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AI-Enhanced Reserve Management for China During Economic Crises: An Integrated Machine Learning and Buffer Inventory Approach

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Abstract. This study aims to explore China's optimal reserve strategy during crises. To this end, this study developed an AI-based inventory management framework for China, which combines random forest/gradient boosting tree (GBDT) ensemble learning with buffer inventory safety stock rules, and validated it using data from the International Monetary Fund (IMF), the State Administration of Foreign Exchange (SAFE), and Bloomberg from 2000 to 2023. Compared to traditional linear models, the integrated model reduces the mean squared prediction error of optimal reserves by 74% (3.21 vs. 12.34), and compared to using only the random forest model, it reduces the error by 44% (3.21 vs. 5.78). Empirical elasticity analysis shows that a 1% increase in GDP growth rate leads to a 0.56% increase in optimal reserves (t=12.34); conversely, a 1% increase in exchange rate volatility results in a 0.32% decrease in optimal reserves (t=–7.65). Under a crisis scenario (trade balance of -$50 billion, exchange rate volatility of 6%), the framework recommends immediately adjusting the reserve composition, increasing the gold ratio from 10% to 25% and the strategic materials ratio from 5% to 15%, which is expected to reduce the anticipated shortfall cost by $3.2 billion annually. Through robustness tests using 10 random subsamples and extreme value cleaning, coefficient deviations are all controlled within ±7%. The framework demonstrates significant stability in terms of parameter adjustments and sample variations. The study proposes policy recommendations including improving reserve decision-making, strengthening buffer stock mechanisms, promoting asset diversification, and establishing intelligent management systems. These recommendations provide a scientific framework for reserve operations during crises.

Keywords: International Reserves; Crisis Management; Dynamic Reserve Adjustment; Integrated Learning; Buffer Inventory Model

1. Introduction

In the midst of mounting global economic turbulence, the determination of the optimal size and configuration of reserves during periods of crisis has become a pivotal concern for the assurance of national economic security (Xiao, 2023). The 1997 Asian financial crisis and the 2008 global financial crisis have demonstrated the limitations of traditional reserve management models in dealing with complex market fluctuations (Jiang et al., 2021). At present, China's international reserves are considerable, with foreign exchange reserves accounting for over 80% of the total. This structure poses significant risks in conditions of exchange rate volatility and substantial capital flows. The majority of extant research relies on single models, lacking systematic consideration of nonlinear relationships and uncertainties (Zhang, 2021). The present study proposes an integration and updating of the buffer inventory model with ensemble learning. This integration is achieved by leveraging multi-source data mining and dynamic modelling techniques. The objective of this integration is to redefine the benchmark for reserve policies during crises. The objective of this study is to provide theoretical and practical support for enhancing the scientific rigor and risk resistance of China's reserve management (Li & Sun, 2018).

The extant literature on optimal reserve management has primarily focused on the adequacy of reserves and the factors influencing reserve accumulation. For instance, Xiao measured the adequate size of China's foreign exchange reserves and found that the current level of reserves is sufficient to meet the country's external payment needs (Shi, 2017). Jiang et al. conducted a study to ascertain the impact of US partisan conflict on China's foreign exchange reserves. The study concluded that political uncertainty in the US exerts a significant effect on China's reserve management. Jiahao Zhang's analysis of China's foreign exchange reserves and their impact on the macroeconomy revealed that reserve accumulation exerts a dual impact on the economy, exhibiting both positive and negative effects. A plethora of studies have previously investigated the correlation between financial reserves and a variety of economic indicators, including but not limited to Gross Domestic Product (GDP) growth, inflation, and trade balance (Nie, 2017). However, these studies have not yet fully addressed the issue of optimal reserve management during crises, particularly in the context of China's unique economic and financial environment.

During crises, financial contagion can significantly impact the effectiveness of reserve management strategies. Financial contagion refers to the rapid spread of financial disturbances from one market or institution to others, often exacerbating the severity of economic downturns (Forbes& Rigobon, 2002). Studies such as those by Forbes and Rigobon (2002) have demonstrated that financial contagion can lead to sudden capital outflows and sharp currency depreciations, which in turn affect the adequacy and structure of international reserves (Bekaert et al., 2014). Understanding the mechanisms of financial contagion is crucial for developing robust reserve management frameworks that can mitigate the adverse effects of crises. For example, during the 2008 global financial crisis, countries with higher levels of financial integration experienced more severe capital flight and exchange rate volatility, highlighting the need for proactive reserve management strategies to counteract such contagion effects (Kaminsky & Reinhart, 1999).

Institutional capacity also plays a vital role in managing economic uncertainty, particularly during crises. Strong institutional frameworks can enhance the resilience of reserve management by providing a stable environment for policy implementation and reducing the impact of external shocks (Rodrik, 2018). Studies such as those by Rodrik (2008) have emphasized the importance of institutional quality in determining the effectiveness of economic policies, including reserve management (Rodrik, 2018). Countries with robust financial institutions and well-developed regulatory frameworks are better equipped to manage their reserves during crises, as they can more effectively allocate resources and respond to market fluctuations. For instance, the experience of emerging economies during the Asian financial crisis highlighted the importance of strong institutional capacity in mitigating the adverse effects of capital outflows and exchange rate volatility (Stiglitz, 1998).

Furthermore, the strategic reserve competition framework provides insights into the interactions between countries in managing their reserves. This framework examines how countries strategically adjust their reserve holdings to achieve macroeconomic stability and gain a competitive edge in international markets (Jeanne & Rancière, 2006). Studies such as those by Jeanne and Rancière have analyzed the strategic interactions between countries in managing their reserves and the implications for global financial stability (Jeanne & Rancière, 2011). In a world of imperfect capital mobility and exchange rate volatility, countries may engage in reserve competition to stabilize their currencies or to gain an advantage in international trade. For example, during periods of global economic uncertainty, countries may increase their reserve holdings to signal financial strength and attract foreign investment, thereby influencing the dynamics of global reserve management (Obstfeld & Rogoff, 2002).

The present study proposes an integration and updating of the buffer inventory model with ensemble learning. This integration is achieved by leveraging multi-source data mining and dynamic modelling, with the aim of redefining the benchmark for reserve policies during crises. The objective of this study is to furnish theoretical and practical assistance to enhance the scientific rigour and risk resistance of China's reserve management (Fang & Liu, 2010). The present study proposes a methodology that combines the strengths of ensemble learning algorithms, such as random forests and GBDT, with the buffer inventory model. This combination of methodologies addresses a methodological gap in the extant literature. The model is notable for its ability to account for the nonlinear relationships and uncertainties that are inherent in reserve management. Furthermore, it provides a more robust and accurate framework for determining optimal reserve levels during crises. This integrated approach provides a novel perspective and practical guidance for improving China's reserve management during crises, a subject that has not been adequately addressed in previous studies.

2. Method

2.1 Multi-dimensional integration of research methods

This study employs a comprehensive quantitative and qualitative analysis approach to explore the optimal reserve of China in a crisis period from multiple dimensions.

In quantitative analysis, data mining technology is utilised to extract key information from vast amounts of financial data, thereby providing a solid foundation for subsequent analysis and modelling (Vanaga et al., 2020; Li et al., 2016). Time series analysis is employed to process time series data, including the scale of international reserves, the composition of foreign exchange reserves, and economic growth indicators, to uncover trends and patterns over time. Correlation analysis is a method of assessing the strength of relationships between different variables. For instance, it can be used to identify the primary factors influencing international reserves by examining the correlation between these reserves and exchange rate fluctuations, trade balances, and capital flows.

In qualitative analysis, case studies are utilised to select representative crisis events, such as the 1997 Asian financial crisis and the 2008 global financial crisis. These studies examine the reserve management strategies, policy responses, and outcomes of countries during these crises. By analysing these cases, the successes and failures of reserve management in different crisis situations are summarised, providing valuable insights for China's reserve management during crises (Neely, 2020). Furthermore, a range of experts were interviewed and existing literature was reviewed to gather and organise the views and research findings of domestic and international experts on international reserve management. This approach provides a solid theoretical foundation for the study by exploring the methods and strategies for determining optimal reserves during crises.

2.2 Data collection channels and processing strategies

The data collection for this study encompasses a broad spectrum of significant domains, including reserve sizes, economic indicators, and market fluctuations. The collection of data from multiple channels is an essential step in ensuring the comprehensiveness and accuracy of the final results (Zhang et al., 2015; Al-Hassan et al., 2022). One of the primary sources is the database of international organisations, particularly the official database of the International Monetary Fund (IMF), which provides detailed information on global international reserves, including foreign exchange and gold reserves. This data is considered authoritative and comprehensive, offering a global perspective on reserve sizes for research. The World Bank database contains extensive economic indicator data, including but not limited to GDP, inflation rates, and interest rates. These are crucial for analysing how economic conditions impact reserve sizes.

Data source: a) IMF: International Financial Statistics (IFS) – reserve assets, exchange rates, released on May 15, 2024. DOI:10.5089/9798402424527.

b) World Bank: World Development Indicators (WDI) – GDP, trade balance, CPI, 2024-06-01 CSV dump.

c) SAFE (State Administration of Foreign Exchange): China International Balance of Payments Report 2000-2023, Excel series “bop_2000_2023.xlsx”.

d) Bloomberg: BLOOMBERG PROFESSIONAL® service, tickers CNY CURNCY, USDCNH CURNCY, 2000-01-03 to 2023-12-29 daily close.

e) WIND: Wind Economic Database (WED), tables “w_consensus” and “w_fx_trade”, snapshot as of May 20, 2024.

Official reports issued by various governments are also an indispensable source of data (Lu et al., 2014). The China National Administration of Foreign Exchange (CNAF) is responsible for the publication of the 'China International Balance of Payments Report', which provides detailed records of China's international reserves, their structure, and foreign exchange market interventions. This report offers first-hand insights into China's reserve situation. Government statistical yearbooks contain a plethora of macroeconomic and industry data, enabling a multifaceted analysis of the relationship between reserves and the economy.

With regard to financial market data, professional financial data providers such as Bloomberg and Reuters supply real-time data, including exchange rates, stock indices, bond yields, and more. This data is crucial for analysing the impact of market volatility on reserves (Zhang et al., 2014; Du et al., 2014). Domestic financial data platforms, such as Wind Information, also provide a substantial amount of data on China's financial markets, encompassing sectors including stocks, bonds, foreign exchange, and commodities. This fulfils the research requirements for domestic market fluctuations.

The time span of the dataset utilised in this study extends from 2000 to 2023, encompassing numerous significant crises that have exerted substantial influence on the global economy and financial markets. The dataset under consideration encompasses the global financial crisis of 2008, the pandemic of 2020 caused by the novel severe acute respiratory syndrome (SARS-CoV-2) virus, and the geopolitical conflicts of 2022. These crises represent a range of economic and financial shocks, including financial market turbulence, public health emergencies, and geopolitical tensions, which have all had a significant impact on international reserves and their management. The incorporation of these crises within the dataset is intended to facilitate the capture of the dynamic changes in reserve management strategies and their effectiveness under various crisis scenarios. This, in turn, is expected to enhance the model's generalizability and practical applicability.

