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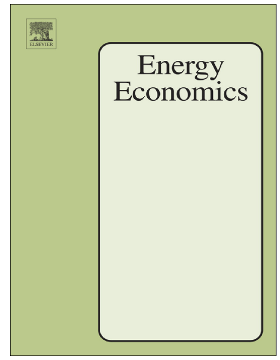

Different strokes for different folks: The case of oil shocks and emerging equity markets

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PII: S0140-9883(22)00078-0

DOI: https://doi.org/10.1016/j.eneco.2022.105897

Reference: ENEECO 105897

To appear in: *Energy Economics*

Received date: 25 August 2021

Revised date: 23 January 2022

Accepted date: 9 February 2022

Please cite this article as: I.D. Raheem, Different strokes for different folks: The case of oil shocks and emerging equity markets, *Energy Economics* (2021), https://doi.org/10.1016/j.eneco.2022.105897

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Different Strokes for Different Folks: The Case of Oil Shocks and Emerging Equity Markets

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Abstract

This study examines the relationship between oil shocks and stock returns. Taking a cue from Ready (2018), oil price is decomposed into demand, supply, and risk shocks. Building a dataset for emerging markets, we examine the extent to which oil shocks could accurately make in- and out-of-sample forecasts on stock returns. Three striking results emanate from our analyses. First, the three types of shock are significant determinants of stock returns in the selected countries. Second, the shocks are able to accurately make out-of-sample forecasts for all the countries across the forecasting horizon. Third, accounting for asymmetry in the shocks provided mixed results; essentially, we show that asymmetry and symmetry models provide opposing results. In all, the forecasting power of oil shocks is heterogeneous across countries, as the exact effect is dependent on: (i) the types of shock, (ii) countries and (iii) symmetry or asymmetry model. These results have important policy implications.

Keywords: Oil shock, Emerging markets, Forecasting and Asymmetry
JEL classifications: E44, G15, Q40.

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Introduction

The relationship between energy and financial markets has been extensively studied to the extent that one could erroneously assume no new hypothesis could be tested (Salisu et al., 2019a). The oil price-stock returns nexus is at the centre of this discourse and can simultaneously be considered one of the most studied issues in financial economics (see Degiannakis et al., 2018; Smyth and Narayan, 2018; for excellent literature surveys). Making a brief evolution, the literature can be classified into three strands. The first set of studies examines the relationship between oil price and stock returns (Martin-Barragan et al., 2015; Balcilar et al., 2015; Bouri et al., 2016; Chen et al., 2017; Basher et al., 2018). Kilian and Park (2009) changed the narration of the debate by arguing that oil shock, rather than price, is a better predictor of stock returns. Kilian (2009) further argued that oil shocks have heterogenous impacts on equity markets, thus necessitating the decomposition of oil shock. Kilian was able to decompose shocks into demand- and supply-driven. This strand of the literature has become the order of the day, as subsequent studies have shown that the sources of oil shocks are better able to explain the activities of the equity markets. The third strand extends Kilian (2009) by creating an additional source of shock: risk-driven. This strand is championed by Ready (2018) and argued that apart from the already known sources of shock (i.e. demand and supply), the recent global rising tides of uncertainty and geopolitical tension appear to be another source of the shock that could have important stake in both energy and financial markets.

Hence, Ready decomposed oil price into three shocks: demand, supply, and risk. The intuition of Ready (2018) is to construct an index using three variables: a measure of uncertainty and adjustment in the expected returns proxied by VIX, a measure to capture fluctuations in oil prices and an index for oil producer firms. The novelty of Ready's approach over Kilian's is due to the ability of the former to: (i) work with high frequency data (Umar et al., 2021); and (ii) account for the forward-looking nature of traded financial asset prices; thus making it easier to determine whether demand shocks are influenced by concerns about future supply (Riza et al., 2020). Studies are increasingly taking a cue from Ready to test the varying hypothesis. For instance, Riza et al. (2020) examined oil shock and the bond markets and further explored the role of oil shock on the degree of connectedness of international financial markets. Umar et al. (2021) tested a similar hypothesis but focused on the equity markets for both oil- import and exporting countries. Anand and Paul (2021) use Time-Varying Parameter Structural Vector Autoregression-Stochastic Variance to show that the three sources of shocks impact the Indian stock market differently. Clements et al. (2019) made a simple modification to Ready's model by providing a clearer delineation between shocks to equity market discount rates and aggregate demand leading to an oil shock specification which attributes substantially more explanatory power to the latter in explaining equity market variation. Gomez-Gozanlez et al. (2021) showed robust dynamic relationship between oil shocks and seven stock markets by examining the volatility

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spillover, networks and causality among these markets. Liu et al. (2021) examined the nonlinear effects of variants measures of oil shocks on China's financial stress index. The authors show that oil supply shocks have a significantly positive effect in the low-volatility state, while the effects of demand shocks are negative and significant in both regimes. Das and Kannadhasan (2020) found that while demand shock is a positive determinant of stock returns, the inverse is the case for supply and risk shocks. The authors also reveal countries react more to lower demand shocks and higher supply and risk shocks.

Despite the impressive nature of the studies reviewed above, there are some apparent shortcomings. Chief among these is their inability to account for the importance of asymmetry in the nexus. Essentially, we hypothesize that the responses of the stock market to oil shocks are direction specific. In essence, we orate that financial markets respond differently to positive and negative changes in oil shock. Take demand shock, for instance; the markets' response to positive demand shock would be different from negative demand shocks. A positive demand shock would beneficially stimulate the economy, thus having an advantageous effect on the stock market. An exact opposite argument holds for negative demand shock. Previous studies have confirmed the importance of asymmetry in the nexus, albeit the focal lens was directed to oil price (Trabelsi, 2017; Raheem, 2017; Badeeb and Lean, 2018; Salisu et al., 2019 a, b, Das and Kannadhasan, 2020).

