Oil Shocks and Stock Market Volatility of the BRICS: A GARCH-MIDAS Approach

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Abstract

In this study, we employ the GARCH-MIDAS model to investigate the response of stock market volatility of the BRICS to oil shocks. We utilize the recent datasets of Baumeister & Hamilton (2019) where oil shocks are decomposed into four variants - oil supply shocks, economic activity shocks, oil consumption shocks, and oil inventory shocks. We further decomposed each of these shocks into positive and negative shocks, and our findings show heterogeneous response of stock market volatility of the BRICS countries to the alternative oil shocks including the positive and negative shocks. The differing responses across the BRICS countries could be attributed to the difference in the economic size, oil production and consumption profile, market share distribution across firms, as well as financial system and regulation efficiency.

JEL Codes: C32, G12, G15, Q02

Keywords: Oil shocks, Stock market volatility, BRICS, GARCH-MIDAS

1. Introduction

The existing international literature on the impact of oil price and/or - oil supply, economic activity, oil consumption demand, and oil inventory demand shocks (following the seminal works of Kilian (2009) and Kilian & Park (2009) suggesting that not all oil shocks are alike) on stock prices and/or returns of oil exporting and importing developed and emerging countries (via the stock valuation, monetary, output, fiscal, and uncertainty channels) is huge, to say the least (see Degiannakis et al., (2018a), and Smyth & Narayan (2018) for detailed reviews in this regard). From a theoretical perspective, oil shocks are also expected to affect stock market volatility, since increased energy prices generate uncertainty to firms, resulting in the delay of investment decisions (Bernanke, 1983; Pindyck, 1991). Furthermore, some studies like that of Elder & Serletis (2010), Rahman & Serletis (2011), Ratti et al., (2011) opine that oil price innovations exercise an impact on aggregate uncertainty[1] and they have significant negative effects on investments. Given these points, and the well-established fact that the aforementioned firm's and aggregate uncertainties can be represented by individual stock price volatility and stock market volatility in general (Bloom, 2009; Baum et al., 2010), the effect of oil price shocks on stock market volatility should not be surprising. Empirical evidence of the impact of oil shocks on stock market volatility is scarce compared to the effect of oil shocks on stock returns, and is limited to the works of Jung & Park (2011), Degiannakis et al., (2014), Bastianin et al., (2016), Antonakakis et al., (2017), Bastianin & Manera (2018).[2] These studies, based on developed equity markets, consistently show that oil demand rather than supply shocks dominate the impact on stock market volatility.

Against this backdrop, the objective of our paper is to analyze the impact of various types of demand and supply oil shocks on the stock market volatility of five emerging countries namely, Brazil, Russia, India, China and South Africa, i.e., the BRICS group, and in the process extend the knowledge of second moment impact of oil shocks beyond developed equity markets. The decision to choose the BRICS as our preferred set of emerging countries emanates from the importance of the varying roles played by these economies in the global oil market. Note that, according to the

[1] Direct empirical evidence in this regard can be found in Antonakakis et al., (2014), Degiannakis et al., (2018b), Rehman (2018), and Hailemariam et al., (2019).
[2] There is of course a large literature on the spillovers of volatility across the oil and stock markets (see Degiannakis et al. (2018a) and Eraslan & Ali (2018) for a detailed review of the literature).

World Fact Book, China, India and South Africa ranks 1st, 3rd and 22nd respectively in terms of oil imports, while Russia is the 2nd largest oil exporter, with Brazil also being a net oil exporter, though at a much smaller scale (ranked 24th). In the process, the study of the BRICS allows us to analyze the possible heterogenous impact of oil shocks on volatility, conditional on their oil export and import profiles. In addition, trade by these economies with the rest of the world has been growing at a fast rate, with the strong economic performance of these countries linked to the high level of foreign direct investment in the private sector (Mensi et al., 2014; Ruzima & Boachie, 2018). Naturally, volatility in these key emerging stock markets is likely to contribute to uncertainty in global equity markets through the trade channel (Balli et al., 2019). Hence, appropriate modeling and prediction of financial market volatility of this bloc due to oil shocks in particular, is of high importance to the stability of the world financial system. Besides it must be realized that return volatility is a key component of asset valuation, hedging as well as portfolio optimization models. Hence, inaccurate predictions of volatility may lead to mis-pricing in financial markets, over/under-hedged business risks and incorrect capital budgeting decisions, with significant implications on earnings and cash flows. To that end, monitoring and modeling stock market volatility is crucial not only for investors and corporate decision makers, but also for policy makers in their assessment of financial fundamentals and investor sentiment.