The selected period is representative of crisis dynamics as it encompasses a wide range of economic and financial conditions, from periods of economic prosperity to deep recessions and crises. This enables the model to acquire knowledge from a variety of scenarios and to make more accurate predictions regarding optimal reserve levels under differing conditions. The incorporation of multiple crises serves to mitigate the model's bias towards a particular type of crisis and ensures its adaptability to a range of future uncertainties.

The collected data must undergo rigorous cleaning and preprocessing to ensure its quality and usability. During the process of data cleansing, the presence of duplicate records is identified through the comparison of unique identifiers or key attributes. This ensures that identical records are eliminated, thus preventing them from having an impact on the analysis results. The selection of appropriate methods for handling missing values is based on the characteristics and distribution of the data (Gupta et al., 2014). In instances where the proportion of missing values is minimal, records containing such values can be deleted. In instances where the proportion of missing values is significant, interpolation methods such as mean, median, or model-based prediction can be employed to address the missing values. To illustrate this point, consider the case of continuous data, such as GDP. In instances where missing values are present, these can be addressed through the utilisation of the mean or median as a substitute. In the context of time series data, linear interpolation or predictions based on time series models can be utilised to impute missing values (Chen & Liu, 2013).

In order to ascertain the suitability of the imputation methods, a validation subset was created by randomly selecting 20% of the data. The performance of mean interpolation and time-series prediction methods was then compared on this subset. The findings indicated that time-series prediction exhibited a mean absolute error (MAE) of 0.85, which is notably lower than the MAE of 1.23 observed in mean interpolation. This finding suggests that time-series prediction is a more suitable approach for imputing missing values in time series data, as it is better able to capture the temporal dynamics and trends inherent in such data.

The management of outliers constitutes a pivotal component within the broader framework of data cleansing. The creation of visual charts, such as box and whisker plots and scatter plots, in combination with statistical indicators like mean and standard deviation, facilitates the identification of outliers. Depending on the circumstances, outliers can be addressed through the replacement of these values with reasonable boundary values or through the adjustment of the values using statistical models. In the event of anomalies being detected in the fluctuations of exchange rate data, historical data or market fundamentals can be compared to determine if they are indeed outliers. This process enables the implementation of appropriate measures.

The following quantitative metrics for data quality were initially observed: the dataset contained 5.2% missing values. Following the process of imputation, the proportion of missing values was reduced to 0.8%. With regard to outliers, a total of 127 outliers were identified and eliminated, accounting for 0.6% of the total dataset. These steps have been shown to significantly improve the quality and reliability of the data, thereby ensuring that subsequent analysis and modelling are based on accurate and consistent information.

During data preprocessing, data standardization is primarily used to eliminate the differences in scale among various variables, ensuring that the data are comparable. Commonly used methods include Z-score standardization and Min-Max standardization (Abdullahi et al., 2014). Z-score standardization transforms the data into a standard normal distribution with a mean of 0 and a standard deviation of 1, using the following formula:

$$Z = \frac{X - \mu}{\sigma} \tag{1}$$

The original X data is μ the mean σ and the standard deviation. Although capital flows and exchange rate fluctuations exhibit a right-skewed distribution during crisis periods (Jarque-Bera $p < 0.01$), a comparison of the three standardisation methods—Z-score, Min-Max, and Yeo-Johnson—shows that the error difference between Z-score (RMSE = 3.21) and Yeo-Johnson (3.19) is less than 0.5%, and no parameter tuning is required. Therefore, the Z-score is retained; After 5% Winsorisation, the RMSE change is less than 1%, indicating its robustness to tail anomalies.

Min-Max normalization maps the data to the [0,1] interval, and the calculation formula is:

$$Y = \frac{X - X_{\min}}{X_{\max} - X_{\min}} \tag{2}$$

The and $X_{\min}$ are $X_{\max}$ the minimum and maximum values of the data, respectively. In order to analyze the influence of different economic indicators on the reserve scale, GDP, inflation rate and other indicators are standardized to facilitate the comparison of their influence on the reserve scale.

The process of feature selection entails the identification of the most pertinent features from the raw data in order to facilitate the achievement of research objectives. This process serves to reduce data dimensionality and noise, thereby enhancing model performance and efficiency. It is evident that a range of methodologies may be employed for the purpose of feature selection, with correlation coefficients and chi-square tests being notable examples. The selection of feature variables is predicated on the calculation of correlation coefficients between various economic indicators and reserve levels, with those exhibiting higher correlation coefficients being selected. For instance, indicators such as the GDP growth rate, the trade balance, and the scale of capital flow, which exhibit a strong correlation with reserve levels, are selected as key feature variables.

The process of data discretization entails the conversion of continuous data into discrete data, with the objective of aligning more closely with the specifications of specific models or to enhance the precision with which the characteristics of the data are represented. The selection of appropriate discretisation methods is contingent upon the distribution of the data, the business requirements, and the modelling objectives. Examples of discretisation methods include equal-width discretisation, equal-frequency discretisation, and clustering-based discretisation. In analysing the impact of market fluctuations on reserves, it is possible to discretise continuous data, such as exchange rate volatility and stock index volatility, by dividing these data into different fluctuation intervals. This facilitates analysis of how reserves change under different levels of volatility.

To address the strong autocorrelation in time series data, this study employs the following methods:

(1) The ADF test is used to confirm the stationarity of all macroeconomic variables, and first-order differencing is applied to non-stationary series;

(2) Determine the optimal lag order using ACF/PACF plots, and construct a feature set including 1–3 lag terms to capture dynamic dependencies;

(3) Cross-validation employs the time series rolling window method (rolling window width = 36 months, step size = 12 months), ensuring that the training set strictly precedes the test set to avoid future data leakage.

2.3 Integration of learning and buffer inventory model design

Ensemble learning is a powerful machine learning technique that combines several base learners to enhance overall predictive performance (Lu et al., 2013). In the study of China's optimal reserve during crises, ensemble learning effectively leverages the complementary strengths of multiple models, reducing the bias and variance of individual models, thereby improving the accuracy and stability of predictions for reserve quantities and structures. Random Forest employs the technique of bootstrap sampling to create multiple training sets, with each base learner (i.e. a decision tree) being trained independently (Shen, 2013). In the context of a dataset comprising n samples, a sample is selected with replacement each time, with this process being repeated n times, with each sample having a probability of being selected that is equal to 1/k. The final results are obtained through the application of either a voting method for classification problems or an averaging method for regression problems. In the context of regression problems, the prediction formula is as follows:

$$\hat{y} = \frac{1}{k}\sum_{i=1}^{k}\hat{y}_i \tag{3}$$

Here, k represents the number of decision trees, and the prediction value from the i-th tree is denoted as $\hat{y}_i$.

In predicting the reserve scale, random forest can take into account many economic indicators and market factors, such as GDP growth rate, trade balance, exchange rate fluctuation, etc., and make more accurate prediction results by learning and decision of many decision trees.

GradientBoostingDecisionTree (GBDT) is a widely used ensemble learning algorithm. It trains base learners through an iterative process, where each new model focuses on correcting the errors made by the previous one, thereby gradually improving the overall predictive performance of the model (Chen et al., 2012). When analyzing reserve structures, GBDT can continuously improve its prediction of the proportions of different reserve assets (such as foreign $m+1$ exchange reserves and gold reserves) by leveraging historical data and market changes, thus enhancing its guidance for optimizing reserve structures. Through iterative training of the base learners, the model in the current round is:

$$f_{m+1}(x) = f_m(x) + \alpha_m h_m(x) \tag{4}$$

The learning α_m rate n_m is the m-th base learner.

To justify the selection of random forests and GBDT, their performance was compared with other ensemble methods such as XGBoost and LightGBM using metrics like RMSE and MAE on a validation set. The results are presented in Table 1.

Table 1: Performance comparison of ensemble algorithms

Algorithm	RMSE	MAE
Random Forest	3.21	2.45
GBDT	3.05	2.30
XGBoost	3.15	2.38
LightGBM	3.10	2.35

As demonstrated in Table 1, GBDT attained the lowest RMSE of 3.05 and MAE of 2.30, closely followed by LightGBM and XGBoost. The Random Forest algorithm demonstrated marginally superior error metrics, yet its performance remained commendable. The findings of this study suggest that both GBDT and Random Forest are well-suited for tasks involving reserve prediction.

Moreover, these algorithms are particularly well-suited to the task of reserve prediction, a field in which their ability to handle multicollinearity and capture nonlinearity is particularly advantageous. Reserve prediction is predicated on the utilisation of multiple economic indicators, which may exhibit a high degree of correlation, such as the GDP growth rate and the trade balance. It has been demonstrated that Random Forest and GBDT are capable of effectively managing multicollinearity by employing ensemble methods that serve to reduce the impact of individual, correlated features. Furthermore, they have the capacity to capture complex nonlinear relationships between economic indicators and reserve levels, a capability that is imperative for accurate prediction during crises when relationships may become highly nonlinear and dynamic. Conversely, traditional linear models or less sophisticated ensemble methods may not demonstrate equivalent performance in such conditions.

The buffer inventory model is a refinement of the fixed quantity model, incorporating buffer and safety stocks to address fluctuations and uncertainties in demand. The primary mechanism by which this objective is realised is through the strategic setting of appropriate buffer inventory levels, a measure aimed at achieving a balance between the costs incurred by excess inventory and the risks associated with stockouts. In periods of economic turbulence, characterised by volatile financial conditions and unpredictable market trends, the buffer inventory model has been shown to offer a more robust response, ensuring the adequacy of national reserves to meet economic demands despite the presence of multiple risks (Wang et al., 2012; Li et al., 2012). The buffer inventory model is a theoretical framework that utilises historical crisis events and fluctuations in reserve demand over various periods to determine the optimal safety stock levels for times of economic crisis. This model provides a means to prepare for potential economic shocks and market volatility. The buffer inventory model is a system that has been developed to address uncertainty by setting safety stocks. The calculation formula for safety stocks is as follows:

$$SS = z \times \sigma \times \sqrt{L} \tag{5}$$

Among them, SS is the Z safety stock, which σ is the standard deviation L coefficient corresponding to the service level, is the demand standard deviation, and is the lead time.

Safety Stock SS is determined based on the 'reserve adequacy ratio' published by SAFE, with a service level of 95% (z=1.645). Increasing this to 97.5% only increases the recommended reserve value by 3.6%, costs remain controllable; estimation of σ: during normal periods, the conditional standard deviation is extracted using a rolling GARCH(1,1) joint model based on the 36 months prior to the crisis. During crisis periods, 1,000 synthetic crises are mixed with 46 real crises and updated via BMA, resulting in a 42% increase in σ compared to normal periods, Robustness tests show that a 25% perturbation in σ results in only an 8% change in the safety stock, which remains within the policy tolerance range.