Based on the foregoing, the objective of this study is two-fold. First, we seek to inquire the predictive prowess of oil shock on stock markets. Second, we test for the role of asymmetry in the nexus. Plainly, the second objective is to examine the degree of the importance of the partial sums decomposition of shocks. These objectives are achieved in three phases. First, we rely on Ready's (2018) approach to decompose oil shock into demand, supply, and risk. Second, we fit these shocks singly as predictors of stock returns. Our specified predictive model is in the spirit of Westerlund and Narayan (2015)[1]. Third, shocks are further decomposed into positive and negative partial sums following the recommendation of Shin et al. (2014).

We make four contributions to this growing literature. First, we join the burgeoning list of studies to advocate for a three-way shock type, thus making us among the early disciples of Ready (2018). Second, no study we are aware of has examined the asymmetric influence of oil shocks. The third novelty lies in the scope of the study. Similar existing studies have relied on developed economies. In our case, we focus on a group of emerging countries; our rationale for choosing these economies is due to their varying role in the global oil market. World Fact Book shows that China, India, South Africa, Turkey are among the top world oil consumer. At the same time, Russia is a strategic oil producer, on the average, accounts for 10% of the global oil supply. Furthermore, these economies have recorded improved performance of their stock markets and increasingly becoming important global players.

[1] Salisu et al (2019a) provide the advantages of this model over its contemporaries.

Fourth, we rely on an updated dataset (01/05/2012 – 30/04/2021). Coincidentally, this time frame features periods of massive spikes in the three types of shocks. At the onset of the pandemics, governments made concerted efforts to contain the spread of the virus. These efforts led to plum in the demand for and supply of oil. The rest of this study is organized as follows. Data and methodology are discussed in Section 2. Section 3 presents the empirical results. Section 4 concludes the study and also enumerates some policy implications.

2 Methodology and Data

2.1 Methodology

The empirical framework of this study is based on three approaches. The first relates to computing oil shock following the conceptualization of Ready (2018). The second approach dwells on specifying a forecasting model based on the ideology of Westerlund and Narayan (2015)

2.1.1: Oil Shock Computation

As mentioned earlier, Kilian's (2009) approach to compute oil shock has several shortcomings, among which is its inability to distinguish between oil-specific demand shocks that are driven by concerns about future oil supply and concerns driven by changes in aggregate demand for oil. Also, Kilian approach is designed for monthly data frequency, thus implying its irrelevance for higher frequency data. To this end, Ready (2018) overcome these shortcomings by defining demand shock as the proportion of returns on the global stock index of oil-producing firms that is orthogonal to the innovation of the VIX. The innovation to the VIX is incorporated to account for aggregate changes in the discount rate that affects stock returns of oil-producing firms. Similarly, supply shock is defined as the residuals of the changes in oil supply that is orthogonal to demand and risk shocks. The three-way decomposition model is represented in the matrix form:

$$X_t = AZ_t \qquad (1)$$

Where X_t is a 3x1 vector representing changes in oil price (Δoil), return on global stock index of oil-producing firms (R_t^p) and innovation to VIX (ξ_{vix}), based on ARMA(1,1). Z_t is also a 3x1 vector of oil demand, supply, and risk shocks represented by $d_t, s_t, and\ v_t$, respectively. A is a 3x3 matrix defined as:

$$A = \begin{bmatrix} 1 & 1 & 1 \\ 0 & \alpha_{22} & \alpha_{23} \\ 0 & 0 & \alpha_{23} \end{bmatrix} \qquad (2)$$

To achieve orthogonality among the shocks, there is the need to impose some conditions:

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$$A^{-1}\sum_X (A^{-1})^T = \begin{bmatrix} \sigma_s^2 & 0 & 0 \\ 0 & \sigma_d^2 & 0 \\ 0 & 0 & \sigma_v^2 \end{bmatrix} \quad (3)$$

Where $\sum_X$ is the covariance matrix of the variables in X_t. σ_s^2, σ_d^2, σ_v^2 are the variance of supply, demand and risk shocks respectively. Equation 3 is the renormalization of the standard orthogonalization used to define structural shocks based on Structural VAR framework. Instead of normalizing the volatility of oil shock to one, the sum of the three shocks is expected to equal to the total variation in the oil price.

2.1.2 The Forecasting Model

This section seeks to inquire the extent to which shocks can predict emerging market stocks returns. Hence, the predictive model is specified as:

$$r_t = \alpha + \beta s_{t-1} + \varepsilon_t \quad (4)$$

Where r is the return on stock prices; S represents the three types of oil shock, i.e. demand, supply and risk. Studies have concluded that high frequency variables are vulnerable to some statistical problems such as conditional heteroscedasticity, persistence and endogeneity effect (Salisu et al., 2019a, b; Isah and Raheem, 2019). These features thus inhibit the use of OLS models. However, Westerlund and Narayan (2015), hereinafter W.N., propose that accounting for these features would require re-specifying equation 4 as:

$$r_t = \alpha + \beta_1 s_{t-1} + \beta_2(s_t - \gamma s_{t-1}) + \varepsilon_t \quad (5)$$

Where $\beta_1 s_{t-1}$ is the first order autocorrelation, $\beta_2(s_t - \gamma s_{t-1})$, captures the persistence effect and the resulting endogeneity incorporated in the parameter. Testing for persistence requires estimating equation 6 by OLS

$$s_t = \alpha + \beta s_{t-1} + \mu_t, \text{ where } \mu_t \sim N(0, \sigma_v^2) \quad (6)$$

W.N. state that Feasible Quasi Generalized Least Squares (FQGLS) estimator is a better estimator to OLS, as the former is able to extract any information embedded in the conditional heteroscedasticity effect.

