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Abstract

China’s monetary policy is unconventional and constantly evolving as a result of its rapid economic development. This paper proposes to use fore-cast combinations to predict the People’s Bank of China’s monetary policy stance with a large set of 73 macroeconomic and financial predictors covering various aspects of China’s economy. The multiple instruments utilised by the People’s Bank of China are aggregated into a Monetary Policy Index (MPI). The intention is to capture the overall monetary policy stance of the People’s Bank of China into a single variable that can be forecasted. Forecast combina-tion assign weights to predictors according to their forecasting performance to produce a consensus forecast. The out-of-sample forecast results demonstrate that optimal forecast combinations are superior in predicting the MPI over other models such as the Taylor rule and simple autoregressive models. The corporate goods price index and the US nominal effective exchange rate are the most important predictors.

Keywords: Monetary policy indicators, China, forecast combination, optimal weights.

JEL classification: C53, C58

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1 Introduction

China has been a key player for global economic growth over the past 20 years. Naturally, Chinas monetary policy is important both for its domestic economy and for its international trade partners. Recently, there has been heightened concern over rising credit levels in China as well as its potential trade war with the U.S. Monetary policy reflects in part the governments intended response to these challenges, and hence the ability to forecast monetary policy accurately allows observers to understand Chinas response to its economic events.

The monetary policy framework in China is unconventional and complex. The People's Bank of China (PBoC) has three primary objectives: to maintain (i) price stability, (ii) economic growth and (iii) financial stability. These objectives are similar across central banks. The PBoC does not solely target interest rates but also adopts secondary monetary policy targets, including money supply and a stable foreign exchange regime, which require using a multitude of policy instruments. See Glick and Hutchison (2009) and He et al. (2015) for discussion. Hence, the PBC's overall monetary policy stance cannot be captured by a single instrument as it utilises multiple policy tools to implement its monetary policy.

This paper proposes to forecast the PBoC's overall monetary policy stance with a large set of 73 macroeconomic and financial predictors covering all aspects of China's economy. The overall monetary policy stance is captured in a single Monetary Policy Index (MPI) constructed from selected policy instruments. The MPI tracks whether the PBoC is changing its monetary policy stance, either by loosening or tightening policy. A monetary policy index for China was first introduced by He and Pauwels (2008) and variation of this MPI is also found in Xiong (2012), Sun (2013) and Girardin et al. (2017) among others. However, none of these indices include the 7-day reverse repurchase rate introduced in 2012, which has replaced the benchmark deposit and lending rates, and contributed to liberalising China's interest rate system. This paper updates the methods and the data pertaining to the MPI, and incorporates the latest changes in Chinese monetary policy tools by including the 7-day reverse repurchase rate.

Furthermore, the PBoC uses credit-based tools, such as window guidance to manage banking liquidity and control credit levels in financial markets. These instruments are qualitative and unobservable, and hence previous MPIs exclude them. The MPI featured in this paper contains an approximation for credit-based administration tools proposed by Girardin et al. (2017), which results in a comprehensive MPI covering all three categories of monetary policy instruments.

The overall monetary policy stance of the PBoC is forecasted using many predictors and forecast combination methods. Each predictor produces probability forecasts of changes in the PBoC policy stance, and are then combined into a consensus forecast which is evaluated against the observed changes in the MPI. Forecast combinations are well suited to the evolving nature of China's monetary policy because the weights for each predictor changes over time. This means that such combinations are robust to structural changes, as shown in Pesaran and Timmermann (2007), and attribute higher weights to predictors that demonstrate greater forecasting accuracy. The forecast combination weights are estimated optimally following Hall and Mitchell (2007) and Geweke and Amisano (2011), and also estimated with scoring functions by Vasnev et al. (2013). Forecasts from multivariate models arising from stepwise selection method, Taylor rule or simple autoregressive model with on lag of the MPI are also used for comparison. All models and forecast combinations are benchmarked against a simple equally weighted forecast combination. The forecast performance is evaluated with relative scoring rule and statistical tests against the benchmark.

The probability forecasts are obtained by modelling the relationship between the MPI and the macroeconomic and financial predictors with discrete choice models. Discrete choice models are well suited to modelling the discrete timing and magnitude of central banking decision as shown for the European Central Bank in Gerlach (2007), the Bank of Korea in Kim et al. (2016), the Reserve Bank of Australia in Vasnev et al. (2013), the US Federal Reserve in Kauppi (2012) and Kim et al. (2009) and the People's Bank of China in He and Pauwels (2008). Kim and Shi (2018) conducted out-of-sample forecasts for the benchmark lending and deposit rates using an ordered probit model but do not attempt to forecast an overall PBoC monetary policy stance. Vasnev et al. (2013) and Pauwels and Vasnev (2017) demonstrate that forecast combinations of ordered probit models provide greater forecast accuracy than multivariate probit models and do not require a model selection procedure.

Overall, the results indicate that optimal forecast combinations produce greater forecast accuracy and are statistically significant compared to equally weighted forecast combinations. The optimal weights reveal that the PBC's monetary policy stance is highly influenced by the Consumer Goods Price Index, an indicator of wholesale price fluctuations for enterprises. This seems intuitive as China's manufacturing and export sectors have been the strongest drivers of its economic growth. Interestingly, the US Nominal Effective Exchange Rate, a proxy for the strength of the US dollar, is consistently highly weighted among the majority of forecast combination models. This highlights the importance of China's international trade partners for the PBoC's monetary policy.

The remainder of the paper is organised as follows. Section 2 provides the details of the construction of the MPI. Section 3 describes the methodology for modelling monetary policy and combining probability forecasts. The dataset is summarised in Section 4, which discusses the predictors, the forecasting strategy and the key results. Section 5 provides concluding remarks.

2 Monetary policy indices

2.1 Background

There are three broad categories of policy tools typically available to central banks: quantity-based instruments, price-based instruments and credit-based instruments. These tools include the Reserve Requirement Ratio (RRR), Open Market Operations (OMO) and interest rates. Revisions to the RRR have been repeatedly implemented to make large-scale adjustments to money supply in response to heavy foreign capital inflows. OMOs are another quantity-based tool that have been primarily used for sterilisation and stabilisation of large fluctuations in foreign exchange rates. The PBoC's primary interest rates have been the benchmark lending and deposit rate. China has also relied on credit-based tools to influence the level of banking liquidity and direction of credit in the economy.

China has been transitioning towards a market-determined interest rate framework, with the gradual adjustments to the ceilings and floors of the benchmark lending and deposit rate since 2004. The benchmark interest rates have effectively been retired as they have not been adjusted since 2015. Instead the 7-day reverse repurchase rate has replaced the benchmark interest rates.

China's monetary policy stance cannot be solely captured by the interest rates, however. Instead, composite indices of monetary policy, which aggregate multiple instrument, have been used by several research papers. He and Pauwels (2008) present one of the first attempts of aggregating China's multiple instruments into a monthly index from January 1998 to December 2007. The Monetary Policy Index

(MPI) combines four instruments: the RRR, the benchmark lending rate and deposit rate and OMOs measured by the net outstanding amount of central bank bills.