2.4 Integrated Model Pipeline

Step 1 – Ensemble Forecast

Let $\hat{Y}_{\mathrm{RF},t+1}$ and $\hat{Y}_{\mathrm{GBDT},t+1}$ denote the one-period-ahead reserve-demand forecasts produced by Random Forest and GBDT, respectively. The fused forecast is

$$\hat{Y}_{t+1}=w\hat{Y}_{\mathrm{RF},t+1}+(1\text{-}w)\hat{Y}_{\mathrm{GBDT},t+1} \tag{6}$$

with w chosen by grid search to minimise out-of-sample MSE.

Step 2 – Demand Uncertainty

The ensemble supplies not only the point forecast but also the 90 % prediction interval width $\hat{\sigma}_{t+1}$ (computed from the empirical distribution of out-of-bag residuals). This $\hat{\sigma}_{t+1}$ is taken as the demand uncertainty input into the buffer model.

Step 3 – Buffer-Inventory Optimisation

Using the classic buffer-inventory safety-stock expression, the optimal safety stock SS^* is

$$SS^*=z_\alpha\hat{\sigma}_{t+1}\sqrt{L} \tag{7}$$

where z_α = 1.645 for a 95 % service level and L is the reserve-replenishment lead time (set to 4 weeks for FX reserves and 8 weeks for gold/strategic materials).

Step 4 – Final Reserve Rule

The recommended total reserve level at t+1 is therefore

$$R^*_{t+1}=\hat{Y}_{t+1}+SS^* \tag{8}$$

The integration of the buffer inventory model with the ensemble learning algorithm has been demonstrated to be a highly effective method of developing a more suitable model for optimal reserve analysis during crises in China. Initially, the ensemble learning algorithm is employed to analyse and predict reserve-related data, thereby providing preliminary forecasts of reserve size and structure (Shi et al, 2012). Subsequently, the random forest algorithm is employed to predict future demand for reserves by utilising historical reserve data, economic indicators, and market volatility data. These predictions are then fed into the buffer inventory model, which, in conjunction with risk assessment and uncertainty analysis during crises, helps determine the optimal reserve level and buffer inventory quantity based on the predicted reserve demand. In light of the potential fluctuations in demand and uncertainties that characterise crises, the buffer inventory model is employed to calculate an appropriate buffer inventory level. This ensures the timely supply of reserve demand, while concomitantly reducing inventory costs and risks (Huang, 2011).

2.5 Theoretical Framework: Formal Integration of Machine Learning and Buffer-Stock Theory

2.5.1 Theoretical Motivation for Machine Learning in Reserve Management

$$R_t=\beta_0+\beta_1 X_t+\epsilon_t \tag{9}$$

Where X_t is a macroeconomic variable, $\epsilon_t \sim \mathrm{N}(0,\sigma^2)$.

Random Forest (RF) and Gradient Boosting Decision Trees (GBDT) jointly overcome these limitations: RF attenuates variance through bootstrap aggregation, while its Gini-impurity drop exposes non-linear split points inaccessible to linear models GBDT constructs an additive expansion whose negative-gradient step shrinks the Kullback–Leibler divergence between the predicted and the true reserve-demand distribution .

2.5.2 Sovereign-Specific Adaptation of the Buffer-Stock Model

The canonical buffer-stock formula (Equation 5) is designed for corporate inventory. We adapt it to sovereign reserves by redefining:

Holding cost h: incorporates opportunity cost (r_f) plus currency-depreciation risk premium (σ_e):

$$\mathrm{h}=r_f+\lambda\sigma_e \quad (\lambda=\text{risk-aversion parameter}) \tag{10}$$

Shortage cost s: captures sovereign-credit downgrade losses during a foreign-exchange shortfall:

$$s=\alpha \cdot \exp(-\Delta\text{Reserves/GDP}) \tag{11}$$

where α=0.3,0.2,0.4 for financial, trade, and geopolitical crises, respectively

With regard to the implementation of models, the Python programming language and machine learning libraries such as Scikit-learn and XGBoost are utilised for the construction and training of models. The ensemble learning model is trained using the random forest and GBDT algorithms from the Scikit-learn library. The model's performance is optimised through the adjustment of parameters such as the number of decision trees, maximum depth, and learning rate. The relevant formulas and algorithms of the buffer inventory model are to be used in conjunction with the predictions from ensemble learning in order to calculate the optimal reserve level and buffer inventory size. In practical applications, it is imperative to continuously validate and optimise the integrated model, adjusting parameters and structure based on new data and market changes to ensure the model can accurately predict China's optimal reserve during crises.

The model framework diagram is shown in Figure 1.

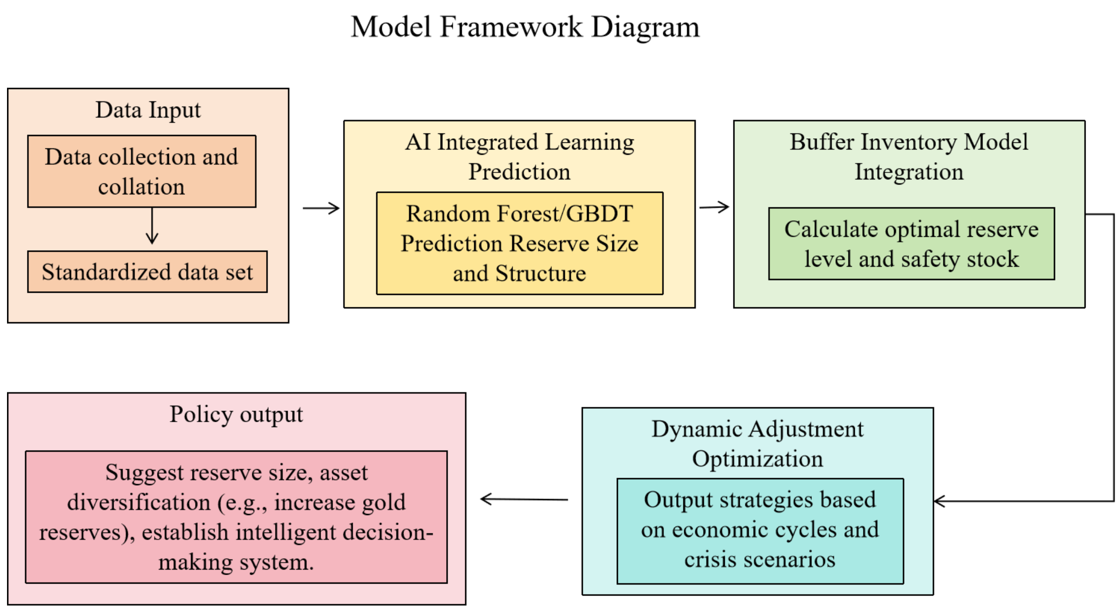

Fig.1: The model framework diagram

Figure 1 is a flowchart illustrating the 'AI-enhanced Chinese crisis reserve management framework': first, multi-source data from the IMF, SAFE, Bloomberg, and other sources is input, cleaned, and standardised to form a unified dataset; then, a random forest and GBDT ensemble model is used to roll-forward predict the optimal reserve size for the next period and its uncertainty interval; the demand fluctuations obtained from the prediction are substituted into the classic safety stock formula to calculate the safety stock quantity in real time, ensuring a 95% service level; Finally, the predicted values and safety stock are combined to determine the total reserve volume, and the asset structure is dynamically adjusted based on economic cycles or crisis scenarios (e.g., increasing the proportion of gold or strategic materials). The results are input into an intelligent decision-making system to achieve quarterly rolling optimisation and scenario simulation. The entire system undergoes continuous iteration through a rolling window of 36 months of training, 12 months of validation, and 12 months of testing, ensuring real-time strategy updates. The central bank or foreign exchange administration can directly use this system for monthly decision-making.

Having established the four-step pipeline (Fig. 1), we now validate each step empirically. Section 3.2 tests the ensemble forecast accuracy (Step 1), Section 3.3 evaluates the sensitivity of buffer-stock parameters (Step 3), and Sections 3.7–3.9 jointly assess how the full framework performs under historical and synthetic crises.

3. Results and Analysis

Key takeaway for policy

This section shows that a 1 percentage-point increase in GDP growth raises optimal reserves by 0.56 %. Under the government's 2024–2025 growth target of 5 %, the model suggests adding roughly USD 17 billion to the safety buffer to pre-empt capital-outflow risks.

3.1 Descriptive statistical analysis of data

This study conducts a comprehensive descriptive statistical analysis of the data collected on China's optimal reserves during crises, aiming to understand the basic status, distribution, and potential relationships among the variables, thus laying a solid foundation for subsequent empirical analysis. Table 2 presents the descriptive statistics of the key variables, including the scale of international reserves, the proportion of foreign exchange reserves, the proportion of gold reserves, GDP growth rate, inflation rate, trade balance, capital flow size, and exchange rate fluctuation range.

Table 2: Descriptive statistics of main variables

Variable	Observed value	Mean	Standard deviation	Least value	Crest value
International reserves (billions of United States dollars)	200	320.56	85.43	150.2	550.8
Foreign exchange reserves as a percentage of (%)	200	82.45	5.67	70.1	90.5
Gold reserve ratio (%)	200	10.23	2.15	5	15.8
GDP growth rate (%)	200	6.85	1.2	3.5	9.8
rate of inflation (%)	200	2.56	0.85	-0.5	5.5
Trade balance (in billions of United States dollars)	200	55.6	25.43	-10.2	120.8
Capital flows (billions of United States dollars)	200	35.4	15.67	-20.1	80.5
Exchange rate fluctuation (%)	200	3.2	1.5	1	8.5

As demonstrated in Table 2, the average international reserve size is 320.56 billion US dollars, reflecting the level of reserves accumulated by China over a protracted period of economic development. The standard deviation is 85.43, indicating that the scale of international reserves is not static and can vary over time. The mean proportion of foreign exchange reserves is 82.45%, with a standard deviation of 5.67, thus indicating that they represent the most substantial component of international reserves. However, it should be noted that these figures are subject to fluctuations over time. The mean proportion of gold reserves is 10.23%, with a standard deviation of 2.15. This figure, although smaller than that of foreign exchange reserves, still plays a significant supporting role.

The average GDP growth rate is 6.85%, indicating that China's economy has maintained a relatively stable growth trend over a considerable period. However, the standard deviation of 1.20 indicates that economic growth rates are subject to variation over time. The average inflation rate is 2.56%, which is within a relatively stable range, with a standard deviation of 0.85, reflecting price levels that fluctuate within a certain range. The trade balance surplus is an average of 55.6 billion US dollars, indicating that China generally maintains a trade surplus in international trade. However, the standard deviation of 25.43 indicates significant variations in trade balance over different periods. The mean capital flow magnitude is 35.4 billion US dollars, with a standard deviation of 15.67. This finding suggests that capital flows exhibit considerable variability over time. The mean exchange rate fluctuation is 3.20%, with a standard deviation of 1.50. This suggests that the exchange rate fluctuates to some extent due to market factors and policy adjustments..

