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Forecasting CPI and PPI Using Commodity Prices and Crude Oil Prices: A Comparison of China and United States

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Abstract

This paper examines the forecasting of the Consumer Price Index (CPI) and Producer Price Index (PPI) using commodity price index and crude oil price, focusing on a comparison between China and the United States. Using an autoregressive moving average model with exogenous variables and a rolling window extrapolation method, we analyze data from July 2018 to December 2023. The results show that CPI forecasting consistently outperforms PPI forecasting in both nations. Additionally, both commodity price index and crude oil price enhance CPI and PPI forecasts. Crude oil futures prices significantly improve CPI predictions, while commodity price indices benefit PPI forecasts. Furthermore, WTI crude oil futures outperform INE crude oil futures in forecasting CPI for both China and the United States.

Keywords

CPI Forecasting, PPI Forecasting, Commodity Prices, Crude Oil Prices, China, United States

1. Introduction

The Consumer Price Index (CPI) and Producer Price Index (PPI) are critical economic indicators for all nations, reflecting price changes for consumers and producers, respectively. These indices are widely used to measure inflation and help firms, investors, and governments make informed financial strategies and economic policies. Consequently, accurate forecasting of CPI and PPI is vital.

China and the United States, being the two largest economies, have their CPI

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and PPI indices closely monitored globally. Figure 1 shows the trends in CPI for China and the U.S., including year-on-year (YoY) and month-on-month (MoM) indices. From July 2018 to December 2023, China's year-on-year CPI exceeded that of the U.S. until September 2020, after which it became lower. The month-on-month CPI remains relatively stable and can be modeled as a stationary time series.

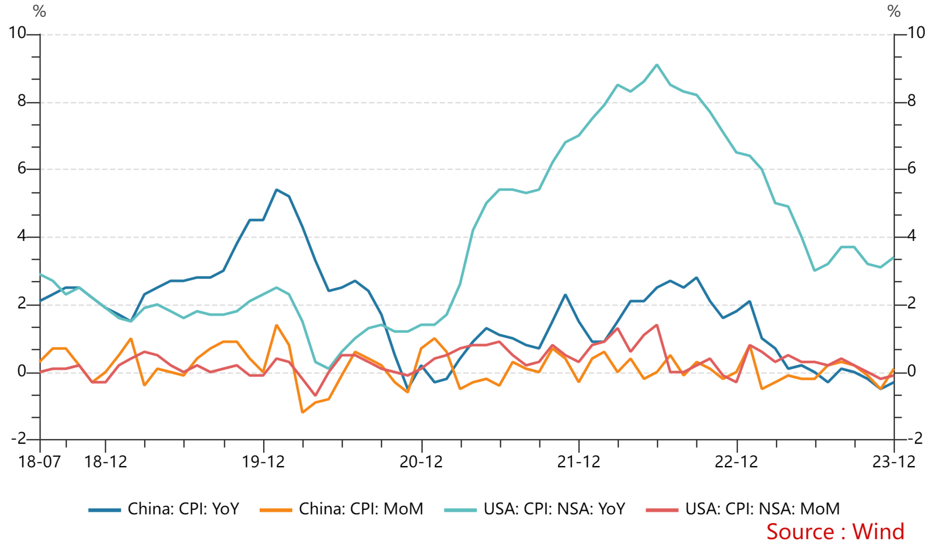

Figure 1. CPI trends of China and the U.S.

Figure 2 illustrates the PPI trends, with China's year-on-year PPI consistently lower than that of the United States. China's year-on-year PPI is lower than that of the United States. Just like CPI, the month-on-month PPI is also stationary. ARIMA models are suitable for year-on-year forecasts, while ARMA is more appropriate for month-on-month forecasts, the latter being the foundation for year-on-year predictions.

