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RESEARCH ARTICLE

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The asymmetric impact of oil price uncertainty on emerging market financial stress: A quantile regression approach

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Abstract

This study investigates the effects of the crude oil implied volatility index (OVX) upon emerging market financial stress (EMFS). We resort to a quantile regression framework as this approach is a better alternative to disentangle the relationship under different market conditions. Besides, we also examine how EMFS responds to the lags and asymmetries in the OVX. The empirical results show significantly positive impacts of OVX upon EMFS. Further, the effects of OVX become more assertive in the upper quantiles of EMFS, implying higher sensitivity to OVX when stress levels are high. In terms of the lagged effects, the relationship is transient as the OVX coefficients become weaker with increasing lag sizes. We further find that only positive impulses in OVX can significantly predict EMFS. Lastly, we report evidence that the Credit market stress is a crucial driver of EMFS.

KEYWORDS

emerging markets, financial stress, implied volatility, oil market, quantile regression

JEL CLASSIFICATION

C21, E44, G12, G15, G41, Q43

1 | INTRODUCTION

Economists have long cited the dominance of crude oil (oil, hereafter) as a reliable precursor of financial market movements in the past (Jones and Kaul, 1996; Kilian and Park, 2009). Oil being an essential industrial input with constrained substitutability could transpire as a crucial production-cost driver in the event of rising prices. In tandem with surging energy costs, the higher marginal cost of production is expected to restrain corporate earnings. Further, soaring oil prices as the forerunner of the inflationary condition are likely to impact the real balances of households. Thus, the aggregation of these factors could impede economic growth leading to dwindling equity prices (Tiwari et al., 2018). The existing body of literature has examined the link between oil prices with the returns on several financial instruments such as equities (Das and Kannadhasan, 2020; Jones and Kaul, 1996), bonds (Kang et al., 2014) and precious metals (Das et al., 2020; Uddin et al., 2018) among others. Besides, the recent array of studies also establishes the relationship between crude oil volatility with equity returns (Dutta et al., 2017; Xiao, Zhou, et al., 2018) and equity market volatility (Dutta, 2018; Xiao, Hu, et al., 2019). The empirical findings of most of these studies advocate a close link between oil price and financial markets.

The majority of the existing studies link the role of oil price with individual financial or alternative assets. Studies examining the linkages between oil and an index measuring the level of financial stress are limited. While the financial market indicators (equity or bond indexes) are observable, the scale of financial stress is estimated by aggregating several macroeconomic components, such as interest rates, volatility, credit and funding spreads (Monin, 2019). Thus, financial stress is an indicator of financial system instability. Hence, consideration of financial stress indicators could reflect a holistic picture of the impacts of oil price on the financial fragility in an inclusive manner. In this context, Illing and Liu (2006) contend that the jumps in the financial stress index correspond sharply with the spikes in oil prices. At least two recognized channels may explain the underlying association between oil and financial stress: (a) changes in economic activity and (b) investor behaviour (Nazlioglu et al., 2015). The previous studies confirm a significant negative relationship between rising oil prices and economic activity (Hamilton, 1983; Hooker, 1996). Besides, studies also propound a positive association between increasing oil prices and inflationary forces in the economy (Cunado and De Gracia, 2005).

The inflationary conditions impend to drive up the interest rates leading to two consequences described above. First, higher borrowing costs may destabilize the credit markets leading to current production or investment cuts.[1] Such constraints in industrial operation are disposed towards lower future cash inflows. Second, investors may become uncertain about the fundamental value of assets owing to sceptical future corporate revenues. With higher uncertainties, investors might react anomalously to new information. Additionally, there could be a shift in the investor's risk preferences prompting higher compensation for retaining risky assets. The rising oil prices could suffice higher expectations of returns; thus, investors may prefer alternative investments like oil-derived assets (Nazlioglu et al., 2015). Therefore, the financialization of the oil market could contribute further to the falling prices of traditional financial assets through such capital flights (Wan and Kao, 2015).[2]

Since the concept of financial stress is relatively new, the body of literature examining the relationship between oil and composite financial stress index is at a nascent stage. Instead, studies examining oil's role on asset prices are available in abundance. Chen et al. (2014) is probably the first study that observes the relationship between oil and financial stress index. Their study disentangles the oil price changes into structural shocks using the decomposition procedure of Kilian (2009) and links it with financial stress. The results indicate that shocks arising from the financial markets play an essential role in explaining the fluctuations in the oil markets and their potential impacts on economic activity. Nazlioglu et al. (2015) revisit the relationship and posit that the transmission of volatility runs from oil price to financial stress before the global financial crisis of 2008. Nonetheless, the direction of transmission reverses in the post-crisis period. Wan and Kao (2015) highlight the hedging perspective of oil concerning financial stress. Their study concludes that the oil can be a hedging instrument during the normal stress periods as both variables tend to co-move in the same direction. However, oil's ability to shield off heightened financial risk is limited during high-stress periods. Das, Bhatia, et al. (2018) and Das, Kumar, et al. (2018) report the evidence of stronger mean causality transmissions from oil to financial stress. The reverse causality is significant only during the high-stress periods, which is somewhat consistent with Wan and Kao (2015).