Xiong (2012) constructs a quarterly MPI that attempts to deduce a monetary policy stance from qualitative PBoC reports that are released every quarter. Girardin et al. (2017) also constructs a MPI which attempts to capture China's evolution of policy instruments into a more market-determined financial system. Notably, the index includes liquidity management actions, such as administrative window guidance and credit control measures, which are difficult to observe but important for capturing the effects of the 2008 Global Financial Crisis. The model also captures the magnitude or scale of policy changes in terms of 25 basis-points movements.

2.2 A monetary policy index

This paper produces an updated and revised MPI up to June 2018, for which the methodology generally follows He and Pauwels (2008) and Girardin et al. (2017). Additionally, it takes into consideration the PBoC's significant shifts towards a market-orientated monetary policy framework since 2015. Hence, the index is updated for the retirement of policy instruments and the introduction of a new one, namely the 7-day reverse repurchase rate. Credit-based policy instruments play a fundamental role in influencing banking system liquidity, but are generally unobservable and have been excluded from previous attempts of MPIs as a result. This paper uses a proxy to incorporate opaque credit-based tools in order to create a more comprehensive MPI. The final MPI is constructed as a triple choice variable denoted by:

$$\mathrm{MPI}_t = \begin{cases} -1, & \text{PBoC loosened its stance in month } t \\ 0, & \text{PBoC does not change stance in month } t \\ 1, & \text{PBoC tightened its stance in month } t \end{cases} \tag{1}$$

where MPI_t is the observed MPI value at time t.

As the PBoC does not adhere to an announcement schedule, it is assumed that the PBoC meets on a monthly basis. However, the PBoC only communicates shifts in its policy stance to an overall loosening or tightening stance by making observable adjustments to its key policy instruments. The PBoC does not explicitly communicate positions of 'no change' to its policy stance, unlike most central banks. Thus it is important to clarify that when $\mathrm{MPI}_t = 0$ for a given month, this indicates a month where there was no net change to the policy stance of the PBoC, and does not necessarily imply that the PBoC holds a 'neutral' policy stance. This interpretation of a monthly MPI follows the assumptions made by He and Pauwels (2008), Sun (2013) and Girardin et al. (2017).

The full sample period considered in this paper spans from January 2002 until June 2018. Although data from January 1998 is available, time periods starting from 1998 are inappropriate given the widespread evidence of China's change to its current monetary policy approach following its admission to the World Trade Organization in 2002. See Klingelhöfer and Sun (2018), Girardin et al. (2017) and Xiong (2012) for discussion. The 1998 – 2002 period is marked by fewer but larger monetary policy shifts with only six loosening adjustments, unlike the post-2002 periods which marked an era of more frequent but small adjustments. This is discussed in Kim and Shi (2018).

Instrument selection

Category	**Policy tools**
Quantity-based	Reserve Requirement Rate (RRR)
Price-based	Commercial bank 1-year lending rate Commercial bank 1-year benchmark deposit rate 7 day reverse repurchase (repo) rate
Credit-based	Total year-on-year loan growth (LG)

Table 1: Primary policy instruments combined to form the MPI

Table 1 presents the five instruments selected. The RRR is a key policy instrument for the PBoC as it has been one of the most frequently adjusted. It has been a popular tool for controlling inflation and sterilizing the impact of heavy foreign inflows on money supply. Revisions to the RRR have been preferred over adjusting interest rates in China, as the RRR has an amplified effect on banking liquidity (Chen et al., 2017). This is evident in periods of economic distress where the RRR is the preferred response tool over the benchmark interest rates to address for example the 2008 Global Financial Crisis. Over the sample periods considered, the RRR has been adjusted 45 times compared to the 24 and 27 adjustments to the benchmark deposit and lending rates respectively. This comparison is displayed in Table 2. The RRR is included in the MPI as it has been one of the primary policy tools.

The benchmark lending and deposit rates have been consistently employed as the PBoC's primary price-based instruments, from 1987 until 2015, and have played a key role in maintaining banking liquidity. Since 2015, the benchmark rates have been dormant and have been replaced by the 7-day reverse repurchase rate. The 7-day reverse repurchase (7-day repo) rate captures the Chinese short-term interbank interest rate. Kamber and Mohanty (2018) argues that the 7-day repo rate is a reliable and informative indicator of the PBoC monetary policy stance because of its importance in determining market liquidity as a cost of capital for financial institutions. This is supported by the rise in daily OMOs to stabilise the volatility in the 7-day repo rate.

	RRR	**Deposit**	**Lending**	**7d Repo**	**Loans**	**MPI**
Tightening	31	13	14	7		43
Loosening	14	11	13	9	15	41

Table 2: Summary of adjustments to key policy instruments from January 2002 – June 2018.

China adopts various credit-based instruments to manage liquidity and the level of credit in financial markets. Unfortunately, many of these instruments are not observable or measurable. For example, the PBoC is known to hold informal meetings with banks to influence which areas of the economy should receive more accessible financing. This window guidance policy plays a key role in monetary policy transmission for the PBoC, but are difficult to capture given the lack of data (Sun, 2013). As a result, the MPI in He and Pauwels (2008) does not include a credit-based instruments. However, Xiong (2012) and Girardin et al. (2017) propose to approximate credit administration measures by analysing annual growth in China's total loans. The authors are particularly interested in capturing the heavy credit stimulation by state-owned financial institutions that resulted in unusual loan growth from 2003 to 2009. Given the difficulty in measuring credit-based tools, the same 'total loan growth' variable is used as a proxy for the credit-based tools. Whenever the year-on-year growth in total loans exceeds 20% and is accelerating, the MPI is coded as a tightening monetary policy stance.

OMOs have been included as a quantity-based tool in the MPIs by He and

Pauwels (2008) and Girardin et al. (2017). An arbitrary RMB100 billion threshold is proposed by He and Pauwels (2008) as this roughly equated to a 25 basis point change in the RRR between 1997 and 2008. This same threshold is most likely not applicable for the sample under consideration, due to growth in the volume of OMO operations since 2008. This paper, however, excludes OMOs as they are essentially secondary policy instruments used for operational purposes in conjunction with other instruments. Its inclusion would lead to risk of mis-specifying policy signals.

Aggregation of instruments

Monthly changes in the policy instruments are encoded in the MPI given in equation (1), using the effective date rather than the announcement date. This is to avoid the potential time lag between the proposal of instrument adjustments by the PBoC on its announcement date, and its actual implementation by the State Council in another month as highlighted by He and Pauwels (2008).

Monthly changes in the price-based and quantity-based instruments are classified based on the direction of changes relative to the previous month. The credit-based instrument, total loan growth, has a unique classification criteria that follows Xiong (2012) and Girardin et al. (2017). A loosening adjustment is defined when total year-on-year loan growth exceeds 20% and is 'accelerating' by being greater than the previous period. The rationale for this criteria is to capture the periods of abnormally high credit growth from unobservable credit administration measures and window guidance.