As far as the econometric framework is concerned, unlike the existing studies on modeling volatility of the BRICS stock markets based on univariate models from the generalized autoregressive conditional heteroskedasticity (GARCH)-family (see for example, Babikir et al., (2012), Aye et al., (2014), Kishor & Singh (2014), Adu et al., (2015), Bouri et al., (2018) for detailed reviews), we use the GARCH variant of the mixed data sampling (MIDAS), i.e., the GARCH-MIDAS model. The reason behind this is that, while stock market data is at a daily frequency, the oil shocks used as predictors are available only at the monthly frequency, and hence the modeling of volatility requires a MIDAS-based approach. Note that, unlike the existing studies mentioned above on the impact of oil shocks on stock market volatility, which incorporates monthly measures of conditional, realized, and implied volatilities of advanced equity markets in the structural vector autoregressive (SVAR) models of Kilian (2009) and Kilian & Park (2009), we avoid the loss of information that would have resulted by averaging the daily volatility to a lower monthly frequency (Clements & Galvão, 2008; Foroni & Marcellino, 2013; Das et al., 2019).

Furthermore, the need for a MIDAS framework is motivated by our usage of relatively more accurate estimates of monthly oil shocks as derived by Baumeister & Hamilton (2019), who revisit the studies of Kilian (2009) and Kilian & Park (2009) by formulating a less restrictive framework that incorporates uncertainty about the identifying assumptions of SVARs. In sum then, using the GARCH-MIDAS model allows us to go beyond a univariate model by incorporating relatively more realistic estimates of monthly oil shocks, while simultaneously providing a comparatively more precise econometric framework of volatility of the BRICS stock markets, which avoids issues of information loss due to averaging.

To the best of our knowledge, this is the first paper to analyze the impact of oil supply, economic activity, oil consumption demand, and oil inventory demand shocks on equity market volatility of the BRICS using a GARCH-MIDAS approach. The remainder of the paper is organized as follows: Section 2 outlines the methodology, Section 3 presents the data, Section 4 discusses the results, and Section 5 concludes the paper.

2. Methodology

One of the contributions of this study is choice of a predictive framework, i.e., the MIDAS model, which combines variables sampled at different frequencies within a single framework. The choice of this model is to circumvent the loss of information in our analysis of oil shock – stock market volatility nexus as existing literature have mainly applied empirical methods that average either of these shocks into same frequencies (for example see Kilian, 2009; Sakaki, 2019; Salisu & Isah, 2017; Salisu & Oloko, 2015; Tsai, 2015). Using both daily and monthly data respectively for the predicted series (stock returns volatility) and predictor series (oil shocks), we applied the GARCH variant of the MIDAS regressions, which allows for more robust information in the estimation process.[3] Our choice of the GARCH variant of the MIDAS models is to elicit the information in the high frequency series by allowing the low frequency explanatory variable to enter directly into the specification of the long-term component.

[3] See (Salisu & Ogbonna, 2019)for discussion on some of the computational advantages of using the MIDAS regressions. Also, (Engle, Ghysels, & Sohn, 2013) document the technical details of the MIDAS models where the conditional variance is multiplicatively decomposed into a high-frequency and a low-frequency component

The volatility of the respective BRICS stock market is generated as the conditional variance of stock returns of these markets. We define daily stock returns as $r_{i,t} = 100 * \left(ln\left(P_{i,t}\right) - ln\left(P_{i-1,t}\right)\right)$, where $P_{i,t}$ represents stock price on day i in a particular month t; $t = 1,...,T$ denotes the monthly frequency and $i = 1,...,N_t$ denotes daily frequency with N indicating number of days in month t. The conditional mean of stock returns is constant and it is modelled as:

$$r_{i,t} = \sqrt{\tau_t \times h_{i,t}\varepsilon_{i,t}}, \qquad \forall \;\; i = 1,...,N_t \tag{1}$$

with

$$\varepsilon_{i,t} \left| \Phi_{i-1,t} \sim N\left(0,1\right)\right. \tag{2}$$

where $\Phi_{i-1,t}$ denotes the available information set at day $i-1$ of period t. Apparently, Equation [1] decomposed the conditional variance into two parts: $h_{i,t}$ which describes the short-run fluctuations and τ_t captures the long-term behaviors. The short-term component, $h_{i,t}$, varies at the daily frequency and its assumed to follows a unit-variance GARCH(1,1) process:

$$h_{i,t} = \left(1-\alpha-\beta\right) + \alpha \frac{\left(r_{i-1,t} - \mu\right)^2}{\tau_t} + \beta \bar{h}_{i-1,t} \tag{3}$$

where μ is the unconditional mean of the stock return, $\alpha > 0$, $\beta \geq 0$ and $\alpha + \beta < 1$. The long-term component, which varies at monthly frequency is given by:

$$\tau_t = m + \theta \sum_{k=1}^{K} \phi_k \left(\omega_1, \omega_2\right) X_{t-k} \tag{4}$$

where X_t denotes the explanatory variable of interest, in this case the various oil shocks under consideration, and $\phi_k\left(\omega_1, \omega_2\right)$ is the weighing scheme. We apply the One-parameter Beta polynomial weighing scheme because of its flexibility and popularity (see Colacito, Engle, & Ghysels, 2011):

$$\phi_k(\omega_1,\omega_2)=\frac{\left[k/(K+1)\right]^{\omega_1-1}\times\left[1-k/(K+1)\right]^{\omega_2-1}}{\sum_{j=1}^{K}\left[j/(K+1)\right]^{\omega_1-1}\times\left[1-j/(K+1)\right]^{\omega_2-1}} \quad [5]$$

By construction, the weights $\phi_k(\omega_1,\omega_2)\geq 0, k=1,...,K$ and sum to one, such that the parameters of the model are identified.