In order to account for the role of asymmetry, each shock type is decomposed into positive and negative partial sums. Thus, the asymmetric version of equantion 6 is expressed as:

$$s_t = \alpha + \beta^+ s_{t-1}^+ + \gamma^- s_{t-1}^- + \mu_t \quad (7)$$

Where s_{t-1}^+ and s_{t-1}^- are the positive and negative partial sum decompositions, respectively. The computation of the partial sums is in line with Shin et al. (2014) given as:

$$s_{t-1}^+ = \sum_{k=1}^t \Delta s_{ik}^+ = \sum_{k=1}^t max(\Delta s_{ik}, 0) \quad (8)$$

$$s_{t-1}^- = \sum_{k=1}^t \Delta s_{ik}^- = \sum_{k=1}^t min(\Delta s_{ik}, 0) \quad (9)$$

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2.1.3: Forecast Evaluation

The predictive model is based on out-of-sample, and the forecasting horizons are h = 1, 10, 30, 60 and 90 days ahead. Taking a cue from similar studies, we divided our data into in- and out-of-sample periods, by using 75:25 ratio (Salisu et al., 2019 a and b; Raheem and Vo, 2020).

We tagged model 1 the restricted model, which is coincidentally the benchmark model and is also based on two specifications: historical averages and AR(1). Model 2 is the unrestricted model. The forecasting evaluation is based on three different measures: Campbell and Thompson (2008), hereafter (C.T.) test; Theil-U statistics and the Clark and West (2007) hereafter (C.W.) test. Guidance from the literature reveals that Theil-U statistics is computed as the ratio of forecasting error of the unrestricted model to that of the restricted model. Theil-U statistics less than unity imply that the unrestricted model has higher predictive power than the restricted model.

The CT test is considered to be out-of-sample R^2 (OOS_R) statistics, which is computed as OOS_R = 1- Theil's U-statistics $\{(\widehat{RMSE}_2/\widehat{RMSE}_1)\}$, where $\widehat{RMSE}_2$ and $\widehat{RMSE}_1$ are the Root Mean Square Error for models 2 and 1, respectively. A positive C.T. value suggests that model 2 outperforms model 1 and vice-versa. The shortcoming of C.T. is its inability to show its level of statistical significance[2]. However, Clark and West (2007), hereinafter C.W., provide test to examine the statistical significance of C.T. C.W. test determines whether the difference between the forecast errors of the two models are statically different from zero[3].

2.2 Data and Preliminary Analyses

This study focuses on emerging markets due to their neglect by previous studies. Based on data availability, we built a dataset for 10 emerging countries (Brazil, Chile, China, India, Korea, Malaysia, Russia, Mexico, South Africa, and Turkey) for the period 01/05/2012 – 30/04/2021. Obviously, the two variables of interest are stock returns and oil price. Stock prices are measured in national currency units. To decompose oil price in the spirit Ready (2018), we rely on daily price for the following variables: (i) the world integrated oil and gas producer index[4]; (ii) CBOE volatility index[5]; and (iii) nearest maturity NYMEX crude-light sweet oil futures contract. These data are sourced from the Thomson Reuters DataStream.

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[2] Due to the inter-linkage between Theil's U-statistics and CT test and for ease to understand the results tabulation, we refrain from presenting the CT test results. In situations where the U-statistics is less than 1, mathematically, it is expected that the CT test would be positive and vice-versa.

[3] See Salisu et al. (2019a) for a detail explanation and procedures for estimating CW.

[4] Nationalized oil companies, such as Saudi Aramco or ADNOC are not captured in the computation of this index.

[5] This is the residuals from an ARMA (1,1) model to capture stocks related to changes in the discount rate that co-vary with attitudes towards risk.

Table 1 presents the descriptive statistics of the variables of interest. Panel A gives statistics for stock returns only. Some countries (Brazil, Chile, China and Mexico) have negative stock returns, implying a general decline in their stock exchange valuation over the years. Korea happens to have the most volatile stock market, judging by the value of the standard deviation. There is absence of unit root among the stock returns. Statistics of the oil shocks are presented in Panel B. All the oil shock measures have negative mean values, with demand shock taking the lead and followed by supply shock and risk, respectively. Also, the three variants of shocks are level stationary. Panel C shows the statistics for autocorrelation and heteroscedasticity, depicted by Q-statistics and ARCH-LM test, respectively.

Table 1: Preliminary Analysis

Sectors	Mean	Std Dev	Unit Root (ADF)		Persistence	Endogeneity
Stock Returns			Level	1st Diff		
Panel A: Descriptive Statistics					N/A	N/A
Brazil	-0.0021	0.2865	-50.307***	-	N/A	N/A
Chile	-0.0051	0.1493	-28.774***	-	N/A	N/A
China	-0.0023	0.2259	-34.036***	-	N/A	N/A
India	0.0060	0.1386	-30.394***	-	N/A	N/A
Korea	0.0157	0.8627	-32.973***	-	N/A	N/A
Malaysia	-0.0007	0.1082	-29.1988***	-	N/A	N/A
Mexico	-0.0022	0.1522	-28.926***	-	N/A	N/A
Russia	0.0015	0.1870	-32.712***	-	N/A	N/A
South Africa	0.0047	0.0985	-25.985***	-	N/A	N/A
Turkey	0.0018	0.1075	-34.515***	-	N/A	N/A
Panel B: Oil Shocks						
Supply	-0.0004	0.0276	-15.417***	-	0.0027*** (0.0001)	-0.0004 (0.0005)
Demand	-0.0003	0.0149	-15.869***	-	0.0063*** (0.0010)	-0.0002 (0.0003)
Risk	-0.0016	0.0780	-46.943***	-	0.0099*** (0.0003)	-0.0016 (0.0016)
Panel C: Autocorrelation and Heteroscedasticity						
Variable	Q-Stat		Q^2-Stat		ARCH-LM	
	K=10	K=20	K=10	K=20	K=10	K=20
Supply	69.854***	96.912***	1464.3***	2209.2***	1.7156*	6.7088***
Demand	118.79***	160.69***	1174.1***	1569.6***	7.0703***	3.7201***
Risk	20.481**	32.332**	93.021***	94.394***	1.2101	0.3558