This aggregation incorporates the assumption that all instrument adjustments are equal in weight and importance. Thus instrument adjustments in opposite directions are able to offset each other and cancel each other out. Instruments adjusted in the same direction are still encoded as either loosening or tightening of stance.

2.3 Analysis of the MPI

The resulting MPI is graphed in Figure 1. The MPI is compared to the one constructed by He and Pauwels (2008) from January 2002 until December 2007 in Figure 2, where the primary differences are from the inclusion of loan growth and the exclusion of the arbitrary classification of OMOs. The loosenings around May 2003 are the result of abnormal loan growth from credit-administration measures. Generally the period of tightening decisions from May 2005 to December 2007 align with

He and Pauwels (2008), but differ slightly as the OMOs classification specifies more tightenings.

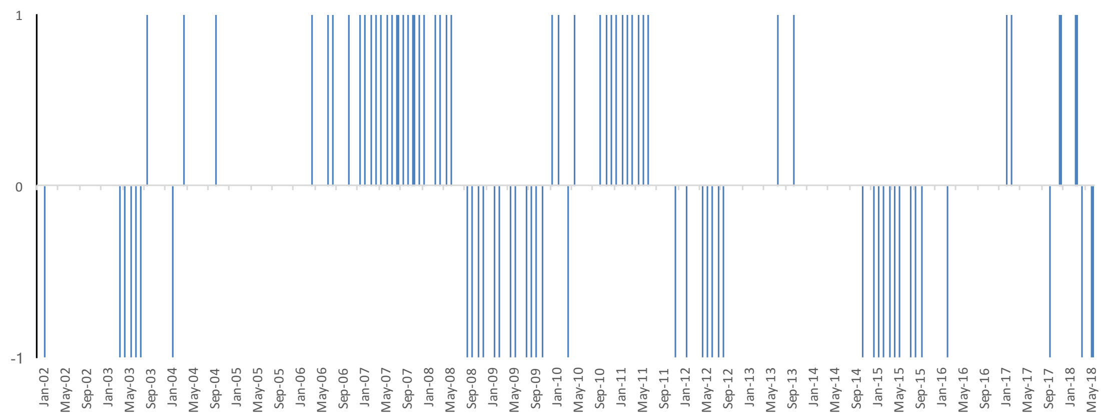

Figure 1: Monthly MPI from January 2002 – June 2018. The bars indicate the PBoC's monetary policy stance. The vertical axis shows whether there is a loosening (-1), no change (0) or a tightening (1) in the stance.

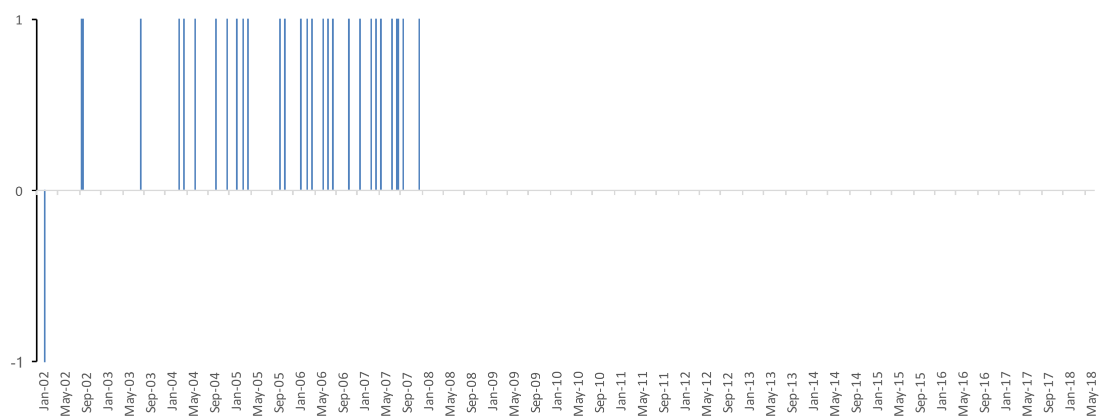

Figure 2: PBoC policy stance: Monthly MPI from January 2002 – December 2007, constructed by He and Pauwels (2008). The bars indicate the PBoC's monetary policy stance. The vertical axis shows whether there is a loosening (-1), no change (0) or a tightening (1) in the stance.

Most revisions to the benchmark interest rated and the 7-day repo rate align with the timing and direction of the RRR changes. This occurred until October 2017 when China faced a slowdown in economic growth and also alarming corporate credit levels. This resulted in loosening the RRR to increase liquidity while tightening to the 7-day repo rate to curb excessive debt levels. Consequently, the MPI values alter between loosening and tightening stances in the last 10 observations of Figure 1. Revisions to the benchmark deposit and lending rate are also generally synchronised to ensure commercial banks retain a consistent spread between rates for their lending businesses (Porter and Xu, 2016).

3 Methodology

3.1 Modelling monetary policy

The PBoC monetary policy stance is modelled similarly to He and Pauwels (2008) following from the seminal work of Dueker (1999). The PBoC is assumed to have a latent and continuous implicit policy stance expressed as

$$s^*_{t+1} = X_t'\beta - \varepsilon_{t+1}, \quad \varepsilon_{t+1} \sim \mathcal{N}(0, \sigma^2_\varepsilon), \tag{2}$$

where the time period is $t = 1, \ldots, T$ and X_t is a $k \times 1$ predictors. β is a $k \times 1$ vector of coefficients and the error ε_{t+1} is assumed to be Normal. The MPI, denoted by y_t, takes on the following three possible values:

$$y_{t+1} = \begin{cases} -1, & \text{if } s^*_{t+1} < \mu_1^T \\ 0, & \text{if } \mu_1^T \leq s^*_{t+1} \leq \mu_2^T \\ 1, & \text{if } s^*_{t+1} > \mu_2^T. \end{cases} \tag{3}$$

Equation (3) shows that for example, the model would predict a loosening stance, i.e. $y_{t+1} = -1$, if the latent policy stance, s^*_{t+1}, is below the threshold, μ_1^T. The thresholds, μ_1 and μ_2, are scaled by the sample size, T, to account for nonstationarity in macroeconomic predictors, X_t. Defining the thresholds as $\mu_1^T = \sqrt{T}\mu_1$ and $\mu_2^T = \sqrt{T}\mu_2$ ensures that they have the same scale as the latent stance variable if there are integrated time series as shown in Hu and Phillips (2004).

The probability distribution of y_{t+1} is expressed as $P(y_{t+1} = d|X_t, \theta)$ for $d = -1, 0, 1$, and is dependent on $(X_t; \theta)$ where $\theta = (\beta', \mu_1^T, \mu_2^T, \sigma^2_\epsilon)'$. This probability can be expressed using the cumulative distribution function of the normally distributed error terms, denoted by $F(\cdot)$. The probabilities for the three possible PBoC policy stance outcomes are:

$$\begin{aligned} P_{-1}(X_t;\theta) &= 1 - F(X_t'\beta - \sqrt{T}\mu_1) \\ P_0(X_t;\theta) &= F(X_t'\beta - \sqrt{T}\mu_1) - F(X_t'\beta - \sqrt{T}\mu_2) \\ P_1(X_t;\theta) &= F(X_t'\beta - \sqrt{T}\mu_2) \end{aligned} \tag{4}$$

The parameter θ is estimated by maximum likelihood. This produces $\hat{\theta} = (\hat{\beta}, \hat{\mu}_1^T, \hat{\mu}_2^T)'$, which are consistent and asymptotically normal according to Hu and Phillips (2004).

