

Forecasting China's Foreign Exchange Reserves Using Dynamic Model Averaging: The Role of Macroeconomic Fundamentals, Financial Stress and Economic Uncertainty

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Abstract

We develop models for examining possible predictors of growth of China's foreign exchange reserves that embrace Chinese and global trade, financial and risk (uncertainty) factors. Specifically, by comparing with other alternative models, we show that the dynamic model averaging (DMA) and dynamic model selection (DMS) models outperform not only linear models (such as random walk, recursive OLS-AR(1) models, recursive OLS with all predictive variables models) but also the Bayesian model averaging (BMA) model for examining possible predictors of growth of those reserves. The DMS is the best overall across all forecast horizons. While some predictors matter more than others over the forecast horizons, there are few that stand the test of time. The US-China interest rate differential has a superior predictive power among the 13 predictors considered, followed by the nominal effective exchange rate and the interest rate spread for most of the forecast horizons. The relative predictive prowess of the oil and copper prices alternates, depending on the commodity cycles. Policy implications are also provided.

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1. Introduction

The world's economic system has been characterized by significant external imbalances in the last two decades or so. This global phenomenon has manifested itself clearly by the accumulation of international exchange reserves and external assets particularly in developing countries. The international reserves have mounted to more than 30% of developing countries' GDP and 8 months' worth of their imports (Rodrik, 2006). These reserves are used as insurance against financial crisis and default risk. It's well known that countries with large scale foreign reserves like Singapore and Taiwan were the least affected by speculation during the 1997 Asian crisis (Lane, 2004). Foreign reserves can also serve as an additional source of national income in the form of interest-yielding time deposits or interest-earning bonds and bills denominated in foreign currencies. This is the case of oil-exporting countries. Other countries such as emerging market economies use the accumulation of large scale foreign reserves as a tool of foreign exchange intervention to resist currency appreciation in the face of accommodative monetary policy (Mahanty and Turber, 2006). Countries that follow an export-oriented growth strategy may end up with competitive hoarding similar to competitive devaluation, depicting a return to mercantilist strategies. Foreign reserves may also mitigate the real exchange rate effects of terms of trade shocks and export promotion. Moreover, countries with less flexible exchange rate regimes should require higher levels of international reserves to sustain exchange rate stability.

There is also the question of the adequacy of foreign reserves in terms of some criterion expressing the need for reserves. There is an opportunity cost of holding international reserves which can be represented as an income loss for those countries that do not hold the optimal reserves holdings. The difference between the return on liquid international reserve assets and

the cost of foreign borrowing, or the return on domestic assets and investment, makes up the opportunity cost of holding international reserves.

Most of the BRICS countries -Brazil, Russia, India, China and South Africa- are developing countries known for holding large international reserves. These countries have experienced strong economic growth fueled by strong exports, which has led to accumulation of large reserves. China's foreign reserves are mainly composed of US dollars in the forms of US government bonds and institutional bonds. Growing from \$600 billion ten years ago, those reserves stood at \$3.5 trillion in June 2013, making them the highest foreign exchange reserves in the world with the US dollar and yen holdings taking up 60% and 10% of the total, respectively.

The literature has shown that reserve holdings by similar countries seem to be a predictable outcome of a few key factors including the size of international transactions, their volatility, the exchange-rate arrangement, financial risks and political considerations (Aizenman and Marion, 2003). The objective of this study is to examine possible predictors of the growth of China's international reserves and to generally shed new light on the 'puzzling' pattern of international reserves, using fairly recent prediction models. It will be interesting to discern the prowess of real economic and financial variables in predicting changes in China's international reserves. In particular, we are keen to understand the predictability power of industrial production, trade openness, interest rate spreads, financial stress and economic policy uncertainty, among other variables of China's accumulation of international reserves. While interest rate spreads are associated with opportunity cost of holding reserves (e.g., Edison, 2003; Aizenman and Marion, 2004; Aizenman and Lee, 2007), the stress and uncertainty variables represent volatility of external disturbances which influences the need for international reserves.

The prediction results of China's international reserves are of interest to both capital markets and policy-makers due to their huge size and their relation with the management of China's exchange rate and the intention to putting them to innovative uses in the future. They would also help send signals to the Chinese policy-makers regarding the adequacy and optimality of these reserves. They can signal to the Chinese central bank of how the amount of foreign currencies it holds relates to the three months of imports rule. They also have implications for exchange rate policy arrangements and currency controls in China and levels of interest rates in major foreign countries like the United States. Currently, the Chinese State Council is calling for innovative uses of those reserves instead of placing the majority in low yielding US securities. The IMF also urges China to make systematic economic adjustments as it views China's pace of economic expansion as not sustainable and raising vulnerabilities in the future. In such circumstances, forecasting China's reserves matters a great deal as the margins of safety are diminishing.

Methodologically against this backdrop, this paper applies the dynamic model averaging (DMA) strategy developed by Raftery *et al.* (2010), which can also be used for the dynamic model selection (DMS) methodology (where a single but potentially different model can be employed as a forecasting model at each point of time) to forecast China's foreign exchange reserves based on a wide array of predictors, ranging from macroeconomic variables to economic policy uncertainty and financial stress measures. The DMA or DMS seems ideally suited for forecasting a variable as volatile as the foreign exchange reserves that have gone through periods of major events and crises, since these methodologies not only allow the forecasting model to change over time, but also the coefficients in each model to evolve over time simultaneously. These two methods involve only standard econometric methods used for state space models, such as the Kalman filter, but through some sensible empirical approximations, they achieve vast

gains in computational efficiency so as to allow one to apply DMA and DMS despite the computational difficulties. In an emerging market economy like China, which has undergone and still is going through structural changes, it is important to not only allow for parameter uncertainty, but also for model uncertainty when forecasting key macroeconomic variables such as the international exchange reserves. The advantages of using the DMA approach over standard predictive regression methods are three folds. (1) The coefficients on the predictors can change over time, while the use of dummy variables to capture possible structural breaks or recursive methods to take care of time variations is not suited to solve this issue. Hence ideally, one needs to build models designed to capture the changing of slope parameters of the models. (2) Given that we use a wide variety of predictors, the number of potential predictors is in general quite large, thereby in the process making the number of models quite large as well. For instance, if the set of models is defined by whether each of the m potential predictors are included or excluded, then we have 2^m possible models to work with. This would raise substantial statistical problems involved in model selection, which in turn, has resulted in researchers resorting to the Bayesian model averaging (BMA) as in Wright (2008) and Tortora (2009). (3) Finally, the model that is relevant for forecasting can itself potentially change over time due to a change in the set of predictors or with some variables better capable of forecasting during, for example, recessions than expansions. This makes the situation even more complicated, since with 2^m models the number of combinations of models required to be estimated in order to forecast at time τ is $2^{m\tau}$ to allow for the possibility of a different model being applicable at each point in time. Even in relatively simple forecasting exercises, it can be computationally impossible to forecast by simply going through all of these $2^{m\tau}$ combinations.

The results show that DMA and DMS models forecast generally well, with DMS being the best overall, underlying the importance of catering for model uncertainty. The sum of the log predictive likelihoods clearly shows that DMS performs better across all forecast horizons. This result also carries over to the mean squared forecast error (MSFE). Both the sum of the log predictive likelihoods and the MSFE indicate that using a TVP model for forecasting produces weak results relative to the forecasting performance of the DMA and DMS models on average. Interestingly, based on the results provided by the predictive likelihoods, we see that most of the improvements in forecast performance found by DMA or DMS are due to model evolution rather than parameter evolution, since the DMA and DMS models perform better than the DMA model with λ set equal to 1 (implying the model is not allowed to change here). It can therefore be concluded that allowing for model uncertainty and not only for parameter uncertainty improves the forecasting performance of these models. Our study also shows the China's international reserves in recent years (i.e., 2009-2012) are greatly affected by different factors in the short run (based on one-month ahead forecasting) than in the longer horizon (based on one-year ahead forecasting). Among the 13 predictors, the US-China interest rate differential stands out for having superior predictive power that endures over time. On the other hand, the predictive powers of and copper prices alternate over the business and crisis cycles

The rest of the paper is structured as follows: Section 2 presents the literature review; Section 3 outlines the methodology used; Section 4 presents the data description and Section 5 discusses the empirical results and offers alternative model comparisons in terms of forecasts. Finally, section 6 concludes.

2. Literature Review

The literature has been active in investigating the determinants of demand for international reserves. This literature relies on the buffer stock model which was developed in the 1960s and 1970s (e.g., Heller, 1966; Kenen and Yudin, 1965; Kelly, 1970; Frenkel and Jovanovic, 1981). According to this model, central banks choose the optimal level of reserves to balance the costs of macroeconomic adjustment for having inadequate levels of reserves with the opportunity cost of holding reserves.

