ISSN: 2692-7608 DOI: 10.6981/FEM.202412_5(12).0029

Can Detrended Oil Prices Predict Currency Returns?

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Abstract

Exchange rate forecasting has long been considered as a puzzle. With the acceleration of the financialization in crude oil market, increased speculation leads to more unusual volatility in oil prices, which finally results in the oil prices providing information about future economic fundamentals that contains lots of noise. In our study, we provide a feasible approach to solving the puzzle by introducing a detrended predictor based on the standardized fitted residual of oil prices. Empirical results show that it can generate significant predictive power for currency returns in Canada, New Zealand and South Africa both in- and out-of-sample. In addition, the trading strategies based on the detrended predictor can generate higher economic significance.

Keywords

Currency Returns; Standardized Fitted Residuals; Oil Prices; Out-of-Sample.

1. Introduction

Exchange rate forecasting has received widespread attention from academics, practitioners and policy makers. However, Meese and Rogoff (1983) indicate that the random walk forecasts of exchange rates generally outperform the models on economic fundamentals, especially in out-of-sample prediction, which is known as “Meese-Rogoff” puzzle(1).

Oil price shocks may have a significant impact on economic conditions and hence contain prospective information about future economic trend. When market participants anticipate and then act on the information embedded in the oil price shocks, this expectation can lead to the changes in exchange rates. With the increased financialization of the crude oil market, oil futures become one of the important investment products. However, this financialization may result in more frequent and violent fluctuations in oil prices. That is, oil prices may provide information about future economic fundamentals that contains much more noise(Chiang at el., 2015; Chiang and Hughen, 2017)(2,3).

In our study, we provide a potential way to resolve the puzzle by introducing a detrended predictor based on the standardized fitted residual of oil prices that removes its own lagged term and a linear time trend. Using the data of West Texas Intermediate (WTI) oil future prices and exchange rates of four commodity currency countries including Australia, Canada, New Zealand and South Africa from January 1985 to December 2021, our study finds that the standardized fitted residual of oil prices can significantly predict 3 of the 4 currency returns except Australia both in- and out-of-sample. Moreover, the economic value analysis shows that the trading strategy based on our predictive model can generate higher average annualized returns and Sharp ratios for all four countries compared with the benchmark of random walk with drift.

Our study is related to Han et al.(2024) who uses the oil trend factor to eliminate the noisy information embedded in the oil prices and finds it can significantly predict the exchange rate for developed countries and emerging markets(4). The difference is that our study employs the

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standardized fitted residual of oil prices that removes both its own lagged term and the a linear time trend to the filter the noisy information.

The remainder of the paper is structured as follows. Section 2 introduces the methodology and data sources. Section 3 describes the empirical methods and results. Section 4 draws the final conclusions.

2. Methodology and Data

2.1. Currency Return

We calculate the monthly currency return by using its first logarithms,

$$s_{i,t+1}=\log(S_{i,t+1})-\log(S_{i,t}) \quad (1)$$

where $S_{i,t}$ denotes the nominal exchange rate of the *i*-th currency, quoted as the number of foreign currencies per unit US dollar.

Followed by Liu et al. (2020)(5), we use monthly average spot exchange rates for four commodity currencies, including the Australian dollar (AUD), Canadian dollar (CAD), New Zealand dollar (NZD) and South African rand(ZAR) from the Board of Governors of The Federal Reserve System. The exchange rate is quoted as one US dollar to units of the foreign currency so that an increase in the exchange rate implies a appreciation of the US dollar. The sample period ranges from January 1985 to December 2021.

Table 1 represents the summary statistics of 4 commodity currencies. ZAR shows a relatively large standard deviation. Except the CAD, the remaining currecies are right-skewd, with the largest kurtosis reaching 3.870 for AUD.