3.2 Forecasting methods and evaluations

Forecast combinations are capable of handling a large number of explanatory variables. This is particularly relevant for this paper as it uses 73 predictors. Moreover, Pauwels and Vasnev (2017) demonstrate that a forecast combination approach produced more accurate predictions of the US Fed Funds rate than Hu and Phillips (2004). Forecast combinations are shown to be more robust for breaks in trends and intercepts as shown in Vasnev et al. (2013).

As shown in Pauwels and Vasnev (2017), combining ordered probit models does not yield an ordered probit with tractable properties. Hence, the discrete models can be aggregated by combining their probability forecasts. The combined one-step ahead probability forecast is given by:

$$\widehat{P}_{t+1,d}^{(C)} = \sum_{i=1}^{n} \omega_{t+1,d}^{(i)} \times \widehat{P}_{t+1,d}^{(i)}(X_t^{(i)}; \hat{\theta}^{(i)}) \tag{5}$$

where $\widehat{P}_{t+1,d}^{(C)}$ is the combined probability forecast for each possible policy stance $d = -1, 0$ or 1. The probability forecast for a change in the policy stance is given by $\widehat{P}_{t+1,d}^{(i)}$ for the ith individual probit model. And its respective weight is denoted by $\omega_{t+1,d}^{(i)}$.

The optimal forecast combinations seek to maximise the average log score of the combined probability forecast, following Hall and Mitchell (2007) and Geweke and Amisano (2011). As a result, the optimal weights minimize the Kullback-Leibler information criterion (KLIC) to reduce the distance between the combined probability forecast and the true probability density. The optimal weights are determined by maximizing the log score:

$$\omega^* = \underset{\omega}{\operatorname{argmax}} \frac{1}{\tau_2 - \tau_1} \sum_{t=\tau+1}^{\tau_2} \log(\widehat{P}_{t+1,j}^{(C)}), \tag{6}$$

where $\widehat{P}_{t+1,j}^{(C)}$ is the combined probability of the actual state j for the period $(\tau_1, \tau_2]$ determined in (5).

Scores are used to evaluate the forecasting performance of models, such as the optimal weighted combination as proposed in (6). Consider the log score:

$$S_t^L = \log(\hat{P}_{j,t}) \tag{7}$$

where S_t^L is the log score at time t and $\hat{P}_{j,t}$ is the probability of the actual PBoC policy stance j, as proposed by Ng et al. (2013). Log scores reward models for their ability to correctly predict the actual PBoC policy stance.

The predictive ability of forecast models can also be evaluated with the Diebold and Mariano (1995) test which evaluates whether there is a statistical difference between forecast performance of models, typically with the mean square forecast errors. Diks et al. (2011) provides a version of the test that can be applied to log scoring rules. The test is asymptotically standard Normal.

Other weighting methods include equal weights, i.e. $\omega_{t+1,d}^{(i)} = \frac{1}{n}$, or simple rule of thumb such as weights based on scoring functions. For example, the average score can be used to determine the weights of forecast combinations. The rationale is to attribute higher weights to models with better scores. The log score weights can be written as

$$\omega_i^L = \frac{\frac{1}{|\overline{S}_i^L|}}{\sum_{i=1}^{n} \frac{1}{|\overline{S}_i^L|}} \tag{8}$$

where ω_i^L is the weighting applied for the ith model and $\overline{S}_i^L = \frac{1}{\tau_1 - \tau_2} \sum_{t=\tau_1+1}^{\tau_2} S_{i,t}^L$ are the average log score of one-step ahead forecasts over the period $(\tau_1, \tau_2]$.

4 Empirical Results

4.1 Predictors

The dataset consists of 73 monthly macroeconomic and financial predictors, spanning from January 2002 to June 2018 (198 observations). It is compiled from a diversified number of sources, including the CEIC database, the International Monetary Fund, the Bank for International Settlements, the Chinese National Bureau of Statistics, and the People's Bank of China, Shanghai Stock Exchange, and the Shenzhen Stock Exchange. The foreign indicators are taken from the official statistical organisation for each country, such as the US Federal Reserve and the UK Office for National Statistics.

The predictors cover six broad aspects of China's economy, including real activity, money and reserves, stock markets, interest rates, exchange rates and prices. See Table A1 in the Appendix for a complete list of predictors. The predictors are chosen to cover most facets of China's economy and capture its complexity. China's most important sector, manufacturing, is measured by producer price indices and production such as GDP, primary energy production, corporate goods price index and fixed asset investment. International trade dynamics are captured by exchange rates and China's trade balance. Stock market variables are included to capture financial activity and sentiment. A number of credit-based data series, such as domestic credit and total inter-bank loans, are included to investigate the impact of China's growing debt levels on the monetary policy. Macroeconomic indicators from the US, UK, Europe, and Japan are included to explore the influence of China's extensive trade links and the impact of foreign economic activity on China's monetary policy. These include the industrial production indices, CPI, nominal effective exchange rates, and inter-bank rates. This follows the findings of Girardin et al. (2017) who demonstrate that including foreign macroeconomic indicators, namely the US Federal Funds rate, led to improved estimation of China's monetary policy reaction function in their application of modified Taylor models.

In general, all indicators are in yearly growth rates, with the exception of interest rates. Macroeconomic variables often exhibit non-stationarity and the proposed methodology includes measures to adjust for potential non-stationary explanatory variables. Seasonality adjustments are made to the relevant series. This is done by taking the average of the January and February observations to account for the

Chinese New Year effect. The data is lagged by one period to match the real-time release of economic information available to policy makers.

4.2 Preliminary results

A sequential stepwise model selection process for probit models using the 73 predictors and the full sample is implemented. The variables selected are a healthy mix of areas of the economy and listed in Table 3. Important price indicators such as the corporate goods price index and producer price index are selected. These indicators reflect the importance of China's manufacturing sectors to its monetary policy. Furthermore, the Shenzhen Stock Market predictors are also an indication that the PBoC is watching the financial market closely. Not surprisingly, monetary aggregate, such as Quasi Money and Foreign Reserves, are determinants of China's monetary policy path. The predictor selection also points to China's trade partner including several predictors for the US, including the US Fed funds rate, and the UK policy rate.

Selected predictors
Corporate goods price index
Foreign reserves
Government revenue
Producer price index
Quasi Money
Retail sales
Shenzhen market capitalisation
Shenzhen stock exchange index
UK Policy base rate
US CPI
US Federal Funds rate

Table 3: Results of the stepwise model selection process for 2002 – 2018.