Source: Author's computation

Note: "***", "**", "*" implies level 1s statistical significance at 1%, 5%, and 10% respectively. The unit root test is performed using Augmented Dickey–Fuller (ADF) approach. For autocorrelation and heteroscedasticity tests, the reported values are the Ljung-Box test Q-statistics for the former and the ARCH-LM test F-statistics in the case of the latter. The chosen lag length are 10 and 20, respectively. The null hypothesis for the autocorrelation test is that there is no serial correlation, while the null for the ARCH-LM (F distributed) test is that there is no conditional heteroscedasticity.

3. Empirical Results

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Table 2 presents the results of the predictive model. It can be deduced that, in most cases, supply and demand shocks are positive determinants of stock returns. Similarly, risk shock serves as a drag to stock returns. These results are similar to previous studies. For instance, the negative coefficient on risk shock is consistent with Riza et al. (2020), who argued that investors become risk averse as uncertainty increases. Similarly, several studies have reported the positive effect of demand shock (e.g. Zhu et al., 2017; Ready,2018; Basher et al., 2018; Das and Kannadhasan, 2020). One explanation for this could be that positive demand shock implies improvement in aggregate global economic activities, which positively spills over to the stock market. We show that the classification of countries (exporter/importer) does not change the results. Taking the three shocks, on the whole, it seems demand shock has the greater effect; a conclusion also reached in the literature (Kilian and Park, 2009; Zhu et al., 2017). The significance of these results is limited to Brazil, Chile, China and Mexico. A potential explanation for this could be linked to being a dominant and strategic player, irrespective of being either a producer or consumer, in the global oil and energy market (as in the case of Brazil and China) and higher exposure of the equity market to the energy sector (in terms of high number of oil trading firms listed on the equity market).

Table 2: Predictive Model

Countries	Supply	Demand	Risk
Brazil	2.1694*** (0.3411)	2.1688*** (0.6633)	-0.8853*** (0.1048)
Chile	1.3197*** (0.1854)	4.8608*** (0.3660)	-0.6574*** (0.0550)
China	1.9903*** (0.4208)	0.6367*** (0.06[illegible])	-0.4406*** (0.0971)
India	0.0773 (0.1825)	0.1871 ([illegible])	-0.0327 (0.0560)
Korea	0.6642 (1.1416)	1.7[illegible]8 (2.3523)	0.0421 (0.3507)
Malaysia	0.756 (0.355)	0.169 (0.210)	-0.323 (0.198)
Mexico	1.2245*** (0.1947)	0.8046*** (0.0398)	-0.7025*** (0.0586)
Russia	0.3216 (0.3536)	0.1302 (0.5140)	-0.0146 (0.0823)
South Africa	-0.0024 (0.1863)	0.0516 (0.2715)	-0.0205 (0.0433)
Turkey	0.0208 (0.1392)	0.1995 (0.2929)	0.0083 (0.0436)

Note: *, **, *** imply level of statistical significance at 1, 5, and 10%, respectively. Values in parenthesis are the standard error.

We now proceed to the forecasting model. In essence, this empirical enquiry aims to examine the extent to which the variants of oil shocks could make accurate in- and out-of-sample forecasts. The results of this exercise are presented in Table 3, which displays the Theil-U statistics. To recall, statistics less than unity (i.e. 1) show that the model is able to predict stock returns. The Table reveals that shock is generally a good and reliable predictor of stock returns across countries, types of shocks and forecasting horizons[6]. We next examine Theil-U statistics' statistical significance by conducting the Clark and West (C.W.) test, whose results are presented in Table 4. The Table shows that significance is achieved for Brazil, Chile, China, and Mexico. Coincidentally, these are the four countries with significant coefficients, as already shown in Table 2. Thus, the performance of the in-sample prediction also affects the out-of-sample forecast. In sum, we have established that the importance of oil shocks on the equity market is limited to Brazil, Chile, China, and Mexico.

We next study the reaction of the equity markets to the decomposition of shocks into positive and negative partial sums. The asymmetry Theil-U statistics is presented in Table 5, and the accompanying C.W. test results are shown in Table 6. Some interesting results were obtained. Starting with the supply shock, China, India and South Africa respond to both positive and negative partial sums decomposition, while Korea and Turkey respond only to negative supply shocks. In terms of the C.W. test, only China and Russia have significant effects. Focusing on demand shock, again, China, India and South Africa respond to the decomposition of shocks, while Mexico, Russia, Turkey, and Korea respond only to positive shock. This implies that countries react more to positive demand shock than negative demand shock. Also, virtually all the countries respond to either positive or negative demand shocks. The C.W. test shows high level of significance for China, Korea, and Mexico. Lastly, we considered risk shock, whose results reveal that asymmetry is important and negative partial sum has higher predictive prowess. These results are significant for Brazil, Chile, China, and Mexico. To summarize, the asymmetric risk shock has the highest forecasting power, followed by demand and supply shock, respectively.

