times 1$ vector of i.i.d. structural shocks satisfying:

$$E(\epsilon_t|y_{t-s}, s > 0) = 0 \text{ and } E(\epsilon_t\epsilon_t' \mid y_{t-s}, s > 0) = I_n.$$

In this paper, since we focus on forecasting, we follow the convention of Sims (1980) and Christiano, Eichenbaum, and Evans (1999) and make the contemporaneous coefficient matrix A_0 triangular. The order of the variables, however, is inconsequential for our forecasting exercises. The reduced form of (1) is:

$$y_t' = c' + \sum_{l=1}^{p} y_{t-l}'B_l + e_t', \text{ for all } t, \tag{2}$$

where $c = A_0'^{-1}d$, $B_l = -A_lA_0^{-1}$ for $l = 1, ..., p$, $e_t = A_0'^{-1}\epsilon_t$, and $\Sigma = E(e_te_t' \mid y_{t-s}, s > 0) = A_0'^{-1}A_0^{-1}$.

Define $\mathbf{Y} = [y_1\, y_2\, \ldots\, y_T]'$, $\mathbf{y} = vec(\mathbf{Y})$, $x_t = [y_{t-1}'\, y_{t-2}'\, \ldots\, y_{t-p}', 1]'$, $\mathbf{X} = [x_1\, x_2\, \ldots\, x_T]'$, $\mathbf{B} = [B_1'\, B_2'\, \ldots\, B_p'\, c]'$, $\mathbf{b} = vec(\mathbf{B})$, $\mathbf{E} = [e_1\, e_2\, \ldots\, e_T]'$ and $\mathbf{e} = vec(\mathbf{E})$. The reduced form (2) can be rewritten as:

$$\mathbf{Y} = \mathbf{XB} + \mathbf{E}$$

or

$$\mathbf{y} = (I_n \otimes \mathbf{X})\mathbf{b} + \mathbf{e}, \, \mathbf{e} \sim N(0, \Sigma \otimes I_T), \tag{3}$$

where $N(\cdot, \cdot)$ represents a normal probability distribution.

We implement the Sims-Zha prior for the reduced-form (3) as

$$\mathbf{b}|\Sigma \sim N(\bar{\mathbf{b}}, \bar{\Psi}) \text{ and } \Sigma^{-1} \sim \widetilde{W}(\bar{S}, \bar{V}),$$

where $\widetilde{W}(\cdot, \cdot)$ denotes a tractable distribution similar but not equal to the Wishart distribution.[2] The prior vector $\bar{\mathbf{b}} = vec([I_n, \mathbf{0}_{n \times (n(p-1)+1)}']')$ to reflect beliefs that each variable follows a random walk. The prior hyperparameter matrix $\bar{S}$ is an $n \times n$ diagonal matrix $diag(\sigma_1, \sigma_2, ..., \sigma_n)$, where σ_i is set to the standard deviation of the residuals from estimating a univariate AR(p) fit by ordinary least squares to the time series of ith variable. The hyperparameters λ_0, λ_1, λ_3, and λ_4 determine the prior diagonal covariance matrix $\bar{\Psi}$. For each of n^2p combinations of variable i, equation j, and lag length l ($1 \leq i \leq n$, $1 \leq j \leq n$, $1 \leq l \leq p$), $[\lambda_0\lambda_1/(\sigma_j l^{\lambda_3})]^2$ is the prior variance appearing at position $(i-1)[np+1] + (l-1)n + j$ on the diagonal of $\bar{\Psi}$. The term appearing at position $i[np+1]$ on the diagonal of $\bar{\Psi}$, for each i with $1 \leq i \leq n$, is $[\lambda_0\lambda_4]^2$ (the prior variance on the constant term).

The most important part of the Sims-Zha prior consists of two sets of dummy observations from the data to capture prior beliefs about unit roots (not just random walk) and *cointegration* in the time series. We call this component of the prior "the cointegration prior," which is paramountly important because many of the Chinese time series tend to be highly

---

[2]The prior parameter matrix $\bar{V}$, the exact probability density form for $\widetilde{W}(\cdot, \cdot)$, and how to sample from it are discussed in Sims and Zha (1998).

cointegrated. The unit-root prior is mathematically expressed as the following n dummy observations

$$Y_{ur} = \mu_5 \, diag(\bar{y}) \text{ and } X_{ur} = \mu_5 \left[\mathbf{1}_{1 \times n} \otimes diag(\bar{y}), \mathbf{0}_{n \times 1} \right],$$

where the subscript "ur" stands for unit root, $\bar{y} = \frac{1}{p} \sum_{t=-(p-1)}^{0} y_t$ is the average of the initial p observations, and μ_5 a prior hyperparameter. As $\mu_5 \to \infty$, the prior implies a unit root in each equation with no cointegration. The cointegration prior is implemented with one dummy observation:

$$Y_{co} = \mu_6 \bar{y} \text{ and } X_{co} = \mu_6 \left[\mathbf{1}_{1 \times n} \otimes \bar{y}, 1 \right],$$

where the subscript "co" stands for cointegration and μ_6 is a hyperparameter. As $\mu_6 \to \infty$, the prior implies that the variables have up to $n-1$ cointegration relationships but allows for a single or multiple stochastic trends. Define $\mathbf{X}^* = [\mathbf{X}', X_{ur}', X_{co}']'$ and $\mathbf{Y}^* = [\mathbf{Y}', Y_{ur}', Y_{co}']'$. Posterior estimation is based on $\mathbf{Y}^*$ and $\mathbf{X}^*$ (not $\mathbf{Y}$ and $\mathbf{X}$).

Li (2016) applies the Sims-Zha prior to a large set of China's quarterly time series and find that a decay value of λ_4 as large as 5 is the key to achieving robust results of accurate out-of-sample forecasts of GDP growth and CPI inflation. By combining Li (2016)'s new finding for China with the standard Sims-Zha prior for the *monthly* U.S. economy documented by Zha (1998), we propose the following values of hyperparameters for our monthly benchmark model: $\lambda_0 = 0.57$, $\lambda_1 = 0.13$, $\lambda_3 = 0.1$, $\lambda_4 = 5.0$, and $\mu_5 = \mu_6 = 10$.

II.2. **Conditional forecasts.** Given equation (2) and the data up to time T, the h-step ahead forecast at time T is

$$y_{T+h}' = \underbrace{c' K_{h-1} + \sum_{l=1}^{p} y_{T+1-l}' N_{l,h}}_{\text{Unconditional forecast:} y_{T+h}^{u\,\prime}} + \underbrace{\sum_{k=1}^{h} \epsilon_{T+k}' M_{h-k}}_{\text{Cumulative responses}} , \tag{4}$$

where

$$K_0 = I_n, \ K_i = I_n + \sum_{k=1}^{i} K_{i-k} B_k \ , \ i = 1, 2, ..., h-1;$$

$$N_{l,1} = B_l \ , \ N_{l,j} = \sum_{k=1}^{j-1} N_{l,j-k} B_k + B_{j+l-1}, \ l = 1, ..., p; \ j = 2, ..., h;$$

$$M_0 = A_0^{-1}, \ M_i = \sum_{k=1}^{i} M_{i-k} B_k, \ i = 1, ..., h-1;$$

with the convention $B_k = \mathbf{0}$ for $k > p$.