A group of studies also addresses the adequacy of constant coefficients of the demand for foreign reserves in the cross section data. To deal with this problem, Frenkel (1974) examines the difference between coefficients of the demand for foreign reserves of 55 developed and less-developed countries and shows that the demand parameters of the two groups are significantly different. He attributes the differences to factors such as the degree of sophistication of financial structures, the ability of the monetary authorities to satisfy the increased demand for money as an asset in the process of economic growth, among others. Sula (2011) estimates the determinants of the demand for international reserves, using quantile regressions. Employing data for 108 developing nations, this author finds considerable differences at different points of the conditional distribution of reserves and that the level of reserves is as important as the other determinants of the demand for reserves. Ford and Huang (1993) investigate the demand for international reserves in China, using the error-correction model with account of monetary disequilibrium. The authors show that China has maintained a stable long-run relationship with the determinants of the demand for reserves, and that the monetary disequilibrium has short-run effect on reverses, implying a general balancing policy,

Another strand of the literature offers the precautionary demand explanation of holding reserves as a protection against sudden stops of capital flows (e.g., Ben-Bassat and Gottlieb,

1992; Lee, 2004; Aizenman and Lee, 2007). Aizenman (1998) also shows that precautionary demand will be strong if governments have high aversion to loss. In addition to analyzing the demand for foreign reserves, there are studies that focus on the optimal amount of foreign reserves (see Jean and Rancière, 2006; Calvo et al., 2012) based on the sudden stops in the capital inflows. Calvo et al. (2012), for example, derived the optimal foreign reserves model by balancing the expected cost of a sudden stop against the opportunity cost of holding reserves. They found that Eastern Europe held the reserve below the equilibrium level while Asian countries hold more reserves than the optimal level.

Accumulating international reserves can also be an outcome of industrial policies, where governments deliberately prevent the exchange rate from appreciating to promote trade competitiveness. This explanation is motivated by China's demand for reserves in the 1990's (Dooley et al., 2003). Aizenman and Lee (2007), however, argue that the precautionary demand for international reserves explains the behavior of emerging markets better than the mercantilist view in the period after the Asian financial crisis.

A survey of the literature shows that the research on international reserves in China is very limited. Obstfeld et al. (2008) propose a model based on financial stability and financial openness to explain reserve holdings. The size of domestic financial liabilities that could potentially be converted into foreign currency, financial openness, the ability to access foreign currency through debt markets, and exchange rate policy are all significant predictors of reserve stocks. The authors claim that this financial-stability model outperforms both traditional models and recent explanations based on external short-term debt. Remoro (2005) used an intervention model to examine predictors of the demand for reserves for China and India. The author finds that the current account has a greater impact on China's reserves holdings than the other

predictors included in the model, since its current account balance is the principal mechanism through which countries get official reserves.

To our knowledge, there is no study that deals with predictors of those reserves for China (or other countries), despite the importance of this topic to China and major other countries such as Russia, Korea, Singapore etc., as explained earlier. Our paper will set the pace for this strand of the literature.

3. Methodology

The time-varying parameter (TVP) models employ state space methods such as the Kalman filter, which is commonly used in empirical macroeconomic research on structural analysis and forecasting. These types of models, however, do not allow predictors to vary over time (Koop and Korobilis, 2012).⁵ If large sets of predictors are used, then the TVP models tend to over-fit in-sample, and therefore have a poor out-of-sample forecasting performance. Even extensions of these models such as the TVP-VAR models suffer from this same limitation (Koop and Korobilis, 2012). To address these shortcomings in the TVP models, the DMA models present a possible and better alternative.

Dynamic model averaging (DMA), as the name implies, averages across various models. BMA, which is a specific form of the DMA model, is only used for static linear models with parameter uncertainty. The uncertainty is accounted for by averaging over all the sets of possible explanatory variables that may be included in the models (Raftery *et al.*, 2010). A short fall with the BMA approach is that it is limited to static models only. It was observed that the dynamics of

⁵ This section relies heavily on the discussion available in Koop and Korobilis (2012), to the extent that we have also retained the mathematical symbols they used in their equations.

the various models tend to follow a hidden Markov chain which can be incorporated using a recursive updating method such as the Kalman filter (Raftery *et al.*, 2010). Using the DMA framework, the BMA can be easily derived by simply excluding any dynamics from the DMA estimates.

To understand the econometric methodology, suppose that we have a set of K models which are characterized by having different subsets of z_t as predictors. Denoting these by $z^{(k)}$ for $k = 1, \dots, K$, our set of models can be written as:

$$\begin{aligned} y_t &= z_t^{(k)} \theta_t^{(k)} + \varepsilon_t^{(k)} \\ \theta_{t+1}^{(k)} &= \theta_t^{(k)} + \eta_t^{(k)} \end{aligned} \quad (1)$$

where $\varepsilon_t^{(k)}$ is $N(0, H_t^{(k)})$ and $\eta_t^{(k)}$ is $N(0, Q_t^{(k)})$. Let $L_t \in \{1, 2, \dots, K\}$ denote which model applies at each time period, $\Theta_t = (\theta_t^{(1)'}, \dots, \theta_t^{(K)'})'$ and $y^t = (y_1, \dots, y_t)'$. The fact that we are allowing different models to hold at each point in time and performing model averaging, gives rise to the terminology “dynamic model averaging”. To be precise, when forecasting time t variables using information through time $t-1$, DMA involves calculating $Pr(L_t = k | y^{t-1})$ for $k = 1, \dots, K$, and averaging forecasts across the K models, using these probabilities. DMS involves selecting the single model with the highest value for $Pr(L_t = k | y^{t-1})$ and using this to forecast. However, there are problems with such a framework, since many of the models can have a large number of parameters, and the computational burden which arises when K is large implies that estimation can take a long time. Thus, a full Bayesian approach to DMA can be quite difficult. Following Koop and Korobilis (2012), we in this paper use approximations as suggested by Raftery *et al.*, (2010). The approximations used by Raftery *et al.* (2010) involve two parameters for the coefficients and the models, λ and α , which these authors refer to as the *forgetting factors* and fix

them to numbers slightly below one. To explain the role of these forgetting factors, first consider the standard state space model below for $t = 1 \dots T$:

$$y_t = z_t \theta_t + \varepsilon_t \quad (2)$$

$$\theta_t = \theta_{t-1} + \eta_t \quad (3)$$

In our case, the output vector y_t is the foreign exchange reserves, $z_t = [1, x_{t-1}, y_{t-1}, \dots, y_{t-p}]$ is an $1 \times m$ vector of predictors for the (growth rate of the) foreign exchange reserves which also includes an intercept and lags of the dependent variable, $\theta_t = [\beta_{t-1}, \gamma_{t-1}, \dots, \gamma_{t-p}]$ is an $1 \times m$ vector of states, $\varepsilon_t \sim N(0, H_t)$ and $\eta_t \sim N(0, Q_t)$, with the errors assumed to be mutually independent at all leads and lags. For given values of the variance-covariance matrices H_t and Q_t , the standard filtering and smoothing results can be used to carry out recursive estimation or forecasting. Kalman filtering begins with the result that

$$\theta_{t-1} | y^{t-1} : N(\hat{\theta}_{t-1}, \Sigma_{t-1|t-1}) \quad (4)$$

where formulae for $\hat{\theta}_{t-1}$ and $\Sigma_{t-1|t-1}$ are standard. Note here only that these formulae depend on H_t and Q_t . Then Kalman filtering proceeds, using:

$$\theta_t | y^{t-1} \sim N(\hat{\theta}_{t-1}, \Sigma_{t|t-1}), \quad (5)$$

where

$$\Sigma_{t|t-1} = \Sigma_{t-1|t-1} + Q_t.$$

Raftery *et al.* (2010) note that things simplify substantially when one involves a forgetting factor (λ) in the state equation for the parameters. This is done by replacing this latter equation by:

$$\Sigma_{t|t-1} = \frac{1}{\lambda} \Sigma_{t-1|t-1} \quad (6)$$

or, equivalently, $Q_t = (1 - \lambda^{-1}) \Sigma_{t-1|t-1}$ where $0 < \lambda \leq 1$. The term “forgetting factor” is suggested by the fact that this specification implies that observations j periods in the past have weight λ^j . It can also be noted that it implies an effective window of $1/(1 - \lambda)$. In the literature, it is common to choose a value of λ near one, which suggests a gradual evolution of coefficients. Raftery *et al.* (2010) set $\lambda = 0.99$. For monthly macroeconomic data, this suggests observations five (one) years ago receive approximately 50% (90%) as much weight as last period’s observation. This would be consistent with fairly stable models where coefficient change is gradual. This would suggest substantial parameter instability with rapid change in coefficients. Forecasting in the one model case is then completed by the updating equation:

$$\theta_t | y^t \sim N(\hat{\theta}_t, \Sigma_{t|t}), \quad (7)$$

where

$$\hat{\theta}_t = \hat{\theta}_{t-1} + \Sigma_{t|t-1} z_t (H_t + z_t \Sigma_{t|t-1} z_t')^{-1} (y_t - z_t \hat{\theta}_{t-1}) \quad (8)$$

and

$$\Sigma_{t|t} = \Sigma_{t|t-1} - \Sigma_{t|t-1} z_t (H_t + z_t \Sigma_{t|t-1} z_t')^{-1} z_t \Sigma_{t|t-1}. \quad (9)$$