3. Data Presentation and Preliminary Analysis

The data employed in this study are stock volatility of the BRICS countries (Brazil, Russia, India, China and South Africa) computed as described in equations (1-3), and four different measures of global oil shocks (Oil supply shocks (OSS), Economic Activity Shocks (EAS), Oil Consumption Demand Shocks (OCDS) and Oil Inventory Demand Shocks (OIDS)). The stock prices data is derived from Thomson Reuters Datastream, and the four oil shocks are obtained from the recent study by Baumeister & Hamilton (2019). While the stock return series for the BRICS countries have different start dates but same stop dates owing to data availability, the oil shocks data are monthly series starting from February 1975 to July 2018.[4] The start dates for the daily stock returns are presented in the ninth column of Table 1a; with South Africa having the earliest start date that amounts to a total of 11608 data points, while Russia having the least data points of 6152, had the latest start date.

On the average, the daily returns of Brazil, Russia, India and South Africa are approximately 0.0003, with their standard deviation ranging between 0.0167 and 0.0283. As suggested by the values of standard deviation, Russia stock returns are the most volatile, while South Africa stock returns are the least volatile. China is, however, observed to have a negative average returns. The stock return series for the BRICS countries are skewed (negatively for the case of China stock returns and positively for Brazil, Russia, India and South Africa) and leptokurtic, being more peaked than the normal distribution. These features are in tandem with the styled facts on stock return series generally (see Salisu & Oloko, 2015).

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[4] We would like to thank Professor Christiane Baumeister for kindly providing us with the data of the underlying oil shocks.

On the four different oil shocks, all the oil shocks except oil inventory demand shocks, have negative means, negative skewness and kurtosis values exceeding the conventional threshold. Also, oil consumption demand shocks and economic activity shocks seem to be the most and least volatile oil shocks, respectively, judging by the standard deviation values. On the coefficient of variation in Table 1a, all the returns appear to be widely dispersed, with China having the highest variation, while South Africa had the least. The oil shock proxies were also highly dispersed, with highest coefficient of variation (in absolute terms) observed with the economic activity shocks and the least in oil consumption demand shocks. Following from the mixed frequency nature of the data set, where the dependent and independent variable are in high (daily) and low (monthly) frequencies, respectively, the GARCH-MIDAS framework is employed, not only to examine the predictability of low frequency oil shock for a high frequency stock returns, but also to evaluate the forecast performance of the GARCH-MIDAS model in comparison with the conventional GARCH(1,1) model.

Table 1a: Summary Statistics

	Mean	Std. Dev.	Skewness	Kurtosis	CV	N	Frequency	Start Date	Stop Date
Returns									
Brazil	0.00030	0.02339	-0.12949	9.34644	7796.67	6673	Daily	1/1/1993	7/31/2018
Russia	0.00030	0.02826	-0.43802	15.72004	9420.00	6152	Daily	1/2/1995	7/31/2018
India	0.00032	0.02352	-0.14453	10.58758	7350.00	7456	Daily	1/2/1990	7/31/2018
China	-0.00003	0.01841	0.03736	9.15723	-61366.67	6673	Daily	1/1/1993	7/31/2018
South Africa	0.00030	0.01669	-0.38555	9.70939	5563.33	11608	Daily	2/3/1975	7/31/2018
Oil Shocks									
Oil Supply Shocks	-0.05416	1.63831	-1.17648	9.41811	-3024.94	522	Monthly	Feb-75	Jul-18
Economic Activity Shocks	-0.00618	0.50697	-0.34596	5.13131	-8203.40	522	Monthly	Feb-75	Jul-18
Oil Consumption Demand Shocks	-0.13239	3.27776	-0.12858	3.18430	-2475.84	522	Monthly	Feb-75	Jul-18
Oil Inventory Demand Shocks	0.02492	1.08712	0.27149	3.09922	4362.44	522	Monthly	Feb-75	Jul-18

Note: CV is the coefficient of variation, which is computed as the percentage ration of the standard deviation and the mean.