The last term in (4) gives the cumulative impact of future structural shocks on endogenous variables through the impulse responses M_i. When restrictions are imposed on future values of certain variables, the forecasts generated by (4) are called conditional forecasts. Suppose we would like to constrain a $nh \times 1$ vector of forecasts $\left[y_{T+1}' \, y_{T+2}' \, \cdots \, y_{T+h}' \right]'$ to a particular

path represented by $y^* = \left[y^{*\prime}_{T+1}\, y^{*\prime}_{T+2}\, \ldots\, y^{*\prime}_{T+h}\right]'$. We stack the 1-step ahead through h-step ahead unconditional forecasts from (4) in the vector $y^u = \left[y^{u\prime}_{T+1}\, y^{u\prime}_{T+2}\, \ldots\, y^{u\prime}_{T+h}\right]'$ and define $r = y^* - y^u$. We stack the corresponding impulse responses into the matrix R as

$$
R = \begin{bmatrix}
M_0 & M_1 & M_2 & \ldots & M_{h-2} & M_{h-1} \\
0 & M_0 & M_1 & \ldots & M_{h-3} & M_{h-2} \\
\ldots & \ldots & \ldots & \ldots & \ldots & \ldots \\
0 & 0 & 0 & \ldots & M_0 & M_1 \\
0 & 0 & 0 & \ldots & 0 & M_0
\end{bmatrix}.
$$

By collecting the future structural shocks from $T+1$ to $T+h$ in the vector $\epsilon = \left[\epsilon'_{T+1}\, \epsilon'_{T+2}\, \ldots\, \epsilon'_{T+h}\right]'$, one can see from equation (4) that imposing the condition y^* on the future forecasts is equivalent to imposing the following condition on the structural shocks

$$
R'\epsilon = r.
$$

Now suppose we wish to impose only a subset of y^*. We first determine the row numbers of y^* associated with the restricted subset and then remove these rows from r and R'. We use what is left to create $\tilde{r}$ and $\tilde{R}'$. Thus, imposing a subset of restrictions is equivalent to imposing the condition

$$
\tilde{R}'\epsilon = \tilde{r}. \tag{5}
$$

Waggoner and Zha (1999) show that maximum likelihood estimate of ϵ subject to restriction (5) is $\epsilon^{MLE} = \tilde{R}(\tilde{R}'\tilde{R})^{-1}\tilde{r}$. These shocks are fed into (4) to generate the desired conditional forecasts.

II.3. **Other models in the literature.** It is known that BVAR forecasts are more accurate than VAR forecasts (Doan, Litterman, and Sims, 1984). While the literature on the BVAR methodology is voluminous, Robertson and Tallman (2001) and Carriero, Clark, and Marcellino (2015) discuss it in great details (see other references therein). BVAR models provide an important tool that has long been used by central banks around the world for macroeconomic analysis. There are several variations of BVAR modeling. The most popular one is the BVAR with the Minnesota prior introduced by (Litterman, 1986), whose model generated out-of-sample forecasts as accurate as those used by the best known commercial forecasting services. The Minnesota prior is a special case of the Sims-Zha prior without the unit-root and cointegration prior components.

Bańbura, Giannone, and Reichlin (2010) modify the Minnesota prior for relatively large BVAR models and propose a procedure to adjust a key value of the "overall tightness" hyperparameter as the number of variables increases. The prior proposed by Bańbura, Giannone,

and Reichlin (2010) is further modified by Giannone, Lenza, and Primiceri (2015), who implement a more systematic approach by choosing a very diffuse prior for the hyperparameters—called hyperpriors—and solving for the posterior mode of these hyperparameter values. Furthermore, they incorporate the Sims-Zha dummy observations for co-integration in their prior. With this systematic procedure, Giannone, Lenza, and Primiceri (2015) find that their 22-variable BVAR model has forecast accuracy comparable to their 3-variable and 8-variable BVARs.[3] We will use the prior proposed by Giannone, Lenza, and Primiceri (2015) (called the GLP model), which is the most recent prior proposed in the literature, to compare forecast accuracy to our benchmark model.

Popular alternative models in the forecasting literature include autoregressive (AR) models for each variable and the random walk model of Atkeson and Ohanian (2001) for each variable. For the ith variable, the various AR specifications studied in this paper are

$$y_t^i = \alpha + \beta t + \sum_{l=1}^{p} \gamma_l y_{t-l}^i + u_t,$$

where $p = 1, 6, 12$, x_t is univariate, and $\beta = 0$ whenever a trend is not used. The random walk model is often treated as the gold standard for out-of-sample forecasting. Following Atkeson and Ohanian (2001), we recursively calculate the random walk forecast for the ith variable in one month ahead as[4]

$$\hat{y}_{t+1}^i = \hat{y}_t^i + \left(\hat{y}_t^i - \hat{y}_{t-12}^i \right) / 12,$$

or equivalently

$$\hat{y}_{t+1}^i - \hat{y}_t^i = \left(\hat{y}_t^i - \hat{y}_{t-12}^i \right) / 12. \tag{6}$$

When $t \leq T$ where T is the date prior to the forecast period, $\hat{y}_t^i = y_t^i$.

II.4. **Annual changes according to calendar year.** Following the convention of reporting comparable forecasts established by the BCEI, we calculate the annual rate as the ratio of the average value in the forecast year to the average value in the previous year. This reporting method applies to GDP growth, CPI inflation, M2 growth, and other growth variables, except interest rates and variables that are already expressed in percent. To be consistent

---

[3]Specifically, the 22-variable BVAR's one year ahead forecast of GDP growth is less accurate than the smaller BVARs, but the one year ahead inflation forecast is more accurate.

[4]The original Atkeson and Ohanian (2001) model for foracasting the 12-month inflation rate is $E_t \left[\log \left(\frac{p_{T+12}}{p_T} \right) = \log \left(\frac{p_T}{p_{T-12}} \right) \right]$ (see equation (4) of their paper), where p_T denotes the monthly price level at the end of the sample T. To implement Atkeson and Ohanian (2001)'s model, we would use the model $\hat{y}_{t+1} = \hat{y}_t + \frac{y_T - y_{T-12}}{12}$ for $t > T$. It turns out that the RMSEs produced by this method are larger than those from our modified random walk model (6) except for the two years ahead forecast of CPI inflation, although the differences are very small. Other adapted random walk models include Stock and Watson (2007) and Ang, Bekaert, and Wei (2007).

with calendar years, the time subscript t can be alternatively expressed by double indices as $t = \{yr, mon\}$, where yr represents calendar year and mon represents calendar month. An annual growth rate expressed in percent is calculated as

$$g^i_{yr, mon} = 100 \left[\frac{\frac{\sum_{mon=1}^{12} \exp\left(\hat{y}^i_{yr, mon}\right)}{12}}{\frac{\sum_{mon=1}^{12} \exp\left(\hat{y}^i_{yr-1, mon}\right)}{12}} - 1 \right].$$

Let the first forecast date be $T + 1 = \{yr^*, mon^*\}$. If $yr < yr^*$ or if $yr = yr^*$ but $mon < mon^*$, then $\hat{y}^i_{yr, mon} = y^i_{yr, mon}$. That is, the forecast value is the actual value. Following the literature on forecast comparison, we use the RMSE metric to measure the accuracy of $g^i_{yr, mon}$ against the actual growth rate.