Recursive forecasting is done using the predictive distribution

$$y_t | y_{t-1} \sim N(z_t \hat{\theta}_{t-1}, H_t + z_t \Sigma_{t|t-1} z_t'). \quad (10)$$

The case with many models, (1) uses the previous approximation and an additional one. To understand this, we now switch to the notation for the multiple model case in (1) and let

Θ_t denote the vector of all the coefficients. In the standard single model case, Kalman filtering is based on (4), (5) and (7). In the multi-model case, for model k , these three equations become:

$$\Theta_{t-l|L_{t-l}} = k, y^{t-l} \sim N\left(\hat{\theta}_{t-l}^{(k)}, \Sigma_{t-l|t-l}^{(k)}\right) \quad (11)$$

$$\Theta_{t|L_t} = k, y^{t-l} \sim N\left(\hat{\theta}_{t-l}^{(k)}, \Sigma_{t|t-l}^{(k)}\right) \quad (12)$$

$$\Theta_{t|L_t} = k, y^t \sim N\left(\hat{\theta}_t^{(k)}, \Sigma_{t|t}^{(k)}\right), \quad (13)$$

where $\hat{\theta}_t^{(k)}$, $\Sigma_{t|t}^{(k)}$ and $\Sigma_{t|t-l}^{(k)}$ are obtained via Kalman filtering in the usual way using (6), (8), and (9), except with (k) superscripts added to denote model k .

The previous results are all conditional on $L_t = k$, and we need a method for unconditional prediction. In this paper, we follow the suggestion of Raftery *et al.* (2010) and as used in Koop and Korobilis (2012), based on a forgetting factor for the state equation for the models, α , which in turn, is, comparable to the forgetting factor λ used with the state equation for the parameters. The derivation of Kalman filtering ideas begins with (4). The analogous result, when doing DMA, is

$$P\left(\Theta_{t-l}, L_{t-l} \mid y^{t-l}\right) = \sum_{k=1}^K P\left(\theta_{t-l}^{(k)} \mid L_{t-l} = k, y^{t-l}\right) Pr\left(L_{t-l} = k \mid y^{t-l}\right), \quad (14)$$

where $P\left(\theta_{t-l}^{(k)} \mid L_{t-l} = k, y^{t-l}\right)$ is given by (11). To simplify notation, let $\pi_{t|s,l} = Pr(L_t = l \mid y^s)$ and thus, the final term on the right hand side of (14) is $\pi_{t-l|t-l,k}$.

With,

$$\pi_{t|t-l,k} = \frac{\pi_{t-l|t-l,k}^\alpha}{\sum_{l=1}^K \pi_{t-l|t-l,l}^\alpha}, \quad (15)$$

where $0 < \alpha \leq 1$ is set to a fixed value slightly less than one and is interpreted in a similar manner to λ , i.e., if $\alpha = 0.99$ (our benchmark value and also the value used by Raftery *et al.*, 2010) the forecast performance five years ago receives 50% as much weight as the forecast performance of last period (when using monthly data), while the forecast performance one year ago receives about 90% as much weight as last month's performance. Comparable to those of the updating equation in the Kalman filter, we have a model updating equation of:

$$\pi_{t|t,k} = \frac{\pi_{t|t-1,k} P_k(y_t | y^{t-1})}{\sum_{l=1}^K \pi_{t|t-1,l} P_l(y_t | y^{t-1})}, \quad (16)$$

where $p_l(y_t | y^{t-1})$ is the predictive density for model l , which is the Normal density in (10) with (l) superscripts added and evaluated at y_t . Recursive forecasting can be done by averaging over predictive results for every model using $\pi_{t|t-1,k}$. So, for instance, DMA point predictions are given by:

$$E(y_t | y^{t-1}) = \sum_{k=1}^K \pi_{t|t-1,k} z_t^{(k)} \hat{\theta}_{t-1}^{(k)}.$$

DMS proceeds by selecting the single model with the highest value for $\pi_{t|t-1,k}$ at each point in time and simply using it for forecasting. Note also that, if $\alpha = 1$, then $\pi_{t|t-1,k}$ is simply proportional to the marginal likelihood using data through time $t-1$, and yields the standard approaches to BMA. If we also set $\lambda = 1$, then we obtain BMA using conventional linear forecasting models with no time variations in coefficients. In our forecast comparison exercise, we include BMA in our set of alternative forecasting procedures and implement this by setting $\alpha = \lambda = 1$.

The preceding discussion is all conditional on H_t . Raftery *et al.* (2010) recommend a simple plug in method where $H_t^{(k)} = H^{(k)}$ and is replaced with a consistent estimate. When forecasting the foreign exchange reserves, however, it is likely that the error variance is changing over time. Theoretically, we could use a stochastic volatility or an ARCH specification for $H_t^{(k)}$. However, this is computationally burdensome, so instead, we follow a simple plug-in approach as in Koop and Korobilis (2011), which in turn, is a rolling version of the recursive method of Raftery *et al.* (2010). Specifically, let

$$\tilde{H}_t^{(k)} = \frac{1}{t^*} \sum_{j=t-t^*+1}^t \left[\left(y_t - z_t^{(k)} \hat{\theta}_{t-1}^{(k)} \right)^2 - z_t^{(k)} \sum_{l=t-1}^{t-1} z_l^{(k)'} \right] \quad (17)$$

To allow for more substantial change in the error variances, we set $t^* = 20$ and, thus, use a rolling estimator based on five years data. Following Raftery *et al.* (2010), we can avoid the rare possibility that $\tilde{H}_t^{(k)} < 0$, by replacing $H_t^{(k)}$ by $\hat{H}_t^{(k)}$ where

$$\hat{H}_t^{(k)} = \begin{cases} \tilde{H}_t^{(k)} & \text{if } \tilde{H}_t^{(k)} > 0 \\ \hat{H}_{t-1}^{(k)} & \text{otherwise} \end{cases}.$$

4. Data

This analysis in this paper is based on monthly data, mostly sourced from the People's Bank of China and the International Financial Statistics of the International Monetary Fund. More specifically, other sources include the Bank of International Settlements, China's National Bureau of Statistics, Federal Reserve Bank of Kansas City, and <http://www.policyuncertainty.com/index.html>. Besides, China's foreign exchange reserves (which is obtained from the Chinese State Administration of Foreign Exchange), the growth rate

of which is what we forecast, the predictors include: the nominal effective exchange rate, Chinese short-term interest rate, the Chinese term-structure, the interest rate differential with the US, the oil price, the copper price, the Chinese M1, the Chinese industrial production, the Chinese exports, the Chinese trade balance (exports less imports), the Chinese and US economic policy uncertainty measures,⁶ and the US financial stress index maintained by the Kansas City Federal Reserve.⁷ The monthly sample period under consideration is from January 1997 up to March 2013, with the start and end points being defined by availability of data on all the variables (the foreign exchange reserves and the thirteen predictors). The out-of-sample period ranges from January 2003 to March 2013, a normal choice given the increased volatility of the growth rate of the foreign exchange reserves since the beginning of 2003, as depicted in Figure 1.

Our selection of explanatory variables is based on previous research. For example, Ford and Huang (1994) show that the demand for international reserves in China depends on the transactions-related demand (that is, industrial and agricultural output), the balance of payments, imports, and China's degree of exposure to the international economy. Sula (2011) uses the interest rate differential, volatility of export receipts, exchange rate regime, trade openness, the 1997 Asian crisis dummy, population and real GDP per capita to explain the demand for international reserve. Aizenman and Marion (2003) use variables such as population, real GDP per capita, real export receipts, shares of imports of goods and services in GDP, and the nominal effective exchange rate. Obstfeld et al. (2010) use population, import to GDP ratio, exchange rate volatility, real GDP per capita as explanatory variables in a traditional international reserve model while include M2 to GDP ratio, a measure of financial openness, exchange rate regime dummy, advanced country dummy and foreign trade variable in a financial stability model. They

⁶ The reader is referred to Baker *et al.*, (2013) for further details regarding the construction of the economic policy uncertainty indexes for China and the United States.