Table 1. Summary Statistics

Currency	Mean	Std	Skew	*Kurt*
AUD	1.357	0.214	0.576	3.870
CAD	1.270	0.157	-0.087	2.315
NZD	1.614	0.290	0.891	3.485
ZAR	7.313	4.183	0.593	2.347

2.2. Standardized Fitted Residual of Oil Prices

We compute the detrended predictor of oil prices using ordinary least squares(OLS) method after accounting its own lagged term and a linear time trend, which can be given by,

$$\log(p_{t+1}) = \alpha_t + \beta_t \log(p_t) + \gamma_t t + \varepsilon_{t+1} \quad (2)$$

where p_t denotes the closing price of oil future in the *t*-th month, t denotes the linear time trend. Specifically, we take the standardized fitted residuals $\hat{\varepsilon}_{t+1}$ as our detrended predictor after applying the OLS method. The prices of WTI crude oil have become the global benchmark for the other crude oils due to its good liquidity and high price transparency. Since the price of WTI was regulated by the government until 1985, we use the monthly price data of the WTI crude oil future contract 1 from the U.S. Energy Information Administration from January 1985 to December 2021.

Figure 1 and Figure 2 show the prices of WTI crude oil future contract 1 and the standardized fitted residual of oil prices we calculated from January 1985 to December 2021, respectively. The shaded columns show the recessions of American economy as identified by the National

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Bureau of Economic Research (NBER). From figure 1, it is clear that the prices of WTI crude oil future become higher and more volatile during 1985 to 2021, which reflects a strong time trend. And in figure 2, the standardized fitted residuals of oil prices that removed its own lagged term and a linear time trend become smoother relative to original oil prices in the figure 1.

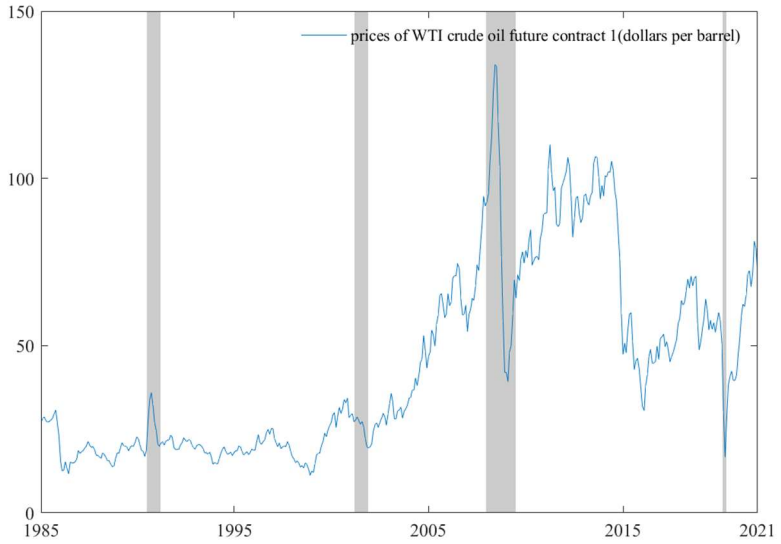

Figure 1. Prices of WTI crude oil future contract 1

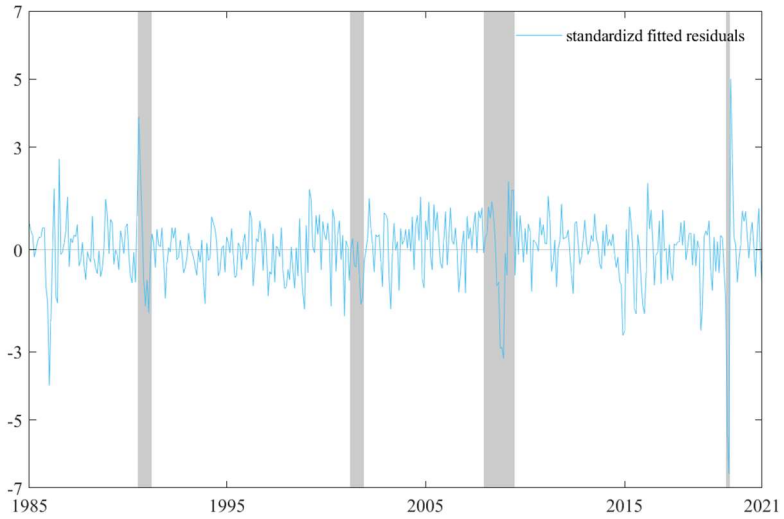

Figure 2. Standardized fitted residuals of oil prices

3. Empirical Results

3.1. In Sample Estimation Results

We employ the univariate predictive regression for currency returns to analyze the in-sample performance,

