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Oil Price Returns Skewness and Forecastability of International Stock Returns Over One Century of Data

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This study examines the out-of-sample predictability of expected skewness of oil price returns for stock returns of 10 (8 advanced plus 2 emerging) countries using long-range monthly data of over a century for each country. Using a distributed lag predictive econometric model, which controls for endogeneity, persistence, and conditional heteroscedasticity, we provide evidence of the strong statistical significance of the predictive impact of the third moment of oil price returns for equity returns for all the countries across various forecast horizons and length of out-of-sample periods. These findings also continue to hold for the shorter sample periods of 3 other emerging markets: Brazil, China and Russia. Our findings have important implications for academics, investors and policymakers.

Keywords: Stock returns; expected skewness of oil returns; forecasting; advanced and emerging equity markets

JEL Codes: C22; G15; G17; Q02

1. Introduction

The international literature associating oil prices and/or returns to the predictability of stock prices and/or returns, as well as the equity-premium, is enormous, to say the least, with the reader referred to Degiannakis et al. (2018) and Smyth and Narayan (2018) for detailed reviews. Within these studies, recent works (see, for example, Narayan and Gupta (2015), Balcilar et al. (2019), Wang et al. (2019), Hashmi et al. (2021)) have highlighted the role of asymmetric oil price/and or returns in predicting stock returns, to the extent that Ebrahimi and Pirrong (2018), Mo et al. (2019) and Dai et al. (2021) have shown the importance of the skewness of oil price returns in forecasting stock returns. Recall that, skewness is a measurement of the distortion of symmetrical distribution or a measure of asymmetry in a data set. Therefore, skewness (in oil returns) can be quantified as a representation of the extent to which a given distribution deviates from the normal distribution (of oil market returns) and hence can act as a metric of the evolution of unbalanced (relative to a baseline) future risks (Sheng et al., 2023).

In light of the definition of skewness, the predictability of stock returns based on the skewness of oil price returns can be explained through the impact on cash flows, discount factor, interest rates

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and inflation (Kilian and Park, 2009), as well as through the recent process of financialization observed around the turn of the century, and especially after the Global Financial Crisis (Ji et al., 2019). In addition, the skewness of oil price returns has been also shown to contain leading information for not only oil price returns (Fernandez-Perez et al., 2018; Yin and Wang, 2019), but also its volatility (Gupta, et al., 2023), which then (indirectly) feeds into movements in stock returns (Balcilar et al., 2022; Salisu et al., 2022).

Against this backdrop, the objective of our paper is to extend the works of Ebrahimi and Pirrong (2018), Mo et al. (2019) and Dai et al. (2021) on forecastability of aggregate and industry-level stock returns of China and the United States (US), due to expected skewness of oil returns spanning three decades of recent data, to as many as 10 (8 developed and 2 emerging) international stock markets covering over a century of data in each case. In fact, for the US and the United Kingdom (UK), our analysis covers the complete modern era of the petroleum industry with the drilling of the first oil well in the US at Titusville, Pennsylvania in 1859, due to the availability of corresponding equity price data even before this period. For the rest of the countries, i.e., Canada, France, Germany, India, Italy, Japan, South Africa and Switzerland, we are able to cover their respective entire history of stock returns movement in relation to oil price returns skewness. Utilization of the longest possible data samples ensures the prevention of the so-called "sample selection bias". And in the process, we capture various positive and negative oil shocks associated with, for example, the U.S. Civil War, the two World Wars, the West Coast gas famine, the Great Depression, the Korean conflict, the Suez Crisis, the OPEC oil embargo, the Iranian revolution, the Iran-Iraq War, the Gulf War, the global financial crisis, the outbreak of the Coronavirus pandemic in 2020, and, of course, more recently the ongoing Russia-Ukraine War.[1]

Note that, as indicated by Rapach and Zhou (2013, 2022), the best test of any predictive model (with regard to the econometric methods used and in terms of the predictors employed) is in its out-of-sample forecasting performance, rather than in-sample predictability. Given this, econometrically speaking, for our forecasting exercise, we adopt the Westerlund and Narayan (2012, 2015; WN)-type distributed lag model framework, which accommodates salient data characteristics, such as endogeneity, persistence, and conditional heteroscedasticity that are commonly found in historical equity and oil markets datasets (Balcilar et al., 2015, 2017; Gupta and Wohar, 2017). To the best of our knowledge, ours is the first work to forecast international

[1] The reader is referred to Hamilton (2013) for a detailed discussion of historical oil shocks from 1859 to 2009.

stock returns spanning over 100 years of monthly data based on the information content of skewness of oil price returns, and in the process also adds to the voluminous literature on forecasting equity returns of developed and emerging countries (see Gupta et al. (2020), Gupta and Salisu (2022), and Salisu et al. (2023) for comprehensive reviews) by relying on a new-metric, i.e., skewness, associated with the (third moment) of oil price returns, which inherently incorporates information of the first and second moments, utilized primarily thus far in this area of stock and oil nexus.