⁷ For more detailed information on the data and the sources, see Table 1A in Appendix.

find that the financial-stability model outperforms both traditional models and explanations based on the external short-term debt. In sum, all the previous research mentioned above seems to agree that the international reserves are affected by: (i) domestic real sectors, (ii) trade factors; (iii) financial factors; and (iv) risk.

Therefore, in forecasting China's foreign exchange reserves, we include the following variables to account for both demand and supply sides of foreign exchange reserves: China's nominal effective exchange rate⁸, China's interest rate, within-China interest rate spread (long-term minus short-term interest rates), short-term interest rate differential with the United States, money supply of China (M1), Chinese industrial production, Chinese export and Chinese net exports. We also include two important commodity price indices: oil and copper. Finally, to account for economic and financial risks, we include the China Economic Policy Uncertainty Index, the US Economic Policy Uncertainty Index and Kansas City Fed's Financial Stress Index. The interest rates represent the opportunity costs of holding the international reserves instead of investing them in more return-yielding assets. Copper is known as Dr. Copper because it predicts changes in economic activity and business cycles and it is also part of China's transactions-related demand. Moreover, China is the largest consumer of this metal, and thus imports of this commodity affect its total imports and foreign reserves. The exports and imports represent changes in the current account which is related to changes in foreign exchange rate reserves.

All the variables are obtained in seasonally adjusted form, and if not available in this form, seasonal adjustment is carried out using the X-12 approach proposed by the Department of

⁸ Since the middle of 2008 and due to economic crisis, China has initiated a soft peg exchange rate regime, pegging its currency to US dollar at a rate of about 6.83 RMB per US dollar. This change in policy terminated Chinese managed float exchange regime that existed between 2005 and 2008. Article Source: <http://EzineArticles.com/4653885>

Commerce of the US Census Bureau. Variables that are available at higher frequencies than a month are averaged out over the respective days or weeks to reach monthly figures.

The Augmented Dickey-Fuller (ADF) (1979), Dickey-Fuller Generalized Least Squares (ADF-GLS), Ng-Perron (2001) and Elliot, Rothenberg and Stock (ERS) (1996) tests are performed on all the variables to test for stationarity. In the cases where the results are ambiguous, the results from the Ng-Perron (2001) unit root test take preference due to the improved finite-sample performance of the test. Transformations similar to those used by Koop and Korobilis (2012) are applied to the data series, in order to transform all of the variables to be stationary. The different transformation codes and detailed descriptions of the data, including their sources, are listed and defined in the Data Appendix. The summary statistics of the variables are presented in Table 1. The highest historical volatility as defined by standard deviation is bestowed on (X-M) followed by China's economic policy uncertainty index. Interestingly, the US financial stress index has the lowest volatility. China's foreign exchange reserves have generally low contemporaneous correlations with all 13 variables; having the highest correlation with the nominal exchange rate (0.335) and the lowest with exports minus imports (0.009). It is also interesting to note that the correlation with the copper price is 0.226, while it is 0.146 with the oil price. As expected, the correlation is negative with the U. S. financial stress index (-0.20) and the U.S. policy uncertainty index (-0.206). Most of the variables have excess kurtosis, with the exceptions being the US economic uncertainty index and the interest rate differential with the United States which have lower kurtosis than the normal distribution. About half of the variables are positively skewed, while the second half is negatively skewed. Interestingly, all the variables do not have normal distribution as evidenced by Jarque-Bera statistics, with the exception of the copper price which has a normal distribution.

5. Empirical Results

The empirical results are divided into two sub-sections. These subsections present results using DMA and DMS in our preferred way, i.e., by setting $\alpha = 0.99$ and $\lambda = 0.99$,⁹ a non-informative prior over the models ($\pi_{0|0,k} = 1/K$ for $k = 1, \dots, K$) and a relatively diffuse prior for the initial state conditions: $\theta_0^{(k)} \sim N(0,100)$ for $k = 1, \dots, K$. The first sub-section provides evidence of which variables are good predictors of the growth China's foreign exchange reserves from the list of the 13 potential variables listed in the Data Appendix. In the second sub-section, we compare the forecast performance of the DMA to a number of alternative forecasting models nested in the DMA, including the BMA, the autoregressive and the random walk models. The considered forecasting horizons are: one ($d=1$), three ($d=3$), six ($d=6$), nine ($d=9$) and 12 ($d=12$) months. All of the models include an intercept and one lag of the dependent variable, chosen by the Schwarz information criterion.¹⁰

5.1. Good predictors for foreign exchange reserves

One of the largest potential benefits using the DMA framework is that it allows the forecasting model to change over time, i.e. the model parameters may change, as well as the set of predictors. Given the difficulty in explaining foreign exchange reserve movements, we include

⁹ Note that, one could choose values for λ and α based on the forecast performance as in Grassi and de Magistris (2013), but this would bias our results in favour of DMA and is not a valid procedure for out-of-sample forecasting (Koop and Korobilis, 2011). Alternatively when forecasting at time τ , we could consider a grid of values for λ and α and select the value which yielded the highest value for the marginal likelihood or an information criterion, which essentially amounts to treating λ and α as unknown parameters. However, this would greatly add to the computational burden; so much so that it might be impossible to do forecasting in real time (Koop and Korobilis, 2011). Hence, we follow Koop and Korobilis (2011, 2012) and simply select values for the forgetting factors, but, we do carry out a sensitivity analysis in Section 4.

¹⁰ Also, experimentation with three lags (as chosen by the Akaike information criterion) of the dependent variable showed that one lag length leads to the best forecast performance.

a set of 13 possible predictors (excluding the lag dependent variable), hence we have 8,192 possible models to choose from.

We now turn to provide the results on the main predictors as selected by the DMA analysis for the foreign exchange reserves for every forecast horizons, $d=1$, $d=3$, $d=6$, $d=9$ and $d=12$, over the out-of-sample period 2003:1 to 2013:3. Through Figures 2 to 6, it appears that the good predictors of the China's foreign exchange reserves vary over time and over the forecast horizons. Particularly, three periods are striking. Before 2005, the interest rate differential with the United States (*INTDIFF*) comes through strongly for horizons $d = 1, 3, 9, 12$, while the nominal effective exchange rate (*NEER*) prevails for $d = 6, 9$ and the interest rate spread (*ISPREAD*) for $d= 3, 9, 12$. The Kansas City Financial Stress Index (*KCFSI*) shows strong predictive power throughout the forecast horizons. Similar strong patterns are observed with the copper price (*CP*) and oil price (*OP*) except for $d = 1$. Furthermore, industrial production (*IP*) shows some predictive power for $d = 1, 3, 6, 12$ forecast horizons. Money supply (*MI*) has some predictive power for $d = 3, 6, 9, 12$. Exports (*X*) come through strongly for $d = 3, 6, 12$ but with a relatively less predictive power than *INTDIFF* and *NEER*. Particularly, the inclusion probability of *X* peaks around 0.8 over the selected forecast horizons, compared to 0.9 for *NEER* ($d= 6$) or 1 for *INTDIFF* ($d= 3, 12$).

Between 2005 and 2009 which was dominated by a commodity boom, the same pattern holds for $d = 3, d = 6$ and $d = 12$, with the interest rate (*INT*), exports minus imports (*X-M*), China and US economic policy uncertainty indexes (*CPUI* and *UPUI*), *ISPREAD*, *CP* and *MI* being the most important predictors. At a shorter horizon ($d = 1$), *INDIFF*, *CP* and *KCFSI* show strong predictive power whereas *INT*, *OP* and *UPUI* are the prevailed predictors for $d = 9$.

Towards the end of the forecasting period, namely after 2009, *INT*, *INDIFF*, *OP*, *MI* and *UPUI* appear to be of considerable importance in predicting the foreign exchange reserves for almost all horizons. This is not the case with *NEER* (important for $d = 3$ and $d = 12$), *CP*, *IP*, *X*, *KCFSI* (important for $d = 1$) and finally *X-M* (important for $d = 9$). Therefore, each of these variables emerges as being an important predictor for the foreign exchange reserves at some time for some forecast horizons.

5. 2. Model forecasting comparison

To analyze the forecast performance of each model, we use the mean squared forecast error (MSFE) in percentages, which is available for all the models. Note that, the preferred method for Bayesian forecast comparisons is the sum of the log predictive likelihoods, involving the entire predictive distribution. For a discussion on predictive likelihoods, refer to Gweke and Amisano (2007) as a representative source. The predictive likelihood is the predictive density for y_t , given data through time $t-1$, evaluated at the actual outcome. Since we use the direct method of forecasting, the log predictive density for the h -step ahead forecast is an obvious extension of the formula for the one-step ahead predictive density in model l as denoted by $p_l(y_t | y^{t-1})$ and described in Section 2. We use the sum of log predictive likelihoods for forecast evaluation of the Bayesian models, with the sum beginning in the first month of 2003 up to the third month of 2013 of the out-of-sample period. MSFEs are reported over the same period.

