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Commodity Risk and Forecastability of International Stock Returns: The Role of Oil Returns Skewness

Afees A. Salisu [1,2,*] and Rangan Gupta [2]

[1] Centre for Econometrics & Applied Research, UI Post Office, Ibadan P.O. Box 105, Nigeria
[2] Department of Economics, University of Pretoria, Private Bag X20, Hatfield 0028, South Africa; rangan.gupta@up.ac.za
* Correspondence: adebare1@yahoo.com

Abstract: This study examines the out-of-sample predictability of expected skewness of oil price returns, which serves as a metric for global future risks, as we show statistically through the association with crises of different nature, for stock returns of 10 (8 advanced plus two 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 the length of out-of-sample periods. These findings also 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

Academic Editor: Carmen González-Velasco

Received: 6 December 2024
Revised: 19 February 2025
Accepted: 4 March 2025
Published: 6 March 2025

Citation: Salisu, Afees A., and Rangan Gupta. 2025. Commodity Risk and Forecastability of International Stock Returns: The Role of Oil Returns Skewness. *Risks* 13: 49. https://doi.org/10.3390/risks13030049

1. Introduction

The existing connection between oil and stock markets is unlikely to weaken in the foreseeable future. Oil remains a critical input that significantly affects corporate earnings and, consequently, stock market behavior. Additionally, fluctuations in oil prices directly impact consumer income, which, in turn, influences the demand for goods and services produced by the listed companies in the stock exchange markets. Other key factors, such as geopolitical and climate-related risks—including the Russia–Ukraine War, the Palestine–Israel conflict, and wildfires in the US and Australia, etc.—have further shaped the relationship between oil and stock markets (Tavor 2024; Salisu et al. 2025). For instance, the recent Russia–Ukraine conflict highlighted this dynamic, as it contributed to a decline in global aggregate demand (Bernanke 2016).

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 Basher et al. (2018), 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 dataset. 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).

Theoretically, the predictability of stock returns based on the skewness of oil price returns can be explained through the impact on cash flows, discount factors, interest rates, 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). More elaborately, oil prices can directly and indirectly influence stock market returns, primarily through their impact on cash flows. The effect of oil price fluctuations on the economic fundamentals of various countries largely depends on their status as oil importers or exporters. This dynamic is well captured by the income transfer theory, which posits that rising oil prices result in income transfer from net oil-importing countries to net oil-exporting countries. Consequently, oil price shocks are likely to produce differential impacts on the stock markets of these two groups of countries.

Moreover, the predictability of oil prices for stock market returns may be attributed to the financialization of oil markets. This phenomenon allows market participants to diversify their portfolios by incorporating oil-related derivatives, thereby improving their ability to hedge against risk (Ma et al. 2019; Ji et al. 2019). Furthermore, the predictability of oil for stock returns arises from oil price changes affecting key economic factors, such as the discount rate, interest rates, and inflation (Kilian and Park 2009), which indirectly contribute to variations in excess returns. In addition, the skewness of oil price returns has also been 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).

Meanwhile, previous studies have largely focused on the first- and second-moment predictability of crude oil for stock returns while overlooking the higher moments. This study, therefore, contributes to the line of literature addressing this gap by examining the out-of-sample predictability of oil return skewness for stock returns in both developed economies (G7 plus Switzerland) and emerging markets (BRICS), enhancing our findings' generalizability.

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 two 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 entire history of stock returns movement in relation to oil price returns skewness.

Utilizing the longest possible data samples prevents the so-called "sample selection bias". In the process, we capture various positive and negative oil shocks associated with, for example, the US 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 ongoing Russia–Ukraine War.[1]

Note that, as indicated by Rapach and Zhou (2013, 2022), the best test of any predictive model (with regards 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)-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 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; Salisu and Gupta 2022; 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; 1859:10–2023:09), the US (S&P500 Index; 1859:10–2023:09), plus Switzerland (All Share Stock Index; 1916:02–2023:09).[2] The two 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 data availability, with all the variables sourced from the Global Financial Data.[3]

Building on the foregoing, the descriptive statistics of our variables (oil and stock returns) are presented, alongside figures illustrating the co-movement between oil return (and skewness) and stock returns across the G7 plus Switzerland, and the entire BRICS countries (see Table A1 and Figure A1 in Appendix A of the paper). The figures provide evidence that both positive and negative oil returns (skewness) exhibit predictive potential for stock returns in these countries, as the latter tends to portray a mean-reverting tendency regardless of fluctuations in the former. Furthermore, we have also partitioned the descriptive statistics into distinct sub-sample periods, including the Great Depression, World Wars, OPEC emergence, COVID-19 period, and Russia–Ukraine War. Importantly, the summary statistics provided additional nuances to the illustrated trends.

2.2. Econometric Model

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

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

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; $\beta_2\Delta\, skoil_t$ represents 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) filter; while ε_t is the residual term that follows a white noise process.

In order to obtain a time-varying measure of the expected skewness of oil returns ($roil_t$), we estimate the following asymmetric version of the Conditional Autoregressive Value at Risk by Regression Quantiles (CaViaR) model, as developed by Engle and Manganelli (2004), with τ depicting the quantile as follows:

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

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, well-established Kelley skewness (Kelley 1947) as follows:

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

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

Skewness captures future risks in the oil market, and can result from variations in expected skewness, which likely originates from extreme directed changes in aggregate demand and supply, geopolitical acts and threats, rare disaster events, including pandemics, and even financial market spillovers. (Gupta et al. 2023). Given this, we identified various types of crises and geopolitical events in Table A2 in Appendix A of the paper; we defined a dummy variable equal to 1 for the months corresponding to such years of events and used 0 for anything otherwise. When we regressed $skoil_t$ on the dummy, we found a positive coefficient of 0.074, with a standard error of 0.015, and a t-statistic of 4.978, implying statistical significance at the 1% level, with a p-value of 0.000. This confirms that our measure of skewness can be associated with global risks, and hence, is likely to serve as a predictor for stock returns, based on the channels discussed in the introduction.