III. Data

Our monthly dataset is based on Chang, Chen, Waggoner, and Zha (2015) and Higgins and Zha (2015), who construct a standard set of quarterly macroeconomic time series comparable to those commonly used in the macroeconomic literature on Western economies. The construction process is based on China's official macroeconomic data series compiled in the CEIC's China Premium Database.

One may question the quality of China's official macroeconomic data, especially the GDP series. Despite the unsettled debates on this issue, our view is that one should *not* abandon the official series of GDP in favor of other less comprehensive series such as electricity consumption or electricity production, no matter how "reliable" one would claim those alternatives are in gauging the pulse of China's overall economy. After all, the series of GDP is what financial markets, researchers, policy analysts, and policymakers would pay most attention to when China's aggregate activity is assessed. In a very recent paper, Nie (2016) forcibly argues that "official GDP figures remain a useful and valid measure of Chinese economic growth."

The sample for estimation is from 2000M1 to the date prior to forecast (starting 2010M12 and rolling forward to 2015M11 month by month). The variables are interpolated real value-added GDP, real retail sales of consumer goods (consumption), real fixed-asset investment (investment), M2, CPI, net exports (as percent of GDP), the 7-day repo rate in the national interbank market (repo), and the one year benchmark deposit rate (the deposit rate). Real consumption and real investment are deflated by the CPI. We have also deflated consumption by its own price index for retail sales of consumer goods and investment by the interpolated GDP deflator.[5] We construct the non-seasonally adjusted M2 times series based on the non-seasonally adjusted level of M2 for the period of 2015M1 to 2015M12 and the year-over-year

---

[5]Fixed-asset investment has its own price index but a release of this price index is often one or two years after the release of nominal fixed-asset investment series.

growth rates from the PBC. This constructed series alleviates serious problems of sudden changes or misalignments of statistical coverage for certain periods of the sample. We then adjusted this series seasonally.

We interpolate the quarterly seasonally adjusted GDP deflator series with monthly seasonally adjusted producer price index, CPI, retail goods price index, and M2 and the quarterly seasonally adjusted nominal GDP series with monthly seasonally adjusted nominal consumption, exports, imports, and industrial value added. The method for interpolating real GDP follows closely Chow and Lin (1971), Leeper, Sims, and Zha (1996), and Bernanke, Gertler, and Watson (1997). Quarterly seasonally adjusted nominal GDP and its deflator are constructed by Higgins and Zha (2015).

All variables are entered in log except for net exports and the two interest rates, which are entered as percentages (divided by 100). All the log variables bar investment are seasonally adjusted using X13-ARIMA-SEATS modified to take into consideration the effect of China's Spring Festival holidays. The Spring Festival has a substantial impact on monthly economic activity; it falls sometimes in January, sometimes in February, and sometimes crosses both. As for the monthly investment series, there are three more challenges for seasonal adjustment. First, the published value of investment is aggregated across January and February. Second, the value for December is significantly higher than those for other months even after seasonal adjustment. Third, there is a level-shift in the series during the year of 2004. We use the method by Fernald, Spiegel, and Swanson (2014) to disaggregate one January-February observation into two observations in separate months and use the approach proposed by Wright (2013) to seasonally adjust the resulting series. Figure 1 plots the investment series before and after our adjustment. Evidently, the adjustment removes the seasonality and level-shift.

IV. Assessing forecast performance

Models usable for day-to-day policy analysis must be able to forecast the economy well. The most important variables concerning policymakers are GDP growth and CPI inflation.[6] Providing accurate forecasts of these two variables has proven to be an extremely challenging task. We show that our benchmark model performs remarkably well in comparison with a host of competing models studied in the literature and in most cases outperform them, as reported in Tables 1-4.

---

[6]The two variables, output growth and inflation, are universally used by central banks around the world to guide their policy actions. In particular, the Summary of Economic Projections (SEP) regularly released in the Federal Open Market Committee (FOMC) minutes by the Federal Reserve Board reports projections of these variables in addition to the unemployment rate and the federal funds rate under appropriate monetary policy.

In addition to the benchmark model and the BCEI forecasts, we consider 11 competing models: (i) the standard VAR model (with no proper prior) estimated by ordinary least squares, (ii) the widely used BVAR model with the Minnesota prior, (iii) the GLP BVAR model, (iv) the gold-standard random walk model, and (v) six univariate AR models, that is, AR(1), AR(6), and AR(12) models with and without trend.

IV.1. **Out-of-sample forecasting.** Out-of-sample forecasts reported in Tables 1-4 are annual growth rates of real GDP and annual inflation rates of CPI. Except the BCEI forecasts, all the models listed in these tables use the sample starting from 2000M1 until the date when actual out-of-sample forecasts are made.[7] The starting sample date accords with the earliest date back to which China's National Bureau of Statistics (NBS) periodically revises its time series. The forecast year ranges from one year ahead (short run) to four years ahead (long run). Long-run forecasts have proven to be a difficult and oftentimes embarrassing exercise. For this and other reasons, the BCEI provides out-of-sample forecasts only over the two years horizon and we report the average of the BCEI forecasts.[8] For policymakers, however, long-run out-of-sample forecasts are essential because monetary policy is known to have long and lagged effects on the real economy (Sims and Zha, 2006).

The forecast evaluation period is from 2011 to 2015. Since data are monthly and forecasts are updated each month, this five-year period gives us enough data points to evaluate out-of-sample forecast performance without disproportionately shortening the length of the sample used for accurate estimation. For this evaluation period and for each variable, we compute the RMSE of forecasts at each forecast horizon (from one to four years ahead).

IV.2. **GDP growth and CPI inflation.** We first analyze forecasts from all models bar the BCEI, which is not model-based and will be discussed later. Except for the one year forecast horizon, the benchmark model's RMSEs for GDP growth over the longer horizons (two, three, and four years ahead) are considerably smaller than those produced from the random walk and the GLP model (Table 1).[9] For the one year horizon, the random walk model perfroms better than both the GLP model and the benchmark model. The popular

---

[7]When some data such as GDP are unavailable within the quarter, one can condition forecasts on other series available within the quarter such as M2 and interest rates with a method described in Section II.2.

[8]Bauer, Eisenbeis, Waggoner, and Zha (2006) show that the average BCEI forecast tends to be more accurate than individual forecasts.