The remainder of the paper is organized as follows: In Section 2, we outline the econometric model, along with the basics of the forecast comparison tests, besides the discussion of the data, while in Section 3, the empirical findings are presented, with Section 4 concluding the paper.

2. Variables and Methodology

2.1. Data

The dataset consists of the market indexes of 8 advanced economies, which include the G7, with the name of the stock index, and sample periods of the corresponding log-returns noted in parenthesis: Canada (S&P TSX 300 Composite Index; 1915:02-2023:09), France (CAC All-Tradable Index; 1898:01-2023:09), Germany (CDAX Composite Index; 1870:01-2023:09), Italy (Banca Commerciale Italiana Index; 1905:02-2023:09), Japan (Nikkei 225 Index; 1914:08-2023:09), the UK (FTSE All Share Index; 1859:10-203:09), the US (S&P500 Index; 1859:10-2023:09), plus Switzerland (All Share Stock Index; 1916:02-2023:09).[2] The 2 emerging markets considered are India (Bombay Stock Exchange Index; 1920:08-2023:09), and South Africa (Johannesburg All Share Stock Index; 1910:2023:09). The crude oil price is represented by the West Texas Intermediate (WTI; 1859:10-2023:09), the expected skewness of which is computed from its log-returns. The coverage of the sample periods is purely driven by the availability of data, with all the variables sourced from the Global Financial Data.[3]

2.2. Econometric Model

As pointed out above, we utilize the WN-type distributed lag model framework, which accommodates salient data characteristics, such as endogeneity, persistence, and conditional heteroscedasticity. The model tackles endogeneity and persistence through the inclusion of a

[2] Stock price data for the UK and the US in fact starts from 1693:01 and 1791:08, respectively.
[3] https://globalfinancialdata.com/.

differencing term while addressing heteroscedasticity involves pre-weighting the model variables using the inverse of the standard deviation of the residuals from the conventional Generalized Autoregressive Conditional Heteroskedasticity (GARCH(1,1)) model. Formally, the WN-type distributed lag model can be described as follows:

$$rstk_t = \alpha + \beta_1 skoil_{t-1} + \beta_2 \Delta skoil_t + \beta_3 ntrend + \varepsilon_t \quad (1)$$

where $rstk_t$ is the log-returns of the stock price (stk) computed as $rstk_t = 100 \times \ln(stk_t / stk_{t-1})$, and $skoil_t$ is oil price returns skewness. α denotes the constant; β_1 denotes the slope coefficients associated with the incorporated predictor; $\beta_2 \Delta skoil_t$ represent the endogeneity/persistence adjustment terms in Equation (1), for $\Delta skoil_t = skoil_t - \rho\, skoil_{t-1}$ with ρ being the autoregressive coefficient of the predictor variable, indicating the corresponding degree of persistence; $ntrend$ is the non-linear trend of the stock returns, which is obtained from the Hodrick and Prescott (1997; HP) filter; while ε_t is the residual term that follows a white noise process.

In order to get a time-varying measure of expected skewness of oil returns ($roil_t$), we estimate the following autoregressive quantile regression, with τ depicting the quantile, as developed by Engle and Manganelli (2004):

$$Q^{\tau}(roil_t) = \gamma_0^{\tau} + \gamma_1^{\tau}(roil_{t-1}) + \gamma_2^{\tau} roil_{t-1} \Pi(roil_{t-1} > 0) + \gamma_3^{\tau} roil_{t-1} \Pi(roil_{t-1} < 0) \quad (2)$$

Using the estimated model parameters from this quantile regression, and assuming that Equation (2) is used to form expectations, we compute the one-step-ahead expected, or predicted, Kelley skewness (Kelley, 1947) as follows:

$$\mathbb{E}_{t-1}[SKEWNESS(roil_t)] = \frac{\mathbb{E}_{t-1}[Q_t^{0.9}] + \mathbb{E}_{t-1}[Q_t^{0.1}] - 2\mathbb{E}_{t-1}[Q_t^{0.5}]}{\mathbb{E}_{t-1}[Q_t^{0.9}] - \mathbb{E}_{t-1}[Q_t^{0.1}]} \quad (3)$$

We simplify the notation by setting $\mathbb{E}_{t-1}[SKEWNESS(roil_t)]$ to $skoil_t$.