Our preliminary tests consist mainly of Autoregressive Conditional Heteroscedasticity (ARCH) effect test, which is a formal test for volatility. As evident from the preliminary results (as presented in Table 1b), stock returns of all the BRICS countries are volatile. This result is confirmed with 1% statistical significance of the ARCH effect at lags 5, 10 and 20. This suggests that stock returns of BRICS countries are really volatile and that the use of GARCH variant modeling is appropriate. Meanwhile, on the oil shock proxies, only oil consumption demand shocks and oil supply shocks were characterized by conditional heteroscedasticity. The weakness of ARCH effect in oil shocks may be expected as these are in relatively higher time series frequency. The results for autocorrelation and higher order autocorrelation as represented by Q-statistic and Q^2 –statistic are similar to that of ARCH effect; showing that stock returns are also more serially correlated than oil shocks indicators. This study proposes the use of GARCH-MIDAS model for generating stock market volatility from its modified stock market return equation (equation 1).

Table 1b: Preliminary Results

	ARCH(5)	*ARCH(10)*	*ARCH(20)*	*Q(5)*	*Q(10)*	*Q(20)*	*Q^2(5)*	*Q^2(10)*	*Q^2(20)*
				Returns					
Brazil	283.80***	159.54***	85.62***	11.59	28.04***	56.57***	2088.70***	3314.80***	4744.10***
Russia	216.98***	122.38***	73.55***	2.25	12.87	72.30***	1400.30***	2020.20***	3336.90***
India	209.51***	119.65***	64.41***	8.78	28.33***	62.05***	1572.10***	2466.50***	3535.20***
China	236.31***	130.73***	76.34***	1.83	19.58	49.86***	1943.80***	2903.40***	4371.20***
South Africa	188.94***	119.78***	68.55***	5.53	33.20***	54.07***	1436.40***	2452.30***	3879.40***
				Oil Shocks					
Economic Activity Shocks	17.98	10.51	5.61	0.79	4.49	13.47	103.45***	111.08***	123.07***
Oil Consumption Demand Shocks	1.91*	1.91**	1.69**	1.42	5.37	8.23	10.218*	18.71**	30.12*
Oil Inventory Demand Shocks	1.24	1.19	1.29	1.67	4.80	20.10	6.78	15.67	28.41
Oil Supply Shocks	2.16*	0.94	2.96***	1.18	1.38	17.75	11.59**	13.74	63.29***

Note: The ***, ** and * indicate statistical significance at 1%, 5% and 10% level, respectively.

4. Predictability of Oil Shocks for Stock Returns Volatility

The predictability of oil shocks for stock market volatility has been established for developed economies under supply- or demand-driven shocks as discussed in the introduction. For robustness purposes, our analysis of stock volatility reaction to oil shocks for each of the BRICS countries is carried out under three different measures. The first uses the aggregated oil shocks for the four different oil shocks (OSS, EAS, OCDS and OIDS). The second and third measures respectively involves disaggregating the each of the four oil price proxies into negative and positive shocks, using dummy variables. For the negative oil shocks, the dummy variable assumes the value one whenever the oil shock is negative and zero, otherwise. Similarly, for the positive oil shocks the dummy variable assumes one when the oil shock is positive and zero, otherwise. The positive and negative shocks are then derived by interacting the aggregate values of these shocks with the dummy variables. Therefore, the predictability of the aggregated, negative and positive oil shocks' results are presented in Tables 2a, 2b and 2c, respectively, along with the GARCH-MIDAS model coefficients, and reported for each of the BRICS countries. Tables 2a – 2c are structured in four panels corresponding to the oil shock being considered. Panel 1 reports results for the BRICS countries when oil supply shocks are employed; Panel 2 reports for the case of economic activity shocks; while Panels 3 and 4 report for oil consumption demand shock and oil inventory demand shock, respectively.

4.1 Predictability of Aggregated Oil Shocks

In Table 2a, the result of the GARCH-MIDAS framework that examines the predictability of aggregate oil shocks is presented for the BRICS countries under four different oil shock measures. Across the oil shocks, we find the coefficient of the unconditional mean for stock return (μ), the ARCH and GARCH terms (α and β, respectively), as well as the long term constant term (m) of the MIDAS filter to be positive and statistically significant. While we also find across the BRICS countries and the oil shocks high degrees of volatility persistence indicated by β, the persistence is observed to be mean reverting, given that the sum of α and β is less than unity, that is $(\alpha + \beta < 1)$. More important, is the statistical significance of the coefficient, θ, which is the sum of weighted rolling window realized volatilities, indicating the predictability of the monthly oil shocks for the daily stock returns. We however examine the statistical significance of the coefficient, θ, across the BRICS countries and for each of the oil shocks, while noting that non-significance of the coefficient θ would indicate that the specific oil shock does not have significant impact on the long term volatility of the specific BRICS country.