[9]When we use the series of real consumption (divided by its own price deflator) and real investment (divided by the GDP deflator), the RMSEs are similar and in many cases more accurate. For example, the RMSEs for real GDP growth in two, three, four years ahead are respectively 0.754%, 0.744%, and 0.540%. For the meaning of these number, for example, 0.754% means that the root mean square error is less than 1% for predicting the actual GDP growth rate over the two years horizon. Thus, the forecast accuracy for both one and two years ahead is highly competitive with the BCEI forecast.

Minnesota-prior model fares much worse than the benchmark model, especially in forecast horizons longer than one year ahead. All other models, including the standard VAR model (i.e., with no proper prior) that has been widely used and all parsimonious AR models, perform even worse over all forecast horizons.

For CPI inflation, , the GLP model's RMSE is much smaller than that of the benchmark over the one year horizon but substantially larger over the longer horizons from two to four years (Table 3). Compared to the benchmark, both the random walk model and the Minnesota-prior model perform well over the one year horizon but lose their strength considerably over the horizons of two to four years ahead. The standard VAR fares very badly for all forecast horizons. Except for the one year horizon, all AR models have larger RMSEs than the benchmark model.

Since the literature regards the random walk model as the gold standard for gauging the success of other models in forecasting performance, Tables 2 and 4 report the ratio of the RMSE for each model to the RMSE for the random walk model. If the relative RMSE ratio for a particular model is greater than one, the model performs worse than the random walk model. If the ratio is less than one, the model performs better. Thus, the smaller the relative RMSE ratio, the superior the corresponding model's performance. For CPI inflation, in addition to the benchmark model, a number of models beat the random walk model in the longer run (two to four years ahead), including the GLP model and many AR models (4). In fact, both the GLP model and the benchmark model, as well as AR(6) and AR(12) models with trend, beat the random walk model by large margins over longer forecast horizons. This phenomenon is in sharp contrast to the findings for the U.S. economy where the random walk model is the king for predicting inflation (Atkeson and Ohanian, 2001).

The results for GDP growth, however, present a completely different picture. All models other than the benchmark model and the BCEI fail to beat the random walk model. But compared to the benchmark model, the random walk model performs better only over the one year horizon; it gives in to the benchmark model's increasing strength in all other forecast horizons (over two to four years ahead).

The BCEI forecasts are interesting examples. On a monthly basis, the Blue Chip surveys 15-20 respondents specifically for China. All respondents are top professional forecasters and most of them do not strictly adhere to a replicable econometric model. For GDP growth, their forecasts are often judgmentally chosen to be close to the target set by the Chinese government. This strategy pays off as the BCEI forecast of GDP growth fares better than our benchmark model as well as all other models, including the random walk model (Tables 1 and 2). But CPI inflation forecasting is a different matter. Although the Chinese government discusses what an appropriate CPI inflation rate should be, there has never been a serious attempt from the government to adhere to such a "target" for CPI inflation. As a result,

the BCEI forecast of CPI inflation by closely following the government's rhetoric turns out to be much worse than the forecast produced by the benchmark model (Tables 3 and 4).

IV.3. **In the aftermath of the global financial crisis.** In 2009 the Chinese government injected an unprecedented four trillion RMB into the economy, which undoubtedly helped stabilize economic growth and pushed real GDP growth over double digits in 2010. Many economists were stunned by how fast China's economy could turn around so swiftly (in comparison to the U.S. economy with a long and slow recovery). Although few economists at the end of 2010 would predict a *persistently slowing* economy starting in 2011, the turning point is captured by our benchmark model.

As shown in Tables 5 and 6, the benchmark model predicts, out of sample, a persistent decline of GDP growth similar to the actual path of GDP growth. In contrast, the GLP model shows a U-shape pattern of GDP growth with the growth rate turning over double digits in 2013-2015. The GLP model performs better except for 2014-2015 for CPI inflation, but it generates the U-shape prediction of growth rates of investment and M2, a direction opposite to the downward actual paths. The benchmark model, however, predicts paths of investment growth and M2 growth in a downward direction similar to the actual paths.

Chang, Chen, Waggoner, and Zha (2015) argue that the government is effective in controlling bank credit via M2 growth to influence investment and therefore GDP growth. The finding that M2 growth is a powerful policy tool in China applies to this turning point as well. From Table 6 one can see that the benchmark model predicts a path of M2 growth lower than the actual path. This pattern supports the under-prediction of growth rates of investment and GDP.

Consider a policy scenario in which M2 growth follows the actual path in the forecast period 2011-2015. Using the technique of conditional forecasts discussed in Section II.2, we report the prediction results of investment growth, CPI inflation, and GDP growth in Figure 2. Since the actual M2 growth path is higher than the unconditional forecast path (cf. Table 6 and Figure 2), investment and GDP growth rates are higher than the unconditional counterparts (cf. Tables 5-6 and Figure 2). As a result, the prediction path of GDP growth under this policy scenario is very close to the actual path, especially over the long forecast horizon such as three to five years ahead. From the model's perspective, moreover, the upper probability band of predictions does not return to double-digit growth (a level at the time when predictions are model) for a forecast horizon after two years ahead.

In summary, the exercises in this section produce three findings: first, the benchmark model is capable of predicting the difficult turning point when economic growth turned into single digits after it rebounded to double digits in 2010 with the government's unprecedented

expansionary monetary policy; second, the policy variable, M2 growth, proves to be a powerful driving force of GDP growth; and third, the model can be effectively used for analyzing different policy scenarios.

V. Into the future: L-shape versus U-shape of GDP growth

Having established the benchmark model's superior performance of out-of-sample forecasts relative to other competing models, we now use it to predict economic growth and inflation in the future. Such a prediction is very important because of its relevance to the current policy debate on whether China's GDP growth will be of U-shape or L-shape. Academic voice represented by Professor Daokui Li at Tsinghua, former member of Monetary Policy Committee of the People's Bank of China, expressed a view that China's GDP growth rate will likely be of U-shape.[10] An official opinion has added to this academic voice. The press representative from the NBS, Laiyun Sheng, held a regular news conference on 15 April 2016 to express a similar view.[11] On the other hand, People's Daily of 9 May 2016, an official newspaper representing the voice of the Central Communist Party, argues that future GDP growth is likely to be of L-shape.[12]

Which prediction is likely to be more accurate? Given considerable disagreements *within the government* itself, we use the benchmark model to shed light on this important policy debate at a critical juncture of the Chinese economy by providing forecasts to see which shape our prediction path is closer to. Figure 3 plots unconditional forecasts of GDP growth, CPI inflation, and M2 growth based on the information up to 2016M3.[13] The .68 probability bands display a degree of uncertainty that reflects the historical forecast errors, with the lower probability band of GDP growth being as low as 4.2%. But according to the *most likely* path (the posterior mode path) most economists pay attention to, the model predicts a L-shape path of GDP growth that hovers around 6.5% over the next five years while CPI inflation is predicted to be 1.7% except for 2016 (in comparison, the BCEI forecast of GDP growth is 6.5% for 2016 and 6.2% for 2017 and of CPI inflation is 1.9% for 2016 and 2017). This result is in sharp contrast with the results from the GLP model, which predicts CPI

---

[10]See an interview with September 17, 2015 *China Newsweek*. The URL for this interview can be found at http://toutiao.com/i6195428846319583745/.