The baseline model (Model 1) is the historical average model, which is a subset of the model specification in Equation (1), when the comprising slope coefficients are set to zero. Model 2 as specified in Equation (1) assesses the predictability of oil price returns skewness for stock returns after controlling for the existent persistence and non-linear trend.

We employ the Clark and West (2007; CW) test to formally compare Model 2, with the historical average, i.e., Model 1, given that the latter is nested in the former. The CW metric works effectively for nested models, examining whether the difference in the forecast errors of the competing models is negligible. The estimation equation for the CW test statistic is provided in Equation (4):

$$\hat{f}_{t+h} = \left(r_{t+h} - \hat{r}_{1t,t+h}\right)^2 - \left[\left(r_{t+h} - \hat{r}_{2t,t+h}\right)^2 - \left(\hat{r}_{1t,t+h} - \hat{r}_{2t,t+h}\right)^2\right] \tag{4}$$

where h denotes the forecast horizon; $\left(r_{t+h} - \hat{r}_{1t,t+h}\right)^2$ and $\left(r_{t+h} - \hat{r}_{2t,t+h}\right)^2$ denote the squared residuals from the restricted and unrestricted model variants, respectively, of our WN-type distributed lag model; while $\left(\hat{r}_{1t,t+h} - \hat{r}_{2t,t+h}\right)^2$ represents an adjusted squared residual that is peculiar to the CW test and incorporated as a corrective measure for the noisy forecasts of the larger model. The term, $\hat{f}_{t+h}$ is defined as $MSE_1 - \left(MSE_2 - adj.\right)$, where $MSE_1 = P^{-1}\sum\left(r_{t+h} - \hat{r}_{1t,t+h}\right)^2$, $MSE_2 = P^{-1}\sum\left(r_{t+h} - \hat{r}_{2t,t+h}\right)^2$, $adj. = P^{-1}\sum\left(\hat{r}_{1t,t+h} - \hat{r}_{2t,t+h}\right)^2$ and P represents the number of averaged forecast points. The evaluation relies on regressing $\hat{f}_{t+h}$ on a constant and determining whether paired forecast errors from competing models are equal or not, using the t-statistic of the estimated constant. A significant *t*-statistic suggests that our unrestricted predictive model performs better than the restricted benchmark model.

3. Forecasting Results

In this section, we present the CW test results of the forecasting performance of the model with expected skewness of oil price returns which nests the benchmark of the historical average of stock returns, i.e., without our predictor of concern. Table 1 reports the CW test statistics for h =1, 3 and 6, with a 50% in- and out-of-sample split (following the extant literature and in particular Narayan and Gupta (2015)), whereby the stock returns were cumulated for the multi-steps-ahead horizons based on the rolling window approach. We observe that the incorporation of expected oil returns skewness provide vital information that improved the prediction of stock across all the countries, as depicted by the significance of the CW forecast comparison test statistics at the 1% level.

For the purpose of further robustness check, the case of a longer in-sample, and hence shorter out-of-sample, with a 75%-25% split is also examined, to allow us to conduct a forecasting analysis over the most recent periods in line with the recent works of Ebrahimi and Pirrong (2018), Mo et al. (2019) and Dai et al. (2021). We find similar stances under the CW test comparison, i.e., significance at the 1% level, as with the 50%-split case. This is an indication that the improvement of the precision of our predictive model variant with expected skewness of oil returns over the benchmark historical average model transcends data sample; and hence, is robust to the choice of out-of-sample periods.

Table 1: Forecast Evaluation Result using the Clark and West (2007) Test Statistics

Country	$h=1$	$h=3$	$h=6$
Canada	8.749***[1.294]	8.730***[1.290]	8.676***[1.285]
France	9.085***[0.931]	9.084***[0.928]	9.062***[0.925]
Japan	15.151***[2.710]	15.128***[2.702]	15.030***[2.690]
Germany	24.507***[5.041]	24.452***[5.030]	24.373***[5.014]
Italy	20.587***[3.582]	20.559***[3.572]	20.424***[3.559]
US	9.491***[1.064]	9.537***[1.062]	9.536***[1.059]
UK	2.266***[0.294]	2.279***[0.294]	2.265***[0.294]
Switzerland	7.931***[1.156]	7.989***[1.154]	7.953***[1.150]
India	5.378***[0.503]	5.341***[0.502]	5.319***[0.500]
South Africa	4.882***[0.578]	4.871***[0.577]	4.850***[0.575]

Note: The figures in each cell are the estimated coefficients associated with the panel label and their corresponding standard errors in square brackets. *** denote statistical significance at the 1% level.