This study adds a new dimension to the existing literature by examining the links between financial stress and oil price uncertainty. While the majority of the previous studies consider the changes in the realized oil price or structural shocks to link with financial stress (Chen et al., 2014; Das, Bhatia, et al., 2018; Das, Kumar, et al. 2018; Nazlioglu et al., 2015), we consider oil implied volatility (OVX), which is a forward-looking measure of oil price uncertainty. Volatility is a popular measure of market-based uncertainties. It is often closely linked to assessing financial assets (Giot, 2005; Gong and Lin, 2018; Xiao, Zhou, et al., 2018) and economic activity (Van Eyden et al., 2019). Moreover, the implied volatility indexes are derived from the option prices, which encompass additional information concerning the investors' expectations of the future market outlook beyond simple historical data. The incremental futuristic information content in the implied volatility index entitles it to better measure market uncertainty (Liu et al., 2013). Furthermore, the implied volatility index is driven by market fear alongside the future expected volatility; thus, it is advantageous to the track investors' sentiment (Maghyereh et al., 2016). The volatilities in the oil markets may emerge due to several factors, such as financial crises, the financialization of oil, the intervention of the renewable energy policies and geopolitical conflicts (Xiao, Hu, et al., 2019), which could be crucial to the financial system.

Another distinct feature of this study is that we focus primarily on emerging markets. The previous studies mostly examine the association between oil and financial stress in the developed markets, mainly the United States (US) (see Chen et al., 2014; Das, Bhatia, et al., 2018; Das, Kumar, et al., 2018; Nazlioglu et al., 2015 among others).

However, studies focussing on the impacts of oil price on emerging market financial stress (EMFS) are limited. The higher oil-dependence of these markets largely exposes them to oil price risks (Basher and Sadorsky, 2006). The devastating consequences of such exposures were witnessed during the episode of the oil embargo imposed by the Organization of the Petroleum Exporting Countries (OPEC) in 1973. The terms of the embargo propelled the oil prices from 3 to 13 U.S. dollars, which inflated the import bills of majority of the oil-importing emerging markets. In the phase of growing industrial growth, the sudden jump in oil prices compelled these markets to borrow funds to finance the on-going developmental projects. These markets failed to service their debts due to trade imbalances and borrowed further to pay-off their existing loans. By 1985, the debt obligations of these markets collectively surpassed 1 trillion U.S. dollars (Basher and Sadorsky, 2006; Rifkin, 2003). Unquestionably, this was a phase of sluggish economic growth for these markets, with rising unemployment, inflation and interest rates causing fragility in the whole financial system. Therefore, it is imperative to understand the role of oil-related uncertainties on financial system stress in the context of emerging markets.

Regarding the choice of methodology, we resort to the quantile regression technique suggested by Koenker and Bassett (1978) as the prime empirical tool. There are at least two benefits in applying this methodological framework. First, the likelihood that the impacts of the oil volatility may vary across the level of financial stress can be disentangled under this approach. The financial system might depict less responsiveness to oil volatilities when the prevailing stress levels are low. Similarly, when stress is high, the financial sector participants might become more sensitive to oil volatilities. The quantile regression approach is a useful tool to capture such asymmetries as it analyses the responses of the dependent variable across the entire conditional distribution. Thus, this approach can tap both structure and degree of dependence between the dependent and independent variables during the normal and extreme market states (Baur, 2013). Second, quantile regression is a better approach than the ordinary least square regression, especially when the error term of the underlying data is distributed non-normally. Thus, the quantile regression method is a robust econometric approach concerning skewness, heteroskedasticity and outliers (Koenker and Hallock, 2001). In our case, oil implied volatility and financial stress indexes are the main variables under consideration, which are often characterized by fat tails and sharp peaks. Thus, the possible departure of the variables from the normality assumption motivates us to use the quantile regression approach. Further, we also employ several alternative regression specifications in a quantile framework to unravel the lagged and asymmetric relationship between the variables of interest.