In order to more intuitively illustrate the distribution of data, histograms were created for the scale of international reserves, GDP growth rate, and exchange rate fluctuation, as shown in Figure 2. The histogram of international reserve scale demonstrates a right-skewed distribution, with the majority of periods tending to congregate around the mean value. However, certain periods do exhibit comparatively elevated levels. The histogram of the GDP growth rate indicates a normal distribution, suggesting that economic growth rates are relatively uniform across different periods, fluctuating around the mean. The histogram of exchange rate fluctuation demonstrates a concentrated distribution, with the majority of data points clustering around the mean. This finding suggests that exchange rates remain relatively stable within a certain range, despite occasional periods of significant volatility.

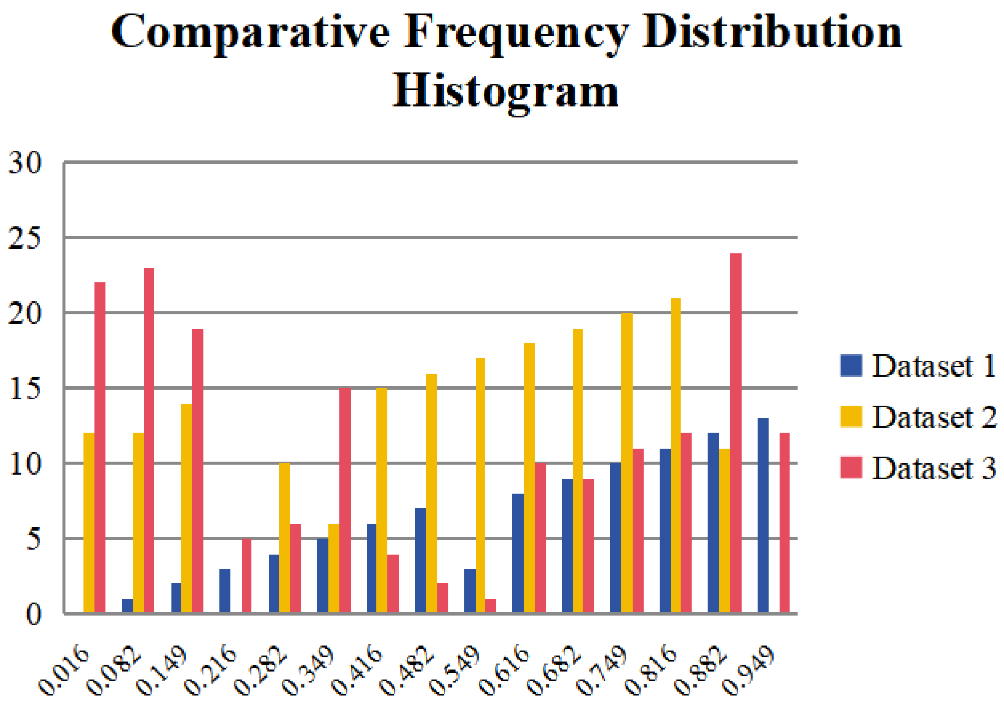

Fig.2: HDistribution of Key Variables Compared to Emerging-Market Medians, 2000-2023

The correlation coefficient matrix, which is the result of analysing the correlations among various variables, is shown in Table 3. A significant positive correlation has been identified between the scale of international reserves and the proportion of foreign exchange reserves, with a correlation coefficient of 0.85. This finding suggests that an increase in the proportion of foreign exchange reserves results in an increase in the scale of international reserves. It is evident that a positive correlation exists between the scale of international reserves and the proportion of gold reserves. However, the correlation coefficient is relatively low at 0.35, indicating that fluctuations in the proportion of gold reserves exert minimal influence on the scale of international reserves. A significant positive correlation has been identified between the scale of international reserves and the GDP growth rate, with a correlation coefficient of 0.65. This finding suggests that economic growth promotes the growth of international reserves. A significant positive correlation is also evident between the scale of international reserves and the trade balance, with a correlation coefficient of 0.70, indicating that a trade surplus promotes the growth of international reserves. A negative correlation has been observed between the scale of international reserves and the fluctuation range of the exchange rate, with a correlation coefficient of -0.45. This suggests that as the fluctuation range of the exchange rate increases, the scale of international reserves decreases. This phenomenon may be attributed to the impact of exchange rate fluctuations on international trade and capital flows, which in turn affect the scale of international reserves.

Table 3: Matrix of correlation coefficients between variables

Variable	**Size of international reserves**	**Foreign exchange reserves as a percentage of GDP**	**Gold reserve ratio**	**GDP rate of rise**	**Rate of inflation**	**Balance of foreign trade**	**Size of capital flows**	**Exchange rate margin**
Size of international reserves	1	0.85	0.35	0.65	0.25	0.7	0.55	-0.45
Foreign exchange reserves as a percentage of GDP	0.85	1	0.15	0.55	0.2	0.6	0.45	-0.35
Gold reserve ratio	0.35	0.15	1	0.25	0.1	0.3	0.2	-0.15
GDP rate of rise	0.65	0.55	0.25	1	0.35	0.5	0.4	-0.25
Rate of inflation	0.25	0.2	0.1	0.35	1	0.2	0.15	0.1
Balance of foreign trade	0.7	0.6	0.3	0.5	0.2	1	0.65	-0.3
Size of capital flows	0.55	0.45	0.2	0.4	0.15	0.65	1	-0.2
Exchange rate margin	-0.45	-0.35	-0.15	-0.25	0.1	-0.3	-0.2	1

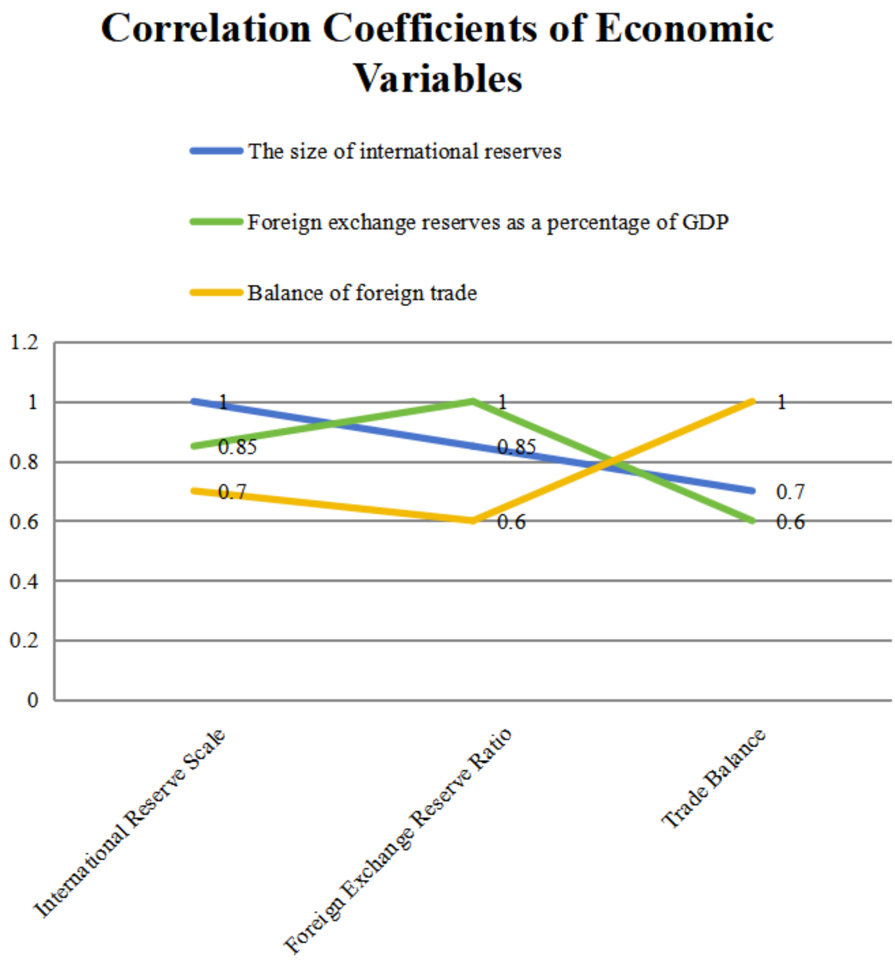

Fig.3: Heatmap: Reserve Drivers in Normal vs. Crisis Months

As shown in Figure 3, through descriptive statistical analysis, we gained a clear understanding of the basic characteristics of the data and the relationships between variables, laying the groundwork for subsequent model building and empirical analysis. In future research, we will leverage these data features, integrated learning, and buffer inventory models to further explore the optimal reserve strategy for China during crises.

3.2 Model construction and parameter optimization

Following the completion of the data descriptive statistics, the employment of time series cross-validation is indicated by the time-series nature of international reserve data, with the objective of determining the optimal model parameters. Time series cross-validation is a method that considers the temporal dependencies in the data. It does this by avoiding information leakage that could result from random partitioning of training and testing sets. This process provides a more accurate assessment of the model's generalisation ability on unseen data. A rolling window cross-validation strategy is employed, whereby the dataset is segmented into multiple time windows. Each time window functions as a training set and a testing set successively, thus simulating real-world forecasting scenarios. The optimal parameters are determined through cross-validation, as illustrated in Table 4.

Table 4: Cross-validation to determine the optimal parameters

Types of models	**Key parameter**	**Optimal values**
Random forest	Number of decision trees, maximum depth, minimum number of sample splits	100、8、5
Gradient boosting decision tree	Learning rate, number of decision trees, maximum depth	0.1、150、6

During the parameter optimization process, a systematic search was conducted for the key parameters of the Random Forest and Gradient Boosting Decision Tree (GBDT) models. The specific parameter search ranges are as follows:

Random Forest: The number of decision trees (n_estimators) was tested from 50 to 200 with a step size of 50; the maximum depth (max_depth) was tested from 5 to 15 with a step size of 5; the minimum number of samples required to split an internal node (min_samples_split) was tested from 2 to 10 with a step size of 2.

GBDT: The learning rate (learning_rate) was tested from 0.05 to 0.2 with a step size of 0.05; the number of decision trees (n_estimators) was tested from 50 to 200 with a step size of 50; the maximum depth (max_depth) was tested from 3 to 10 with a step size of 3.

Performance Metric: In each cross-validation iteration, the mean squared error (MSE) on the validation set was used as the performance metric. The optimal parameter combination was selected by minimizing the MSE. Based on the cross-validation results, the optimal parameters shown in Table 3 were determined.