On the oil supply shocks model, it can be noted from Table 2a that the stock market volatility for all the BRICS countries is highly persistent (as indicated by high coefficient of β) and mean reverting (as $\alpha + \beta < 1$). This suggests that the impact of shocks on the market is not permanent. Also, as evidenced by the coefficient of θ,oil supply shock was found to predict daily stock volatility positively and significantly in the cases of Brazil, Russia and India. This suggests that high oil supply shock tends to increases stock market volatility in Brazil, Russia and India. The predictability is however not significant for China and South Africa.

In the case of economic activity shocks, stock market volatility remained highly persistent and mean reverting; suggesting that the impact of shocks on the market is not permanent as well. The results further suggest that oil price shock due to economic activity shock predicted stock market volatility of Russia and South Africa positively, Brazil and India negatively, and does not predict stock market volatility in China. This indicates that economic activity shock tend to aggravate the stock market volatility in Russia and South Africa while it reduces stock market volatility in Brazil and India. This may suggests that investors in Russia and South Africa tend to experience foreign portfolio investment outflow, while Brazil and India experience foreign portfolio investment inflow during global economic shock. The non-significant impact of economic activity shocks on Chinese stocks might indicate the resilience of China's stocks to higher oil prices.

Meanwhile, oil consumption demand shocks appear to have significantly negative impact on the stock volatility of the Brazil, Russia, India and South Africa. This suggests that stock market volatility responds negatively to changes in oil consumption demand shocks. On the other hand, the results show that oil inventory demand shocks had significantly positive impact on these four countries. The negative response of stock volatility of these countries to oil consumption demand shocks could be as a result of increased precautionary demand driven by anticipated disruptions in future supply of crude oil. For China, one of the major oil-importing countries among the BRICS, we find the stock volatility to be uninfluenced by the different oil shocks. In summary, the results confirm that the stock volatility response to the different aggregated oil shocks proxies vary across BRICS member countries. These heterogenous responses across the countries could further be attributed to the differences in their oil dependence profile, market share distribution across firms, financial system efficiency and the effectiveness of regulation in securities markets as observed in Bouoiyour & Selmi (2016).

Table 2a: Predictability Result (Aggregated Oil Shocks)

	μ	α	β	θ	w	m
			Oil Supply Shocks			
Brazil	0.0009***[0.0002]	0.0982***[0.0054]	0.8836***[0.0064]	0.0071**[0.0029]	46.6230*[28.0540]	0.0005***[0.0001]
Russia	0.0009***[0.0003]	0.0950***[0.0044]	0.8980***[0.0043]	0.0157***[0.0059]	48.5430**[24.3180]	0.0010***[0.0002]
India	0.0009***[0.0002]	0.0962***[0.0051]	0.8888***[0.0056]	0.0064**[0.0030]	49.7510[36.4630]	0.0006***[0.0001]
China	0.0006***[0.0002]	0.0814***[0.0042]	0.9119***[0.0042]	0.0115[0.0077]	8.3916[6.8420]	0.0004***[0.0001]
SA	0.0007***[0.0001]	0.1004***[0.0038]	0.8732***[0.0045]	-0.0031[0.0020]	7.9780[6.7817]	0.0003***[0.0000]
			Economic Activity Shocks			
Brazil	0.0009***[0.0002]	0.1015***[0.0055]	0.8778***[0.0066]	-0.0456**[0.0217]	3.4031*[1.9426]	0.0005***[0.0001]
Russia	0.0007**[0.0003]	0.0491***[0.0022]	0.9004***[0.0045]	0.0406***[0.0015]	5.0038***[0.2369]	0.0004***[0.0000]
India	0.0009***[0.0002]	0.0967***[0.0050]	0.8880***[0.0056]	-0.0190**[0.0087]	48.4090*[28.6050]	0.0006***[0.0001]
China	0.0006***[0.0002]	0.0820***[0.0042]	0.9117***[0.0042]	0.0121[0.0094]	21.7100[23.3180]	0.0004***[0.0001]
SA	0.0007***[0.0001]	0.0997***[0.0039]	0.8728***[0.0044]	0.0047**[0.0020]	10.9660[7.6552]	0.0003***[0.00001]
			Oil Consumption Demand Shock			
Brazil	0.0009***[0.0002]	0.0971***[0.0055]	0.8836***[0.0065]	-0.0283***[0.0064]	1.7771***[0.2311]	0.0005***[0.0001]
Russia	0.0009***[0.0003]	0.0951***[0.0043]	0.8983***[0.0043]	-0.0091***[0.0031]	48.2490***[17.1790]	0.0010***[0.0003]
India	0.0009***[0.0002]	0.0949***[0.0052]	0.8877***[0.0058]	-0.0349***[0.0069]	1.7313***[0.1988]	0.0006***[0.0001]
China	0.0006***[0.0002]	0.0836***[0.0043]	0.9101***[0.0043]	-0.0103[0.0073]	1.9927[1.4766]	0.0005***[0.0001]
SA	0.0007***[0.0001]	0.1016***[0.0042]	0.8669***[0.0049]	-0.0122***[0.0015]	1.0064***[0.0990]	0.0003***[0.0000]
			Oil Inventory Demand Shock			
Brazil	0.0009***[0.0002]	0.0992***[0.0054]	0.8831***[0.0063]	0.0657***[0.0208]	1.8688***[0.5738]	0.0006***[0.0001]
Russia	0.0007***[0.0003]	0.0500***[0.0026]	0.9000***[0.0052]	0.0996***[0.0035]	5.0000***[0.1574]	0.0007***[0.0000]
India	0.0009***[0.0002]	0.0968***[0.0050]	0.8886***[0.0056]	0.0801***[0.0248]	1.9260***[0.5371]	0.0007***[0.0001]
China	0.0004**[0.0002]	0.0848***[0.0042]	0.9074***[0.0044]	0.0003[0.0019]	24.9440[215.6000]	0.0004***[0.00008]
SA	0.0007***[0.0001]	0.0993***[0.0040]	0.8737***[0.0044]	0.0059***[0.0012]	28.9290**[11.2500]	0.0003***[0.0000]