Our results show that OVX is a better measure to track the movements of EMFS as compared to realized oil price returns and volatilities. Further, we find that the impact of OVX upon EMFS is positively significant across quantiles. Moreover, such effects become stronger in the upper quantiles. It implies that the market participants are more responsive to oil-related concerns when the existing stress levels are high. These results stand consistent even after considering VIX as a control. Also, we observe the evidence of stronger first-lagged effects of OVX when the stress levels are low. Nevertheless, the contemporaneous effects are stronger than the lagged effects when high-stress levels. Regarding the asymmetric responses of EMFS, we find only positive impulses in OVX can significantly predict EMFS. These findings are robust to alternative model specifications with substituting the variables. Lastly, we also find evidence that the Credit market stress is a crucial driver of EMFS.

The rest of the paper is structured as follows: Section 2 presents the methodological framework. Section 3 describes the data, whereas Section 4 discusses the preliminary results. The main empirical results are reported and discussed in Section 5. The robustness test results to compare and contrast the main findings are reported in Section 6. The additional analysis results are illustrated in Section 7. Lastly, Section 8 concludes.

2 | METHODOLOGY

2.1 | Baseline regression models

We aim to study the impacts of oil OVX on the EMFS.[3] Thus, the following baseline regression model is estimated:

$$\Delta EMFS_t = \alpha + \beta \Delta OVX_t + \theta \Delta EMFS_{t-1} + \varepsilon_t \qquad (1)$$

In Equation (1), $\Delta EMFS_t$ is the first difference change in EMFS at time t. Similarly, ΔOVX_t is the change in OVX at time t. In order to control for the autocorrelation, EMFS at one time-lag is also used in the model which is expressed as $EMFS_{t-1}$ and ε_t is the error term.

Additionally, the previous literature provides a common consensus that the implied volatility index of the U.S. equity market (VIX) is a crucial stream of financial risk to global financial markets and it is also closely associated to OVX (Badshah et al., 2018; Bekiros et al., 2017; Liu et al., 2013). Several studies also use VIX as the control variable while examining the transitive relationship between oil price changes/volatility on non-U.S. financial market returns/volatility (Dutta, 2017, 2018; Xiao, Hu, et al., 2019). Therefore, the Equation (1) is modified by including VIX as below:

$$\Delta EMFS_t = \alpha + \beta \Delta OVX_t + \gamma \Delta VIX_t + \theta \Delta EMFS_{t-1} + \varepsilon_t \quad (2)$$

where the changes in VIX at time t is denoted by ΔVIX_t.[4]

It is also noteworthy that market participants and regulators may not react to oil price information immediately. It is well established in the case of financial markets that investors react to new information after a certain time lags. It is popularly known as the gradual information diffusion hypothesis. We examine this hypothesis in our case by specifying the following regression model:

$$\Delta EMFS_t = \alpha + \sum_{i=0}^{8} \beta_i \Delta OVX_{t-i} + \gamma \Delta VIX_t + \theta \Delta EMFS_{t-1} + \varepsilon_t \quad (3)$$

The lag length of this model is set to eight following the previous studies (Driesprong et al., 2008; Xiao, Hu, et al., 2019). These studies posit that such number of lags is sufficient to captivate lagged impacts of oil on financial markets. To control for contemporaneous effects, we also incorporate OVX at time t in the regression model. Further, the inclusion of OVX_t also enables us to compare and contrast the contemporaneous and lagged effects. Similar model specifications that include both contemporaneous and lagged variables can be traced in the previous studies (see Driesprong et al., 2008; Narayan and Sharma, 2011; Xiao, Hu, et al., 2019).

Several studies in the past report the evidence of the asymmetric impact of oil prices on the financial markets (Das and Kannadhasan, 2020; Xiao, Hu, et al., 2019; Xiao, Zhou, et al., 2018). Using a similar modelling approach from the reference studies, we examine whether the increase or decrease in oil price uncertainty impacts financial stress asymmetrically. To fulfil this objective, we decompose the changes in OVX into positive and negative auxiliary variables defined as follows: $\Delta OVX_t^+ = \max(0, \Delta OVX_t)$ and $\Delta OVX_t^- = \min(0, \Delta OVX_t)$. After that, the regression model is specified as below:

$$\Delta EMFS_t = \alpha + \beta_1 \Delta OVX_t^{(+)} + \beta_2 \Delta OVX_t^{(-)} + \gamma \Delta VIX_t + \theta \Delta EMFS_{t-1} + \varepsilon_t \quad (4)$$