3.2 Additional Analyses

We conducted some robustness tests to verify the reliability of the results. The first test relates to using alternative measures of oil shock[7]. This is due to the stance in the literature that financial series, stock returns inclusive, are sensitive to the measures of shocks (Gu et al., 2021; Assaf et al., 2021). To verify this claim, we use a measure of oil shock in the spirit of Baumeister and Hamilton (2019) by decomposing oil shocks into Oil supply shocks, Economic Activity Shocks, Oil Consumption Demand Shocks, and Oil Inventory Demand Shocks. One of the attractions to the suggested alternative measures of oil shocks is that they allow for the consideration of the transmission channels of oil shock to stock markets.

[6] Although, in some few instances, the Theil U-statistics is =/> 1. An example is the demand shock for South Africa where the statistics is not less than 1 at forecasting horizon 30 days ahead and beyond.

[7] We thank an anonymous reviewer for this suggestion.

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The results of this check are presented in the online appendix Tables 1-3. Comparing the results of this check to those presented earlier (i.e. Ready, 2018 vs Baumeister and Hamilton, 2019), we deduce that the results of both oil shock measures are similar in terms of Theil U-Statistics and C.W. test.

The second test focuses on expanding the model to account for some control variables. For instance, the Arbitrage Pricing Theory advocated for controlling risk factors in the predictive model of stock returns (Lin et al., 2019, Cosemans and Frehen, 2020). Also, studies have shown that some macroeconomic variables enhance the performance of predictive models (Raheem and Vo, 2020). In the light of the above, we use the world stock index, inflation rate and monetary policy rate as control variables. The results of this check are presented in the Online Appendix Tables 4-5. Indeed, the inclusion of the control variables enhanced the predictive prowess of the model. For instance, relative to the statistics presented in Tables 3 and 4, the expanded model yields lower Theil-U statistics, and more countries report significance of the C.W. test. The final check relates to examine whether the choice of countries matters. As such, we replicated the analyses for a group of advanced countries (i.e. G-7 countries). The results of the analyses are presented in the online appendix Tables 6-9. Pithily, our results confirm that oil shock matters more the G-7 countries relative to the emerging countries.

4. Conclusion

This study examines the relationship between oil shock and stock returns. In line with the extant literature, we take a cue from Ready (2018) by decomposing oil shock into demand, supply and risk. Broadly, the study's objective is to examine the extent to which oil shocks are able to forecast stock returns. Next, we inquire whether the decomposition of these shocks, into positive and negative partial sums, is important for the forecasting models.

Building dataset for ten emerging countries, some interesting results were obtained. First, the three types of shock are significant determinants of stock returns in Brazil, Chile, China and Mexico. While risk shock is a negative determinant, demand and supply shocks have positive estimated coefficients. Second, the oil shocks are able to accurately make out-of-sample forecasts for all the countries across the forecasting horizon. Albeit the significance of the forecast is only limited to Brazil, Chile, China, and Mexico. Mixed results were obtained for the asymmetric model. In all, we show that decomposition of shocks plays an opposing role, as it is noted that countries, where symmetric oil shock is important is accompanied by negligible asymmetric effect. Hence, shock is heterogeneous across countries. The exact predictive power of oil shock is dependent on: (i) the types of shock, (ii) countries and (iii) whether the shock is decomposed. This implies that shocks affect stock returns differently. The relatively poor performance of oil shock in emerging markets could be attributed to the small size of the equity markets in relation to their developed economies counterparts. It thus seems to suggest that the equity markets of emerging countries are not mature enough to be influenced by occurrences in the global oil market.

Hence, we conclude that the oil shock is able to forecast stock returns, albeit with weak intensity. These results have important policy implications for investors and policymakers. In the case of investors in Brazil, China, Chile and Mexico, oil shock is an important consideration to take cognizance of when assessing the response of financial markets to fluctuations in oil prices. This becomes a pertinent issue when making strategies about portfolio construction and designing optimal asset allocation against uncertainty in the oil market. Whereas other countries in the analyses are immune from the shenanigans of oil shocks. Hence, investors and policymakers in these countries should be less bothered about the effect of oil shocks on equity markets. Also, and on a more general note, it appears that emerging markets do not respond to the dichotomy between being an oil exported or imported. Hence, the hitherto perception about the comparative advantage of being either producer or consumer seize to hold, at least for emerging markets.

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Table 3: Single Predictor: Theil U- statistics