[11]See the NBS report at http://www.stats.gov.cn/tjgz/tjdt/201604/t20160415_1344240.html as well as the report from *China Economic Net* at http://www.ce.cn/xwzx/gnsz/gdxw/201604/15/t20160415_10515154.shtml.

[12]See the link http://paper.people.com.cn/rmrb/html/2016-05/09/nw.D110000renmrb_20160509_6-01.htm#.

[13]The forecasts conditional on the additional data available in May 2016 at the time when this article was written are so similar that we do not report to conserve the space. These additional data are CPI, consumption, investment, M2, the repo rate, and the deposit rate in April 2016; and the repo rate and the deposit rate in May 2016.

inflation as high as 2.9% by 2019 and a robust rebound of GDP growth from 7% in 2016 to 9.4% in 2020. The GLP model's forecast path of economic growth is certainly of U-shape. The predicted U-shape rebound, however, is so high that one may judge it a low probability event (as indicated by the upper probability band of GDP growth in Figure 3).

We use the benchmark model to analyze several policy scenarios. For the U.S. and other developed countries, the impact of interest rates on the aggregate real economy has proven to be powerful. The People's Bank of China has been discussing the possibility of controlling interest rates such as the repo rate as a major policy instrument. Thus, it is informative to see how changes in future interest rates affect the Chinese economy. We consider a policy scenario in which the repo rate or the deposit rate would be raised by 1% above the unconditional forecasts to 3.5% for the repo rate and 2.5% for the deposit rate in from 2017 to 2020. As one can see, the impact on GDP growth and CPI inflation in comparison to the unconditional forecasts is very limited (Tables 7 and 8).[14] This finding, though not surprising for China's economy, is contrary to the conventional wisdom about the impact of interest rates, a wisdom applicable to the U.S. and other developed economies.

Changes in M2 growth exert considerable impact on GDP growth as we illustrate in Section IV. Consider a policy scenario in which M2 growth will slow down from 11.0% in 2016 and 9.5% in 2017 to 9% afterwards (in comparison to the unconditional forecast of 11.8% in 2016, 11.2% in 2017, and around 11.4% afterwards).[15] CPI inflation prediction is lower that the unconditional forecast path (Table 8). Future GDP growth is now predicted to be 5.8% (Table 7), producing an even steeper L-shape trajectory. For our monthly dataset, the standard deviation is 3.76% for year-over-year M2 growth, 1.01% for the repo rate, and 0.64% for the deposit rate. For our various policy scenarios, therefore, changes in M2 growth from the unconditional forecasts are well within one standard deviation, while changes in the repo rate are about one standard deviation and changes in the deposit rate are well above one standard deviation. Yet, the impact of changes in M2 growth on GDP growth is much larger than that of changes in interest rates. A slowdown in M2 growth would be a sensible policy scenario to consider because it allows time for China to adjust from an investment-driven economy to an economy more oriented to services and consumption.

VI. CONCLUSION

We provide an empirical model for China's macroeconomy that can be replicated and evaluated independently. We show that this model has superior forecast performance relative

---

[14]We experiment with the lending rate instead of the deposit rate and the impact on GDP growth is even weaker.

[15]All conditional forecasts, including the previous exercises with conditions on the repo rate and the deposit rate, use the data available up to May 2016 when this paper was completed.

to other competing models. Given this performance, the model should serve as a benchmark for comparison of forecast accuracy.

Accurate and timely macroeconomic forecasting is an essential part of the policymaking process. Contrary to the common belief based from the robust studies on the U.S. and other developed economies, we find that the impact of interest rates on the aggregate economy is relatively muted while changes in M2 growth have considerably larger impact. These findings imply that macroeconomic analysis of China should be based on these facts, not on off-the-self models working for other economies.

China's economy, as well as its monetary policy, has reached a stage that is mature enough for rigorous empirical macroeconomic analysis comparable to the international standards (Wen, 2016). In more ambitious projects for future research, for example, Markov-switching models taking into account of regime changes and stochastic volatility and mixed-frequency models incorporating weekly or daily financial variables would be useful tools to address many practical and policy-related issues. We view our analysis in this paper as a first step toward this goal.

TABLE 1. RMSEs of GDP growth forecasts out of sample (percent)

Model	Year 1	Year 2	Year 3	Year 4
BCEI	0.213	0.721	na	na
GLP	0.431	1.286	2.288	2.795
Benchmark	0.439	0.921	0.964	0.774
Minnesota	0.656	2.534	3.234	3.904
Standard VAR	1.821	2.639	3.371	11.563
Random walk	0.257	1.001	1.248	1.666
AR(1) without trend	0.624	2.436	3.121	3.799
AR(6) without trend	0.541	2.229	2.884	3.521
AR(12) without trend	0.549	2.245	2.840	3.480
AR(1) with trend	0.984	3.504	3.988	4.002
AR(6) with trend	0.843	3.286	3.966	4.040
AR(12) with trend	0.872	3.427	4.094	4.069

Note: Out-of-sample evaluation period is 2011-2015. The sample for estimation begins in 2000M1. The acronym "na" stands for "not available."

TABLE 2. RMSEs (relative to random walk) of GDP growth forecasts out of sample

Model	Year 1	Year 2	Year 3	Year 4
BCEI	0.830	0.720	na	na
GLP	1.674	1.284	1.834	1.678
Benchmark	1.707	0.920	0.773	0.464
Minnesota	2.551	2.530	2.592	2.344
Standard VAR	7.079	2.635	2.702	6.941
Random walk	1.000	1.000	1.000	1.000
AR(1) without trend	2.427	2.433	2.502	2.280
AR(6) without trend	2.104	2.226	2.312	2.114
AR(12) without trend	2.133	2.242	2.276	2.089
AR(1) with trend	3.827	3.500	3.197	2.403
AR(6) with trend	3.276	3.282	3.179	2.425
AR(12) with trend	3.390	3.423	3.281	2.443

Note: Out-of-sample evaluation period is 2011-2015. The sample for estimation begins in 2000M1. The acronym "na" stands for "not available."

TABLE 3. RMSEs of CPI inflation forecasts out of sample (percent)

Model	Year 1	Year 2	Year 3	Year 4
BCEI	0.538	1.206	na	na
GLP	0.260	0.810	0.681	1.084
Benchmark	0.468	0.596	0.595	0.331
Minnesota	0.450	1.741	2.337	3.010
Standard VAR	1.594	2.400	4.977	4.496
Random walk	0.253	1.682	2.006	2.707
AR(1) without trend	0.491	2.075	3.067	4.370
AR(6) without trend	0.296	1.285	1.757	2.465
AR(12) without trend	0.322	1.356	2.001	2.807
AR(1) with trend	0.426	1.317	1.560	1.877
AR(6) with trend	0.316	0.769	0.877	1.067
AR(12) with trend	0.313	0.810	0.972	1.256

Note: Out-of-sample evaluation period is 2011-2015. The sample for estimation begins in 2000M1. The acronym "na" stands for "not available."