2.2 | Quantile regression models

The ordinary least-square (OLS) regression models specified in Section 2.1 mainly suggest the average association between the variables. One of the crucial shortcomings of using such a model is that the relationship in the extreme economic conditions remains concealed. Thus, to understand the dependence structure between OVX and EMFS across the various market stress states, we use the quantile regression estimation model proposed by Koenker and Bassett (1978). The quantile regression model endows certain advantageous features over the traditional OLS model; we briefly discuss two of them. First, it offers a holistic view regarding the conditional distribution of the predicted variable, which would enable one to understand the degree of impact of the predictor variables at different market states. Second, Koenker and Hallock (2001) state that quantile regression outperforms the standard regression models in terms of estimation accuracy. Besides, they also argue that the quantile regression results are robust to estimation issues concerning outliers, heteroskedasticity and skewness of the predicted variable. Koenker and Bassett (1978) specify the quantile regression of y_i given x_i as follows:

$$q_{y_i}(\tau|x) = \alpha(\tau) + x_i' \beta(\tau) \quad (5)$$

In Equation (5), y_i's τth conditional quantile is denoted by $q_{y_i}(\tau|x)$ and $0 < \tau < 1$. The unobserved effect is depicted by $\alpha(\tau)$, whereas the estimate of the quantile regression model is indicated by $\beta(\tau)$. The vector of predictor variables is denoted by x. Thus, the $\beta(\tau)$ may be estimated as follows:

$$\hat{\beta}(\tau) = \arg\min_{\beta \in R^p} \sum_{i=1}^{n} \rho_\tau \left(y_i - x_t' \beta(\tau) - \alpha(\tau) \right) \quad (6)$$

Where the check function is expressed as $\rho_\tau(c) = c(\tau - I(c<0))$ and $I(.)$ is an indicator function is given by $\left(c = y_i - x_t' \beta(\tau) - \alpha(\tau)\right)$. Hence, in order to examine the impacts of changes in OVX with respect to EMFS at different stress states in a quantile regression framework, the Equation (1)–(4) is re-estimated as below:

$$q_{\Delta EMFS_t}(\tau|x) = \alpha(\tau) + \beta(\tau) \Delta OVX_t + \theta(\tau) \Delta EMFS_{t-1} \quad (7)$$

$$q_{\Delta EMFS_t}(\tau|x) = \alpha(\tau) + \beta(\tau) \Delta OVX_t + \gamma(\tau) \Delta VIX_t + \theta(\tau) \Delta EMFS_{t-1} \quad (8)$$

$$q_{\Delta EMFS_t}(\tau|x) = \alpha(\tau) + \sum_{i=0}^{8} \beta_i(\tau) \Delta OVX_{t-i} + \gamma(\tau) \Delta VIX_t + \theta(\tau) \Delta EMFS_{t-1} \quad (9)$$

$$q_{\Delta EMFS_t}(\tau|x) = \alpha(\tau) + \beta_1(\tau) \Delta OVX_t^+ + \beta_2(\tau) \Delta OVX_t^- + \gamma(\tau) \Delta VIX_t + \theta(\tau) \Delta EMFS_{t-1} \quad (10)$$

We report the estimation results for seven quantiles, $\tau = (0.05, 0.10, 0.25, 0.50, 0.75, 0.90, 0.95)$. The extreme economic states, that is, lower stress state is denoted by quantiles $\tau = (0.05, 0.10, 0.25)$, whereas the higher stress state is assigned by the quantiles $\tau = (0.75, 0.90, 0.95)$. The normal or tranquil market stress state is denoted by $\tau = (0.50)$. The analysis is performed using the STATA software, version 14.

3 | DATA

To examine the relationship described above, we use the oil implied volatility index (OVX) constructed by the Chicago Board Options Exchange (CBOE) in daily frequency, as the measure of oil price uncertainty.[5] To proxy for the emerging markets financial stress (EMFS) we use the Emerging Market Financial Stress Indicator reported by the Office of Financial Research (OFR), U.S. Department of the Treasury. The OFR offers a baseline financial stress indicator aggregating 33 financial market variables. The index is further bifurcated based on three geographical regions (US, other advance economies and emerging markets) and five stress category indicators (credit, equity valuation, funding, safe assets and volatility).[6]