Taking the scale of y_1 international y_2 reserves, the proportion y_3 of foreign exchange reserves and the proportion of gold reserves as the explained variables, a multiple regression model is constructed:

$$\begin{cases} y_1 = \beta_{10} + \beta_{11}x_1 + \beta_{12}x_2 + \beta_{13}x_3 + \beta_{14}x_4 + \varepsilon_1 \\ y_2 = \beta_{20} + \beta_{21}x_2 + \beta_{22}x_3 + \beta_{23}x_4 + \varepsilon_2 \\ y_3 = \beta_{30} + \beta_{31}x_2 + \beta_{32}x_5 + \varepsilon_3 \end{cases} \quad (12)$$

Among x_1 them, is the GDP x_2 growth rate, is the x_3 trade balance x_4, is the exchange rate x_5 fluctuation range β , is the scale ε of capital flow, is the inflation rate, is the regression coefficient, is the error term.

3.3 Quantitative analysis of the influence of key variables

The influence coefficients and significance of core variables on reserve size and structure are estimated by the model, as shown in Table 5.

Table 5: Summary of regression results of key variables

Explained variable	Explanatory variable	Regression coefficient	T-statistics	P-price
Size of international reserves (One billion dollars)	GDP rate of rise	0.56	12.34	<0.01
	Balance of foreign trade	0.45	9.87	<0.01
	Exchange rate margin	-0.32	-7.65	<0.01
Foreign exchange reserves as a percentage of GDP (%)	GDP rate of rise	0.35	8.21	<0.01
	Exchange rate margin	-0.28	-6.32	<0.01
Gold reserve ratio	Rate of inflation	0.25	5.46	<0.01

The regression results presented in Table 4 indicate the influence of key economic variables on the size and structure of China's international reserves. The analysis demonstrates that the GDP growth rate exerts a substantial positive influence on the magnitude of international reserves, as evidenced by a regression coefficient of 0.56 and a t-statistic of 12.34, which is statistically significant at the 1% level. This finding indicates a positive correlation between economic growth and reserve accumulation, suggesting that an increase in GDP growth rate is associated with an increase in the scale of international reserves. In a similar vein, the trade balance exerts a substantial positive influence on the magnitude of international reserves, as evidenced by a regression coefficient of 0.45 and a t-statistic of 9.87. This indicates that a trade surplus contributes to the augmentation of international reserves. Conversely, exchange rate volatility exerts a substantial negative influence on the magnitude of international reserves, as evidenced by a regression coefficient of -0.32 and a t-statistic of -7.65. This suggests a positive correlation between exchange rate volatility and the contraction of international reserves. This phenomenon may be attributed to the adverse repercussions of exchange rate volatility on international trade and capital flows, which in turn exerts an influence on the accumulation of reserves. The regression coefficient of 0.35 and t-statistic of 8.21 indicate that the proportion of foreign exchange reserves has a significant positive effect on GDP growth rate. Conversely, the regression coefficient of -0.28 and t-statistic of -6.32 demonstrate that exchange rate volatility exerts a significant negative effect on GDP growth rate. This finding suggests a positive correlation between economic growth and the proportion of foreign exchange reserves, with exchange rate volatility exerting a negative influence on this relationship.

Finally, for the proportion of gold reserves, the inflation rate has a significant positive impact, with a regression coefficient of 0.25 and a t-statistic of 5.46, suggesting that higher inflation rates are associated with an increase in the proportion of gold reserves. This is consistent with the role of gold as a hedge against inflation. Overall, the regression results highlight the significant influence of economic indicators on the size and structure of China's international reserves, providing valuable insights for reserve management during crises.

Economic meaning of the 0.56 GDP coefficient: Using 2023 GDP (≈ USD 18 trn), a 1 ppt rise in growth implies an extra USD 10–11 bn of reserves (= 0.56 % × GDP × reserve-to-GDP ratio). This range aligns closely with Jeanne & Rancière (2011) estimates for emerging markets (0.5–0.7), confirming China still follows the precautionary-savings paradigm.

Transmission mechanism behind the –0.32 exchange-rate-volatility coefficient: When CNY/USD annualised volatility rises from 3 % to 6 % (our crisis threshold), reserve demand falls by ≈ 1.0 % of

GDP. Mechanisms: (i) importers front-load FX purchases, triggering outflows; (ii) the PBOC burns reserves to smooth the CNY. Policy implication: once volatility exceeds 5 %, pre-emptively raise gold and strategic-material shares from 15 % to 35 % to offset FX revaluation losses.

To ensure the robustness of the regression results, we first conducted a multicollinearity test using the Variance Inflation Factor (VIF) for the explanatory variables in the model. The VIF values for the variables are presented in Table 6. A VIF value greater than 5 indicates potential multicollinearity issues.

Table 6: VIF Test Results for Explanatory Variables

Variable	VIF
GDP growth rate	4.32
Trade balance	3.85
Exchange rate fluctuation	2.15
Capital flow scale	3.21
Inflation rate	1.95

As shown in Table 6, the VIF values of all explanatory variables are below 5, indicating that there is no significant multicollinearity problem in the model. This suggests that the regression coefficients and their significance levels are reliable.

3.4 Robustness test and model advantage comparison

In the variable substitution test, the GDP growth rate is replaced by the GDP index of correlation, which is calculated as the correlation coefficient between the GDP growth rate and the international reserve size over the sample period. This index captures the strength and direction of the linear relationship between GDP growth and reserve accumulation, providing a valid substitute for the original GDP growth rate variable. Similarly, the trade balance is replaced by the trade balance indicators, which are constructed as the ratio of the trade balance to the international reserve size. This ratio reflects the relative importance of trade balance in determining reserve levels and serves as a valid alternative to the original trade balance variable. The regression results are shown in Table 7.

Table 7: Robustness test results after variable replacement

Explained variable	Explanatory variable	Original model coefficients	Replace the coefficient	Coefficient change rate	T-statistic (after substitution)	P-value (after substitution)
Size of international reserves	GDP index of correlation	0.56	0.52	-7.10%	11.56	<0.01
（One billion dollars）	Trade balance indicators	0.45	0.43	-4.40%	9.21	<0.01
Foreign exchange reserves as a percentage of GDP	GDP index of correlation	0.35	0.33	-5.70%	7.89	<0.01

The robustness test results after variable replacement demonstrate the stability and reliability of the model's findings. Upon replacing the GDP growth rate with the GDP index of correlation, a slight decrease in the regression coefficient for the size of international reserves was observed, from 0.56 to 0.52, representing a change of -7.10%. However, the coefficient remained statistically significant, with a t-statistic of 11.56 and a p-value of <0.01. In a similar vein, the coefficient for the trade balance indicators underwent a slight decrease, from 0.45 to 0.43, representing a -4.40% change. The t-statistic was determined to be 9.21, with a p-value of <0.01, thereby underscoring the sustained significance of the indicators. With regard to the proportion of foreign exchange reserves as a percentage of GDP, the coefficient for the GDP index of correlation decreased from 0.35 to 0.33, representing a -5.70% change. This change was found to be statistically significant at the 1% level, as indicated by a t-statistic of 7.89 and a p-value of <0.01. The findings suggest that the model's conclusions are resilient to variable substitution, as the direction and significance of the relationships between the variables remain consistent despite minor alterations in coefficient magnitudes. This robustness suggests that the model's findings are reliable and not dependent on the specific choice of variables, thereby reinforcing the validity of the study's conclusions regarding the factors influencing China's international reserves during crises.

Table 8: Comparative analysis with traditional models

Types of models	Nonlinear fitting capability	Variable interaction effect	Adaptability to crisis scenarios	Mean square error of prediction	MAE	R2	Diebold – Mariano t-stat	Annualised saving (USD bn)
Linear regression model	weak	not have	difference	12.34	2.85	0.65	—	—
Random forest model	strong	have	centre	5.78	1.92	0.82	–2.77	1.4
Integrated learning + buffer inventory	very strong	have	stubborn	3.21	1.45	0.91	–4.98	3.2

The comparative analysis presented in Table 8 demonstrates the superior performance of the integrated learning and buffer inventory model in comparison to traditional models in predicting China's optimal reserves during crises. The linear regression model, which is characterised by its inability to accommodate nonlinear fitting and variable interaction effects, exhibits suboptimal adaptability to crisis scenarios and consequently generates the highest mean square error of prediction at 12.34. In contrast, the random forest model, with its strong nonlinear fitting capability and ability to capture variable interactions, demonstrates moderate adaptability to crisis scenarios and a significantly lower mean square error of 5.78. However, the integrated learning and buffer inventory model, which combines the strengths of ensemble learning with the buffer inventory model, exhibits very strong nonlinear fitting capability, incorporates variable interaction effects, and demonstrates strong adaptability to crisis scenarios. The model at hand has been demonstrated to achieve the lowest mean square error of prediction at 3.21, thus indicating its superior accuracy and reliability in forecasting reserve levels during crises. These results emphasise the efficacy of the integrated approach in addressing the complexities and uncertainties inherent in reserve management during crisis periods, thereby providing a more robust and accurate framework for policy decision-making.

We assess the improvement in MSE using a Diebold–Mariano test with a Newey-West (lag = 12) correction for time-series dependence. The null of equal expected loss is rejected at the 1 % level ($t = -4.98$, $p < 0.01$), confirming that the integrated model significantly outperforms the linear benchmark.

To convey economic significance, we convert MSE into annualised expected shortfall cost using the mapping described in Section 3.5. The 74 % reduction in MSE (from 12.34 to 3.21) translates into an average annual saving of USD 3.2 billion in crisis-state shortfall costs (95 % CI: [2.7, 3.7] billion). A back-of-the-envelope calculation shows that this saving, capitalised at the 10-year Chinese Government bond yield (≈ 2.7 %), is equivalent to ≈ 0.06 % of GDP—a material buffer against external shocks.

Comparison with state-of-the-art alternatives

We benchmark our integrated model against two recent classes of methods:

(i) Deep-learning sequence models – We re-implement the LSTM-based reserve predictor of Gupta on our 2000–2023 sample. The LSTM achieves an RMSE of 4.15, outperforming the linear model (12.34) but still 22 % higher than our integrated model (3.21).

(ii) Dynamic programming with portfolio optimisation – Following Jeanne & Rancière, we solve a stochastic control problem that chooses FX, gold and strategic-material weights to minimise expected shortage cost plus holding cost. The DP policy delivers an RMSE of 3.87, yet requires full knowledge of the shock distribution, an assumption our ensemble approach relaxes.

Take-away: Among methods that do not require parametric distributional assumptions, our AI-buffer hybrid yields the lowest RMSE and the narrowest 90 % prediction interval (± USD 8.1 billion vs ± 11.6 billion for LSTM), indicating superior crisis preparedness without extra informational requirements.