	Supply						Demand					
		Out-of-Sample						Out-of-Sample				
Countries	In-Sam	H=1	H=10	H=30	H=60	H=90	In-Sam	H=1	H=10	H=30	H=60	H=90
Brazil	0.9816	0.9817	0.9817	0.9813	0.9816	0.9826	0.9254	0.9254	0.9257	0.9268	0.9294	0.9317
Chile	0.9741	0.9743	0.9751	0.9741	0.9756	0.9754	0.9207	0.9209	0.9269	0.9213	0.9248	0.9286
China	0.9855	0.9857	0.9866	0.9877	0.9909	0.9931	0.9692	0.9690	0.9700	0.9694	0.9696	0.9691
India	0.9999	0.9990	0.9991	0.9993	0.9994	0.9991	0.9997	0.9997	0.9998	0.9998	0.9998	0.9998
Korea	0.9998	0.9997	0.9998	0.9993	0.9999	0.9998	0.9997	0.9686	0.9996	0.9997	0.9865	0.9986
Malaysia	0.9986	0.9985	0.9988	0.9948	0.9969	0.9965	0.9874	0.9881	0.9883	0.9884	0.9888	0.9889
Mexico	0.9790	0.9790	0.9787	0.9791	0.9803	0.9808	0.9326	0.9326	0.9322	0.9331	0.9362	0.9380
Russia	0.9996	0.9996	0.9995	0.9997	0.9992	0.9989	0.9999	0.9999	0.9996	0.9998	0.9998	0.9999
South Africa	0.9999	0.9999	0.9991	0.9998	0.9998	0.9996	0.9990	0.9996	0.9998	1.0000	1.0001	1.0002
Turkey	0.9999	0.9999	0.9999	0.9999	0.9999	0.9999	0.9998	0.9998	0.9997	0.9997	0.9995	0.9998
				Risk								
					Out-of-Sample							
				In-Sam	H=1	H=10	H=30	H=60	H=90			
Brazil				0.9689	0.9688	0.9688	0.9687	0.9695	0.9699			
Chile				0.9337	0.9339	0.9391	0.9396	0.9423	0.9436			
China				0.9771	0.9768	0.9763	0.9756	0.9747	0.9743			
India				0.9998	0.9998	0.9997	0.9998	0.9999	0.9999			
Korea				0.9999	0.9999	0.9999	0.9999	0.9999	0.9999			
Malaysia				0.9999	0.9999	0.9999	0.9999	0.9999	0.9999			
Mexico				0.9343	0.9343	0.9346	0.9356	0.9377	0.9390			

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Russia				0.9998	0.9997	0.9999	1.0000	1.0000	1.0001			
South Africa				0.9999	0.9999	0.9999	0.9999	0.9999	0.9999			
Turkey				0.9999	0.9999	0.9999	1.0000	1.0000	1.0001			

Source: Author's computation

Table 4: C.W. test

	Supply						Demand					
		Out-of-Sample						Out-of-Sample				
Countries	In-Sam	H=1	H=10	H=30	H=60	H=90	In-Sam	H=1	H=10	H=30	H=60	H=90
Brazil	4.6532[a]	4.7591[a]	4.6769[a]	4.7414[a]	4.6459[a]	4.6846[a]	9.6191[a]	9.6223[a]	9.6315[a]	9.6224[a]	9.5766[a]	9.5204[a]
Chile	5.5853[a]	5.7744[a]	5.6818[a]	5.6253[a]	5.5692[a]	5.7965[a]	8.7305[a]	8.7216[a]	8.8262[a]	8.7384[a]	8.7423[a]	8.7562[a]
China	5.3030[a]	5.2837[a]	5.1837[a]	5.0472[a]	4.6936[a]	4.4929[a]	7.2148[a]	7.2556[a]	7.1756[a]	7.3517[a]	7.4970[a]	7.6501[a]
India	0.4902	0.3957	0.4681	0.4244	0.4927	0.4850	0.7856	0.8821	0.8832	0.8815	0.8816	0.8822
Korea	0.6149	0.5979	0.6682	0.6583	0.6795	0.7046	0.7667	0.8050	0.7970	0.7704	0.7792	0.6921
Malaysia	0.8978	0.8996	0.9012	0.9114	[illegible]	0.9423	0.9883	1.0124	1.1003	1.2003	1.2036	1.3012
Mexico	5.2441[a]	5.1967[a]	5.3152[a]	5.2855[a]	[illegible]	5.1775[a]	8.7385[a]	8.7425[a]	8.8016[a]	8.7827[a]	8.6803[a]	8.6586[a]
Russia	0.8591	0.8200	0.9377	0.7607	1.3225	1.6958[c]	0.1847	0.2084	0.1911	0.4969	0.2899	0.1508
South Africa	0.0769	0.0789	0.2299	0.1519	0.0636	0.0567	0.0941	0.0926	0.0143	0.0089	0.0598	0.0674
Turkey	0.1423	0.1220	0.1111	0.1623	0.1455	0.1470	0.7173	0.7097	0.7658	0.8118	0.8683	0.8695

	Risk					
		Out-of-Sample				
	In-Sam	H=1	H=10	H=30	H=60	H=90
Brazil	6.5454[a]	6.5539[a]	6.5877[a]	6.6220[a]	6.6103[a]	6.6860[a]
Chile	8.1484[a]	8.1397[a]	7.7210[a]	7.7534[a]	7.6970[a]	7.6974[a]
China	6.4892[a]	6.5460[a]	6.6362[a]	6.8014[a]	7.0752[a]	7.2063[a]
India	0.64	0.64	0.580	0.666	0.65	0.62

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				01	16	9	6	80	61			
Korea				0.1495	0.1129	0.1860	0.1234	0.1440	0.2763			
Malaysia				0.5863	0.5899	0.5846	0.5833	0.5840	0.5842			
Mexico				5.2441[a]	5.2464[a]	5.2464[a]	5.2855[a]	5.1967[a]	5.1775[a]			
Russia				0.1948	0.2241	0.2897	0.1843	0.2016	0.2171			
South Africa				0.4118	0.4132	0.4186	0.4620	0.5755	0.5504			
Turkey				0.1383	0.1422	0.1162	0.0656	0.1881	0.0972			

Source: Author's computation. Note a, b, c imply level of statistical significance at % 5% and 10%, respectively