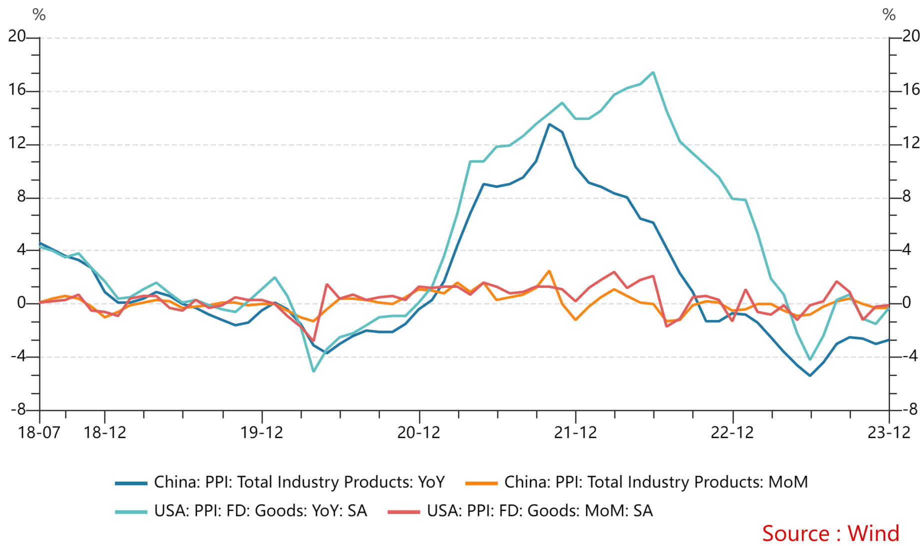

Figure 2. PPI trends of China and the U.S.

This paper focuses on forecasting for month-on-month CPI and PPI in both nations. While time series models like ARMA, VAR, and MIDAS are commonly used in CPI and PPI forecasting and other data are also imported in the models (such as GDP, commodity price, crude oil price), few studies have simultaneously forecast CPI, PPI, and directly compared forecasts for China and the U.S.

This paper incorporates commodity futures prices, particularly crude oil futures, into the forecasting framework for CPI and PPI in China and the U.S. The study examines the predictive power of commodity price indices such as the Nanhua Futures Index (China) and the RJ/CRB Index (U.S.), alongside crude oil futures like INE (China), WTI, and Brent (global). Firstly, the commodity futures market plays a crucial role in price discovery, with futures prices often leading to spot prices. Thus, futures prices can forecast goods prices in both the production and consumption sectors, which directly relate to PPI and CPI, respectively. The RJ/CRB and Nanhua indices are used to represent U.S. and Chinese futures markets. Secondly, crude oil, as a key energy and production input, can directly impact PPI by influencing production and transportation costs, while indirectly affecting CPI through downstream products like gasoline. The complexity of the relationship between oil prices and economic variables makes forecasting CPI and PPI particularly challenging. WTI, Brent, and INE crude oil futures prices are examined to assess their utility in improving CPI and PPI predictions. Thirdly, this paper employs an ARMA model with exogenous variables and utilizes a rolling window extrapolation method for both static and dynamic predictions. Finally, this paper also draws comparisons between the forecasting models for China and the U.S., identifying key similarities and differences. These insights can inform policymakers on how changes in commodity prices influence price indices, aiding in inflation control and economic stability.

The key findings are as follows. CPI forecasting consistently outperforms PPI forecasting. Additionally, both commodity price index and crude oil price enhance CPI and PPI forecasts. Crude oil futures prices significantly improve CPI predictions, while commodity price indices benefit PPI forecasts. Furthermore, WTI crude oil futures outperform INE crude oil futures in forecasting CPI for both China and the United States.

The remainder of this paper is structured as follows: Section 2 reviews the relevant literature. Section 3 outlines the data and forecasting methods. Section 4 presents the main forecasting results for CPI and PPI. The final section provides concluding remarks.

2. Literature Review

Macroeconomic forecasting, particularly for CPI and PPI, has long been a central topic in economics and finance research. Various time series and machine learning models have been applied to CPI forecasting. For instance, Álvarez-Díaz and Gupta (2016) use both linear (e.g., random walk, autoregressive, and seasonal ARIMA) and nonlinear models (e.g., artificial neural networks and genetic programming) to forecast U.S. CPI. They find that the seasonal ARIMA model outperforms other models, indicating that nonlinearity does not necessarily offer statistical advantages. Mandalinci (2017) compares several models to forecast CPI in Emerging Markets, including univariate and multivariate models, fixed and time-varying parameter models, and models with stochastic volatility. Models accounting for stochastic volatility and time-varying parameters provide more accurate inflation forecasts in Emerging Markets. Similarly, Domit et al. (2019) use a Bayesian VAR to forecast CPI inflation in the UK. Additionally, machine learning models such as support vector regression and multivariate adaptive regression splines have been applied to forecast U.S. CPI (Nguyen et al., 2023).