Figure 3 plots the estimated latent variable $\hat{s}_t^*$, alongside the estimated threshold parameters, and compares it to the actual MPI. The model estimates a loosening or tightening policy stance when $\hat{s}_t^*$ crosses the thresholds. This classification generally aligns with the actual MPI values observed. It is interesting to note that the forecasting performance of the model deteriorates over time. This could be indicative of potential structural breaks in the PBoC monetary policy reaction function. This

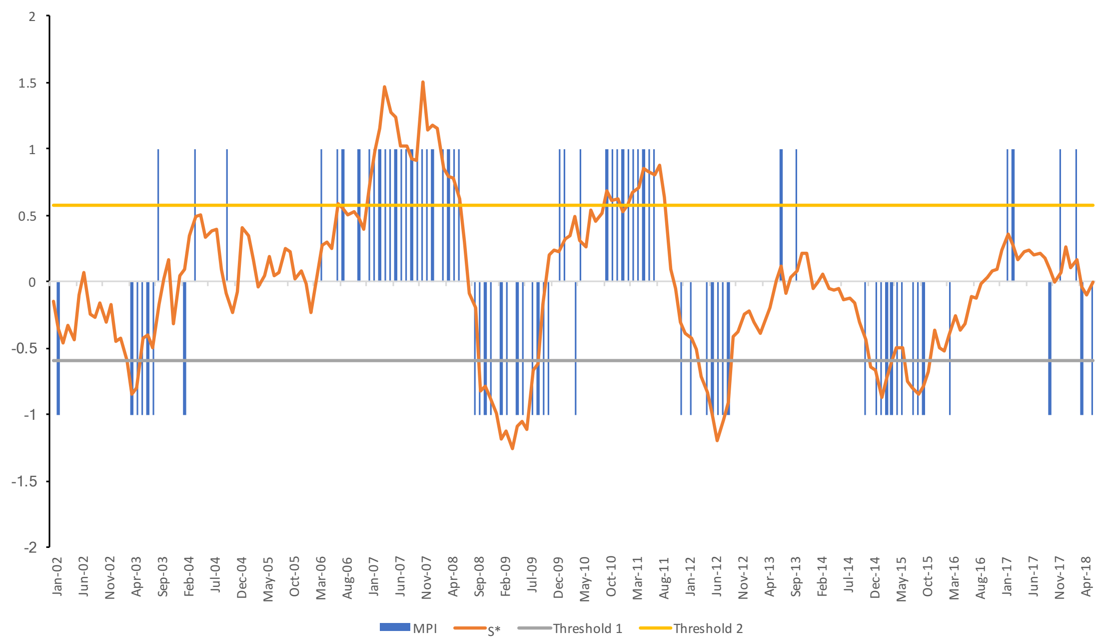

Figure 3: Latent $\hat{s}_t^*$ estimated from a model with selected predictors listed in Table 3compared to the actual MPI. Predicted loosening or tightening PBoC policy stance values occur when $\hat{s}_t^*$ crosses one of the estimated thresholds.

resonates with the findings of a regime-switching monetary policy reaction function in China around the 2008 GFC by Klingelhöfer and Sun (2018). Fortunately, forecast combination methods used for out-of-sample forecasting are robust to potential structural breaks as discussed in Pesaran and Timmermann (2007).

4.3 Out-of-sample forecasting

Forecasting strategy

Out-of-sample forecasts are conducted with a recursive forecasting approach. The dataset is halved to produce the estimation sample, with the estimation period spanning from $\{1, \ldots, \lfloor T/2 \rfloor\}$ where T denotes the size of the entire sample, and $\lfloor \cdot \rfloor$ is a floor function for integer round up. The data from the most recent month is added to the estimation period once that month has been forecasted, thereby expanding the estimation window.

In order to reduce the initial volatility of forecast combination weights, a 24 observations burn-in period is used, as recommended by Pauwels and Vasnev (2016). The first forecast combination is contructed over 24 observations from the end of the estimation period, i.e. from $\{\lfloor T/2 \rfloor - 24, \ldots, \lfloor T/2 \rfloor\}$ which produces more stable weights over time as the weights are re-estimated throughout the forecasting sample.

Three weighting methodologies for forecast combinations are implemented: a benchmark equal weight combination, the optimal combination from equation (6) and the log score weighted combination from equation (7). The combination models are constructed using the complete set of 73 predictors. Note that none of China's monetary policy instruments or the MPI are used in the set of predictors for forecast combinations.

Alongside these forecast combination models are three models: a multivariate model, a Taylor rule and an Autoregressive model with a one period lag of the MPI. The multivariate model features a focused set of predictors obtained by the stepwise model selection process as in section 4.2 using the estimation periods, i.e. half of the sample in consideration. The Taylor model uses lagged CPI inflation and industrial output for the output gap, which follows the construction method by Kim and Shi (2018). The Taylor model is included as benchmarks due to their importance in the monetary policy literature. The autoregressive model features the MPI lagged by one period to incorporate the impact of policy inertia and the tendency for central banks to issue the same policy stance over a number of consecutive periods. All three models are also compared to the equal weight combination benchmark.

Forecasting performance is evaluated over three time periods to test for the impact of major economic events and the existence of potential breaks. The first period is from January 2002 to June 2008 to exclude the GFC. The second time period from January 2002 to June 2013 intends to capture the full impact of the GFC. It also allows for comparison of the PBoC's monetary policy conduct prior to its significant interest rate liberalisation changes from late 2013. The final time period from January 2002 to June 2018 attempts to measure the impact of all the aforementioned major economic events.

Results

The out-of-sample forecasting results are presented in Table 4. The forecasting performance is evaluated using log scoring rule in equation (7) relative to equal weighted combination. Numbers greater than 1 indicate an improvement in forecasting performance. The results are also evaluated with the Diebold and Mariano (1995) test that evaluated whether there is a statistical difference between the scores of equal weight forecast combination and the other combinations and models, as mentioned in section 3.2.

	2002 – 2008		2002 – 2013		2002 – 2018	
	Score	DM test	Score	DM test	Score	DM test
Combinations:						
Equal weights (Benchmark)	1		1		1	
Log weights	1.101	-1.198	1.005	-0.131	1.069	-1.507
Optimal weights	1.453	-2.158	0.993	0.391	1.198	-6.476
Regression models:						
Multivariable model	1.147	-0.685	0.755	1.149	0.850	1.751
Taylor rule	1.093	-0.949	1.017	-0.367	1.088	0.354
Lagged MPI	1.361	-1.674	1.137	-1.240	1.167	0.247

Table 4: Expanding window out-of-sample forecast results. The log scores are relative to the benchmark. Numbers greater than 1 indicate a better score relative to the benchmark. The Diebold and Mariano (1995) test is asymptotically standard Normal. It tests the difference in scores between the benchmark and the other models.