TABLE 4. RMSEs (relative to random walk) of CPI inflation forecasts out of sample

Model	Year 1	Year 2	Year 3	Year 4
BCEI	2.123	0.717	na	na
GLP	1.027	0.481	0.339	0.401
Benchmark	1.846	0.354	0.297	0.122
Minnesota	1.777	1.035	1.165	1.112
Standard VAR	6.294	1.427	2.481	1.661
Random walk	1.000	1.000	1.000	1.000
AR(1) without trend	1.940	1.234	1.529	1.614
AR(6) without trend	1.169	0.764	0.876	0.911
AR(12) without trend	1.272	0.806	0.998	1.037
AR(1) with trend	1.680	0.783	0.778	0.693
AR(6) with trend	1.246	0.457	0.437	0.394
AR(12) with trend	1.235	0.481	0.484	0.464

Note: Out-of-sample evaluation period is 2011-2015. The sample for estimation begins in 2000M1. The acronym "na" stands for "not available."

TABLE 5. Unconditional out-of-sample forecasts made at 2010M12 (percent)

Horizon	GDP growth			CPI inflation		
	Actual	Benchmark	GLP	Actual	Benchmark	GLP
2006	12.7			1.7		
2007	14.2			4.8		
2008	9.7			5.9		
2009	9.1			-0.7		
2010	10.7			3.2		
2011	9.5	7.7	9.1	5.5	3.5	5.5
2012	7.7	6.0	8.8	2.6	1.4	2.7
2013	7.7	6.1	10.2	2.6	1.5	2.9
2014	7.3	6.1	10.1	2.1	1.5	3.6
2015	7.0	6.2	10.0	1.6	1.5	3.6

Note: The forecast period is from 2011 to 2015.

TABLE 6. Unconditional out-of-sample forecasts made at 2010M12 (percent)

Horizon	Investment growth			M2 growth		
	Actual	Benchmark	GLP	Actual	Benchmark	GLP
2006	21.5			18.1		
2007	19.4			17.6		
2008	19.1			16.6		
2009	31.5			26.6		
2010	20.4			20.6		
2011	20.1	17.8	21.0	15.6	13.7	15.6
2012	17.6	13.2	23.8	17.2	10.2	17.2
2013	16.5	13.3	23.8	14.8	10.3	19.1
2014	12.8	13.4	23.0	12.7	10.4	18.2
2015	8.5	13.5	22.9	11.9	10.5	18.4

Note: The forecast period is from 2011 to 2015.

Table 7. Into the future: GDP growth forecasts (percent)

Horizon	Unconditional	GLP	On M2	On repo	On deposit rate
2016	6.5	7.0	6.4	6.5	6.8
2017	6.5	8.4	5.9	6.5	6.9
2018	6.5	9.2	5.7	6.5	6.7
2019	6.6	9.3	5.8	6.6	6.8
2020	6.6	9.2	5.8	6.6	6.9

Note: The forecasts are made with the estimation period 2000M1-2016M3. "Unconditional" is the benchmark model's forecast. "On M2" indicates forecasts conditional on the path of slower M2 growth specified in the text, "On repo" indicates forecasts conditional on the path of higher repo rates specified in the text, and "On deposit rate" indicates forecasts conditional on the path of higher deposit rates specified in the text.

Table 8. Into the future: CPI inflation forecasts (percent)

Horizon	Unconditional	GLP	On M2	On repo	On deposit rate
2016	2.2	2.5	2.2	2.2	2.8
2017	1.7	2.6	1.6	1.7	2.2
2018	1.7	2.8	1.5	1.7	1.8
2019	1.7	3.0	1.5	1.7	1.8
2020	1.7	3.0	1.5	1.7	1.8