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) 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 forecast errors of the competing models is negligible. The estimation equation for the CW test statistic is provided in Equation (4):

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

where h denotes the forecast horizon; $(r_{t+h} - \hat{r}_{1t,t+h})^2$ and $(r_{t+h} - \hat{r}_{2t,t+h})^2$ denote the squared residuals from the restricted and unrestricted model variants, respectively, of our WN-type distributed lag model; while $(\hat{r}_{1t,t+h} - \hat{r}_{2t,t+h})^2$ 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 $MSE_1 - (MSE_2 - adj.)$, where $MSE_1 = P^{-1}\sum(r_{t+h} - \hat{r}_{1t,t+h})^2$, $MSE_2 = P^{-1}\sum(r_{t+h} - \hat{r}_{2t,t+h})^2$, $adj. = P^{-1}\sum(\hat{r}_{1t,t+h} - \hat{r}_{2t,t+h})^2$ 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 the 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[4], 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 provides vital information that improved the stock prediction across all the countries, as depicted by the significance of the CW forecast comparison test statistics at the 1% level.

Table 1. Forecast evaluation result using the Clark and West (2007) test statistics [50:50 data split].

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.

For further robustness check, the case of a longer in-sample, and hence shorter out-of-sample, with a 75–25% split is also examined (see Table 2), 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 indicates that the improvement of the precision of our predictive model variant with expected skewness of oil returns over the benchmark historical average model transcends the data sample and, hence, is robust to the choice of out-of-sample periods. Our findings are consistent with the established literature highlighting the predictability of oil returns for stock returns (e.g., Narayan and Gupta 2015; Gupta and Wohar 2017; Ebrahimi and Pirrong 2018; Mo et al. 2019; Dai et al. 2021; Salisu et al. 2023). For example, Dai et al. (2021) provide evidence that forecasts of stock market returns, derived from the skewness of oil price returns, are statistically and economically significant in out-of-sample performance.

Table 2. Forecast evaluation result using the Clark and West (2007) test statistics [75:25 data split].

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.

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 (refer to Table 3). 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 mentioned, 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.

Table 3. Forecast evaluation result using the Clark and West (2007) test statistics.

Panel A: 50–50%–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.

As an alternative representation of our findings, we present in Figure A2[5] in Appendix A, the cumulative sum of squared errors for the benchmark model and the extended model with skewness over time, following Welch and Goyal (2008). As can be seen clearly, this metric is consistently lower for the model with skewness compared to the model without it, thus confirming graphically our statistical findings of out-of-sample forecasting reported in Tables 1–3.

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

4. Conclusions

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, which serves as a metric of global risks, 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 eight developed and two emerging markets, with the result being robust to multi-steps-ahead forecast horizons and choices of the length of the out-of-sample periods. These findings also continue to hold for three other emerging markets, Brazil, China, and Russia, but with shorter sample periods.

On the one hand, finance practitioners require stock return forecasts for asset allocation. On the other hand, academics are interested in stock return forecasts since they have important implications for producing robust market efficiency measures, which, in turn, help to produce more realistic asset pricing models. Understandably, our results have important multi-layer implications. First, investors would need to account for the 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 the expected skewness of oil price returns to understand the future movements in output and inflation and accordingly design policy responses.

As part of future research, extending our analysis to forecasting stock return volatility would be interesting due to the expected skewness of oil price returns. Future research could explore whether the predictive power of oil price return skewness for stock return volatility varies across sectors, such as energy and technology, and how this relationship behaves, particularly during periods of economic crises, geopolitical tensions, or shifts in energy policy.

Author Contributions: Conceptualization, R.G.; methodology, A.A.S.; software, A.A.S.; validation, R.G.; formal analysis, A.A.S.; investigation, R.G. and A.A.S.; resources, R.G. and A.A.S.; data curation, R.G.; writing—original draft preparation, R.G. and A.A.S.; writing—review and editing, R.G. and A.A.S.; visualization, R.G. and A.A.S.; project administration, R.G.; supervision, A.A.S. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: Data will be made available upon request.

Acknowledgments: We would like to thank editor and the four anonymous referees, and the Editor of the Special Issue, for many helpful comments. Any remaining errors are solely ours.

Conflicts of Interest: The authors declare no conflict of interest.

Appendix A

Table A1. Descriptive statistics of oil and stock returns across various periods.