Overall, the optimal weight forecast combination consistently outperforms the other models especially for the 2002 – 2008 and 2002 – 2018 samples. The optimal weight combinations produce the best scores, and the only scores that are statistically significant at the 5% level. It outperforms the simple autoregressive lagged MPI model. These results align with the findings of Hall and Mitchell (2007) and Pauwels and Vasnev (2017). The optimal weights adapt over time and are better suited to forecasting monetary policy in China, given the changes in China's multiple-instrument monetary policy.

It is interesting to note that while the autoregressive lagged MPI model scores the highest for 2002 – 2008, yet it is not statistically different from the equal weighted combination as indicated by the DM test. This highlights the difficulty of forecasting through the GFC period. The lagged MPI model, however, scores the best out of the regression models and the second best overall.

Figure 4 presents the one-step ahead combined probability forecasts for the optimal weight combination and the log-score combination. The line above 0 is indicative of higher probability of a tightening stance, and the line below 0 represents minus the probability of a loosening stance. The optimal weight model forecast more periods of loosening and tightening stances than the other forecast combination models.

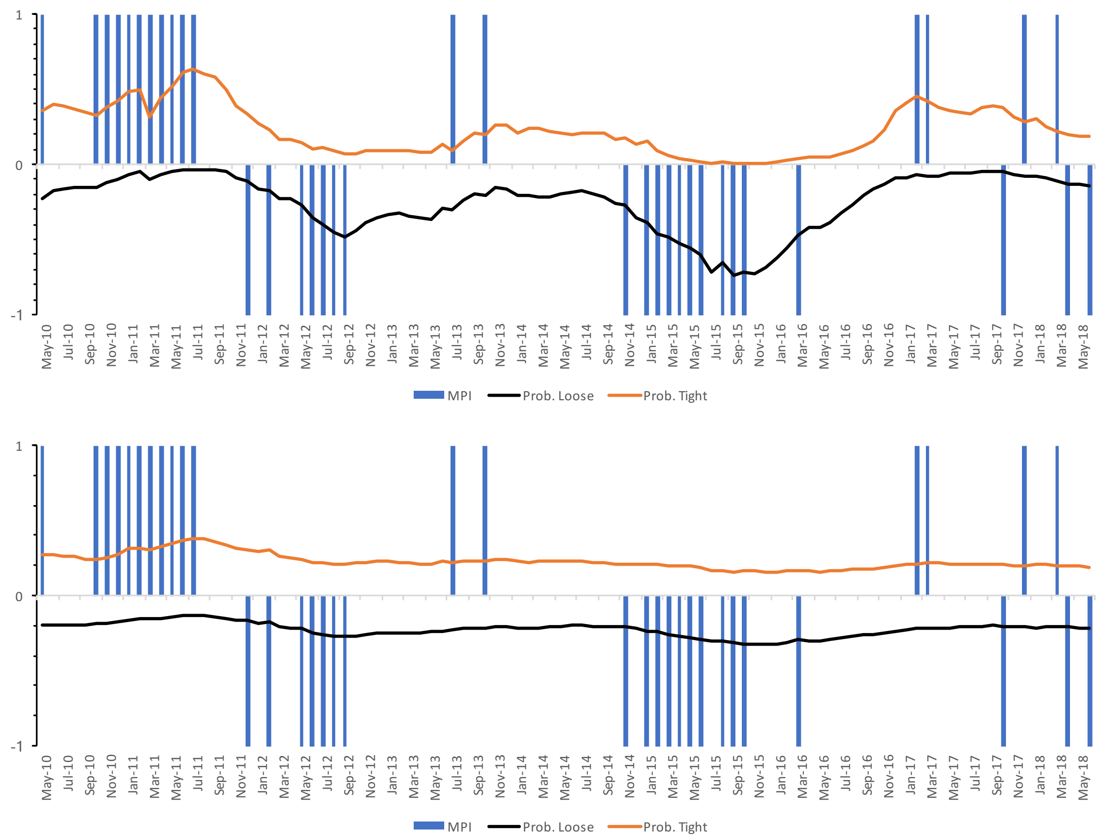

Figure 4: One-step ahead combined probability forecasts. The line above 0 represents the probability forecasts of a tightening in the PBoC policy stance, and below 0 it represents minus the probability forecasts of a loosening in the PBoC policy stance. The first panel presents the probability forecasts using optimal weights and the second log-score weights.

It is the only model that identifies the tightening decisions in late 2016 and early 2017. The log-score and equally weighted combinations identify similar periods of tightening and loosening stances.

The optimal weights are non-zero for nine main predictors of out 73 for the 2002 – 2018 forecasting sample. Further analysis into the weights of individual models reveals that the Corporate Goods Price Index (CGPI) and the US Nominal Effective Exchange Rate (US NEER) are the most heavily weighted univariate models from 2015, as presented in Figure 5. The other important predictors include industrial production of trade partners including the US, the UK and Japan. Monetary aggregates such as Quasi Money is also important. All of these predictors echo the findings presented in section 4.2.

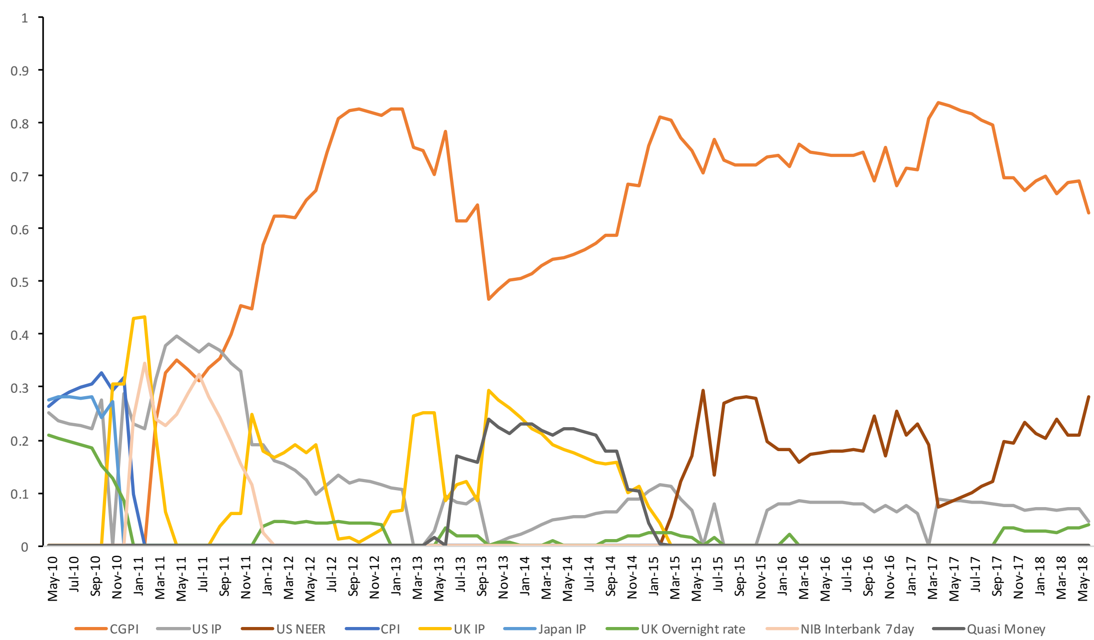

Figure 5: Optimal weights (expanding window) for the combination of 73 univariate models for 2002 – 2018.