Note: The forecasts are made with the estimation period 2000M1-2016M3. "Unconditional" is the benchmark model's forecast. "On M2" indicates forecasts conditional on the path of slower M2 growth specified in the text, "On repo" indicates forecasts conditional on the path of higher repo rates specified in the text, and "On deposit rate" indicates forecasts conditional on the path of higher deposit rates specified in the text.
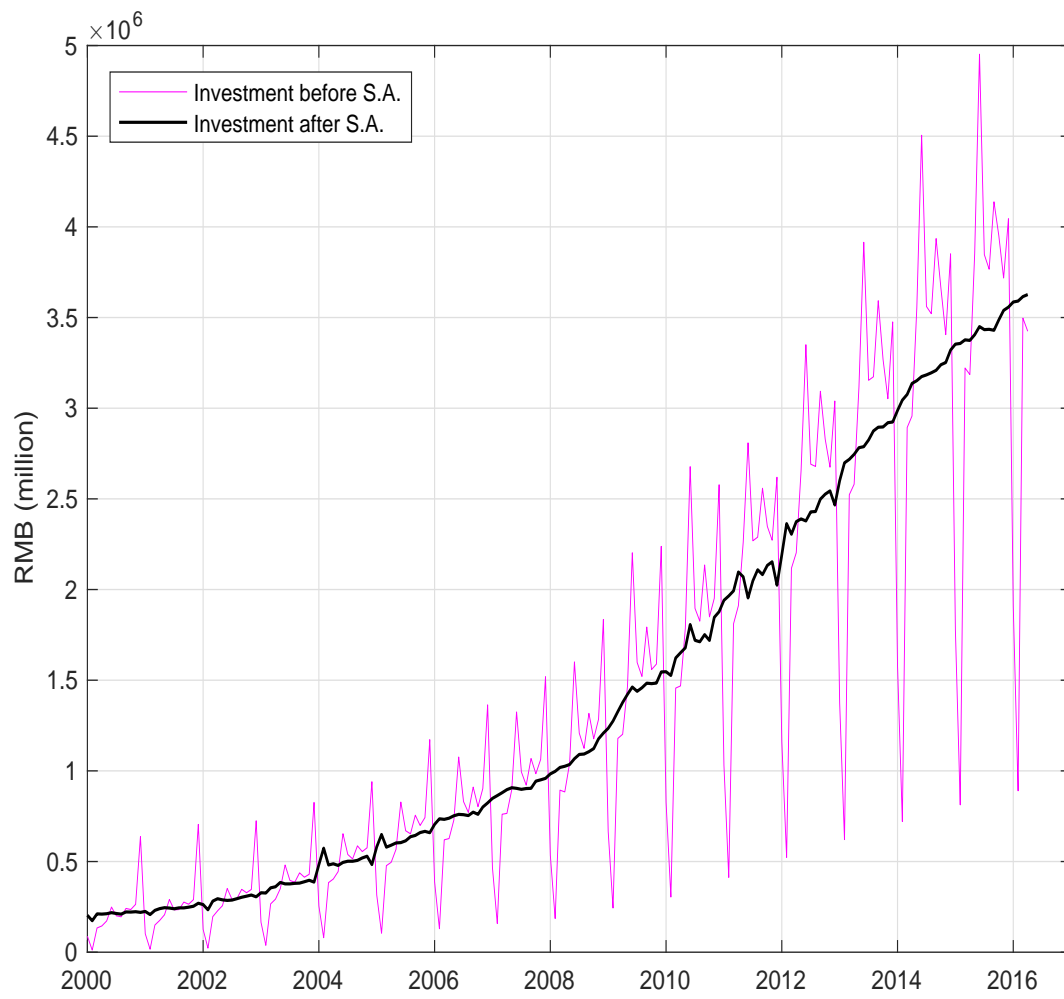
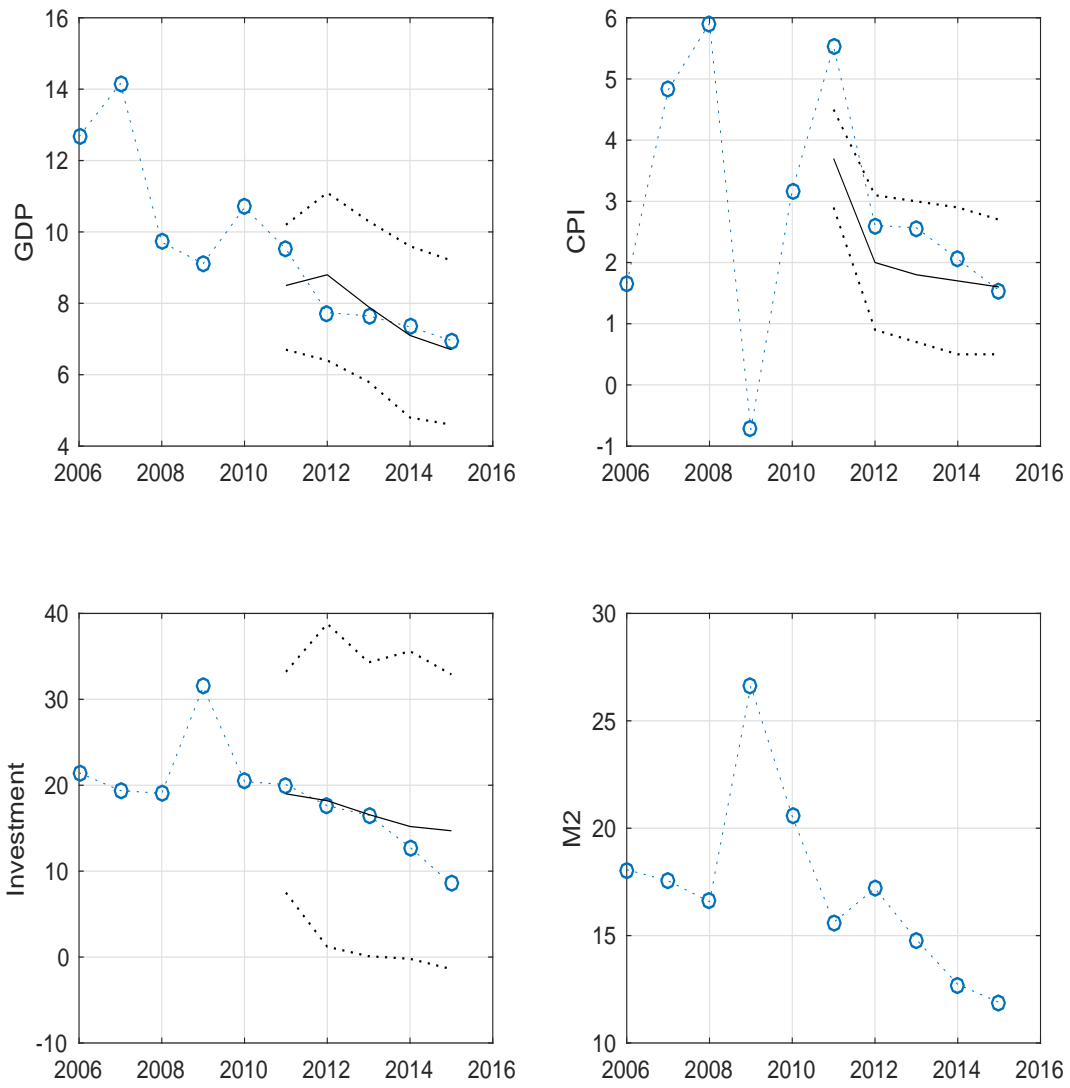FIGURE 1. Monthly series of fixed asset investment.

FIGURE 2. Out-of-sample forecasts made at 2010M12 with .68 probability bands (the dotted lines) conditional on the actual M2 path. Circle lines (from 2006 to 2015) indicate actual data and solid lines (from 2011 to 2015) represent mode forecasts.
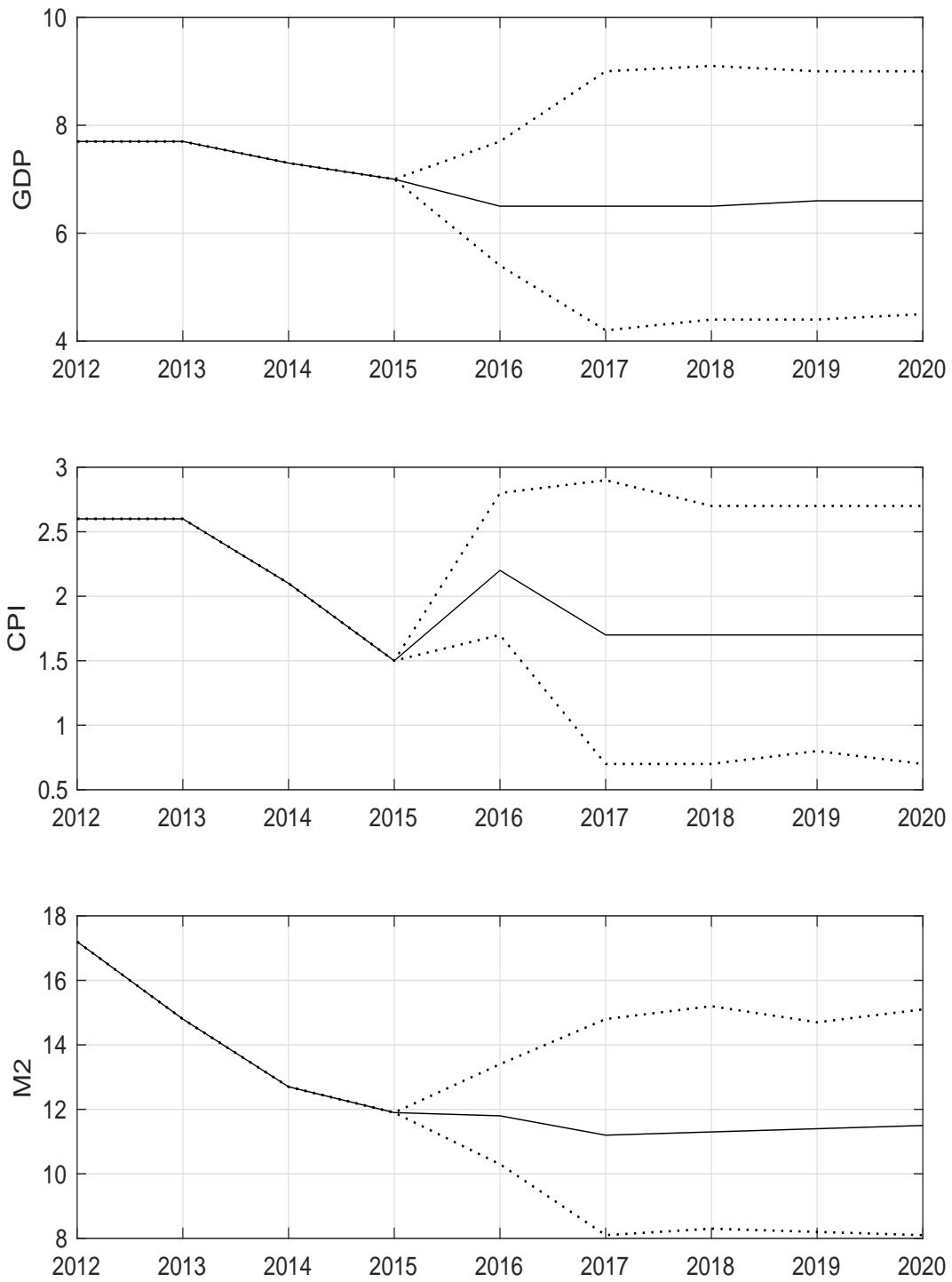
FIGURE 3. Unconditional out-of-sample forecasts made at 2016M3 with .68 probability bands (the dotted lines).