In terms of alternative forecasting models, the results for the models below are reported:

- (1) Forecasts using Dynamic Model Averaging (DMA) with $\alpha = \lambda = 0.99$.
- (2) Forecasts using Dynamic Model Selection (DMS) with $\alpha = \lambda = 0.99$.

- (3) Forecasts using all the variables in a single model with time varying parameters (TVP) (100% of the prior weight is attached to the model with all the variables in this special case of DMA, with all other modeling choices being identical including $\lambda=0.99$).
- (4) Forecasts using DMA, but the coefficients do not vary over time (a special case of DMA where $\lambda = 1$ and $\alpha = 0.99$).
- (5) Forecasts using Bayesian Model Averaging (BMA: a special case of DMA where $\alpha = \lambda = 1$).
- (6) Recursive ordinary least squares (OLS) forecasts using an autoregressive model of order one, i.e., AR(1).
- (7) Recursive OLS forecasts using all predictors.
- (8) Forecasts using the random walk (RW).

Model (1) applies the dynamic model averaging (DMA), using the benchmark values $\alpha = \lambda = 0.99$. This allows not only for the parameters to change over time, but also for the set of predictors. As stated earlier, values of 0.99 are consistent with fairly stable models with gradual coefficient change over time, where forecasts are averages across models using associated probabilities, calculated as $Pr(L_t = k|y^{t-1})$. Model (2), where dynamic model selection (DMS) is used, involves selecting the single model with the highest probability and using this to forecast. Model (3) is a special case of model (1) where all predictors are included for all time periods, but parameter values are allowed to change. Model (4) is a constant parameter model, but model evolution is allowed, while in model (5), through setting both forgetting factors to one, we obtain the Bayesian model averaging (BMA) which uses conventional linear forecasting models with no time variations in the coefficients. Understandably, the last three models are non-Bayesian, which means that there is no predictive likelihood for the random walk (RW) model.

Table 2 presents the results from our forecasting exercise for China's foreign exchange reserves for five forecasting horizons, namely 1-month-ahead (horizon 1) , 3-months-ahead (horizon 3), 6-months-ahead (horizon 6), 9-months-ahead (horizon 9), and 12-months-ahead (horizon 12). From the results in Table 2, it is clear that DMA and DMS forecast generally well, with DMS being the best overall. The sum of the log predictive likelihoods clearly shows that DMS performs better across all forecast horizons. This result also carries over to MSFE. Both the sum of the log predictive likelihoods as well as the MSFE indicates that using a TVP model for forecasting results in poorer forecasting performance, relative to the DMA and DMS on average. The poor forecast performance of the TVP model as well as the recursive OLS model with all predictors, compared to DMA and DMS is an indication that the shrinkage provided by the latter models is of great value in forecasting. Also note that, the predictors matter in forecasting, since all the models that include the predictors outperforms the AR(1) and the RW models. However, to obtain best forecast performances, one not only needs to include information from the fundamentals, but also allows for model evolution and parameter evolution as carried out by the DMA and DMS. Interestingly though, based on the results provided by the predictive likelihoods, we see that most of the improvements in forecast performance found by DMA or DMS are due to model evolution rather than parameter evolution, since DMA and DMS perform better than the DMA model with λ set equal to 1 (implying the model is not allowed to change here). It can therefore be concluded that allowing for model uncertainty and not only parameter uncertainty, improves the forecasting performance of these models.

6. Conclusion

In this paper, we use the dynamic model averaging techniques based on 13 predictors for predicting China's foreign exchange reserves that embrace macroeconomic, trade, financial and risk (uncertainty) factors and examine possible predictors of this country's international reserves. Specifically, by comparing with other alternative models, we show that dynamic model averaging (DMA) and dynamic model selection (DMS) models outperform not only linear models (such as random walk, recursive OLS-AR(1) models, recursive OLS with all predictive variables models) but also the Bayesian model averaging (BMA) model of China's foreign exchange reserves. Furthermore, sensitivity analysis reveals that in China's foreign exchange reserve modeling, accounting for model uncertainty may even be more important than parameter uncertainty. We obtain these results based on the thirteen potential predictors used to forecast China's international reserves. In the process, we also unveil what variables which tend to vary over time are good predictors of China's international reserves at different forecasting horizons. This implies that the single static and constant parameters models are not good vehicles for predicting China's foreign reserves.

Besides the forecasting power of the DMA and DMS models, our study shows that in the short run ($d=1$), the China's international reserves in recent years (2009-2012) are strongly affected by the US-China interest rate differential, nominal exchange rate, Chinese industrial production, copper price, US policy uncertainty index and Kansas City Financial stress index. However, at a longer horizon (one-year forecasting horizon), the reserves in the recent year (i.e., 2009-2012) are greatly affected by the exchange rate, the US-China interest rate differential, Chinese interest rate, money supply, net export, oil price and US economic policy uncertainty index.

It seems that the US-China interest rate differential has superior predictive power among the other predictors in both the short and long runs. This return differential generally governs the growth of China's reserves, which also directs the movement of financial assets that seek higher yields across borders. Given the importance of return differential, the result implies that China's foreign reserves can be classified into different investment categories which can yield higher returns, in addition to the category that caters for safety in order to ensure liquidity and meet short term obligations. Norway's sovereign wealth fund which is the world's largest is now considering such investment categories. The prediction importance of the interest rate differential with the United States is also high for the U.S. economy and financial markets. A narrowing of the interest rate differential may lead to lower growth in the demand for foreign reserves in China. This result has strong bearing on the potential safety investment category of the expected sovereign wealth fund for China.

In terms of the relevance of predictors based on commodity prices, it seems that the copper price predicts China's foreign reserves better than the oil price during the commodity boom of 2005-2008. However, since the global financial crisis many commodity prices have suffered, while the oil price dipped for a short period of time at the beginning of the crisis. Therefore, the results suggest that the oil price predicts those reserves better than the copper price since 2009.

We can conclude that policymakers should be cognizant of the fact that there are many possible financial and economic predictors that can help to predict the international exchange rate reserves for China. These predictors can command different predictive powers during different time horizons and periods.

A forecast of foreign reserves can be compared with the equilibrium reserves derived from an equilibrium foreign reserve model, and the resulting excess reserves can be measured. The

estimated excess reserves can be assessed in terms of GDP and a sense of adequacy can be concluded. Estimating an equilibrium foreign exchange reserve model and comparing it with our forecast model are other big tasks and we leave it for a future work.

Table 1: Descriptive statistics

Variables	Mean	Max	Min	Std.	Skew^a	Kurto^b	J-B^c	Correlations of FEX with the Predictors
Dependent Variable								
FEX	1.781	6.111	-4.155	1.59	-0.205	3.82	1.526*	0.355***
NEER	-0.162	3.645	-4.175	1.267	-0.17	4.087	1.229**	-0.078
INT	6.204	10.08	5.31	1.122	1.979	6.836	130.31***	-0.088
ISPREAD	0.685	2.43	0.36	0.515	2.477	8.043	204.74***	-0.014
INTDIFF	3.65	6.55	-0.32	1.909	-0.301	1.966	3.196***	0.146**
OP	0.764	20.145	-31.184	8.546	-0.862	4.408	24.52***	0.2263***
CP	0.591	22.982	-35.45	6.946	-0.742	7.931	23.88***	0.03
Predictors								
M1	1.182	6.111	-6.472	2.178	-0.774	4.554	19.973***	-0.075
IP	1.155	49.831	-44.554	19.653	-0.106	3.609	0.456	0.015
X	1.417	45.334	-55.614	13.736	-0.304	5.766	4.901***	0.009
X-M	-12.809	37168	-59032	7587.46	-2.302	25.347	296.188***	-0.151***
CPI	110.267	363.523	9.067	67.568	1.305	4.764	55.842***	-0.20***
UPI	110.299	245.126	57.202	39.263	0.823	2.825	21.907***	-0.206***
KCFSI	0.216	5.84	-0.89	1.095	2.579	11.457	232.937***	

Notes: 1. The sample period is from 1997:1 to 2013:3.