The CGPI is a wholesale price index that reflects the price changes of commodities traded by enterprises in Chinese wholesale markets (Xiong, 2012). It captures the year-on-year change in wholesale prices for businesses, and differs from the popular inflation metric, CPI, as this is a measure of fluctuations in prices for household consumers. Since late 2011, CGPI is consistently attributed the highest weights, averaging roughly 70% from 2012 to 2018. Figure 6 charts the MPI against the

CGPI from 2002 to 2018 and reveals a positive relationship. In general, periods of high CGPI growth result in a tightening stance, and the opposite occurs for negative changes in CGPI. This relationship aligns with the PBC's primary objective of targeting inflation, and verifies evidence of a shift towards an 'anti-inflation' monetary approach since China's admission to the WTO in 2002. See Klingelhöfer and Sun, 2018 for a discussion.

The US NEER averages a 18% weighting from early 2015 to 2018. This is not surprising as the US is China's major trading partner. The US NEER is the weighted average of US foreign exchange rates that is proportioned by its trade value with other countries. The year-on-year change is a measure of the US international competitiveness, and the strength of the US dollar (USD) against foreign currencies. As a nominal rate, the US NEER also captures movements in US domestic inflation compared to the real effective exchange rate.

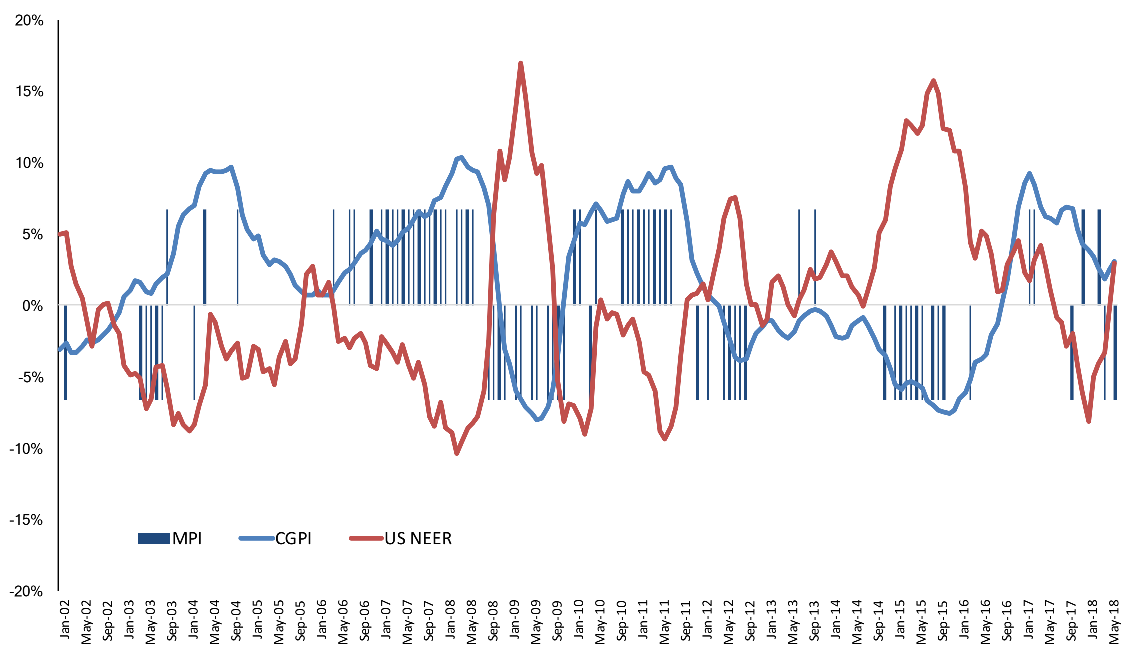

Figure 6: Plot of CGPI and US NEER against MPI

Plotting US NEER against the MPI shows it is negatively correlated, where appreciations in the US NEER result in a loosening stance and vice versa. These results imply that China continues to track the USD, and the strength of the USD has a major influence on monetary policy decisions in China. An increase in the US NEER indicates appreciation of the USD, and a relatively weaker RMB. This could warrant monetary policy easing in China to combat a slowdown in economic growth and to fulfil the PBoC's intention to maintain a steady appreciation of the RMB against the USD (Zhao et al., 2018). From 2013 to 2015, the optimal combination also assigns noticeable weights to Quasi Money and both the US and UK industrial production indices. Not surprisingly, the former shows the importance of monetary aggregates for China's monetary policy, while the latter two predictors are capturing foreign demand for Chinese goods.

4.4 Robustness

A fixed rolling estimation window is also used to test the robustness of the forecast combination models as an alternative approach compared to the expanding window. The rolling window has a fixed size of $\lfloor T/2 \rfloor$ and the results are shown in Table 5.

The optimal weighted forecast combination produces the only statistically significant scores in the forecasting sample 2002 – 2018. This result is not surprising as optimal weights do require large sample size to work best. Overall, the forecast combination models outperform the other models in the 2002 – 2008 and 2002 – 2018 forecasting samples consistent with the expanding window forecast results. Moreover, in the 2002 – 2008 forecasting sample, both the log score combination and the optimal weighted combination produce the highest scores.

As with the expanding window, the lagged MPI produces the highest scores in 2002 – 2013. However, neither of these results are significantly different from equally weighted combination as indicated by the DM test. The DM test results are in general statistically less significant than those presented in Table 4.

	2002 – 2008		2002 – 2013		2002 – 2018	
	Score	DM test	Score	DM test	Score	DM test
Combinations:						
Equal weights (Benchmark)	1		1		1	
Log weights	1.145	-1.633	0.963	0.839	1.061	-1.482
Optimal weights	1.018	-0.816	0.920	1.127	1.196	-5.605
Regression models:						
Multivariable model	0.793	-0.197	0.817	0.699	0.856	1.221
Taylor rule	0.914	-0.443	1.055	-1.400	1.093	-0.750
Lagged MPI	1.014	-0.891	1.189	-1.937	1.170	-0.315

Table 5: Rolling window out-of-sample forecast results. The log scores are relative to the benchmark. Numbers greater than 1 indicate a better score relative to the benchmark. The Diebold and Mariano (1995) test is asymptotically standard Normal. It tests the difference in scores between the benchmark and the other models.