	Full Sample		Ward War I [1914–1918][6]		Great Depression [1929–1941][7]		Ward War II [1939–1945][8]		OPEC Formation [September 1960–Present][9]		COVID-19 [December 2019–December 2023][10]		Invasion of Ukraine by Russia [February 2022–Present][11]	
G7 Countries + Switzerland	**Oil Return**	**Stock Return**	**Oil Return**	**Stock Return**	**Oil Return**	**Stock Return**	**Oil Return**	**Stock Return**	**Oil Return**	**Stock Return**	**Oil Return**	**Stock Return**	**Oil Return**	**Stock Return**
Canada (1915:01–2023:09)	0.31 (7.00)	0.40 (4.47)	2.11 (4.26)	0.18 (2.25)	−0.26 (5.75)	−0.67 (7.02)	0.47 (3.42)	0.33 (4.19)	0.45 (8.00)	0.49 (4.36)	0.98 (16.91)	0.37 (4.60)	0.36 (8.44)	−0.28 (3.09)
France (1898:01–2023:09)	0.33 (6.72)	0.54 (5.1)	0.78 (5.40)	0.36 (3.59)	−0.26 (5.75)	0.30 (6.64)	0.47 (3.42)	1.58 (7.15)	0.45 (8.00)	0.43 (5.21)	0.98 (16.91)	0.37 (5.51)	0.36 (8.44)	−0.03 (3.89)
Japan (1914:08–2023:09)	0.3 (7.0)	0.55 (6.03)	1.56 (4.68)	1.15 (5.69)	−0.26 (5.75)	0.32 (4.61)	0.47 (3.42)	0.09 (3.17)	0.45 (8.00)	0.43 (5.31)	0.98 (16.91)	0.74 (4.01)	0.36 (8.44)	0.98 (2.49)
Germany (1870:01–2023:09)	0.15 (7.63)	0.22 (7.03)	0.78 (5.40)	−0.40 (6.40)	−0.26 (5.75)	−0.01 (4.04)	0.47 (3.42)	0.51 (1.61)	0.45 (8.00)	0.30 (5.07)	0.98 (16.91)	0.00 (5.61)	0.36 (8.44)	−0.65 (4.40)
Italy (1905:02–2023:09)	0.29 (6.80)	0.42 (6.70)	0.78 (5.40)	0.18 (5.00)	−0.26 (5.75)	0.23 (5.21)	0.47 (3.42)	1.97 (11.32)	0.45 (8.00)	0.25 (6.23)	0.98 (16.91)	0.42 (6.05)	0.36 (8.44)	0.01 (4.58)
UK (1859:10–2023:09)	0.08 (9.28)	0.28 (3.80)	0.78 (5.40)	−0.21 (1.90)	−0.26 (5.75)	−0.18 (4.67)	0.47 (3.42)	0.50 (4.57)	0.45 (8.00)	0.48 (5.07)	0.98 (16.91)	0.07 (4.44)	0.36 (8.44)	0.05 (2.71)
USA (1859:10–2023:09)	0.08 (9.28)	0.41 (4.09)	0.78 (5.40)	−0.03 (3.18)	−0.26 (5.75)	−0.62 (8.19)	0.47 (3.42)	0.37 (4.05)	0.45 (8.00)	0.58 (3.61)	0.98 (16.91)	0.76 (4.66)	0.36 (8.44)	−0.18 (3.94)
Switzerland (1916:07–2023:09)	0.27 (7.02)	0.29 (4.30)	1.44 (3.65)	−0.32 (2.00)	−0.26 (5.75)	−0.10 (5.20)	0.47 (3.42)	0.07 (3.06)	0.45 (8.00)	0.32 (4.51)	0.98 (16.91)	0.07 (3.87)	0.36 (8.44)	−0.75 (3.12)
BRICS														
Brazil (1954:02–2023:09)	0.41 (7.62)	5.19 (19.86)	- -	- -	- -	- -	- -	- -	0.45 (8.00)	5.47 (20.78)	0.98 (16.91)	0.18 (6.97)	0.36 (8.44)	0.45 (4.58)
Russia (1997:10–2023:09)	0.48 (10.28)	1.71 (10.45)	- -	- -	- -	- -	- -	- -	0.48 (10.28)	1.71 (10.45)	0.98 (16.91)	0.47 (7.85)	0.36 (8.44)	−0.04 (10.15)

Table A1. *Cont.*

	Full Sample		Ward War I [1914–1918][12]		Great Depression [1929–1941][13]		Ward War II [1939–1945][14]		OPEC Formation [September 1960–Present][15]		COVID-19 [December 2019–December 2023][16]		Invasion of Ukraine by Russia [February 2022–Present][17]	
G7 Countries + Switzerland	**Oil Return**	**Stock Return**	**Oil Return**	**Stock Return**	**Oil Return**	**Stock Return**	**Oil Return**	**Stock Return**	**Oil Return**	**Stock Return**	**Oil Return**	**Stock Return**	**Oil Return**	**Stock Return**
India (1921:07–2023:09)	0.28 (6.98)	0.48 (5.17)	- -	- -	−0.26 (5.75)	0.20 (3.74)	0.47 (3.42)	0.92 (3.96)	0.45 (8.00)	0.79 (6.01)	0.98 (16.91)	1.08 (5.10)	0.36 (8.44)	0.56 (3.32)
China (1991:01–2023:09)	0.32 (9.56)	1.58 (14.76)	-	-	-	-	-	-	0.32 (9.56)	1.58 (14.76)	0.98 (16.91)	0.26 (4.27)	0.36 (8.44)	−0.29 (4.49)
South Africa (1910:02–2024:05)	0.30 (6.92)	0.60 (4.46)	0.78 (5.40)	0.20 (2.48)	−0.26 (5.75)	0.41 (3.88)	0.47 (3.42)	0.88 (2.69)	0.45 (8.00)	0.87 (5.38)	0.98 (16.91)	0.58 (4.79)	0.36 (8.44)	−0.05 (3.55)

Note: The mean and standard deviation (shown in parentheses) are reported. Due to variations in data scope, some countries are missing out from certain sub-sample periods. The oil return for some sample periods including OPEC emergence, COVID-19 and invasion of Ukraine by Russia have the same start and end dates across the countries (barring Russia and China which have shorter period for OPEC emergence), hence, their uniform values for both mean and standard deviation.