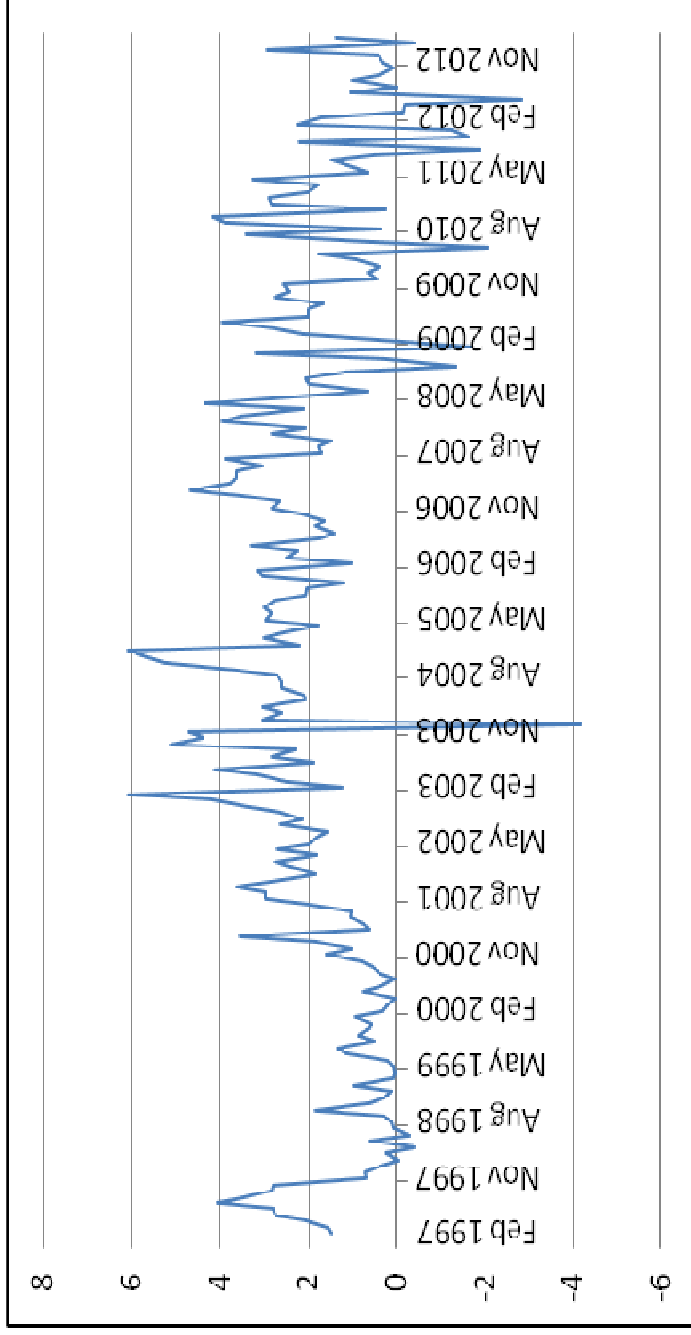
2. a, b, c refer to skewness, kurtosis and Jarque Bera statistics, respectively.

3. *, ** and *** denote significance at the 10%, 5% and 1% significance levels, respectively

Table 2: Comparing different forecasting methods: China's Foreign Exchange Reserves

Forecast Method	Sum of Log. Pred. Like.	MSFE	Forecast Method	Sum of log. Predict. Like.	MSFE
<u>d=1</u>			<u>d=9</u>		
DMA	-238.988	1.910	DMA	-219.699	1.817
DMS	-231.689	1.946	DMS	-206.871	1.763
TVP	-244.179	1.964	TVP	-224.069	2.089
DMA ($\lambda=1$)	-236.711	1.909	DMA ($\lambda=1$)	-217.842	2.024
BMA	-241.244	1.942	BMA	-222.467	2.082
Recursive OLS-AR(1)		2.985	Recursive OLS-AR(1)		3.096
Recursive OLS-All Preds.		3.545	Recursive OLS-All Preds.		4.854
Random Walk		4.010	Random Walk		5.157
<u>d=3</u>			<u>d=12</u>		
DMA	-216.458	1.826	DMA	-234.73	1.817
DMS	-212.45	1.775	DMS	-227.918	1.762
TVP	-222.166	2.067	TVP	-238.848	2.297
DMA ($\lambda=1$)	-212.193	1.908	DMA ($\lambda=1$)	-235.776	2.300
BMA	-213.998	1.915	BMA	-239.668	2.369
Recursive OLS-AR(1)		2.963	Recursive OLS-AR(1)		2.999
Recursive OLS-All Preds.		3.457	Recursive OLS-All Preds.		5.096
Random Walk		4.091	Random Walk		5.289
<u>d=6</u>					
DMA	-219.955	1.827			
DMS	-209.216	1.782			
TVP	-222.688	1.883			
DMA ($\lambda=1$)	-217.569	1.842			
BMA	-220.659	1.882			
Recursive OLS-AR(1)		3.034			
Recursive OLS-All Preds.		4.499			
Random Walk		4.524			

Figure1: Growth rate of China Foreign Exchange Reserves (in percentage)



Sources: Authors' calculation from the IMF Data.

Figure 2: Posterior inclusion probabilities of predictors ($d=1$)

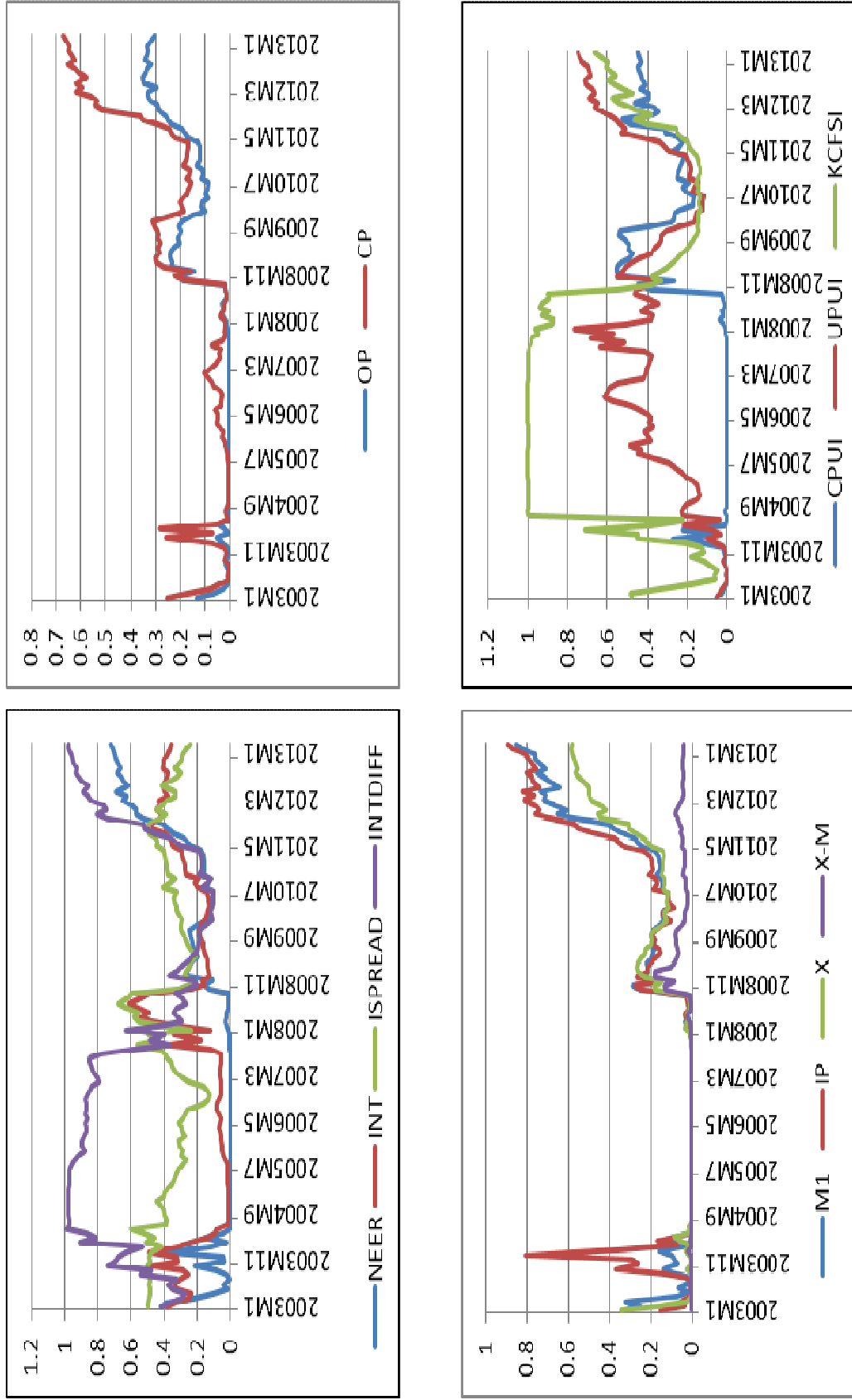


Figure 3: Posterior inclusion probabilities of predictors ($d=3$)