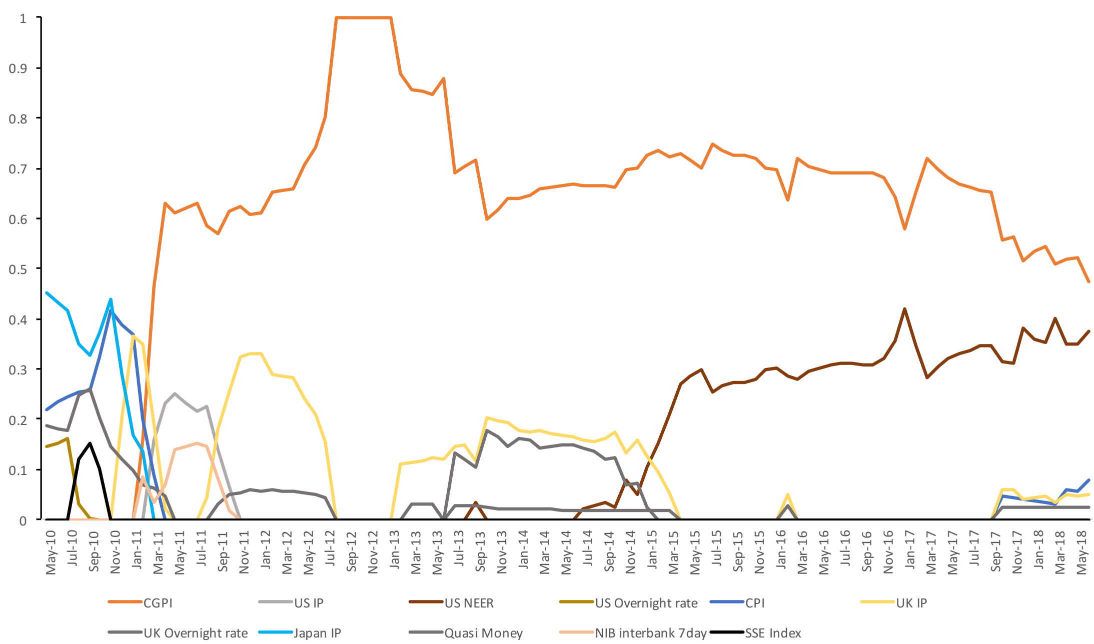

Figure 7: Optimal weights (rolling window) for the combination of univariate models for sample 2002 – 2018.

Figure 7 shows 11 main predictors that the optimal weights attributes some weights to during the 2002 – 2018 forecasting periods. Again the highest weights are given to CGPI and US NEER. The picture depicted is very similar to the one shown in Figure 5, and include similar predictors.

Additionally, the same density forecast combination methods have been applied for out-of-sample forecasts of the 7-day reverse repurchase rate, instead of the MPI. The optimally weighted method produced weights similar to forecasts of the MPI, with CGPI and US NEER being the heaviest weighted models. The results are available upon request.

5 Concluding remarks

This paper aims to forecast Chinese monetary policy stance using a forecast combination approach. Given the multiple instruments employed by the People's Bank of China, it is difficult to derive an overall monetary policy stance by analysing the adjustments made to a single instrument. This paper proposes an updated method to aggregate the observable adjustments of key policy instruments into a Monetary Policy Index. The MPI also features the increasingly important 7-day reverse repurchase rate.

The MPI is forecasted using information from 73 macroeconomic and financial predictors. A multivariate model composed of selected variables tracks the proposed MPI well. Furthermore, probability forecast combinations are shown to produce greater forecast accuracy out-of-sample rather than popular multivariate models, consistent with the findings of Vasnev et al. (2013) and Pauwels and Vasnev (2017). The optimally weighted forecast combination proves to be the best performing. Both corporate goods price index and the US nominal effective exchange rate are found to be the most important predictors in the forecast combinations.

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Appendix

Table A1: Complete dataset

Variable description	Group	Unit
Benchmark deposit rate	Policy	% pa
Benchmark lending rate	Policy	% pa
Reserve requirement ratio	Policy	% pa
Total Loan growth	Policy	% pa
7-Day reverse repurchase rate	Policy	% pa
RMB Nominal effective exchange rate	Exchange rates	% pa
RMB Real effective exchange rate	Exchange rates	% pa
Japan Nominal effective exchange rate	Exchange rates	% pa
UK Nominal effective exchange rate	Exchange rates	% pa
US Nominal effective exchange rate	Exchange rates	% pa
EU Nominal effective exchange rate	Exchange rates	% pa
RMB/USD exchange rate	Exchange rates	% mom
Medium-term lending facility: 1-year rate	Interest rates	% pa
Rediscount rate	Interest rates	% pa
Standing lending facility: 1-day rate	Interest rates	% pa
Euro Overnight interbank rate	Interest rates	% pa
Japan Overnight call rate	Interest rates	% pa
US Effective federal funds rate	Interest rates	% pa
UK Policy base rate	Interest rates	% pa
Overnight interbank offered rate	Interest rates	% pa
US Prime lending rate	Interest rates	% pa
NIB interbank 7-Day rate	Interest rates	% pa
SHIBOR: 3-month rate	Interest rates	% pa
10-year treasury bond yield	Interest rates	% pa
M1	Money	% pa
M0	Money	% pa
Quasi Money	Money	% pa
Net outstanding amount of central bank bills	Money	Bn RMB
Foreign reserves	Money	% pa

Table A1: Complete dataset

Variable description	**Group**	**Unit**
M2	Money	% pa
New loans in foreign currency	Money	% pa
New loans in local currency	Money	% pa
Total interbank loans	Money	% pa
Total financial institution loans	Money	% pa
Total financial institution deposits	Money	% pa
Industrial enterprise	Money	% pa
Total deposits	Money	% pa
Domestic credit	Money	% pa
House prices	Prices	% pa
Consumer price index	Prices	% pa
Corporate goods price index	Prices	% pa
Purchasing price index	Prices	% pa
Producer price index	Prices	% pa
Commodity building price average	Prices	% pa
UK Consumer price index	Prices	% pa
Japan Consumer price index	Prices	% pa
US Consumer price index	Prices	% pa
Europe Consumer price index	Prices	% pa
US Industrial production index	Prices	% pa
UK Industrial production index	Prices	% pa
Japan Industrial production index	Prices	% pa
Retail price index	Prices	% pa
Producer price index: Industrial products	Prices	% pa
Industrial production index	Prices	% pa
Industrial sales	Prices	% pa
Consumer confidence index	Prices	% pa
OECD Composite leading indicator	Prices	% pa
Foreign direct investment	Real activity	% pa
Government revenue	Real activity	% pa
Government expenditure	Real activity	% pa

Table A1: Complete dataset

Variable description	**Group**	**Unit**
Value added of industry (real)	Real activity	% pa
Production of primary energy	Real activity	% pa
Product sales rate	Real activity	% pa
Retail sales growth	Real activity	% pa
Fixed asset investment	Real activity	% pa
Real estate investment	Real activity	% pa
Motor vehicle sales	Real activity	% pa
Real GDP	Real activity	% pa
Nominal GDP	Real activity	% pa
Unemployment	Real activity	% pa
Business confidence	Real activity	% pa
Trade balance	Real activity	% pa
Shenzhen stock exchange index	Stock markets	% pa
Shanghai stock exchange index	Stock markets	% pa
Shenzhen market capitalisation	Stock markets	% pa
Shenzhen PE ratio	Stock markets	NA
Shanghai market capitalisation	Stock markets	% pa
Shanghai PE ratio	Stock markets	NA