Table 2: Forecast Evaluation Result using the Clark and West (2007) Test Statistics

Country	$h=1$	$h=3$	$h=6$
Canada	8.073***[0.932]	8.113***[0.931]	8.093***[0.928]
France	9.661***[0.836]	9.690***[0.835]	9.677***[0.833]
Japan	12.754***[1.860]	12.716***[1.857]	12.734***[1.852]
Germany	25.356***[5.656]	25.327***[5.648]	25.457***[5.636]
Italy	19.393***[2.500]	19.414***[2.496]	19.353***[2.489]
US	8.156***[0.747]	8.166***[0.746]	8.184***[0.745]
UK	4.731***[0.615]	4.734***[0.615]	4.749***[0.613]
Switzerland	7.465***[0.876]	7.511***[0.875]	7.637***[0.876]
India	11.455***[1.738]	11.583***[1.738]	11.602***[1.733]
South Africa	8.686***[0.835]	8.711***[0.834]	8.684***[0.832]

Note: The figures in each cell are the estimated coefficients associated with the panel label and their corresponding standard errors in square brackets. *** denote statistical significance at the 1% level.

Table 3: Forecast Evaluation Result using the Clark and West (2007) Test Statistics

Panel A: 50%-Split

Country	$h=1$	$h=3$	$h=6$
Brazil	89.049***[11.790]	101.046***[14.810]	107.183***[15.543]
China	14.467***[4.120]	14.326***[4.081]	14.051***[4.025]
Russia	26.248***[10.590]	26.024***[10.481]	25.398***[10.332]

Panel B: 75%-25%-Split

Country	$h=1$	$h=3$	$h=6$
Brazil	326.514***[108.257]	325.859***[107.913]	324.538***[107.403]
China	10.758***[2.826]	10.685***[2.807]	10.602***[2.779]
Russia	17.548***[6.665]	17.416***[6.6175]	17.275***[6.548]

Note: The figures in each cell are the estimated coefficients associated with the panel label and their corresponding standard errors in square brackets. *** denote statistical significance at the 1% level.

While we do not have over a century of data for Brazil (Brazil Bolsa de Valores de Sao Paulo (BOVESPA) Stock Index), China (Shanghai Stock Exchange (SSE) Composite Index) and Russia (MOEX Russia Composite Index), with our sample periods for the log-returns starting in 1954:02, 1993:01, and 1995:01, respectively, we consider these three countries to produce results for the entire BRICS bloc, just as the G7. This is primarily in light of their importance in the global financial system in terms of their ability to provide portfolio diversification benefits relative to advanced markets (Pan and Mishra, 2022). Also, this allows us to compare our findings with the work of Mo et al. (2019), wherein the authors dealt specifically with China, with the works of Ebrahimi and Pirrong (2018) and Dai et al. (2021) devoted to the US. As before, all data are sourced from the Global Financial Data and ends in 2023:09. As with the 10 international stock returns with over a century of data, our results tend to carry over for the three additional emerging markets, which have relatively shorter data samples, consistently across alternative forecast horizons and in- and out-of-sample-splits. In other words, we continue to confirm the strong statistical importance (at the 1% level) of the expected skewness of oil price returns for the future path of stock returns of Brazil, China and Russia.

In sum, in line with the existing literature, we provide evidence of historical importance of the expected skewness of oil price returns in forecasting stock returns of both developed and emerging countries.

4. Conclusion

In this paper, we conduct an out-of-sample forecasting analysis of 10 international stock returns based on the information content of expected skewness of oil price returns spanning over a century of data in each case. Based on a distributed lag predictive econometric framework, which controls for endogeneity, persistence, and conditional heteroscedasticity, we provide evidence of strong statistical significance of the third moment of oil price returns for equity returns of the 8 developed and 2 emerging markets, with the result being robust to multi-steps-ahead forecast horizons and alternative choices of the length of the out-of-sample periods. These findings also continue to hold for 3 other emerging markets namely, Brazil, China and Russia, but with shorter sample periods.

On one hand, practitioners in finance require forecasts of stock returns for asset allocation. On the other hand, academics are interested in stock return forecasts since they have important implications for producing robust measures of market efficiency, which in turn, helps to produce more realistic asset pricing models. Understandably, our results have important multi-layer implications. First, investors would need to account for expected skewness of oil price returns in their portfolio decisions, which are based on accurate forecasts of stock returns. Second from the perspective of academicians, our results suggest that stock markets are at least weakly inefficient, and the role of global risks, as captured by the third moment of oil returns, must be incorporated into asset pricing models. Finally, with stock market movements being a predictor of the real economy (Stock and Watson 2003), policy authorities would need to closely monitor expected skewness of oil price returns to get an understanding of the future movements in output and inflation, and accordingly design policy responses.

As part of future research, it would be interesting to extend our analysis to forecasting stock returns volatility due to the expected skewness of oil price returns.

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