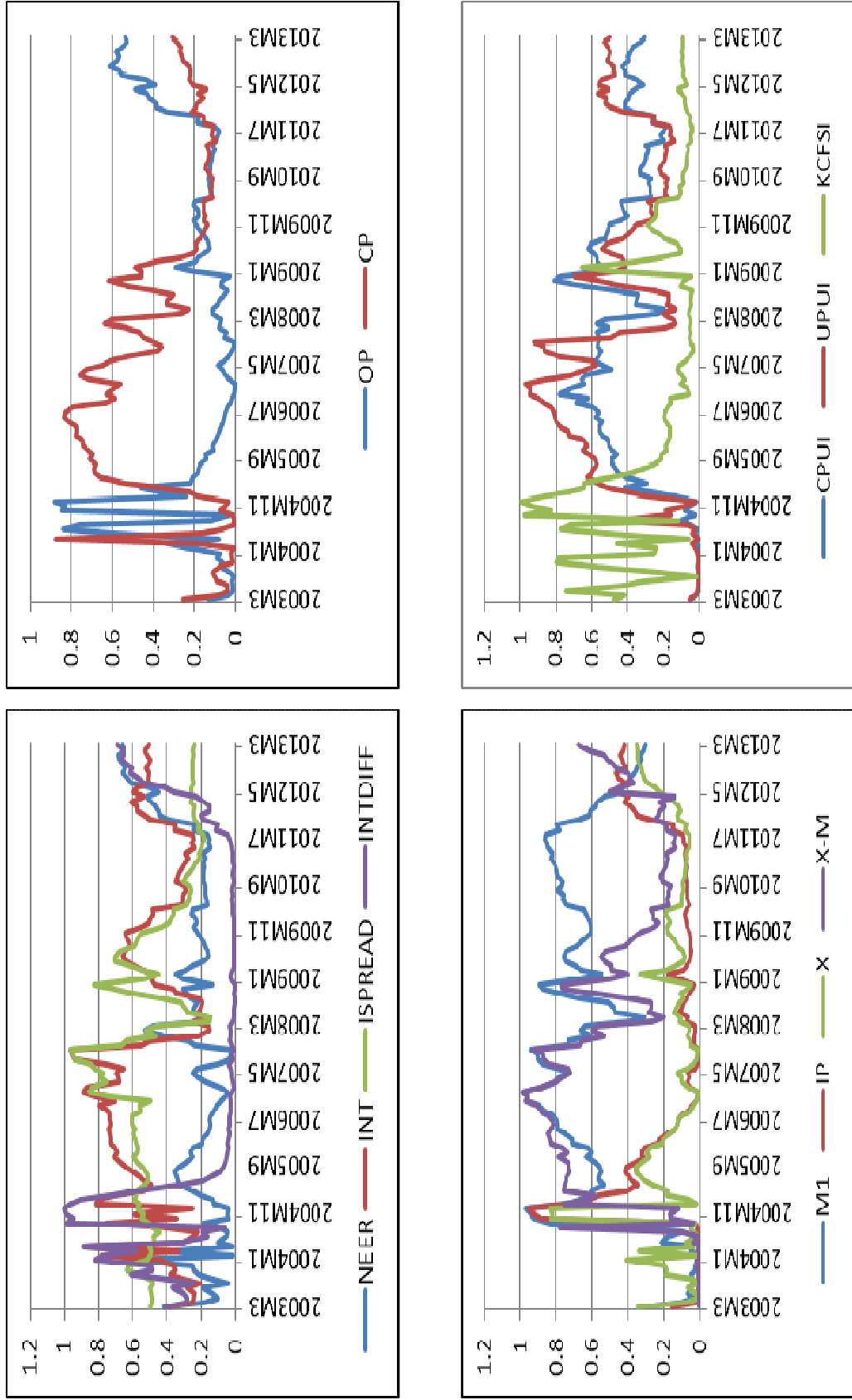


Figure 4: Posterior inclusion probabilities of predictors ($d=6$)

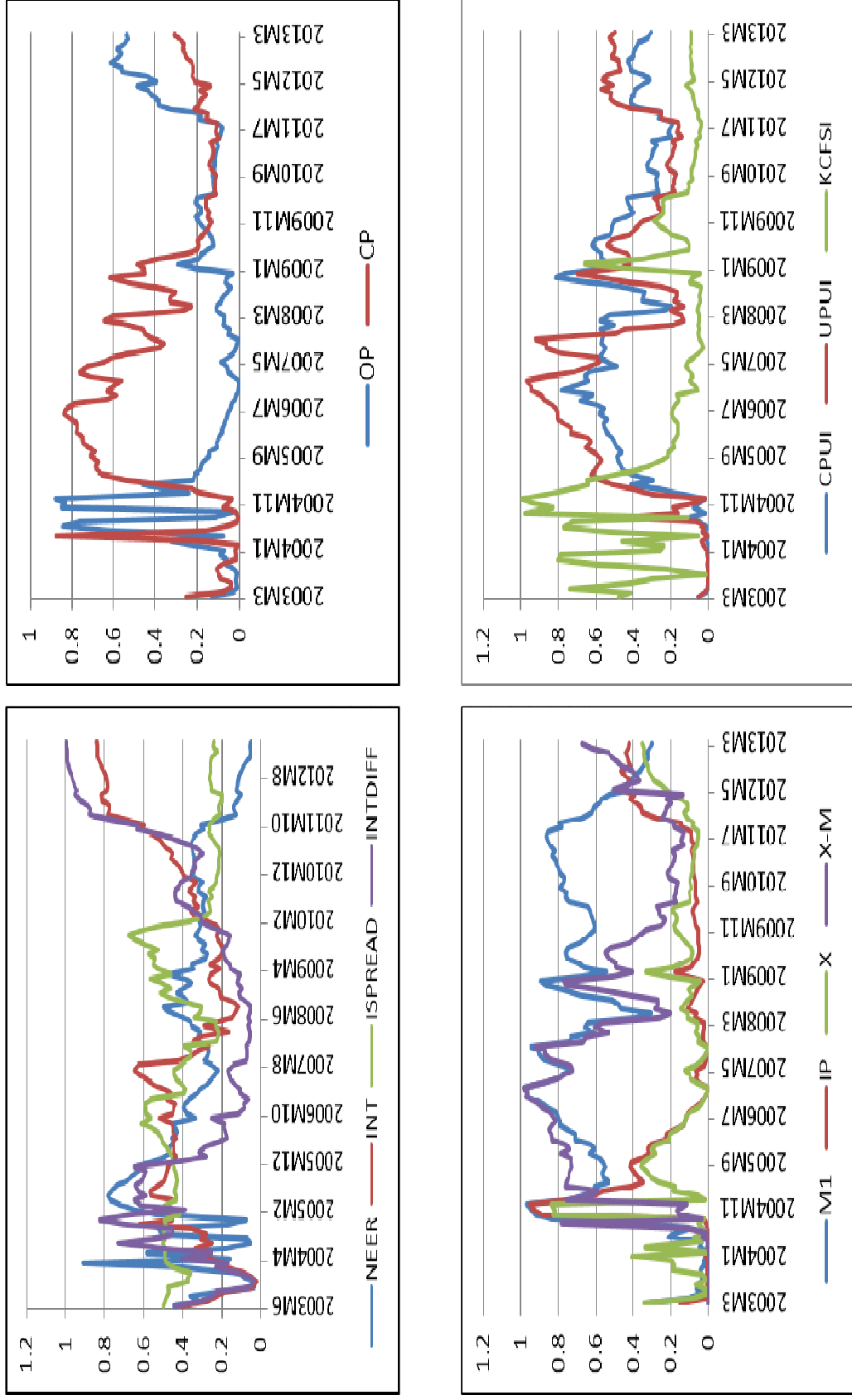


Figure 5: Posterior inclusion probabilities of predictors ($d=9$)