The index of financial stress, pertaining to emerging markets, benefits our study in at least two ways: first, the previous studies mainly use the financial stress indexes such as the St. Louis Fed Stress Index (SLFS) (Das, Bhatia, et al., 2018; Das, Kumar, et al., 2018), National Financial Conditions Index (NFC) (Wan and Kao, 2015), Kansas City Financial Stress Index (KCFS) (Chen et al., 2014). These indexes primarily reflect the level of financial stress in the context of the US, whereas EMFS is specific to emerging markets. It is constructed from financial market variables of the emerging markets, such as yield spreads, valuation measures, and interest rates. Thus, this index enables us to represent the case of the emerging markets explicitly, which is seldom in the existing literature. Second, the US-based indexes (SLFS, NFC and KCFS) are used predominantly in the academic literature are available in monthly or weekly frequency.[7] Whereas EMFS index provides a daily market-based snapshot of stress in the emerging markets. Therefore, this study can capture the relational dynamics of risk transmission at a relatively higher frequency, which can be useful for making investing decisions. In addition to these two variables of interest, we also consider the implied volatility index of the U.S. stock market (VIX). The VIX is popularly known as the market-based investor's fear gauge (Whaley, 2000), thus used as the control variable taking reference from previous studies (see Xiao, Hu, et al., 2019). The period of study ranges from March 16, 2011 to December 31, 2019.[8] The analysis is performed, taking the first difference between the natural logarithm of the implied volatility indexes. In the case of EMFS, we use the first differenced values since this index contains negative values during periods of low financial stress.[9]

Figure 1 exhibits the movements of the OVX and EMFS over the sample period of study. As it can be observed, the two different indexes tend to depict similar activities across time.[10] Interestingly, the figure also reveals some spikes in the indexes during similar time-window. Thus, we may infer the existence of co-spiking behaviour among the two variables. Moreover, these spikes can be attributed to some political and economic events of relevance. For instance, the risk of European and the U.S. debt defaults could be the underlying reason for the spike appearing around August 2011 (Liu et al., 2013). Another time-window of frequent spikes may be observed during the late 2014 to 2016. Dutta (2018) opines that these spikes are stimulated by several oil market and other events such as oil oversupply, declining global oil demands, Iran nuclear and/or strong the U.S. dollar rates. As for EMFS, the spikes could be concomitant to the oil market and other international economic instabilities.

Table 1 reports the descriptive statistics for the changes in OVX, EMFS and VIX. The unconditional volatilities represented by the standard deviation (Std. dev.) suggest that VIX is most volatile index followed by OVX and EMFS. The skewness and kurtosis coefficients of the variables indicate the underlying distribution of the variables to depart from normality conditions. Besides, the null hypothesis of the Jarque-Bera test is also rejected, confirming the indications of non-normality. The results suggesting non-normalities of the underlying variables motivate us to consider quantile regression framework as the OLS regression assumes normal distributions of the error term. Also, we check the stationarity condition of the variables using the Augmented Dickey-Fuller (ADF), Phillips-Perron (PP) and the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) tests. The null hypothesis of ADF and PP test is the presence of a unit root in the underlying time-series against the null of stationarity. Whereas, in the case of KPSS, the null hypothesis is stationarity of the time-series under consideration. The results of all the three tests signify stationarity of the underlying variables used in the study.

4 | PRELIMINARY RESULTS

In this segment, we report preliminary results relating to two significant aspects of the relationship between OVX and EMFS before proceeding to the main empirical