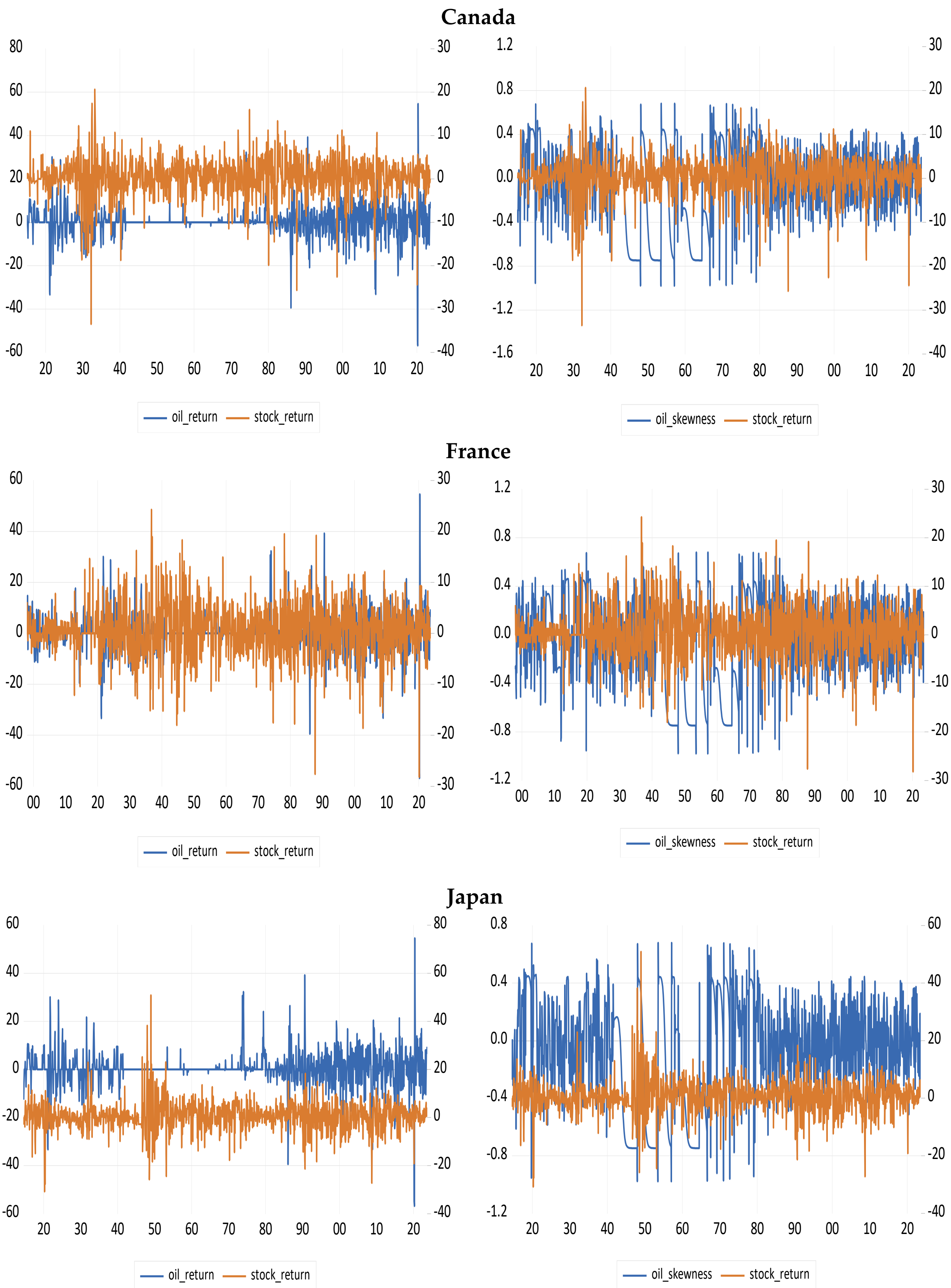


Figure A1. *Cont.*

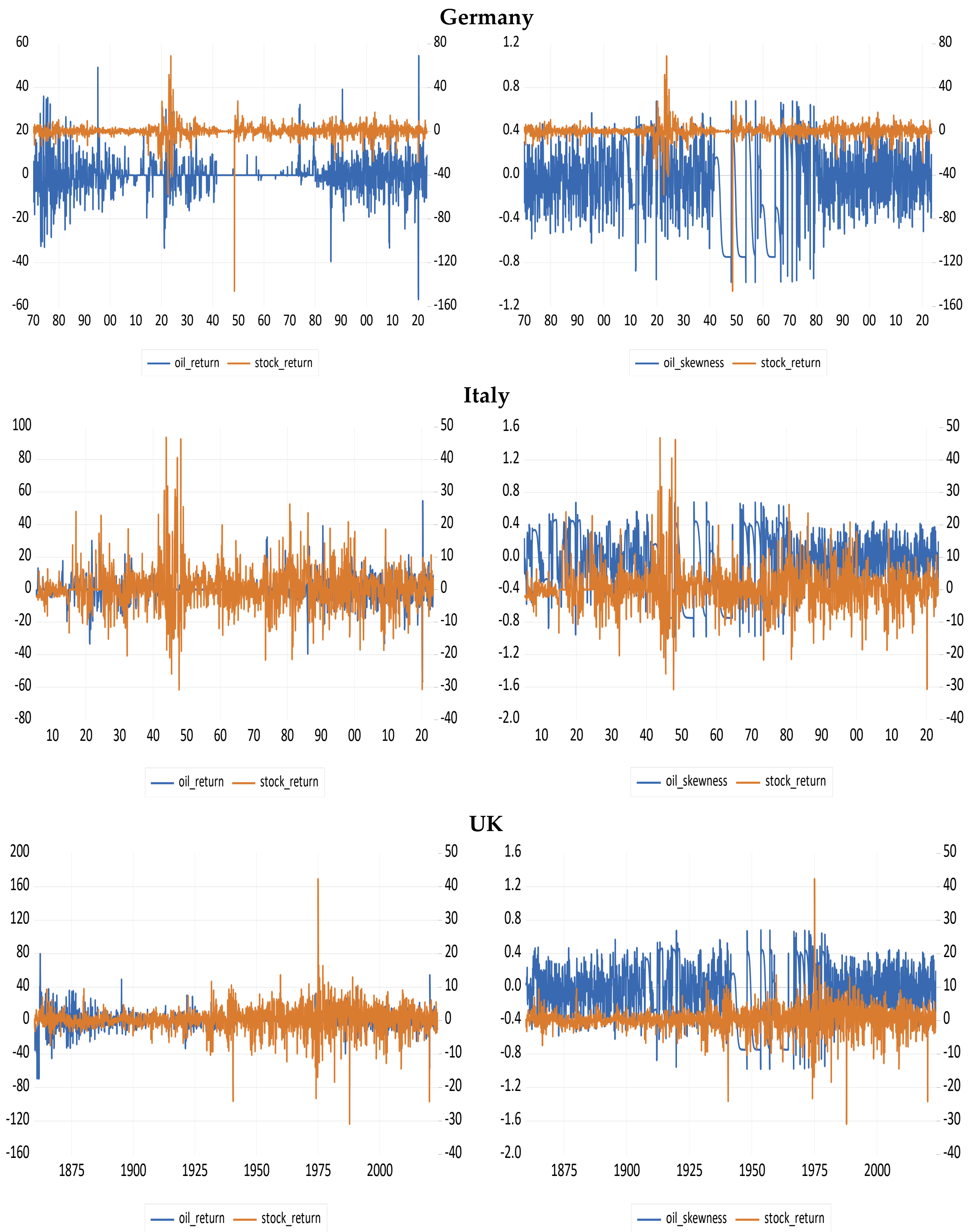