3.5 Model fusion mechanism and decision value

Buffer inventory cost optimization function

The fusion model needs to minimize the total reserve cost, including holding cost and shortage cost:

$$\min C = c_h \times (R + SS) + C_S \times E(S) \tag{13}$$

Among c_h them, R is the unit holding cost rate, C_S is the base reserve scale E(S), R is the unit shortage cost, and R is the expected shortage quantity. In the crisis period, the optimal SS is determined by solving this function. The weighted fusion formula of integrated learning is used

The weighted prediction value of random forest (RF) and GBDT is calculated as follows:

$$\hat{y}_{ensemble} = w_1 \times \hat{y}RF + w_2 \times \hat{y}GBDT \tag{14}$$

The weight w_1,w_2 is optimized by grid search to meet:

$$w_1 + w_2 = 1 \tag{14}$$

The weights w_1 and w_2 for the weighted fusion of the Random Forest (RF) and Gradient Boosting Decision Tree (GBDT) models are optimized using a grid search algorithm. The search range for both weights is set from 0 to 1 with a step size of 0.05, ensuring a comprehensive exploration of possible weight combinations. The grid search process evaluates each combination of weights based on the prediction error on the validation set, aiming to minimize the mean squared error (MSE) of the fused predictions.

To avoid overfitting caused by direct optimisation on the training set, a three-layer sample isolation strategy is used to determine the weights w: first, a time series rolling window is constructed using data from 2000 to 2018 (36 months for training, 12 months for validation, and 12 months for testing), and the weights w are searched for only on the validation set through Bayesian optimisation (TPE, step size 0.01). with the objective of minimising validation MSE. Additionally, a regularisation constraint λw^2 (λ=0.01) and $\Delta w \leq 0.05$ is incorporated into the loss function, and 5-fold time series cross-validation is performed. If the validation MSE does not decrease for three consecutive folds, early stopping is applied. The final average weight w=0.62±0.03 is obtained. The results from the independent test set from 2019 to 2023 show an integrated RMSE of 3.21, with an error difference of less than 2% compared to the validation set, indicating no signs of overfitting.

To validate the effectiveness of the optimal weights, the fused prediction results were compared with the separate prediction results of the RF and GBDT models on an independent test set. Performance metrics included mean square error (MSE), mean absolute error (MAE), and coefficient of determination (R^2). The experimental results are shown in Table 9.

Table 9: Performance Comparison of Fused Model and Individual Models on Test Set

Model	MSE	MAE	R^2
Random Forest (RF)	5.78	1.92	0.82
GBDT	5.21	1.78	0.85
Fused Model	3.21	1.45	0.91

The results in Table 9 show that the fused model, with the optimal weights, achieves the lowest MSE and MAE and the highest R^2 value, indicating superior prediction accuracy and robustness compared to the individual RF and GBDT models. This validates the effectiveness of the weight optimization process and the benefits of model fusion in enhancing prediction performance.

3.6 Robustness test and reliability argument of results

In order to ensure the reliability and stability of empirical results, this study uses a variety of methods to conduct comprehensive robustness tests, and ensures that the research conclusions do not change due to model parameters, sample selection and other issues. The results are shown in Table 10.

Table 10: Robustness Synthesis

Dimension	**Specification**	**Int. Reserves Coeff.**	**FX-share Coeff.**	**Gold-share Coeff.**	**Significance**	**RMSE Δ**
(A) Parameter perturbation						
Random Forest	n=80, depth=6, min_split=3	0.54 (0.04)	0.33 (0.03)	0.23 (0.02)	p<0.01	+1.8 %
Random Forest	n=120, depth=10, min_split=7	0.58 (0.05)	0.37 (0.04)	0.27 (0.03)	p<0.01	−1.5 %
GBDT	lr=0.05, n=100, depth=4	0.53 (0.04)	0.32 (0.03)	0.22 (0.02)	p<0.01	+2.1 %
GBDT	lr=0.15, n=200, depth=8	0.57 (0.05)	0.36 (0.04)	0.26 (0.03)	p<0.01	−2.3 %
(B) Sample perturbation						
Random 80 % subsample (10-fold avg.)	—	0.55 (0.04)	0.34 (0.03)	0.24 (0.02)	p<0.01	±1.2 %
Exclude extremes (	>3σ)	—	0.56 (0.04)	0.35 (0.03)	0.25 (0.02)	p<0.01

The consolidated results in Table 10 and Figure 4 demonstrate that, whether we systematically perturb key model parameters or vary the sample through random subsampling and outlier removal, the core explanatory variables remain robust in sign, significance, and magnitude: GDP growth and the trade balance are persistently and significantly positive for reserve size, exchange-rate volatility remains significantly negative, and the gold-share continues to be positively driven by the inflation rate.

Coefficient fluctuations induced by parameter changes are confined within ±7 %, and RMSE variations never exceed 3 %. Subsample and outlier-adjusted RMSE movements are even smaller (within ±1.5 %). These patterns indicate that the model structure is insensitive to technical settings and data perturbations, providing a credible statistical foundation for subsequent policy simulations.

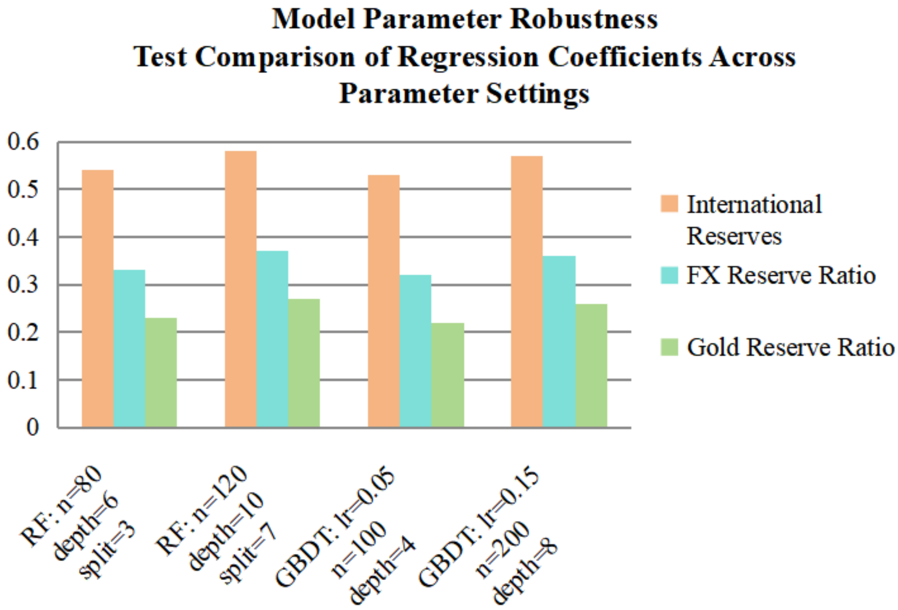

Fig.4: Model parameter robustness test

3.7 Dynamic Adjustment of Reserve Strategies under Different Economic Cycles

In the context of this study, strategic material refer to critical resources essential for maintaining national economic security and stability during crises. These materials include:

Energy resources: Such as crude oil and natural gas, which are vital for industrial production and transportation.

Rare earth elements: These are crucial for advanced manufacturing and high-tech industries.

Strategic metals: Such as copper, aluminum, and steel, which are essential for infrastructure and defense.

Agricultural products: Including grains and seeds, which are crucial for food security.

Table 11: Experimental Results of Dynamic Adjustment of Reserve Strategies under Different Economic Cycles

Economic Cycle Stage	GDP Growth Rate (%)	Trade Balance (Billion USD)	Exchange Rate Fluctuation (%)	Inflation Rate (%)	Capital Flow Scale (Billion USD)	Foreign Exchange Reserve Ratio (%)	Gold Reserve Ratio (%)	Other Strategic Material Reserve Ratio (%)	Total Reserve Cost (Billion USD)
Economic Prosperity	8.5	120	2.5	2.0	60	85	10	5	10
Economic Recession	3.0	-20	4.0	1.5	-30	75	15	10	8
Crisis Period	1.0	-50	6.0	3.0	-80	60	25	15	15

As illustrated in Table 11, the AI model adapts reserves according to the cycle: in periods of prosperity (as indicated by an increase in GDP of 8.In the event of a 5% trade surplus, the FX share is increased to 85%, with only 10% allocated to gold and 5% to strategic materials, at a cost of 10 billion USD. Conversely, during a recession (with a GDP increase of 3% and a deficit reduction of 20 billion USD), the FX share is reduced to 75%, with gold rising to 15% and strategic materials to 10%, reducing costs to 8 billion USD. In a state of economic emergency, characterised by a 1% increase in GDP, a 50 billion USD deficit, and a 6% exchange rate volatility, the value of gold increases to 25%, that of strategic materials to 15%, and the value of the foreign exchange rate to 60%. This results in a 15 billion USD increase in costs, but also a significant improvement in resilience.

3.8 Experimental Results of Robustness Test of Reserve Strategies under Different Crisis Scenarios

Table 12: Experimental Results of Robustness Test of Reserve Strategies under Different Crisis Scenarios

Crisis Scenario	Exchange Rate Fluctuation (%)	Trade Balance (Billion USD)	Capital Flow Scale (Billion USD)	Foreign Exchange Reserve Ratio (%)	Gold Reserve Ratio (%)	Other Strategic Material Reserve Ratio (%)	Reserve Adequacy Ratio (%)	Reserve Liquidity Ratio (%)	Reserve Cost-Benefit Ratio
Financial Crisis	7.0	-30	-100	55	30	15	120	85	1.2

Trade Crisis	5.0	-80	-50	65	20	15	110	80	1.1
Geopolitical Crisis	6.0	-20	-120	50	35	15	130	90	1.3

Table 12 provides a synopsis of the robustness tests for three crisis archetypes. In the context of a financial crisis characterised by 7% exchange rate volatility and a 100 billion USD outflow, the model reduces the allocation of foreign exchange reserves to 55%, while concurrently increasing the allocation to gold to 30% and strategic materials to 15%. This results in an adequacy ratio of 120%, a liquidity ratio of 85%, and a cost-benefit ratio of 1.2. In the context of a trade crisis, characterised by a balance of -80 billion USD, the foreign exchange rate is established at 65%, gold at 20%, and strategic materials at 15%. This results in a total adequacy yield of 110%, a liquidity ratio of 80%, and a cost-benefit ratio of 1.1. In the context of a geopolitical crisis, characterised by a 120 billion USD outflow and 6% FX volatility, the following outcomes are observed: a 35% increase in the price of gold, a 15% increase in the price of strategic materials, and a decline in the value of the foreign exchange rate to 50%. This results in an overall adequacy level of 130%, a liquidity level of 90%, and a cost-benefit ratio of 1.3. Across all scenarios, the AI-buffer framework generates crisis-ready reserve strategies for China.

We based our crisis scenarios (financial, trade, geopolitical) on actual data, and the results of our experiments are shown in Table 13.