$$s_{i,t+1} = \alpha_i + \beta_i \hat{\varepsilon}_t + u_{i,t+1} \quad (3)$$

where $s_{i,t+1}$ denotes the currency returns for i-th currency, $\hat{\varepsilon}_t$ denotes the standardized fitted residuals of oil prices, $u_{i,t+1}$ is the disturbance term. The β_i with the null hypothesis no

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predictability(β_i=0) is tested by the *t*-statistic. We apply the Newey-West(1987)(6) method to compute the standard errors to avoid the serial correlation.

Table 2 represents the in-sample empirical results. The results show that all the 4 currency returns are significantly negatively correlated with the standardized fitted residuals of oil prices at the 10% level and the slopes range from -0.551% to -0.231%. Consistent with Reboredo et al.(2014) and Liao et al.(2018)(7,8), the negative regression coefficients indicate that when the oil price rises, the currency returns tend to decline which reflects the depreciation of United States Dollar(USD). In addition, the R^2 for the 4 commodity currencies are greater than 0.5% benchmark proposed by Campbell and Thompson(2008)(9), with the largest R^2 reaching 2.283% for ZAR.

Table 2. In Sample Estimation Results

Currency	*Coefficient*(%)	*T-stat*	R^2(%)
AUD	-0.236*	-1.883	0.823
CAD	-0.231***	-2.683	2.041
NZD	-0.354***	-2.768	1.759
ZAR	-0.551**	-2.362	2.283

Note: The Coefficients and R2s are shown in percentage. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

3.2. Out-of-sample Performance

Referring to Rapach et al. (2010)(10), we generate the out-of-sample forecasts relying on a recursive estimation window. Specifically, we set the first 15 years(180 observations) as initial estimation period and generate the out-of-sample using recursive window(264 observations).

Both the random walk with and without drift can be served as the benchmarks for currency returns forecast, where the random walk with drift assumes constant changes in exchange rates and the random walk without drift assumes no change in exchange rates. In our study, we consider both two models as the benchmarks, where the random walk with drift we used is simply equal to the historical average changes of currency returns, which is given by,

$$\bar{S}_{i,t+1} = \frac{1}{t}\sum_{j=1}^{t} s_{i,t} \tag{4}$$

To evaluate the accuracy of out-of-sample forecasts, following Campbell and Thompson (2008)(9), we first use the out-of-sample R^2 statistic to assess the out-of-sample forecasting performance, which can be expressed as,

$$R^2_{i,OS} = 1 - \frac{\sum_{k=1}^{q}\left(s_{i,m+k} - \hat{s}_{i,m+k}\right)^2}{\sum_{k=1}^{q}\left(s_{i,m+k} - \bar{s}_{i,m+k}\right)^2} \tag{5}$$

where $s_{i,m+k}$, $\bar{s}_{i,m+k}$, and $\hat{s}_{i,m+k}$ denote the actual returns, benchmark model returns and out-of-sample forecasting returns of the *i*-th currency, respectively. *m* and *q* denote the lengths of in-sample period and out-of-sample period, respectively.

The out-of-sample R^2 statistic measures the reduction in Mean Squared Forecast Error (MSFE) of the predictive model relative to the benchmark model, and it takes the positive value when the predictive model returns outperforms the benchmark model returns .To further assess its statistical significance, we employ the MSFE-adjusted statistic proposed by Clark and West (2007)(11). It tests the null hypothesis that the MSFE of benchmark models is less than or equal

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to the MSFE of predictive models against the one-sided alternative hypothesis that the MSFE of benchmark models is greater than the MSFE of predictive models.