Note: The figures in square bracket – [ ] are the corresponding standard errors of the estimated GRCH MIDAS coefficients. ***, ** and * represent statistical significance at 1%, 5% and 10%, respectively.

4.2 Predictability of Negative Oil Shocks

Next, we evaluate the negative oil shocks predictability for stocks market volatility of the BRICS country. The GARCH-MIDAS results are presented in Table 2b. In the same vein as with the aggregate oil shocks proxies summarized in Table 2a, the predictability of the negative oil shock (OSS, EAS, OCDS and OIDS) are examined. We find that each of μ, α, β and m for the negative oil price shocks are positive and statistically significant, such that the stocks returns are characterized by high degrees of volatility persistence, which are mean reverting, occasioned by the fact that the sum of α and β is less than one. This is observed across the BRICS countries and also across the four negative oil shocks. The coefficient, θ, of the sum of weighted rolling window realized volatilities, indicating how the BRICS country stock volatility respond to negative oil shocks and consequently a measure of the predictability of the former for the later, reveals some distinct patterns in contrast to the aggregate oil shocks.

Moreover, stock market volatility is also highly persistent and mean reverting; suggesting that the impact of shocks on the market is not permanent even when negative oil shocks are considered. We find only Russian and South African stock volatility responding significantly to negative oil supply shocks. However, while the stock volatility of Russia, an oil producing and exporting country, responded positively, South Africa, an oil importing country, responded negatively to oil supply shocks. Meanwhile, when the economic activity shock was considered, we find all the countries' stock volatility to be responding significantly. While the negative economic activity shock had negative impact on the stock volatility of Brazil, India and South Africa, it had a positive impact on the stock volatility of Russia and China. On the oil consumption demand shocks, while all the other countries' stock volatility are observed to be significantly influenced by the negative oil shocks, the case is different for China's stock volatility. A similar pattern is observed in the case of the oil inventory demand shocks, with China again not observed to respond significantly to the oil inventory demand shocks.

Table 2b: Predictability Result (Negative Oil Shocks)