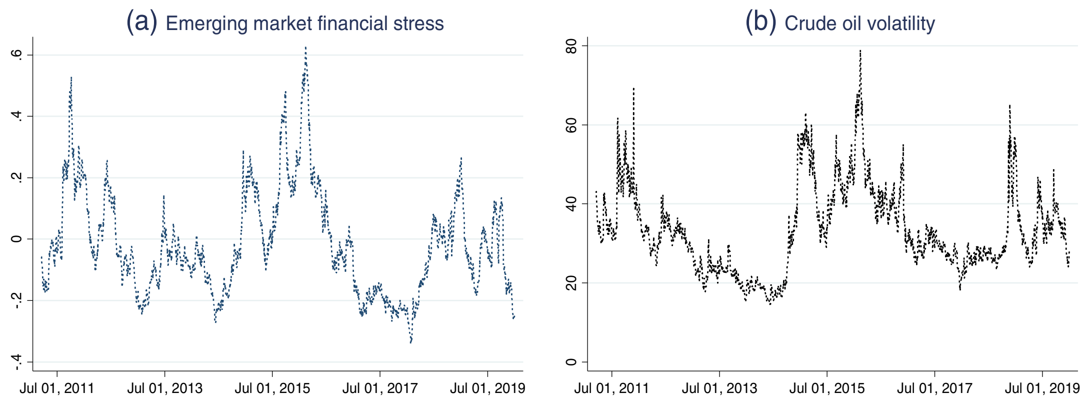

FIGURE 1 EMFS and OVX from march 16, 2011, to December 31, 2019

TABLE 1 Descriptive statistics of all variables

	ΔOVX	ΔEMFS	ΔVIX
Mean	−0.0002	−0.0001	−0.0003
Median	−0.0037	−0.0010	−0.0050
Maximum	0.4250	0.1370	0.7682
Minimum	−0.4399	−0.1130	−0.3141
Std. dev.	0.0498	0.0185	0.0782
Skewness	1.0158	0.5378	1.1262
Kurtosis	13.2255	8.5781	10.0521
Jarque-Bera	9977.0000***	2962.0000***	5031.000***
ADF	−49.7020***	−41.2890***	−50.382***
PP	−50.2380***	−41.5410***	−51.238***
KPSS	0.0235	0.0418	0.0055
Obs.	2203	2203	2203

***Statistical significance at the 1% level.

results. First, we investigate whether OVX annexes additional information to predict EMFS as compared to the oil returns and realized volatilities. Second, though we are primarily interested in examining the causal impacts transmitting from OVX to EMFS, we also pay attention to the case of reverse causality (i.e., EMFS to OVX). The results are discussed in details in the following subsegments:

4.1 | Does OVX annexes additional information as compared to oil returns and realized volatilities?

As discussed before, the majority of the previous studies consider oil prices/returns to assess its impact on financial stress. We use OVX instead of oil price returns since the implied volatility indexes are believed to contain additional information concerning the future economic outlook. Nevertheless, it is imperative to assess and compare the predictive performance of OVX to forecast financial stress regarding oil returns and realized volatilities. Thus, we use West Texas Intermediate (WTI) oil spot and NYMEX 1-month Light Sweet Oil contract futures prices as the representative of two variants of oil prices.[11] Further, the conditional volatilities of the oil spot and future returns are obtained using a Generalized Autoregressive Conditional Heteroscedasticity model of order 1,1 (GARCH [1,1]) to proxy for realized volatilities. The assessment of predictive performance is done considering two popular loss functions: (a) Root Mean Square Error (RMSE) and (b) Mean Absolute Error (MAE). The in-sample estimation period ranges from March 17, 2011 to December 29, 2017 and the out-of-sample forecasting period used to obtain one-step-ahead forecasts is taken from January 03, 2018 to December 31, 2019. Table 2 exhibits the result of the EMFS forecasting performance with different regression models incorporating oil price and realized volatility measures. We observe that though the MAE of OVX corresponds with the MAE of oil future returns (0.0127), however, the RMSE of OVX (0.0180) is lesser than the RMSEs of all other alternative oil returns or realized volatility measures. Besides, the coefficient of determination (adjusted R-squared) for the full sample shows that OVX explains the highest percentage of variation in EMFS (12.79%). Thus, the results are in favour of the claim that OVX yields better out-of-sample EMFS forecasts than oil returns or realized volatilities.

4.2 | Is there a reverse causality transmitting from EMFS to OVX?

Several studies in the past underscore the possibility that the prevailing financial market conditions might encompass an influence upon the oil price movements given the financialization of the oil markets. For instance, Morana (2013) in this regard posits that the financial shocks

TABLE 2 Out-of-sample forecast results

Model	RMSE	MAE	Full sample adj. R^2 (%)
a. $\Delta EMFS_t = \alpha + \delta \Delta \text{Oil\_Spot}_t + \varepsilon_t$	0.0189	0.0128	6.74
b. $\Delta EMFS_t = \alpha + \delta \Delta \text{Oil\_Future}_t + \varepsilon_t$	0.0188	0.0127	7.04
c. $\Delta EMFS_t = \alpha + \delta \Delta \text{Oil\_Spot\_Vol}_t + \varepsilon_t$	0.0191	0.0130	0.63
d. $\Delta EMFS_t = \alpha + \delta \Delta \text{Oil\_Future\_Vol}_t + \varepsilon_t$	0.0191	0.0130	0.57
e. $\Delta EMFS_t = \alpha + \delta \Delta \text{OVX}_t + \varepsilon_t$	0.0180	0.0127	12.79