Table 5: Asymmetry Thiel-U Stat

	Supply_ Positive						Supply_Negative					
		Out-of-Sample						Out-of-Sample				
Countries	In-Sam	H=1	H=10	H=30	H=60	H=90	In-Sam	H=1	H=10	H=30	H=60	H=90
Brazil	1.0119	1.0119	1.0116	1.0109	1.0118	1.0119	1.0001	1.0001	1.0003	1.0004	1.0005	1.0008
Chile	1.0088	1.0086	1.0085	1.0086	1.0084	1.0086	1.0180	1.0178	1.0167	1.0175	1.0174	1.0177
China	1.0033	1.0031	1.0009	0.9989	0.9983	0.9976	1.0000	0.9994	0.9988	0.9981	0.9989	0.9988
India	0.9996	0.9996	0.9996	0.9994	0.9995	0.9996	0.9994	0.9991	0.9993	0.9994	0.9994	0.9995
Korea	1.0001	1.0002	1.0002	1.0003	1.0000	1.0002	0.9997	0.9997	0.9998	0.9999	0.9996	0.9998
Malaysia	1.0048	1.0044	1.0042	1.0044	1.0045	1.0048	1.1021	1.0032	1.0033	1.0032	1.0036	1.0035
Mexico	1.0112	1.0112	1.0116	1.0115	1.0104	1.0102	1.0269	1.0268	1.0268	1.0264	1.0246	1.0252
Russia	0.9988	0.9988	0.9991	0.9989	0.9990	0.9989	0.9999	1.0000	1.0000	0.9999	1.0001	1.0000
South Africa	0.9997	0.9997	0.9998	0.9997	0.9993	0.9999	0.9996	0.9996	0.9996	0.9996	0.9994	0.9994
Turkey	1.0002	1.0002	1.0003	1.0002	1.0002	1.0003	0.9999	0.9989	0.9986	0.9998	0.9999	0.9999
	Demand_Positive						Demand_Negative					
Brazil	1.0246	1.0247	1.0229	1.0220	1.0243	1.0236	1.0308	1.0308	1.0308	1.0304	1.0291	1.0281
Chile	1.01	0.75	0.75	0.75	0.76	0.76	1.00	1.00	1.00	1.00	1.00	1.00

	82	01	47	56	08	30	91	91	96	80	90	85
China	0.9902	0.9111	0.9102	0.9085	0.9061	0.9048	0.9942	0.9941	0.9931	0.9931	0.9951	0.9960
India	0.9997	0.8747	0.8732	0.8720	0.8718	0.8721	0.9994	0.9993	0.9994	0.9994	0.9994	0.9995
Korea	1.0003	0.9967	0.9968	0.9961	0.9966	0.9967	1.0004	1.0000	1.0005	1.0004	1.0005	1.0004
Malaysia	1.0004	0.9985	0.9669	0.9987	0.9991	1.0038	1.0326	1.0426	1.1135	1.2102	1.2202	1.2226
Mexico	1.0106	0.7528	0.7538	0.7547	0.7529	0.7551	1.0038	1.0038	1.0038	1.0035	1.0032	1.0033
Russia	1.0000	0.9383	0.9406	0.9409	0.9377	0.9409	1.0003	1.0001	1.0009	1.0012	1.0004	1.0002
South Africa	1.0001	0.8181	0.8175	0.8122	0.8077	0.8081	0.9997	0.9997	0.9995	0.9996	0.9996	0.9998
Turkey	1.0004	0.8266	0.8259	0.8257	0.8262	0.8192	1.0003	1.0000	1.003	1.0004	1.0002	1.0003
	Risk_Positive						Risk_Negative					
Brazil	1.0087	0.8860	0.8878	0.8875	0.8860	0.8859	1.0037	0.8861	0.8866	0.8859	0.8878	0.8875
Chile	1.0341	1.0340	1.0341	1.0316	1.0305	1.0291	1.0182	0.7501	0.7547	0.7556	0.7608	0.7630
China	0.9886	0.9883	0.9882	0.9868	0.9871	0.9870	0.9902	0.9111	0.9102	0.9080	0.9062	0.9048
India	0.9996	0.9994	0.9993	0.9996	0.9995	0.9995	0.9997	0.8747	0.8732	0.8720	0.8718	0.8721
Korea	1.0006	1.0006	1.0005	1.0006	1.0005	1.0005	1.0003	0.9967	0.9968	0.9966	0.9967	0.9967
Malaysia	1.0001	1.0003	1.0008	1.0010	1.0011	1.0010	1.0012	1.0022	1.0031	1.0026	1.0028	1.0025
Mexico	1.0220	1.0221	1.0223	1.0222	1.0207	1.0199	1.0106	0.7528	0.7538	0.7547	0.7529	0.7551
Russia	0.9998	0.9998	0.9997	0.9999	0.9999	0.9996	1.0000	0.9383	0.9406	0.9409	0.9430	0.9409
South Africa	0.9998	0.9998	0.9997	0.9997	0.9996	0.9996	1.0001	0.8181	0.8175	0.8122	0.8077	0.8081
Turkey	1.0005	1.0005	1.0006	1.0004	1.0006	1.0006	1.0004	0.8266	0.8259	0.8257	0.8262	0.8192

Source: Author's computation

Table 6: Asymmetry C.W.

	Supply_ Positive						Supply_Negative					
		Out-of-Sample						Out-of-Sample				
Count	In-	H=1	H=10	H=30	H=60	H=90	In-	H=1	H=10	H=30	H=60	H=90