Figure A1. *Cont.*

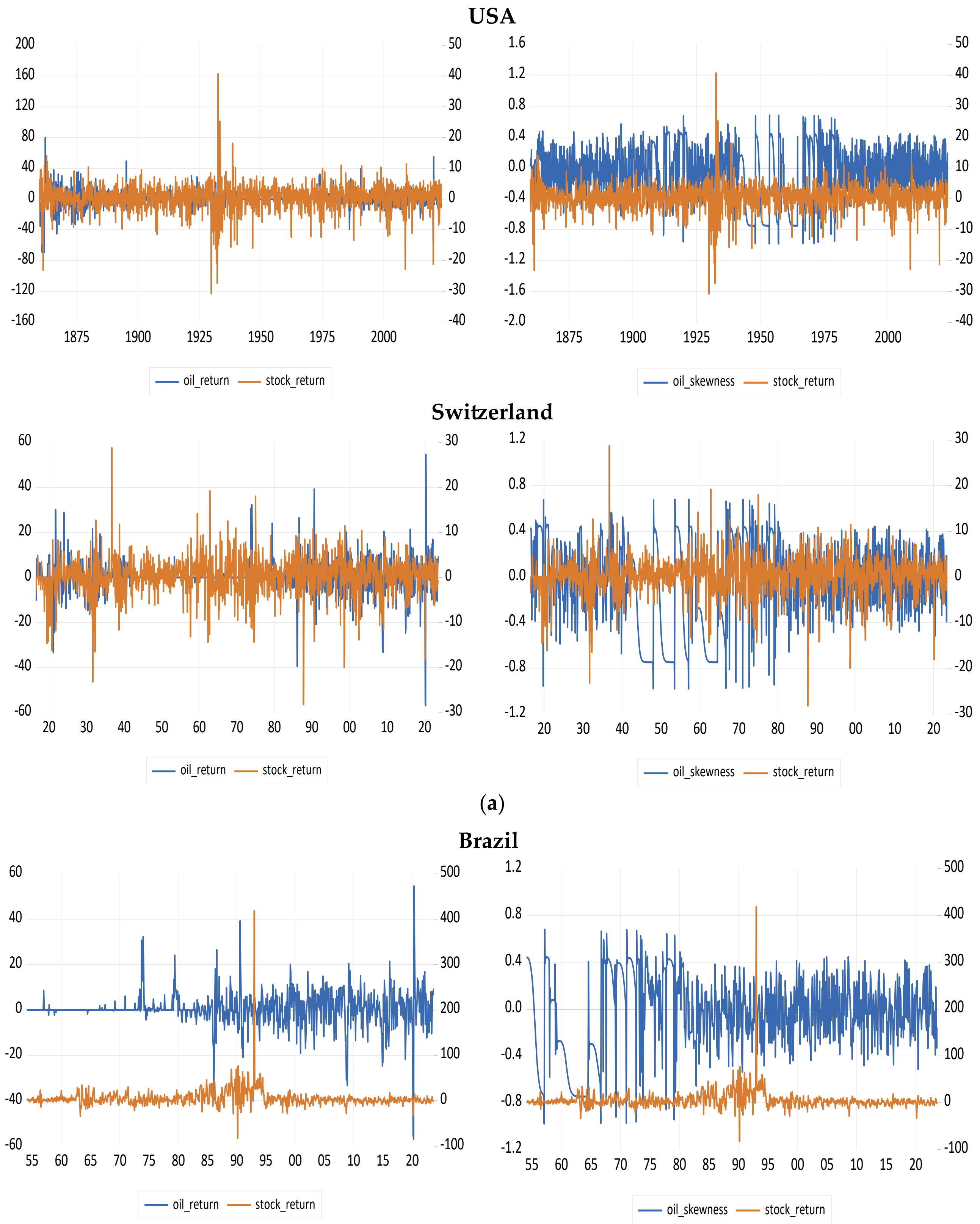


Figure A1. *Cont*.