Notes: The period of the full sample under examination ranges from March 17, 2011 to December 31, 2019 (2203 observations). The in-sample estimation period is from March 17, 2011 to December 29, 2017, and the out-of-sample forecast period is from January 3, 2018 to December 31, 2019 (502 observations). We estimate two popular loss functions RMSE and MAE, for the models specified in (a)–(e). Root Mean Square Error: $\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(\Delta EMFS_{a,t} - \Delta EMFS_{f,t}\right)^2}$, a = actual and f = forecasted $\Delta EMFS$ at time t. Mean Absolute Error: MAE= $\text{MAE} = \frac{1}{n}\sum_{i=1}^{n}\left|\Delta EMFS_{a,t} - \Delta EMFS_{f,t.}\right|$

remarkably contribute to determine the oil prices. Similarly, Chen et al. (2014) examine the association between structural oil supply–demand shocks and financial stress. Their findings suggest that an outlook of worsening financial market conditions result in declining real prices of oil. They further argue that the increasing stress in the financial markets encourage risk-aversive behaviour of investors. Consequently, the asset prices across all segments dwindle including oil. Nazlioglu et al. (2015) pose the view that during the phases of financial stress the true quality of corporate earnings are difficult to assess. Therefore, the lending institutions impose restrictions on credit availabilities leading to a fall in economic activities and oil demands.

Given the fact that some prominent and high growth emerging countries (such as India and China) having ushering importance in world trade are also major oil importers. A fragile financial state in those countries might dampen investments and subsequently, the demand for oil impacting their prices. Hence, we explore such a possibility using the causality tests. Table 3 reports the result for the Vector Autoregressive (VAR) Granger causality test. The result indicates the evidence of statistically significant Granger causalities transmitting from OVX to EMFS. However, the Granger causality in the reverse case stands statistically insignificant. The result affirms that the ability of EMFS to Granger cause OVX is limited over the sample period. As in Figure 1 we observe a sharp peak in EMFS during 2014–15, we believe this was primarily the outcome of surging OVX due to events of global concerns such as excess oil supply, appreciation of the U.S. dollar and geopolitical instabilities in the middle east (Baffes et al., 2015; Dutta, 2018).

Additionally, it is conceivable that the Granger causalities between EMFS and OVX might differ across the frequencies of time, that is, in the short or the long run. The short-run causalities may be attributed to the risk apprehensions of the market participants. At the same time, the long-run causalities could be driven by the government's policy responses through the channels of interest and inflation. Thus, the short-run association could be mere contagion causal effects, while the log-run causalities may signify interdependence. We explore such a possibility using the spectral Granger causality test suggested by Breitung and Candelon (2006).[12] The short-run causality dynamics are captured for the frequencies (ω) scaling between 3 and 1.25 implying ($\approx$) 2 ($2\pi/\omega = 6.28/3$) to 5 days (6.28/1.25). Similarly, $\omega_{1.24}$ to ω_0 designates long-run Granger causalities. Figure 2 exhibits the result for the spectral test, which is fairly consistent with the baseline Granger causality test. The causalities mainly transmit from OVX to EMFS, and the reverse is not statistically valid.

TABLE 3 VAR Granger causality test

	χ^2	p-value
a. OVX → EMFS	40.636	0.000***
b. EMFS → OVX	3.857	0.277

***Statistical significance at the 1% level.

5 | MAIN RESULTS

In this segment, we discuss the main results bifurcated into three sub-segments. First, we discuss the contemporaneous impacts of OVX on EMFS while controlling for autocorrelations and VIX. Second, we discussed the lagged effects of OVX and lastly; we examine the asymmetric effects.

5.1 | Contemporaneous impacts of OVX on EMFS

First, we assess the contemporaneous impacts of OVX on EMFS across the different stress states by resorting to a