	μ	α	β	θ	w	m
			Oil Supply Shocks (Negative)			
Brazil	0.0009***[0.0002]	0.0993***[0.0054]	0.8829***[0.0063]	0.0047[0.0048]	47.3420[67.8050]	0.0006***[0.0001]
Russia	0.0009***[0.0003]	0.0964***[0.0044]	0.8969***[0.0044]	0.0206**[0.0084]	49.5780[30.2230]	0.0012***[0.0003]
India	0.0009***[0.0002]	0.0971***[0.0050]	0.8882***[0.0056]	0.0039[0.0062]	35.5420[75.8850]	0.0006***[0.0001]
China	0.0006***[0.0002]	0.0822***[0.0042]	0.9111***[0.0042]	0.0025[0.0095]	15.2350[70.0350]	0.0004***[0.0001]
SA	0.0007***[0.0001]	0.0995***[0.0038]	0.8732***[0.0047]	-0.0239***[0.0049]	2.5444***[0.5816]	0.0002***[0.0000]
			Economic Activity Shocks (Negative)			
Brazil	0.0009***[0.0002]	0.1034***[0.0056]	0.8733***[0.0071]	-0.0760***[0.0220]	8.4834***[3.2388]	0.0004***[0.0000]
Russia	0.0008***[0.0003]	0.0994***[0.0043]	0.8960***[0.0043]	0.1156***[0.0409]	9.4610***[1.1001]	0.0016***[0.0006]
India	0.0009***[0.0002]	0.0975***[0.0051]	0.8862***[0.0057]	-0.0466***[0.0168]	47.9170**[22.5110]	0.0005***[0.0001]
China	0.0006***[0.0002]	0.0935***[0.0045]	0.9016***[0.0044]	0.0973***[0.0176]	5.0080***[0.0077]	0.0008***[0.0001]
SA	0.0007***[0.0001]	0.1000***[0.0037]	0.8714***[0.0045]	-0.0930***[0.0143]	1.0517***[0.1668]	0.0001***[0.0000]
			Oil Consumption Demand Shock (Negative)			
Brazil	0.0009***[0.0002]	0.1011***[0.0061]	0.8691***[0.0078]	-0.0467***[0.0061]	2.2393***[0.2966]	-0.0001*[0.0001]
Russia	0.0009***[0.0003]	0.0920***[0.0042]	0.9014***[0.0043]	-0.0223***[0.0066]	48.2630***[12.4360]	0.0007***[0.0002]
India	0.0009***[0.0002]	0.0981***[0.0054]	0.8815***[0.0062]	-0.0533***[0.0085]	2.2743***[0.3363]	-0.0001[0.0001]
China	0.0006***[0.0002]	0.0826***[0.0042]	0.9100***[0.0043]	-0.0094[0.0062]	5.5969[4.7778]	0.0003***[0.0001]
SA	0.0007***[0.0001]	0.1047***[0.0041]	0.8663***[0.0048]	-0.0041***[0.0013]	7.6165*[3.9909]	0.0002***[0.0000]
			Oil Inventory Demand Shock (Negative)			
Brazil	0.0009***[0.0002]	0.1004***[0.0055]	0.8816***[0.0064]	0.0118**[0.0047]	43.2500[33.6990]	0.0006***[0.0001]
Russia	0.0009***[0.0003]	0.1007***[0.0045]	0.8918***[0.0045]	0.0594**[0.0260]	13.2200**[6.4464]	0.0013***[0.0003]
India	0.0009***[0.0002]	0.0973***[0.0050]	0.8883***[0.0056]	0.0528*[0.0318]	2.3487*[1.3329]	0.0008***[0.0002]
China	0.0006***[0.0002]	0.0823***[0.0042]	0.9109***[0.0042]	0.0067[0.0053]	43.9620[40.9960]	0.0005***[0.0001]
SA	-0.0008***[0.0002]	0.0751***[0.0035]	0.9058***[0.0044]	0.0985***[0.0003]	4.8418***[0.0416]	0.0010***[0.0000]

Note: The figures in square bracket – [ ] are the corresponding standard errors of the estimated GRCH MIDAS coefficients. ***, ** and * represent statistical significance at 1%, 5% and 10%, respectively.

4.3 Predictability of Positive Oil Shocks

Table 2c presents the GARCH-MIDAS model estimation results, showing the comprising estimates of the model parameters. Here, we examine the response of the stock returns to positive oil shocks. As with previous cases, the coefficients μ, α, β and m are also found to be statistically significant. The value of the sum of the ARCH and GARCH terms being less than one also indicates the high degrees of volatility persistence that are mean reverting in the stock volatility of the BRICS countries. In the case of positive oil supply shocks, the predictability of positive oil supply shock was statistically significant for the stock volatility of Brazil, Russia, India and China, but not for South Africa. However, in the case of economic activity shock, predictability was established for the stock returns volatility of all the countries under study except

Brazil. For positive oil consumption demand shocks, predictability is not established for the cases of India and South Africa, while positive oil inventory demand shocks significantly impact on the returns volatility of Brazil, India and South Africa. From the foregoing, positive oil shocks is more likely to impact positively on the stock volatility of the BRICS countries, while the magnitude of the impact appears to be higher with respect to supply than demand shocks.

Table 2c: Predictability Result (Positive Oil Shocks)