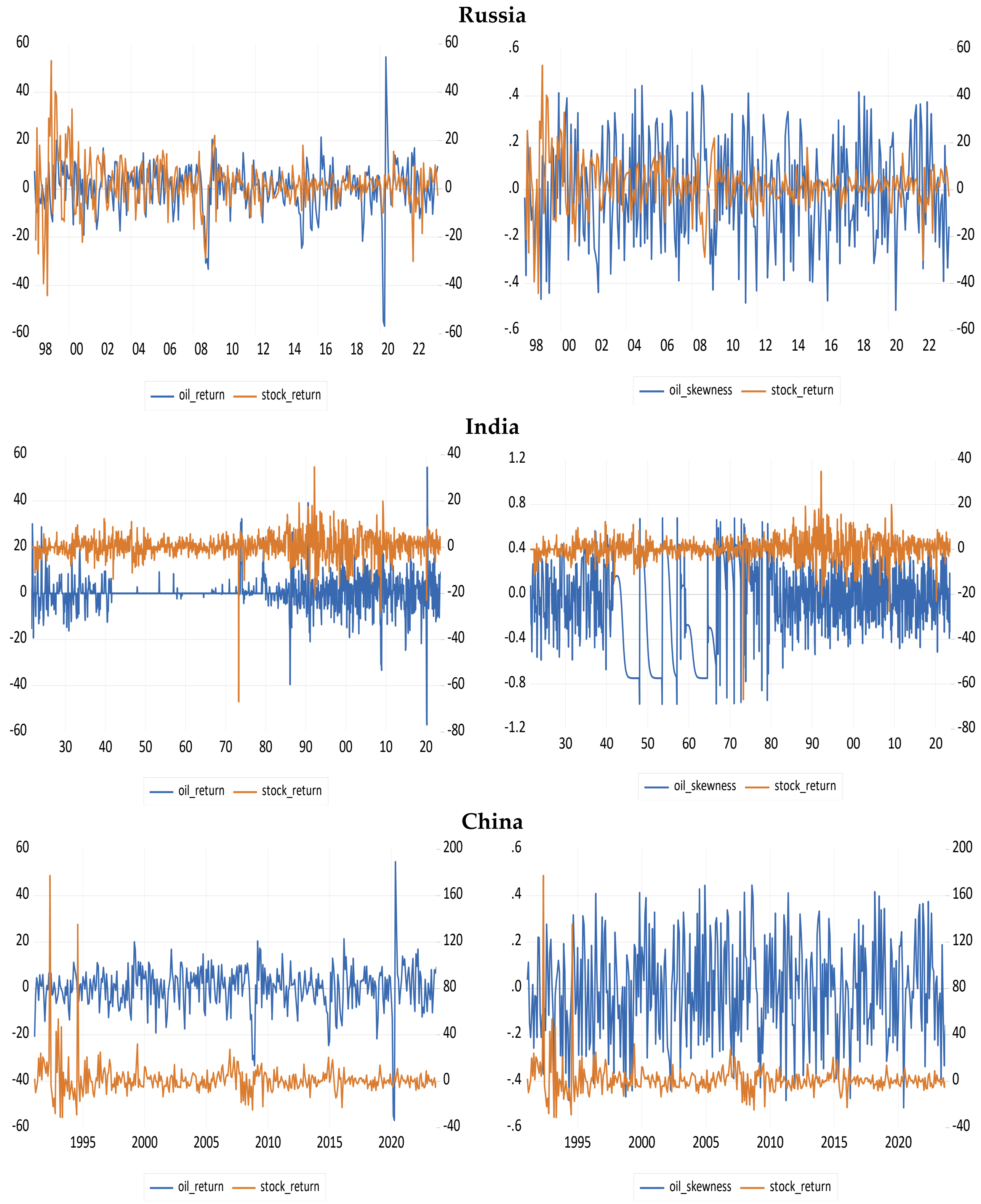
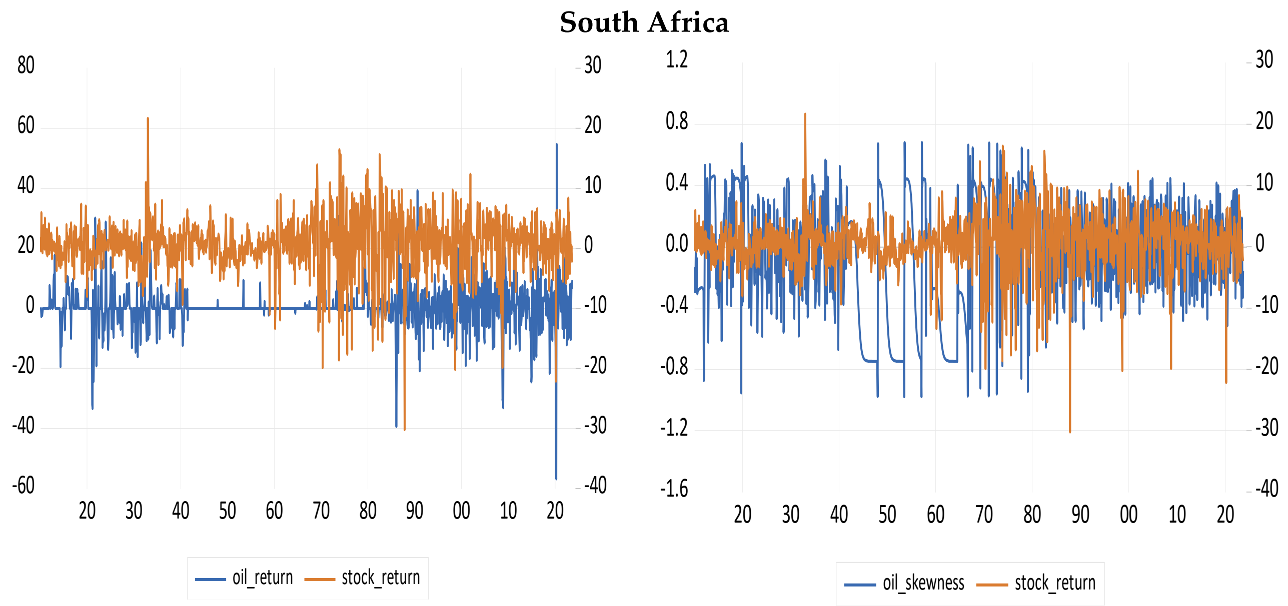


Figure A1. *Cont.*



(**b**)

Figure A1. Data Plots. (**a**): Oil return (skewness)—stock return nexus in the G7 plus Switzerland. (**b**): Oil return (skewness)—stock return nexus in BRICS—Brazil, Russia, India, China, and South Africa.

Table A2. List of global crises and geopolitical events.

Crises	Date
Panic of 1866	1866
Great Depression of British Agriculture	1873–1896
Long Depression	1873–1896
Panic of 1901	1901
Panic of 1907	1907
World War I	1914–1918
Depression of 1920–21	1920–1921
Wall Street Crash of 1929 and Great Depression	1929–1939
World War II	1939–1945
OPEC oil price shock	1973
Energy crisis	1979
Secondary banking crisis	1973–1975
Early 1980s Recession	1981–1982
Latin American debt crisis	1982
Bank stock crisis	1983
Japanese asset price bubble	1986–1992
Black Monday	1987
Savings and loan crisis	1986–1995
Special Period in Cuba	1990–1994
India economic crisis	1991
Finnish banking crisis	1991–1993