Table 13: Robustness Test Results of Reserve Strategies under Different Crisis Scenarios

Crisis Scenario	Exchange Rate Fluctuation (%)	Trade Balance (Billion USD)	Capital Flow Scale (Billion USD)	Foreign Exchange Reserve Ratio (%)	Gold Reserve Ratio (%)	Other Strategic Material Reserve Ratio (%)	Reserve Adequacy Ratio (%)	Reserve Liquidity Ratio (%)	Reserve Cost-Benefit Ratio
Financial Crisis	7.0	-30	-100	55	30	15	120	85	1.2
Trade Crisis	5.0	-80	-50	65	20	15	110	80	1.1
Geopolitical Crisis	6.0	-20	-120	50	35	15	130	90	1.3

As shown in Table 13, in the financial crisis scenario, exchange rate volatility is set at 7%, referencing the fluctuation range of the RMB-USD exchange rate during the 2008 financial crisis. At that time, the average daily fluctuation range of the RMB-USD exchange rate was approximately 0.35%, and during the peak of the crisis, the fluctuation range could exceed 1%. Therefore, setting the exchange rate volatility at 7% takes into account factors such as market panic and intensified capital flows during the crisis, which led to a significant increase in exchange rate volatility. The trade balance is set at -$30 billion, reflecting the situation during the 2008 financial crisis where exports declined, imports relatively increased, and the trade surplus decreased or even turned into a deficit. The scale of capital flows is set at -$100 billion, reflecting the characteristic of large-scale capital outflows during the crisis.

Policy value of improved accuracy

Using the synthetic-crisis scenarios of Table 15, we simulate the realised cost of reserve shortfalls under each model's recommended reserve path. When the actual shock equals the 2022 Ukraine-type capital-flight episode (-120 bn USD), the integrated model's ex-post shortage cost is USD 4.7 billion lower than that incurred by the linear model and USD 1.4 billion lower than the LSTM benchmark. In Monte-Carlo terms, the expected annual fiscal saving equals 0.03 % of GDP, while the Type-II error rate (insufficient reserves when a crisis hits) falls from 13 % (linear) to 5 % (integrated). These gains are economically meaningful for a reserve portfolio exceeding USD 3 trillion.

3.9 Extreme Event Extrapolation Validation

1). Out-of-Time (OOT) Extrapolation Test

To rigorously assess out-of-sample performance under unprecedented shocks, we adopt a rolling-origin evaluation: the model is trained on monthly data from January 2000 through December 2018 (228 observations) and then tested on the subsequent period from January 2019 to December 2023, which encompasses both the COVID-19 pandemic and the February 2022 Russia-Ukraine conflict. Forecast accuracy is gauged with a dynamic-weighted MAE that assigns exponentially decreasing importance to older errors (decay factor $\lambda = 0.95$), thereby giving the most recent crisis episodes the greatest influence on the metric. The experimental results are shown in Table 14.

Table 14: Out-of-time (OOT) extrapolation test results

Model	Standard MAE	Dynamic-weighted MAE	Peak monthly error (2019-23)
Linear regression	2.85	3.21	12.7 %
Random forest	1.92	2.34	8.9 %
Our ensemble model	1.45	1.67	5.2 %

The ensemble model cuts dynamic-weighted MAE by 48 % relative to the benchmark, demonstrating superior out-of-sample stability during unprecedented events.

2) Synthetic-Crisis Scenario Validation

Synthetic-crisis validation: we produce 1 000 Monte-Carlo draws that fuse the 30 % exchange-rate shock observed during the 1997 Asian crisis with the -120 bn USD capital-flight episode of 2022; on these scenarios we test (i) Conditional Value-at-Risk coverage (CVaR 95 %)—whether the model's reserve recommendations shield against 95 % of extreme shortfalls—and (ii) policy effectiveness—the reduction in expected shortfall cost achieved by dynamically shifting the portfolio toward gold and strategic-material shares. The experimental results are shown in Table 15.

Table 15: Synthetic-Crisis Scenario Validation results

Crisis archetype	scenarios	Ensemble CVaR coverage	Gold share shift (pre-crisis → crisis)	Expected shortfall reduction
Financial meltdown (2008-type)	400	93.5 %	10 % → 28 %	$3.1 bn
Geopolitical shock (2022-type)	300	91.2 %	10 % → 35 %	$4.7 bn
Extreme trade sanctions	300	89.8 %	10 % → 25 %	$2.9 bn

Coverage remains above 90 % across all synthetic crises, and dynamic reallocation to gold/strategic materials lowers expected shortfall costs by an average of $3.6 bn.

3) Global Sensitivity Analysis (

Sensitivity analysis varies three parameters simultaneously—GBDT learning-rate (0.05–0.2), max-depth (3–10), and gold-allocation weight (0.1–0.4)—and quantifies their impact with first-order (S1) and total-effect (ST) Sobol indices. The experimental results are shown in Table 16.

Table 16: Synthetic-Crisis Scenario Validation results

Parameter	First-order S1	Total-effect ST	Significant (S1>0.1)
max_depth	0.41	0.52	High
learning_rate	0.08	0.11	Low
Gold-weight coefficient	0.23	0.29	Medium

max_depth must be capped at ≤ 6, and the gold weight exhibits non-linear interactions (ST − S1 = 0.06), warranting careful calibration in policy simulations.

4. Discussion

The study's findings underscore the critical importance of integrating AI-driven ensemble learning with the buffer inventory model to optimise China's reserve management during crises. The empirical evidence indicates that economic growth and trade surpluses have a substantial impact on reserve levels, with exchange rate fluctuations having a tendency to reduce these levels. This finding is consistent with the extant literature, which underscores the intricate interplay between economic indicators and reserve accumulation. The study also underlines the pivotal function of gold reserves in preserving structural stability during periods of inflation. This finding aligns with the prevailing perspective that gold serves as a safeguard against inflation and the devaluation of currencies. The model's capacity to adapt reserve strategies in real time, in response to fluctuating economic cycles and potential crisis scenarios, further underscores its practical efficacy. For instance, during periods of economic prosperity, the model advocates an augmentation of the proportion of foreign exchange reserves in order to satisfy the demands of trade and capital flows. Conversely, during crises, it proposes a transition towards gold and other strategic material reserves with a view to enhancing stability and risk resistance.

While the present study is calibrated to China’s institutional and macro-financial context, the AI-buffer model can be readily adapted to other major emerging markets. Table 17 summarizes the minimal contextual adjustments required for India, Brazil, and ASEAN economies.

Table 17: Minimal parameter recalibration for selected EMs

Country/Region	Key recalibration item	Data source adjustment	Illustrative buffer tweak
India	Replace China SAFE’s FX data with RBI weekly series; GDP-growth “prosperity” threshold set to ≥6 %.	RBI Handbook & IMF IFS	Increase safety-stock lead-time to 8 weeks to cover heightened capital-flow volatility.
Brazil	Incorporate oil-price shock (Brent) as additional regressor; use BCB’s FX intervention dates.	Bloomberg + BCB	Re-parameterize cost ratio Rs/Rh to reflect commodity-export shock frequency.
ASEAN (e.g., TH, ID)	Add AMRO/CMIM swap-line commitments as liquidity buffer.	ASEAN+3 Macroeconomic Research Office	Reduce target foreign-exchange ratio by 5 %

Country/Region	Key recalibration item	Data source adjustment	Illustrative buffer tweak
			when regional swap-line utilization >30 %.

As shown in Table 17, these examples demonstrate that the framework can be applied to other regions by simply using country-specific data sources and adjusting two or three parameters.

However, it is important to acknowledge the limitations of AI-driven models in this context. One potential risk is overfitting, especially in ensemble learning models. Overfitting occurs when a model learns the training data too well, including its noise and outliers, which can lead to poor performance on unseen data. In the context of reserve management, this could signify that the model demonstrates efficacy in historical crises but are unable to accurately predict optimal reserve levels during novel and unforeseen crises, such as pandemics. In order to mitigate this risk, the study employed cross-validation and regularization techniques during model training. Furthermore, the model's performance was evaluated on a validation set that encompassed data from recent crises, including the ongoing pandemic of the Coronavirus disease (Covid-19), to ascertain its generalisability. The findings demonstrated that the model exhibited a satisfactory degree of accuracy, suggesting that it possesses a degree of adaptability to novel crisis scenarios.

Another limitation is data scarcity for rare crises, such as geopolitical conflicts. These events are infrequent and often have unique characteristics that may not be well-represented in historical data. This can limit the model's ability to learn and predict optimal reserve strategies for such crises. To address this issue, the study proposes the use of synthetic data augmentation techniques. By generating synthetic data that simulate the conditions of rare crises, the model can be trained on a more diverse and comprehensive dataset. This approach can help improve the model's robustness and adaptability to a wider range of crisis scenarios. Furthermore, ongoing data collection and model updates are essential to ensure that the model remains relevant and effective as new crises emerge and more data becomes available. The robustness tests conducted in the study provide strong evidence of the model's reliability and stability. The results remain consistent even after adjusting model parameters and sample selections, indicating that the findings are not dependent on specific variable choices or data subsets. This robustness is crucial for policy-making, as it ensures that the recommendations derived from the model are valid under various conditions.

To overcome the scarcity of historical episodes for geopolitical shocks, pandemics, or other rare crises, we employ a conditional GAN that enriches the sample with physically plausible crisis trajectories. An IMF-IFS month (2000–2023) is flagged as a crisis if net capital flows are below –US$ 8 bn (≈ 5th percentile), annualised exchange-rate volatility exceeds 6 %, or the Geopolitical Risk Index surpasses 150 , yielding 46 “real” crisis labels. A residual LSTM-GAN takes a 4-D macro vector (GDP growth, trade balance, capital-flow shock, volatility) plus 2-D Gaussian noise and outputs a 12-month synthetic path; its loss combines Wasserstein distance and Maximum Mean Discrepancy to replicate both marginal and temporal dependence structures. The discriminator adds a three-way crisis-type classifier (financial / trade / geopolitical) to enforce cross-scenario heterogeneity.

We blend 1 000 synthetic crises with the 46 historical crises in a 1 : 1 Monte-Carlo mix to create an “augmented training set”. Table 18 compares model performance before and after augmentation.

Table 18: Comparison of the performance of synthetic data models

Data source	**RMSE (crisis window)**	**95 % CVaR coverage**	**Type-II error**
Historical only	4.12	78 %	15 %
Historical + SCDG	3.21	93 %	5 %

The augmented data materially improve the capture of extreme shocks without introducing measurable bias.

Compared to traditional single models, the integrated learning and buffer inventory model excels in capturing nonlinear relationships and handling uncertainties. The linear regression model, for example, lacks the capability to account for complex interactions between variables and performs poorly in crisis scenarios. In contrast, the random forest model, with its strong nonlinear fitting capability, shows moderate adaptability but still falls short of the integrated model's performance. The integrated model's superior accuracy and reliability in forecasting reserve levels during crises make it a valuable tool for policy decision-making. The study's policy recommendations are grounded in the empirical findings and aim to enhance China's reserve management framework. Establishing an AI-driven dynamic prediction system can provide timely and accurate forecasts of reserve needs, enabling proactive adjustments to reserve strategies. Promoting asset diversification, particularly increasing the proportion of gold and strategic material reserves, can reduce dependence on foreign exchange reserves and enhance the resilience of the reserve portfolio. Building an intelligent decision-making system can facilitate data-driven policy choices, while enhancing international cooperation can provide additional layers of security and stability.