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ries	Sam						Sam					
Brazil	3.3562[a]	1.1230	1.1201	1.1442	1.1228	0.9477	3.3562[a]	3.3583[a]	3.3449[a]	3.3354[a]	3.3691[a]	3.3855[a]
Chile	1.4273	1.4589	1.4280	1.5842	1.6337	1.5714	0.9686	0.9773	0.8902	1.1561	0.9978	1.0736
China	4.9352[a]	4.9668[a]	4.9848[a]	5.1067[a]	5.1836[a]	5.1959[a]	5.1756[a]	5.2128[a]	5.0094[a]	5.1411[a]	5.0630[a]	5.1995[a]
India	0.0977	0.0961	0.1113	0.1557	0.1823	0.1097	1.1814	1.1843	1.1565	1.1646	1.1195	1.0485
Korea	1.1471	0.9474	1.0371	1.1599	0.9854	0.9597	0.3313	0.3827	0.3676	0.3536	0.3178	0.4040
Malaysia	1.2325	1.4236	1.4233	1.4320	1.4320	1.4244	1.5899	1.6018	1.6011	1.5121	1.5681	1.5423
Mexico	0.5715	0.5666	0.6670	0.6645	0.4339	0.4001	2.2567[b]	2.[illegible]450[b]	2.2843[b]	2.3510[b]	2.4481[b]	2.5097[b]
Russia	2.3180[b]	2.2932[b]	2.1220[b]	2.2600[b]	2.2667[b]	2.6313[a]	0.264[illegible]	0.2245	0.3714	0.1628	0.7438	1.0683
South Africa	0.5975	0.5958	0.5635	0.6044	0.5021	0.5301	0.7[illegible]34	0.7649	0.9793	0.8865	0.6310	0.6655
Turkey	0.6204	0.6180	0.5868	0.6233	0.5892	0.5[illegible]	0.1770	0.1715	0.1983	0.1526	0.1877	0.1041
	Demand_Positive						Demand_Negative					
Brazil	3.8812[a]	3.8739[a]	3.9173[a]	3.9972[a]	4.1012[a]	4.2194[a]	2.1827[a]	2.1832[b]	2.1663[b]	2.0888[b]	2.0142[b]	1.8790[b]
Chile	3.8795[a]	3.8915[a]	3.9671[a]	4.0294[a]	4.0417[a]	4.0312[a]	0.9563	0.9644	0.8466	1.0630	1.0029	1.0467
China	2.4599[b]	2.5594[b]	2.6828[a]	2.9589	2.9397[a]	3.0481[a]	2.7397[a]	2.8129[a]	3.0099[a]	3.2575[a]	3.3301[a]	3.3538[a]
India	0.8196	0.8192	0.893[illegible]	0.8684	0.9210	0.8305	0.0342	0.1391	0.1012	0.1382	0.0886	0.0280
Korea	1.9840[b]	1.9877[b]	1.[illegible]45[illegible][b]	1.8623[b]	1.9731[b]	2.2074[b]	0.2488	0.2900	0.2680	0.2487	0.2509	0.1423
Malaysia	1.2256	1.1263	1.2336	1.3625	1.1423	1.1265	1.2589	1.3548	1.4111	1.42126	1.3901	1.3985
Mexico	1.7895[c]	1.7965[c]	1.8017[c]	1.8269[c]	1.9546[c]	2.0302[b]	2.8803[a]	2.8689[a]	2.8023[c]	2.8460[b]	3.1270[a]	3.1400[a]
Russia	0.2513	0.2249	0.2434	0.0529	0.2225	0.3074	0.0284	0.0494	0.0320	0.3217	0.1200	0.0176
South Africa	0.8192	0.8173	0.7877	0.8215	1.0301	0.9936	0.3176	0.3170	0.2484	0.3588	0.3790	0.4263
Turkey	1.6209	1.6188	1.6257	1.6970[c]	1.6783[c]	1.6218	0.2974	0.2902	0.3440	0.3932	0.4095	0.4501
	Risk_Positive						Risk_Negative					
Brazil	2.51	2.51	2.50	2.53	2.50	2.53	1.19	1.20	1.18	1.194	1.352	1.53

	46[b]	26[b]	90[b]	15[b]	50[b]	34[b]	75	50	81	1	1	20
Chile	3.0634[a]	3.0711[a]	3.0903[a]	3.1317[a]	3.1505[a]	3.2255[a]	1.7451[c]	1.7535[c]	1.7140[c]	17197[c]	1.8915[c]	1.9355[c]
China	4.9352[a]	4.9668[a]	4.9848[a]	5.1607[a]	5.1836[a]	5.1959[a]	3.7102[a]	3.7519[a]	3.6843[a]	3.8709[a]	4.0119[a]	4.0285[a]
India	0.1454	0.1464	0.0949	0.1838	0.1661	0.1268	1.5899	1.5906	1.5558	1.6513[a]	1.5847	1.4864
Korea	0.4821	0.4552	0.4800	0.4906	0.4961	0.6068	0.0022	0.0288	0.0445	0.0329	0.0164	0.0869
Malaysia	1.5262	1.4745	1.4588	1.4268	1.4201	1.4236	0.2012	0.2166	0.2231	0.2214	0.2232	0.2245
Mexico	3.5300[a]	3.5193[a]	3.5099[a]	3.5655[a]	3.7872[a]	3.7734[a]	2.2567[b]	2.2450[b]	2.2843[b]	2.3510[b]	2.4481[b]	2.5097[b]
Russia	0.0155	0.0333	0.3735	0.3811	0.0998	0.3844	0.4818	0.4887	0.4724	0.3436	0.31473	0.3496
South Africa	0.2474	0.2487	0.2477	0.2979	0.3948	0.3784	1.0601	1.0603	1.0812	0.9366	1.0728	1.0477
Turkey	0.0707	0.0565	0.0656	0.0368	0.018	0.1180	0.0337	0.0320	0.0171	0.0494	0.0290	0.1742

See note in Table 4.

CRediT authorship contribution statement

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- This study examines the predictive prowess of oil shocks and stock returns.
- Oil shock is computed using Ready' (2018) approach.
- Dataset is constructed for the emerging countries.
- Results show that oil shock is an important determinant of stock returns.
- The predictive power on oil shock is heterogenous.

Journal Pre-proof