Table 3 reports the out-of-sample estimation results. Panel A and Panel B show the results based on the benchmark models of random walk with and without drift, respectively. 3 of the 4 commodity currency returns except AUD generate positive R^2 regardless of the choice of benchmarks, with the largest R^2 reaching 3.378%(3.006%) for random walk without drift and random walk with drift, respectively. Our out-of-sample results further confirms the predictive power of the standardized fitted residuals of oil prices for commodity currencies.

Table 3. Out-of-sample Estimation Results

Currency	Panel A: Random Walk without Drift			Panel B: Random Walk with Drift		
	R^2(%)	*MSFE-adjusted*	*P-value*	R^2(%)	*MSFE-adjusted*	*P-value*
AUD	0.118	0.836	0.202	0.610	1.259	0.104
CAD	1.775**	2.161	0.015	2.170***	2.396	0.008
NZD	2.037***	2.382	0.009	2.270***	2.619	0.004
ZAR	3.378***	2.409	0.008	3.006**	2.189	0.014

Note: The out-of-sample R2s are shown in percentage. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. The in-sample period is January 1985 to December 1999 and the out-of-sample forecasts runs from January 2000 to December 2021.

4. Economic Significance

It is noteworthy that the great out-of-sample performances don't always have economic significance. We follow Ren et al.(2020)(12) and construct the trading strategies based on a single currency to evaluate the economic significance of our out-of-sample forecasts, which buying(selling) one unit of the foreign currency when the benchmark model or predictive model forecasts the appreciation(depreciation) of the foreign currency. The trading strategies can be expressed as,

$$r_{i,t} = \begin{cases} s_{i,t}, \text{ if } \hat{s}_{i,t} \geq 0 \\ -s_{i,t}, \text{ otherwise} \end{cases} \quad (6)$$

where $s_{i,t}$ and $\hat{s}_{i,t}$ denote the actual and out-of-sample forecast returns of the i-th currency, respectively. Besides, we also calculate the Sharpe ratios(SR) of the trading strategies which is given by,

$$SR_i = \frac{\bar{r}_i}{\sigma_i} \quad (7)$$

where $\bar{r}_i$and σ_i are the mean and standard deviation of the trading strategies over the out-of-sample period, respectively.

Table 4 reports the results of economic value analysis. Panel A and Panel B show the results of trading strategies based on the forecasts of predictive model and random walk with drift, respectively. It is obvious that the trading strategies based on the forecasts of our predictive model can generate higher annualized average returns and Sharpe ratios for all 4 commodity currencies relative to the forecasts based on the random walk with drift, with the largest value reaching 7.526% and 0.571 for ZAR, respectively.

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Table 4. Trading Strategies Results

Currency	Panel A: Predictive Model		Panel B: Random Walk with Drift	
	Avg.(%)	*S.R.*	*Avg.*(%)	*S.R.*
AUD	0.444	0.045	-2.509	-0.258
CAD	2.262	0.345	-1.530	-0.233
NZD	2.088	0.213	0.404	0.041
ZAR	7.526	0.571	4.315	0.325

Note: The Avg. denotes the annualized average returns that we multiply the original mean returns by 1200 to represent the annual returns and S.R. denotes the annualized Sharpe ratios that we multiply the original value by square root 12 to represent the annual ratios.

5. Conclusion

In this paper, we use the standardized fitted residuals of oil prices that removed its own lagged terms and a linear time trend as a new predictor to forecast the currency returns. Using the exchange rate data of main commodity currencies including AUD, CAD , NZD and ZAR from January 1985 to December 2021, we find the standardized fitted residuals of oil prices can significantly predict all 4 currency returns in the in-sample period, while remaining the significant predictive power for 3 currency returns except AUD in the out-of-sample with the benchmarks of random walk with and without drift. In addition, the trading strategies based on the standardized fitted residuals can generate higher annualized average returns and Sharper ratios relative to the benchmark of random walk with drift.

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