As commodity markets, particularly futures markets, have evolved, more research has focused on the role of commodity prices in CPI forecasting. Browne and Cronin (2010), using a cointegrating VAR framework with U.S. data, identify long-term dynamic relationships between commodity prices, consumer prices, and money supply. Gospodinov and Ng (2013) demonstrate that the principal components of commodity convenience yields have significant predictive power for inflation. Similarly, Chen et al. (2014) confirm that commodity price aggregates can predict both CPI and PPI inflation.

Due to crude oil's critical role in commodity markets and the broader economy, crude oil prices have been increasingly integrated into CPI forecasting. Zhao et al. (2016) find that oil supply shocks, particularly those driven by political events, primarily have short-term effects on China's output and inflation. Wei (2019) explores the differing impacts of oil and non-oil commodity price shocks on China's PPI and CPI, noting that these effects are closely tied to the underlying causes of price changes. Chen et al. (2020) use a time-varying parameter structural VAR with stochastic volatility to decompose oil price fluctuations into oil supply, global demand, domestic demand, and oil-specific demand shocks. They analyze the time-varying effects of these shocks on China's inflation across import, production, and consumption stages. Elsayed et al. (2021) examine the spillovers between oil price inflation and CPI inflation in the G7 and China, while Wen et al. (2021) show that supply, demand, and risk shocks have dynamic effects on inflation in the G7.

Additionally, research has explored the impact of crude oil shocks on PPI. Sun et al. (2019) use variance decomposition network analysis to examine how crude oil price shocks affect the PPI system, noting a lag in the impact on sub-PPIs. Zhao et al. (2020) investigate the reliability and accuracy of artificial neural networks (ANNs) for modeling and predicting PPI trends in New Zealand.

3. Data and Predictive Methods

3.1. Data

This paper utilizes CPI, PPI, commodity price indices, and crude oil futures prices for both China and the U.S. from Wind. Chinese month-on-month CPI and PPI data are sourced from the National Bureau of Statistics of China, while U.S. data come from the U.S. Department of Labor. The RJ/CRB Commodity Price Index and Nanhua Futures Index are selected as representative commodity price indices. Brent, WTI, and INE crude oil prices are used to represent crude oil futures prices. The dataset spans from July 2018 to December 2023, with INE crude oil data available starting from March 26, 2018. CPI and PPI trends are illustrated in Figure 1 and Figure 2, while commodity and crude oil price trends are shown in Figure 3 and Figure 4.

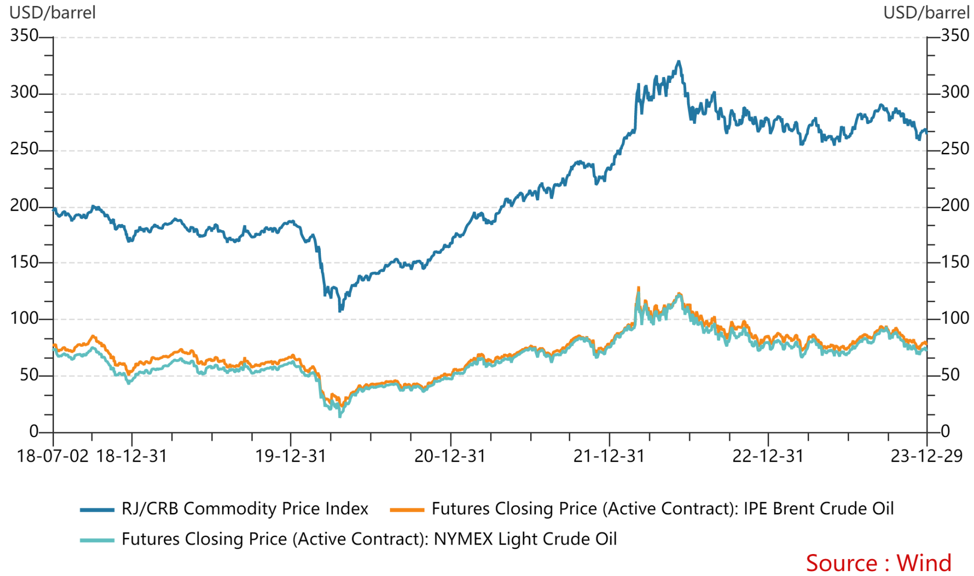

Figure 3. Commodity and crude oil prices in the U.S.