	μ	α	β	θ	w	m
			Oil Supply Shocks (Positive)			
Brazil	0.0009***[0.0002]	0.1015***[0.0057]	0.8767***[0.0069]	0.0852***[0.0155]	1.9835***[0.3792]	0.0002***[0.0000]
Russia	0.0009***[0.0003]	0.0955***[0.0043]	0.8976***[0.0043]	0.0264**[0.0124]	47.9160[29.7180]	0.0009***[0.0002]
India	0.0009***[0.0002]	0.0983***[0.0052]	0.8850***[0.0058]	0.0951***[0.0193]	1.8036***[0.3650]	0.0002***[0.0001]
China	0.0006***[0.0002]	0.0795***[0.0041]	0.9141***[0.0042]	0.0191**[0.0076]	21.4970**[9.1547]	0.0004***[0.0001]
SA	0.0007***[0.0001]	0.1006***[0.0038]	0.8729***[0.0044]	-0.0012[0.0015]	34.4280[67.0160]	0.0003***[0.0000]
			Economic Activity Shocks (Positive)			
Brazil	0.0009***[0.0002]	0.1002***[0.0054]	0.8815***[0.0063]	0.0276[0.0403]	6.3031[13.5750]	0.0005***[0.0001]
Russia	0.0008***[0.0003]	0.1011***[0.0047]	0.8931***[0.0046]	0.4765**[0.2084]	4.9300***[1.6195]	0.0004[0.0002]
India	0.0009***[0.0002]	0.0980***[0.0052]	0.8849***[0.0058]	-0.1770***[0.0565]	1.0025***[0.2514]	0.0009***[0.0001]
China	0.0006***[0.0002]	0.0813***[0.0042]	0.9110***[0.0042]	0.1282**[0.0559]	4.2191*[2.2559]	0.0002[0.0001]
SA	0.0007***[0.0001]	0.1002***[0.0040]	0.8713***[0.0046]	0.0308***[0.0072]	18.6470***[6.5613]	0.0002***[0.0000]
			Oil Consumption Demand Shock (Positive)			
Brazil	0.0009***[0.0002]	0.1015***[0.0055]	0.8797***[0.0064]	0.0178**[0.0089]	1.0524***[0.3280]	0.0003***[0.0001]
Russia	0.0009***[0.0003]	0.0976***[0.0044]	0.8959***[0.0043]	-0.0164*[0.0087]	16.8730*[9.4240]	0.0013***[0.0004]
India	0.0009***[0.0002]	0.0956***[0.0049]	0.8907***[0.0053]	-0.0058[0.0037]	24.3860[18.8170]	0.0007***[0.0001]
China	0.0012***[0.0002]	0.0654***[0.0027]	0.9303***[0.0030]	0.0813***[0.0001]	4.8581***[0.0059]	-0.0004***[0.0000]
SA	0.0007***[0.0001]	0.1017***[0.0039]	0.8707***[0.0045]	0.0019[0.0015]	11.7940[11.7140]	0.0003***[0.0000]
			Oil Inventory Demand Shock (Positive)			
Brazil	0.0009***[0.0002]	0.0991***[0.0055]	0.8818***[0.0064]	0.1467***[0.0372]	1.7023***[0.4157]	0.0000[0.0001]
Russia	0.0009***[0.0003]	0.0989***[0.0044]	0.8943***[0.0044]	0.0599[0.0466]	7.0054[6.4881]	0.0008***[0.0003]
India	0.0009***[0.0002]	0.0968***[0.0051]	0.8879***[0.0055]	0.1419***[0.0421]	1.7341***[0.4996]	0.0001[0.0001]
China	0.0006***[0.0002]	0.0823***[0.0042]	0.9110***[0.0042]	0.0011[0.0096]	16.0160[168.0100]	0.0004***[0.0001]
SA	0.0007***[0.0001]	0.1000***[0.0040]	0.8725***[0.0045]	0.0081***[0.0015]	37.1980**[15.0570]	0.0003***[0.0000]

Note: The figures in square bracket are the corresponding standard errors of the estimated GRCH MIDAS coefficients. ***, ** and * represent statistical significance at 1%, 5% and 10%, respectively.

5. Conclusion and policy implication

In this paper, we examine the response of stock market volatility for BRICS member countries to oil shocks. Disentangling the oil shocks into four different measures of global oil shocks - oil supply shocks, economic activity shocks, oil consumption demand shocks, and oil inventory demand shocks following Baumeister & Hamilton (2019) which extends the demand and supply decomposition of oil shocks by Kilian (2009) and Kilian & Park (2009), we employ the GARCH-MIDAS approach which allows for combining variables sampled at different data frequencies within a single predictability model framework. By utilizing data that covers countries from the BRICS regional bloc, we offer an empirical evidence on oil price shocks predictability of the stock returns volatility of emerging economies from the perspective of both oil importing and exporting nations. We further decomposed each of these shocks into positive and negative shocks using dummy variables. This decomposition allows for evaluation of possible asymmetries in the stock returns predictability of oil price shocks for this group of countries.

Our findings show heterogeneity in the response of stock volatility across the BRICS countries to the four proxies of aggregated oil shocks. Further decomposing the various oil shock proxies into positive and negative shocks, we find the responses of stock volatility for the BRICS countries to differ across the different proxies of oil price shock proxies. An implication of these differing responses across the countries under consideration could be attributed to different size of economy and thus oil production and consumption profile. Besides, the market share distribution across firms, financial system efficiency and securities market regulation effectiveness also vary across the BRICS countries. A common characteristic of the BRICS stock market is that shocks to stock volatility in these markets tends to fizzle out over time; indicating the emerging nature of the stock market.

One policy implication that underscores the findings in this study is the need to devise strategies for portfolio construction and diversification across BRICS as stock volatility in these countries exhibit variant sensitivities to different oil shock proxies. Besides, the variation in stock volatility response to consumption- and inventory-demand related oil shocks across the countries might indicate differential capacity for increasing precautionary demand to forestall anticipated disruptions in future supply of crude oil. Lastly, the findings may provide guidance for market participants, most especially investors in emerging economies stocks, as it would allow them to anticipate the source of different oil-related shocks to stock volatility.

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