Table A2. *Cont.*

Crises	Date
Swedish banking crisis	1990
Economic crisis in Mexico	1994
Asian financial crisis	1997
Russian financial crisis	1998
Ecuador financial crisis	1998–1999
Argentine economic crisis	1999–2002
Samba effect	1999
Dot-com bubble	2000-2002
Turkish economic crisis	2001
Uruguay banking crisis	2002
Venezuelan general strike	2002–2003
Financial Crisis	2007–2009
2000s energy crisis	2003–2009
Subprime mortgage crisis	2007–2010
United States housing bubble and United States housing market correction	2003–2011
Automotive industry crisis	2008–2010
Icelandic financial crisis	2008–2012
Irish banking crisis	2008–2010
Russian financial crisis	2008–2009
Latvian financial crisis	2008
Venezuelan banking crisis	2009–2010
Spanish financial crisis	2008–2016
European sovereign debt crisis	2009–2018, and ongoing
Portuguese financial crisis	2010–2014
Crisis in Venezuela	2012–2018, and ongoing
Ukrainian crisis	2013–2014
Russian financial crisis	2014
Brazilian economic crisis	2014–2017
Chinese stock market crash	2015
Turkish currency and debt crisis	2018
Debt crisis in India	1993–2018, and ongoing
COVID-19 Pandemic	2020
Russia–Ukraine War	2022, and ongoing
Israel–Hamas War	2023

Sources: Galbraith (1990), Reinhart and Reinhart (2010), and Reinhart and Rogoff (2009, 2011), with data beyond 2010 derived from the list of major economic crises available online at: https://en.wikipedia.org/wiki/List_of_economic_crises (accessed on 1 June 2023).