Figure 4. Commodity and crude oil prices in China.

3.2. Predictive Methods

This paper employs the autoregressive moving average model with exogenous variables (ARMA-X) to assess the predictive power of commodity price indices and crude oil prices on CPI and PPI for both China and the U.S. Month-on-month CPI and PPI data, which are stationary, are used in the models. The exogenous variables include the RJ/CRB Commodity Price Index, Brent and WTI crude oil futures closing prices, the Nanhua Futures Index, and INE crude oil futures prices. All exogenous variables are expressed as log returns.

The model is structured as follows:

$$\mathrm{CPI}_{i,t} = \beta_0 + \beta_1 \mathrm{CPI}_{i,t-1} + \beta_2 R_{x,t-1} + \varepsilon_{i,t} \tag{1}$$

$$\mathrm{PPI}_{i,t} = \gamma_0 + \gamma_1 \mathrm{PPI}_{i,t-1} + \gamma_2 R_{x,t-1} + \mu_{i,t} \tag{2}$$

In the models above, $\mathrm{CPI}_{i,t}$ is the Consumer Price Index in country *i* at period *t*. $\mathrm{PPI}_{i,t}$ is the Producer Price Index in country *i* at period *t*. The country *i* includes China and the U.S. $R_{i,t}$ is the exogenous independent variable, including the log returns of RJ/CRB index, Brent crude oil futures price, WTI crude oil futures closing price, Nanhua Futures Index and INE crude oil futures prices. $\varepsilon_{i,t}$ and $\mu_{i,t}$ are normally distributed random disturbances.

Therefore, there are six models for CPI forecast and PPI forecast, including *AR*, *AR with RJ/CRB*, *AR with Brent*, *AR with WTI*, *AR with Nanhua* and *AR with INE*.

This paper employs a rolling window extrapolation method for both static and dynamic predictions. The window size ranges from 12 to 36 months, increasing by 6 months at each iteration. The extrapolation step ranges from 1 to 6 months, increasing by 1 month at each step. Each model generates 60 predictive results. Predictive performance is evaluated using Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE).

4. Predictive Performance

4.1. CPI Forecasting

Six models are employed to forecast CPI for China and the U.S., generating 60 predictive results for each model. The model with the smallest RMSE is selected as the best forecast. The group of models with the smallest RMSE is identified for further analysis.

As shown in Table 1, for CPI forecasting in China, the AR model with WTI crude oil prices yields the smallest RMSE, indicating the best prediction. Similarly, as shown in Table 2, the AR model with WTI crude oil prices provides the best forecast for the U.S. CPI. Thus, WTI crude oil prices demonstrate stronger predictive power compared to commodity price indices, Brent, and INE crude oil prices.

The Consumer Price Index (CPI) primarily reflects prices in the consumption sector, while the commodity price index also captures prices in the production and distribution sectors. Given that many downstream products of crude oil enter the consumption market, crude oil prices have a stronger predictive power for CPI. Whether forecasting U.S. or Chinese CPI, WTI crude oil prices consistently outperform INE crude oil prices, indicating that WTI crude oil conveys more relevant information about price changes in the consumer sector.

Table 1. CPI forecasting results in China.

CPI in China		
Model[a]	RMSE for static prediction[b]	RMSE for dynamic prediction[b]
AR	0.362480	0.330362
AR with RJ/CRB	0.343162	0.309129
AR with Brent	0.332755	0.299134
AR with WTI	**0.331810**	**0.298381**
AR with Nanhua	0.340516	0.327852
AR with INE	0.337924	0.313147

a. In the predictive methods, the window size is 36, and the step is 6. b. The bolded number indicates the minimum RMSE among the models.

Table 2. CPI forecasting results in the U.S.

CPI in the U.S.		
Model[a]	RMSE for static prediction[b]	RMSE for dynamic prediction[b]
AR	0.367288	0.367288
AR with RJ/CRB	0.341288	0.341288
AR with Brent	0.318427	0.318427
AR with WTI	**0.316046**	**0.316046**
AR with Nanhua	0.348209	0.348209
AR with INE	0.317668	0.317668

a. In the predictive methods, the window size is 12, and the step is 1. b. The bolded number indicates the minimum RMSE among the models.

4.2. PPI Forecasting

The process for forecasting PPI is similar to that of CPI. The results are shown in Table 3 and Table 4.