References

ANG, A., G. BEKAERT, AND M. WEI (2007): "Do Macro Variables, Asset Markets, or Surveys Forecast Inflation Better?," *Journal of Monetary Economics*, 54, 1163–1212.

ATKESON, A., AND L. E. OHANIAN (2001): "Are Phillips Curves Useful for Forecasting Inflation?," *Federal Reserve Bank of Minneapolis Quarterly Review*, 25(1), 2–11.

BAŃBURA, M., D. GIANNONE, AND L. REICHLIN (2010): "Large Bayesian Vector Autoregressions," *Journal of Applied Econometrics*, 25(1), 71–92.

BAUER, A., R. A. EISENBEIS, D. F. WAGGONER, AND T. ZHA (2006): "Transparency, Expectations, and Forecasts," *Economic Review*, pp. 1–25, First Quarter.

BERNANKE, B. S., M. GERTLER, AND M. W. WATSON (1997): "Systematic Monetary Policy and the Effects of Oil Price Shocks," *Brookings Papers on Economic Activity*, 1, 91–142.

CARRIERO, A., T. E. CLARK, AND M. MARCELLINO (2015): "Bayesian VARs: Specification Choices and Forecast Accuracy," *Journal of Applied Econometrics*, 30(1), 46–73.

CHANG, C., K. CHEN, D. F. WAGGONER, AND T. ZHA (2015): "Trends and Cycles in China's Macroeconomy," *NBER Macroeconomics Annual*, 30, 1–84.

CHOW, G. C., AND A.-L. LIN (1971): "Best Linear Unbiased Interpolation, Distribution, and Extrapolation of Time Series by Related Series," *The Review of Economics and Statistics*, 53(4), 372–375.

CHRISTIANO, L. J., M. S. EICHENBAUM, AND C. L. EVANS (1999): "Monetary Policy Shocks: What Have We Learned and To What End?," in *Handbook of Macroeconomics*, ed. by J. B. Taylor, and M. Woodford, vol. 1A, pp. 65–148. North-Holland, Amsterdam, Holland.

DING, H., AND H. HE (2016): "A Tale of Transition: An Empirical Analysis of Economic Inequality in Urban China, 1986-2009," Unpublished Manuscript, International Monetary Fund.

DOAN, T., R. B. LITTERMAN, AND C. A. SIMS (1984): "Forecasting and Conditional Projection Using Realistic Prior Distributions," *Econometric Reviews*, 3(1), 1–100.

FERNALD, J. G., M. M. SPIEGEL, AND E. T. SWANSON (2014): "Monetary policy effectiveness in China: Evidence from a FAVAR model," *Journal of International Money and Finance*, 49, 83–103.

GIANNONE, D., M. LENZA, AND G. E. PRIMICERI (2015): "Prior Selection for Vector Autoregressions," *The Review of Economics and Statistics*, 97(2), 436–451.

HIGGINS, P. C., AND T. ZHA (2015): "China's Macroeconomic Time Series: Methods and Implications," Unpublished Manuscript, Federal Reserve Bank of Atlanta.

LEEPER, E. M., C. A. SIMS, AND T. ZHA (1996): "What Does Monetary Policy Do?," *Brookings Papers on Economic Activity*, 2, 1–78.

LI, Z. (2016): "Forecasting China's Economy: A Bayesian Approach," Unpublished Manuscript.

LITTERMAN, R. B. (1986): "Forecasting with Bayesian Vector Autoregressions — Five Years of Experience," *Journal of Business and Economic Statistics*, 4, 25–38.

NIE, J. (2016): "Gauging the Strenth of Chinese GDP Growth," *The Macro Bulletin*, pp. 1–3, http://macrobulletin.kcfed.org.

ROBERTSON, J. C., AND E. W. TALLMAN (2001): "Improving Federal-Funds Rate Forecasts in VAR Models Used for Policy Analysis," *Journal of Business and Economic Statistics*, 19(3), 324–330.

SIMS, C. A. (1980): "Macroeconomics and Reality," *Econometrica*, 48(1), 1–48.

SIMS, C. A., AND T. ZHA (1998): "Bayesian Methods for Dynamic Multivariate Models," *International Economic Review*, 39(4), 949–968.

——— (2006): "Does Monetary Policy Generate Recessions?," *Macroeconomic Dynamics*, 10, 231–272.

STOCK, J. H., AND M. W. WATSON (2007): "Why Has U.S. Ination Become Harder to Forecast?," *Journal of Money, Credit and Banking*, 39(Supplement s1), 3–33.

WAGGONER, D. F., AND T. ZHA (1999): "Conditional Forecasts in Dynamic Multivariate Models," *The Review of Economics and Statistics*, 81(4), 639–651.

WEN, Y. (2016): *The Making of an Economic Superpower: Unlocking China's Secret of Rapid Industrialization.* World Scientific Publishing Co.

WRIGHT, J. H. (2013): "Unseasonal Seasonals?," *Brookings Papers on Economic Activity*, pp. 65–126, Fall.

ZHA, T. (1998): "A Dynamic Multivariate Model for Use in Formulating Policy," *Federal Reserve Bank of Atlanta Economic Review*, 83(1), 16–29, First Quarter.

FEDERAL RESERVE BANK OF ATLANTA; SHANGHAI ADVANCED INSTITUTE OF FINANCE, SHANGHAI JIAOTONG UNIVERSITY; FEDERAL RESERVE BANK OF ATLANTA, EMORY UNIVERSITY, AND NBER