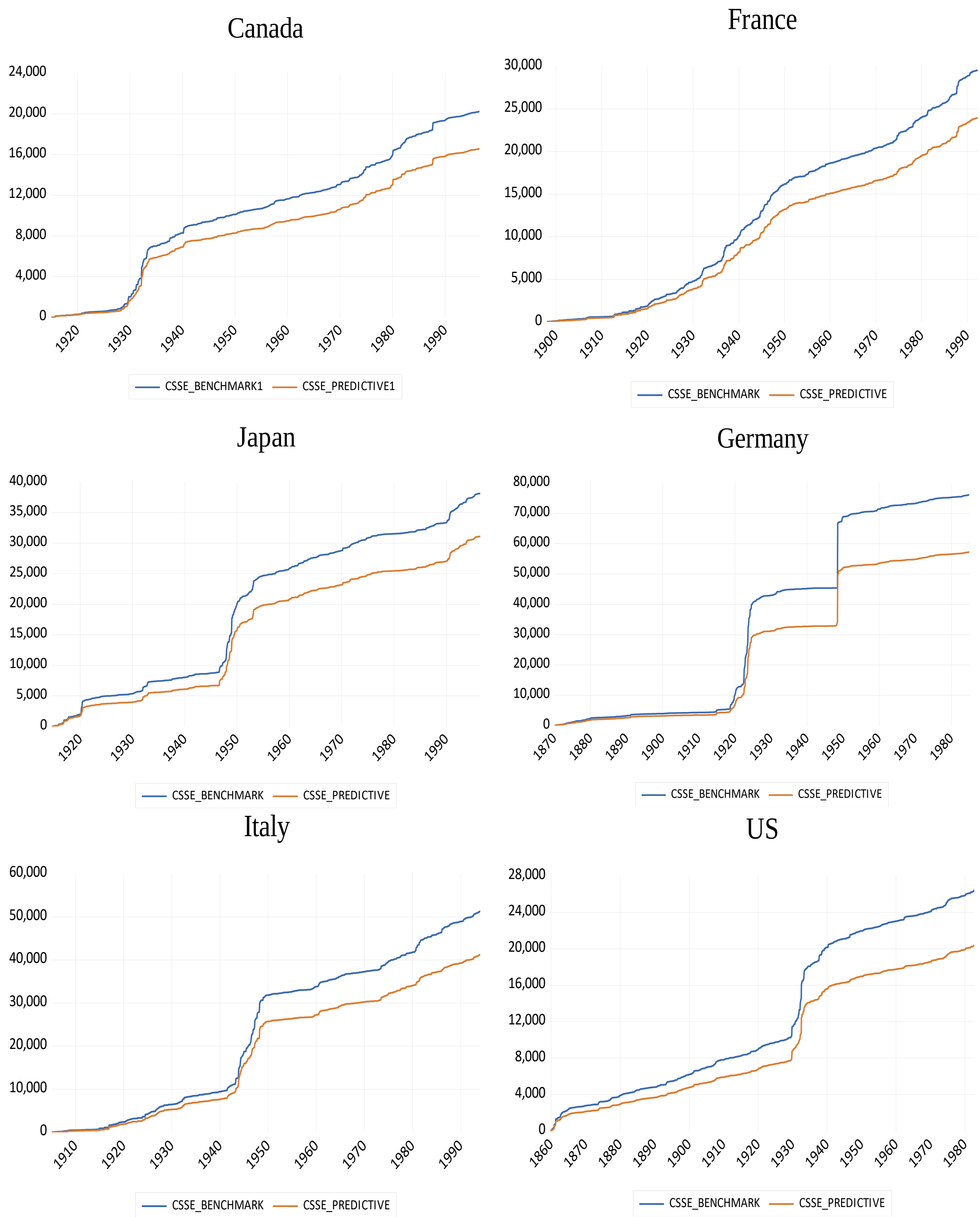


Figure A2. *Cont.*

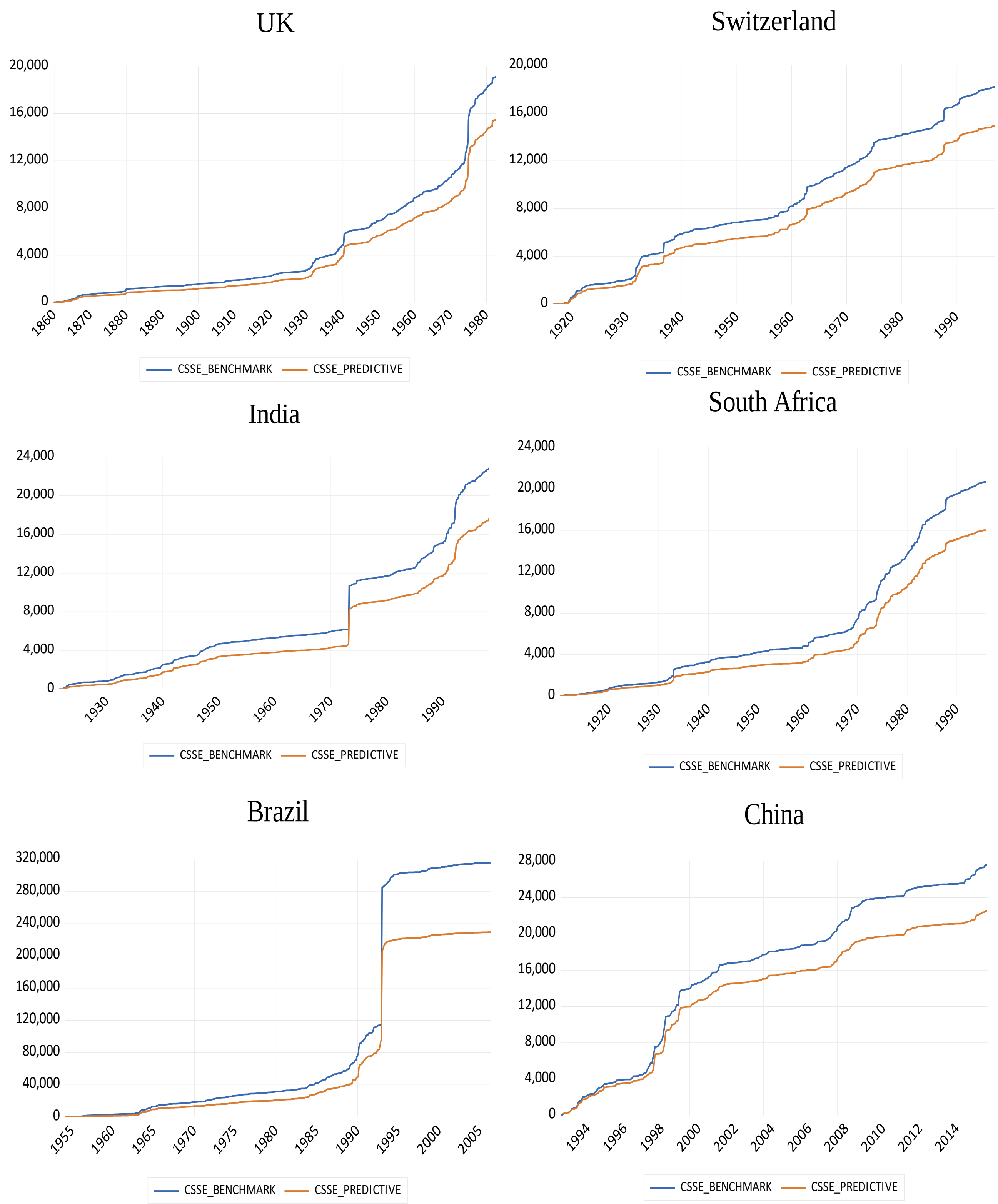


Figure A2. *Cont.*

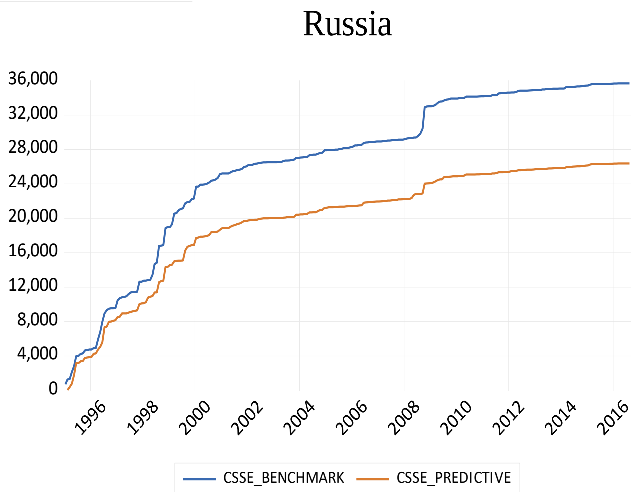


Figure A2. Cumulative sum of squares comparison between the benchmark model and our predictive model.

Notes

1 The reader is referred to Hamilton (2013) for a detailed discussion of historical oil shocks from 1859 to 2009.
2 Stock price data for the UK and the US in fact starts from 1693:01 and 1791:08, respectively.
3 https://globalfinancialdata.com/ (accessed on 1 June 2023).
4 The rationale for multiple forecast horizons is to ensure robustness while capturing short-, medium-, and longer-term effects, and providing a comprehensive understanding of how oil price skewness influences stock return over varying time scales.
5 The plots are based on a one-month ahead rolling window framework. The other forecast horizons (h = 3 and h = 6) follow the same pattern and are therefore suppressed for brevity.
6 See History.com via https://www.history.com/topics/world-war-i. Accessed on 1 June 2023.
7 According to Federal Reserve (see https://www.federalreservehistory.org/essays/great-depression#). Accessed on 1 June 2023.
8 See History.com via https://www.history.com/topics/world-war-ii. Accessed on 1 June 2023.
9 https://www.opec.org/opec_web/en/about_us/24.htm#. Accessed on 1 June 2023.
10 https://www.cdc.gov/museum/timeline/covid19.html. Accessed on 1 June 2023.
11 https://commonslibrary.parliament.uk/research-briefings/cbp-9847/. Accessed on 1 June 2023.
12 See History.com via https://www.history.com/topics/world-war-i. Accessed on 1 June 2023.
13 According to Federal Reserve (see https://www.federalreservehistory.org/essays/great-depression#). Accessed on 1 June 2023.
14 See History.com via https://www.history.com/topics/world-war-ii. Accessed on 1 June 2023.
15 https://www.opec.org/opec_web/en/about_us/24.htm#. Accessed on 1 June 2023.
16 https://www.cdc.gov/museum/timeline/covid19.html. Accessed on 1 June 2023.
17 https://commonslibrary.parliament.uk/research-briefings/cbp-9847/. Accessed on 1 June 2023.

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