Table 3. PPI forecasting results in China.

PPI in China		
Model[a]	RMSE for static prediction[b]	RMSE for dynamic prediction[b]
AR	0.693416	0.693416
AR with RJ/CRB	0.613395	0.613395
AR with Brent	0.650357	0.650357
AR with WTI	0.675883	0.675883
AR with Nanhua	**0.554169**	**0.554169**
AR with INE	0.598709	0.598709

a. In the predictive methods, the window size is 18, and the step is 1. b. The bolded number indicates the minimum RMSE among the models.

Table 4. PPI forecasting results in the U.S.

PPI in the U.S.		
Model[a]	RMSE for static prediction[b]	RMSE for dynamic prediction[b]
AR	1.056329	1.118203
AR with RJ/CRB	**0.905664**	**0.876559**
AR with Brent	0.972980	0.957953
AR with WTI	0.978307	0.975191
AR with Nanhua	0.933590	0.941277
AR with INE	1.005043	0.984784

a. In the predictive methods, the window size is 24, and the step is 5. b. The bolded number indicates the minimum RMSE among the models.

As shown in Table 3, the AR model with the Nanhua commodity price index provides the best prediction for China's PPI, while Table 4 shows that the AR model with the RJ/CRB commodity index yields the best prediction for the U.S. PPI. Therefore, commodity price indices exhibit stronger predictive power for PPI than crude oil prices.

The Producer Price Index (PPI) reflects prices in the production sector. While the commodity price index captures prices in both the production and consumption sectors, crude oil futures may not fully capture the price dynamics of other goods entering the production sector. As a result, commodity price indices provide better predictive accuracy for PPI than crude oil futures prices. Additionally, the most critical factor in PPI forecasting, whether for China or the U.S., is the domestic commodity price index, which tends to be more influential within its own country.

4.3. Discussion

1) CPI Forecasts vs. PPI Forecasts

Based on RMSE, CPI forecasting consistently outperforms PPI forecasting. This suggests that CPI forecasting may be easier than PPI forecasting in both China and the U.S. Maybe there is more information available in the consumer price sector, and CPI exhibits stronger autoregressive patterns.

2) Commodity Prices vs. Crude Oil Prices

AR models with exogenous variables outperform simple AR models, indicating that incorporating external information improves forecasting accuracy for both CPI and PPI. Crude oil futures prices enhance CPI forecasting, while commodity price indices improve PPI forecasting, particularly for domestic markets.

3) International vs. Chinese Crude Oil Prices

In both China's and the U.S.'s CPI forecasting, WTI crude oil futures consistently outperform INE crude oil futures. This suggests that WTI crude oil provides more comprehensive information and better reflects price changes in the consumer sector than INE crude oil.

4) China Forecasts vs. U.S. Forecasts

Based on the RMSE from dynamic forecasting, China's CPI and PPI forecasts outperform those of the U.S., indicating stronger predictive accuracy for Chinese data.

5. Conclusion

This paper incorporates external data, such as commodity price indices and crude oil prices, into the ARMA model and employs a rolling window forecasting method to predict CPI and PPI for both China and the U.S. It focuses on comparing CPI and PPI forecasting, evaluating the predictive power of commodity price indices and crude oil prices, and assessing the differences between international and Chinese crude oil prices. The paper also compares the forecasting performance between China and the U.S. Six distinct models are evaluated using monthly data from July 2018 to December 2023.

CPI forecasting outperforms PPI forecasting in both China and the U.S. AR models with exogenous variables perform better than simple AR models, demonstrating that external information enhances the predictive accuracy of both CPI and PPI forecasts. Crude oil futures prices improve CPI forecasting, while commodity price indices aid in PPI forecasting. WTI crude oil futures consistently outperform INE crude oil futures in predicting CPI for both countries. Additionally, China's CPI and PPI forecasts exhibit better performance than those of the U.S.

Besides, other factors, such as changes in monetary policy, global economic recovery, and additional variables, may also influence the PPI and CPI in both countries. Additionally, the dataset, which spans from July 2018 to December 2023, may not fully capture long-term trends or cyclical shifts. Short-term data may fail to reflect broader economic cycles that impact fluctuations in crude oil markets and economic indicators. Future research could benefit from expanding the time sample to encompass additional economic cycles for more robust analysis.

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Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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