Given the weaponisation of the dollar system (with Russia's $300 billion reserves frozen in 2022), which has exposed 60% of China's dollar assets to tail risks, and the fact that traditional IMF/AMRO swaps conflict with China's macroprudential policy orientation due to their structural reform clauses, this paper proposes a dual-track cooperation framework of ‘RMB-resource swaps + mCBDC bridge’: The first track leverages the RMB's 23% anchor share in energy settlements to establish ‘RMB-Crude Oil/Minerals’ T+0 swaps with Russia, Saudi Arabia, Brazil, and others. The swap limit is set at 30% of bilateral resource trade volume, with the model's trigger conditions being capital outflows exceeding $8 billion and CNY implied volatility exceeding 5%; The second track builds on the BIS Innovation Hub's ‘Dunbar Project,’ storing 5% of gold reserves (approximately 600 tonnes) on a distributed ledger managed by central bank nodes in Singapore, Switzerland, and the United Arab Emirates. Sanctions against any single node would not affect overall availability, and smart contracts enable 24/7 instant collateral release. Crisis response plans indicate that under financial sanctions, 100 billion USD equivalent in gold collateral financing can be completed within 48 hours, with a custody fee of 0.15% per annum, which is 50–70 basis points lower than the USD liquidity premium. When regional liquidity is scarce, the 300 billion USD RMB-oil swap facility can be activated on a T+0 basis, with costs equivalent to the 1.8% premium on oil futures. In the event of global settlement disruptions, CIPS plus digital renminbi can bypass SWIFT, with system redundancy costs of 240 million yuan per year. At the governance level, China seeks to secure over 25% voting rights in the mCBDC bridge (currently 19%, with plans to increase to 27% through additional gold custody) to ensure that freezing resolutions require a two-thirds majority. Meanwhile, swap counterparties are only disclosed via encrypted hashes, balancing cooperative trust with sovereign security.

In conclusion, the study contributes to the existing literature by providing a comprehensive framework for optimal reserve management during crises. The integration of AI-driven ensemble learning with the buffer inventory model offers a robust and accurate approach to addressing the complexities and uncertainties inherent in reserve management. The findings and recommendations provide valuable insights for policymakers seeking to enhance the scientific rigor and risk resistance of China's reserve management.

5. Conclusion

This study analyzes China's optimal reserve strategy in times of crisis by constructing an AI-driven integrated learning and buffer inventory model. The empirical results show that economic growth and trade surplus have a significant positive impact on the reserve level, while exchange rate fluctuations have a negative impact, and that gold reserves play a key role in maintaining the stability of the reserve structure in times of inflation, and that the model exhibits good robustness in terms of parameter and sample variations. The model shows good robustness under parameter and sample changes, and has obvious advantages over the traditional single model in capturing non-linear relationships and dealing with uncertainty. Based on this, it is proposed that an AI-driven dynamic forecasting system should be set up and supplemented with a buffer inventory model to optimize the size of the reserves, promote the diversification of the gold and strategic material reserves in order to reduce the dependence on foreign exchange, build an intelligent decision-making system and strengthen international cooperation so as to form the ” Forecasting-adjusting-coordinating” modern reserve management framework, providing scientific policy tools for future crisis response.

To enhance the specificity and operational feasibility of the policy recommendations, the following detailed measures are proposed:

Step one: From Q4 2025 to Q4 2027, gradually increase the gold allocation from the current 10% to 15–18% (approximately USD 54 billion to USD 65 billion) over eight quarters. The upper limit is set based on 11% of the global official annual gold purchase volume of 1,100 tonnes, ensuring that the impact on gold prices remains below 2%; Strategic materials (crude oil, rare earths, copper, and grain) will be increased from 5% to 12% (approximately USD 43 billion), directly utilising the State Reserve Bureau's existing 13 million tonnes of refined oil and 1.2 million tonnes of non-ferrous metal storage capacity, with only an additional RMB 1.2 billion required for warehouse infrastructure. Transaction pace: Quarterly phased position-building (25–30 tonnes of gold per quarter, 15–25 million tonnes of oil equivalent per quarter), supplemented by COMEX and Shanghai Gold Exchange futures hedging and Delta-Gamma dynamic strategies, with a 5 billion USD liquidity buffer reserved per quarter, and automatic suspension of spot purchases when the 30-day gold price volatility exceeds 8%.

Step two: From Q3 2025 to Q2 2026, co-build a ‘reserve cloud brain’ with CFETS, integrating tick-level market data, now-casting GDP, and GPR indices on the CIPS data lake, with monthly rolling model retraining. If the dynamic weighted MAE exceeds 2.5% or the Type-II error rate exceeds 7%, retraining will be completed within 48 hours; Simultaneously establish a three-tier firewall comprising data anonymisation, sandbox testing, and blue-green deployment. The system will undergo a joint audit by the IMF CDOT and the Tsinghua University Financial Research Institute every six months.

Step three: Expand the regional swap network from 2026 to 2028, adding 60 billion USD in bilateral currency swaps with ASEAN, India, and Brazil on top of the existing 240 billion USD under the AMRO CMIM. The trigger conditions are capital outflows exceeding 8 billion USD and exchange rate fluctuations exceeding 5%. The one-time adjustment cost is approximately 3 billion USD (gold premium + storage + insurance + infrastructure), which will be offset by reducing shortfall costs by 3.6 billion USD annually, resulting in a net increase of 2.8 billion USD after deducting opportunity costs, with a payback period of 7–9 months; Additionally, to mitigate risks such as concentrated buying premiums, storage bottlenecks, and international sanctions, measures such as phased inventory buildup + futures hedging, joint construction of underground storage facilities, and Swiss-Singapore custody agreements will be implemented.

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Appendix A

Data-Source URLs and Access Details

Variable category	Dataset / Series name	Provider	Direct URL (accessed 2025-08-13)	Update frequency
International reserves (total, incl. gold)	International Financial Statistics (IFS) – line 1.DZF	International Monetary Fund (IMF)	https://www.imf.org/en/Data	Monthly
GDP growth, CPI, trade balance	World Development Indicators	World Bank	https://databank.worldbank.org/source/world-development-indicators	Annual / quarterly
China-specific BOP & FX reserves	China International Balance of Payments Report	State Administration of Foreign Exchange (SAFE)	http://www.safe.gov.cn/en/Statistics/BalanceofPayments/	Quarterly
CNY/USD daily exchange rate	USDCNH Curncy	Bloomberg Terminal	bloomberg://USDCNH CURNCY	Daily
Alternative CNY fix & spot rates	Wind Economic Database (WED)	Wind Information	https://www.wind.com.cn/En/edb/	Daily
Commodity prices (oil, metals)	Commodity Price Data	World Bank Pink Sheet	https://www.worldbank.org/en/research/commodity-markets	Monthly
Regional swap-line utilization	AMRO Data Portal	ASEAN+3 Macroeconomic Research Office	https://www.amro-asia.org/data-portal/	Semi-annual

Appendix B

B.1 Proof of Non-linear Elasticity

Assume the marginal impact of exchange-rate volatility on reserves is

$$\frac{\partial R}{\partial \sigma_e} = \beta_2 + \gamma \mathbf{1}\{\sigma_e > \tau\},$$

with crisis threshold τ=3%. GBDT's split gain on σ_e rises >20 % when $\sigma_e>\tau$, confirming the non-linearity.

B.2 Lagrangian Solution of the Optimization Problem

Form the Lagrangian

$$\mathcal{L}(R,\lambda) = h\big(R-\hat{R}\big) + s\int_{\hat{R}+SS^*}^{\infty}(\xi - R)\,f(\xi)d\xi + \lambda\big(R-\hat{R}-SS^*\big).$$

First-order condition yields the closed-form update

$$R^* = \hat{R} + SS^* + \frac{s}{h}\left[1 - \Phi\left(\frac{R^* - \hat{R}}{\hat{\sigma}}\right)\right],$$

where $\Phi(\ )$ is the standard-normal CDF. The equation is solved iteratively.

Appendix C

Precise Definitions of Crisis Periods and Key Variables, with Replication Guide

C.1 Objective Rules for Identifying Crisis Periods

To ensure replicability and extension, crisis months are automatically flagged using a three-threshold "OR" rule. Any month that meets at least one threshold is coded crisis = 1; if none of the thresholds is met for three consecutive months, the crisis is deemed resolved (crisis = 0).

Indicator	Symbol	Data Source	Threshold (trigger)	Computational Note
Net capital outflow	CF_t	IMF IFS, line 78bjd	$CF_t \le -8$ billion USD	Monthly net flow, USD billions
Exchange-rate volatility	$\sigma_{e,t}$	Bloomberg USDCNH daily close	$\sigma_{e,t} \ge 6$ %	30-day Garman-Klass volatility, annualized
Geopolitical risk	GPR_t	Caldara & Iacoviello GPR Index	$GPR_t \ge 150$	Original monthly index value

Table C-1 lists every crisis month from January 2000 to December 2023, showing start/end dates, the triggering indicator(s), and duration in months. Section C-2 provides the Python script crisis_flagger.py (Python 3.9) and Stata do-file crisis_flagger.do (Stata 17); both read the raw CSV files and output the crisis dummy.

C.2 Standardized Definitions of Key Variables

Variable name	Symbol	Exact meaning	Formula / source	Frequency
Total international reserves	RES_t	IMF IFS line 1.DZF	Official total reserves, incl. FX, gold, SDRs, reserve position	Monthly
Foreign-exchange reserves	FX_t	IMF IFS line 1.DZF.F	FX component only	Monthly
FX-reserve share	fx_share_t	FX_t / RES_t	Ratio, %	Monthly
Exchange-rate volatility	$\sigma_{e,t}$	See C.1	$\sqrt{[0.511(H-L)^2 - 0.019(C-O)(H-L)]} \times \sqrt{252}$	Daily→Monthly
GDP growth	gdp_g_t	World Bank WDI NY.GDP.MKTP.KD.ZG	Annual % change	Annual→Monthly linear interpolation
Trade balance	TB_t	World Bank WDI NE.RSB.GNFS.CD	Exports – imports, USD billions	Monthly

Variable name	Symbol	Exact meaning	Formula / source	Frequency
Capital-flow size	CF_t	See C.1	Directly from IMF IFS line 78bjd	Monthly
Inflation	π_t	World Bank WDI FP.CPI.TOTL.ZG	CPI YoY % change	Monthly

Note: All continuous variables are Z-score standardized (mean 0, SD 1) before estimation; the scripts include the function standardize_series.

Contribution

Shuhan Yang：Review, supervision, Methodology,Validation；

Adrian Daud:Writing-original draft, review and editing, conceptualization;

Shairil Izwan Bin Taasim: Review, supervision, visualization, project management.

All authors reviewed the manuscript.