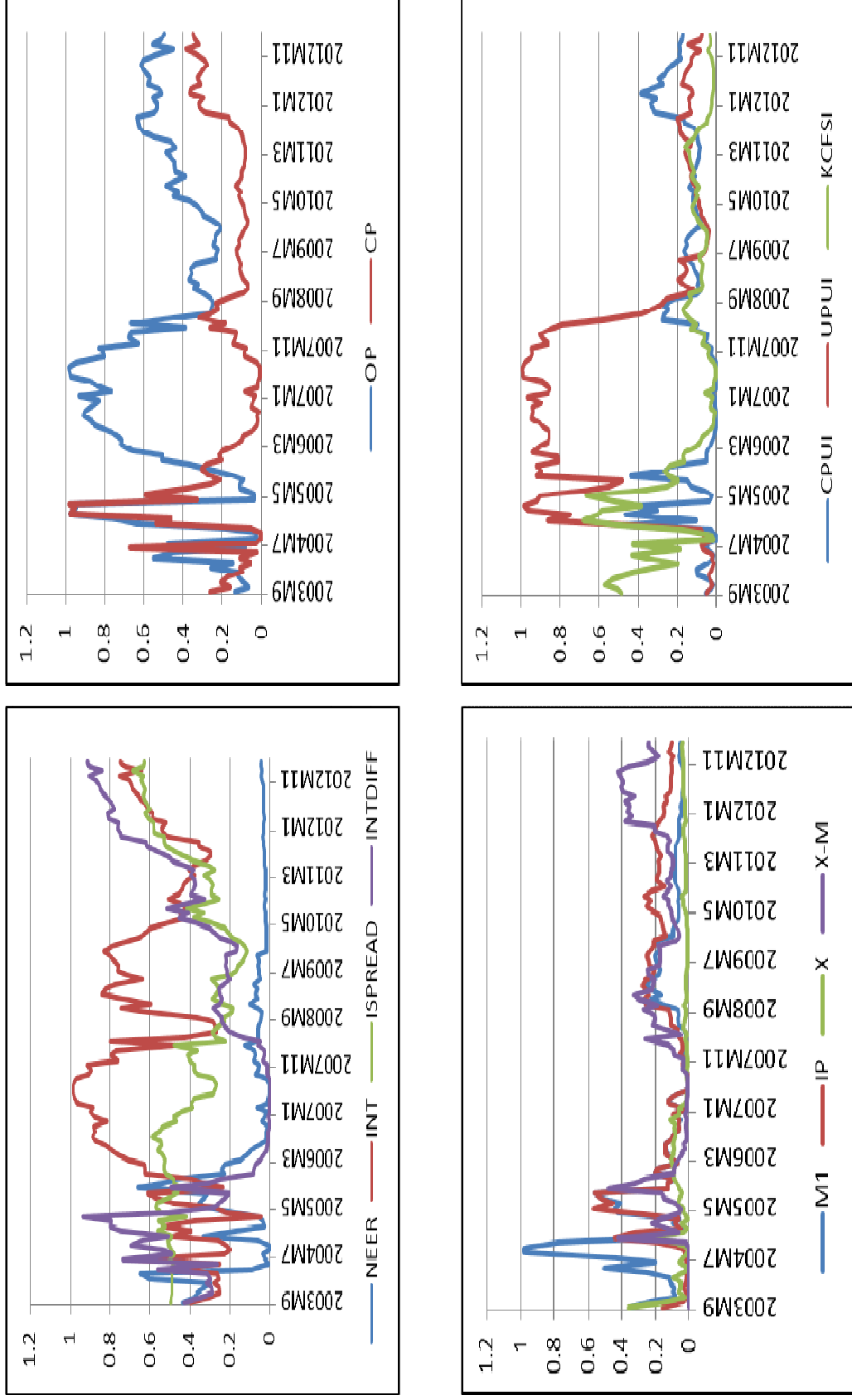
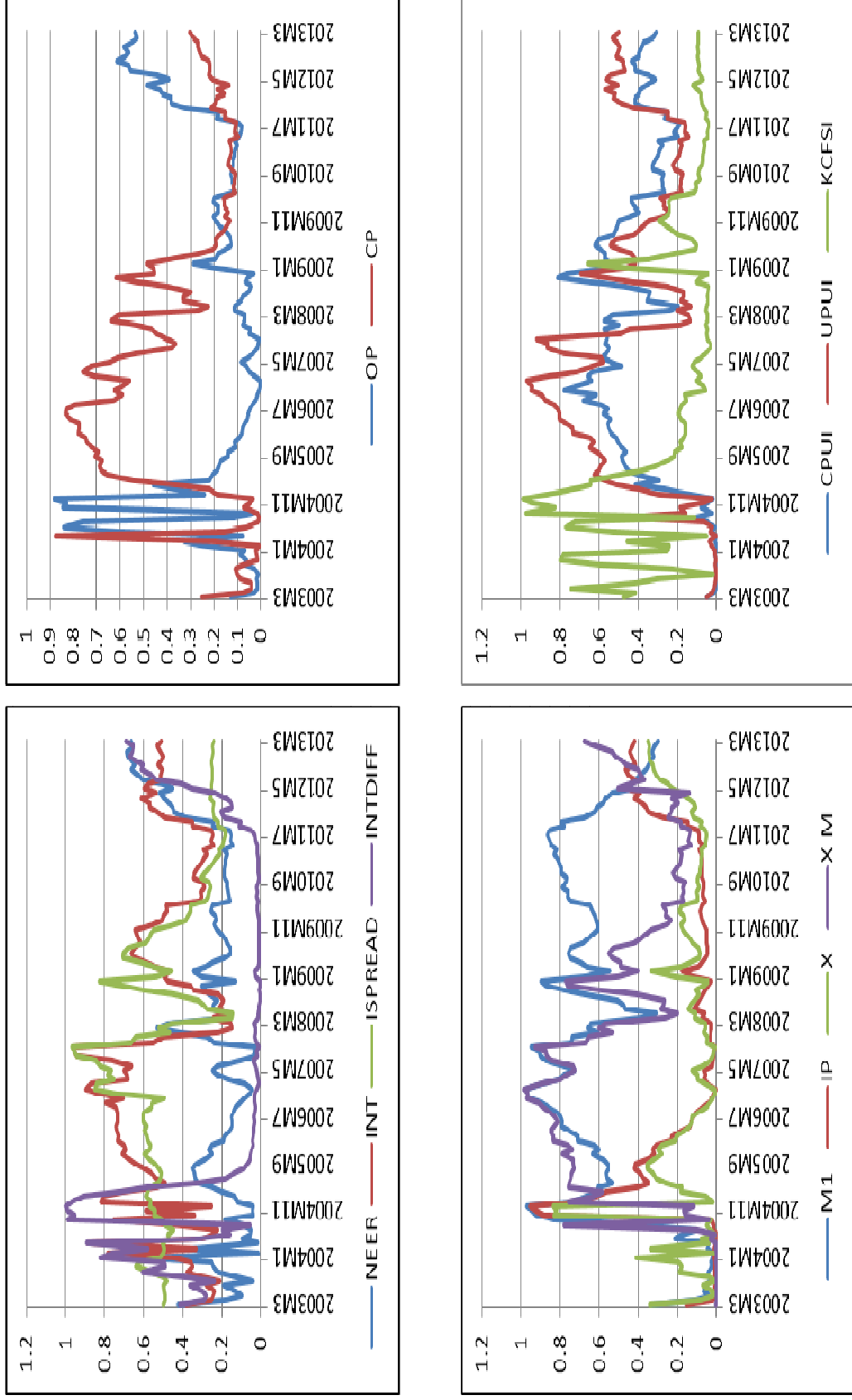


Figure 6: Posterior inclusion probabilities of predictors ($d=12$)



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DATA APPENDIX

The $z_{i,t}$ variables are all transformed to be approximately stationary according to the following codes: 1 – No transformation (levels), $x_{i,t} = z_{i,t}$; 2 – First difference; $x_{i,t} = z_{i,t} - z_{i,t-1}$; 3 – Logarithm, $x_{i,t} = \log z_{i,t}$; 4 – First difference of the logarithm; $x_{i,t} = \log z_{i,t} - \log z_{i,t-1}$ (Koop & Korobilis, 2012).

Table A1: Variables Used in Predicting Chinese Foreign Exchange Reserves

VARIABLE	TCODE	DESCRIPTION ($z_{i,t}$)	SOURCE
NEER	4	Nominal effective exchange rate	Bank for International Settlements (BIS)
INT	1	Short-term interest rate (One-year lending rate)	People's Bank of China
ISPREAD	1	Long-term (five-year plus lending rate) minus short-term interest rates	People's Bank of China
INTDIFF	1	Short term interest rate differential with the USA	People's Bank of China
OP	4	Oil price	International Financial Statistics (IFS) of the International Monetary Fund (IMF)
CP	4	Copper price	IFS of the IMF
M1	4	Money supply (M1)	People's Bank of China
IP	4	Industrial Production	China National Bureau of Statistics
X	4	Exports	Global Insight calculation, IMF
X-M	2	Exports minus Imports	Authors' own computation from Global Insight, IFS Data
CPUI	1	China Economic policy uncertainty index	http://www.policyuncertainty.com/index.html
UPUI	1	US Economic policy uncertainty index	http://www.policyuncertainty.com/index.html
KCFSI	1	Kansas City Fed Financial Stress Index	Federal Reserve Bank, Kansas City