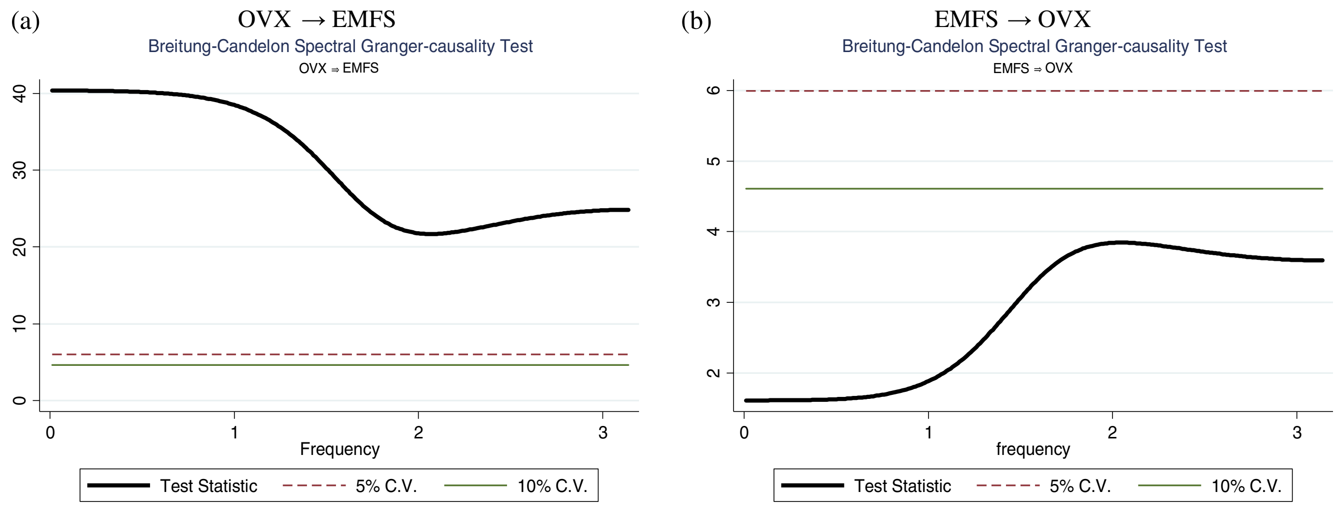

FIGURE 2 Spectral Granger causality between EMFS and OVX. The figures represent the result for the spectral or the frequency-domain Granger causality test. The *x*-axis denotes the frequencies (ω) through 0 to 3. Whereas the *y*-axis designates the computed values of *F*-statistics. The red-dotted and green-solid horizontal straight lines denote Breitung and Candelon critical values at 5% and 10% levels, respectively. The emboldened black solid line is the Breitung and Candelon test statistic for the null hypothesis that there is no spectral Granger causality between EMFS and OVX. Please note that the cycle length T is computed as $2\pi/\omega$, where the value of $\pi = 3.14$.

quantile regression framework. Besides, OVX, we also include VIX as one of the controlling variables to unravel whether the impacts of OVX remain significant after considering the U.S. market volatility. Additionally, we also report the results of the OLS model which captures the average relationship and also facilitates comparison with quantile regression estimates.

Table 4 exhibits the empirical results for the impact of OVX on EMFS. The panel A reports the result based on OLS and quantile regression model specifications in Equations (1) and (7), respectively. The OVX coefficient for the OLS model is positive and significant at the 1% level implying positive stimulus of OVX towards EMFS at the average levels. The Durbin-Watson test statistic (DW Stat.) and Variance Inflation Factor (VIF) estimates provide the evidence that the model does not appear to be plagued by autocorrelation and multicollinearity, respectively. The results for the quantile regression model supplement additional insights. We observe that the OVX coefficients are significant across all the quantiles at the 1% level, which suggests a strong relationship. It is also noteworthy that the values of OVX coefficients increase monotonically from lower to higher quantiles. This finding becomes more apparent by referring to Figure 3, which depicts the OVX coefficients in the graphical form. Thus, it can be inferred that the EMFS is more sensitive to OVX when the prevailing stress levels are high. Further, we resort to the quantile slope equality test to validate whether the OVX coefficients are statistically heterogeneous between higher and the other quantiles. To achieve this objective, we examine and report the results of slope equality test for the higher quantiles (0.95, 0.90 and 0.75) with the median (0.50) and lower quantiles (0.25, 0.10 and 0.05). Panel A of Table 5 exhibits the results, which shows that the null hypothesis of equality is rejected in most of the cases. Thus, the observation of differential impacts of OVX on EMFS across the lower and higher quantiles is validated statistically. The Breusch–Pagan (BP)/Cook-Weisberg (CW) test result shows that the observed heterogeneity in OVX coefficients across quantiles might be due to the presence of heteroskedasticity. Lastly, the estimated coefficients for lagged changes of EMFS (i.e. $EMFS_{t-1}$) are significantly positive. It implies that the past information of financial stress can drive up current stress levels.

Panel B of Table 4 exhibits the results for the specifications in Equations (2) and (8). In this case, we re-assess the association between EMFS and OVX after considering VIX as a control measure. The results indicate that VIX could be a variable of relevance to moderate the EMFS–OVX relationship as it is significant at the 1% level across all the quantiles as well as for the OLS model. The observed OVX coefficients for Equation (8) are weaker than the coefficients obtained previously in Equation (7) due to the moderation of VIX. Nevertheless, the OVX coefficients remain positive and significant for all the quantiles of interest with 0.05th quantile being the only exception. The statistical insignificance at 0.05th quantile signifies that during the phases of lower stress, the growing economies might offset the adverse impacts of OVX. Figure 4 plots the coefficients of the model, which shows higher sensitivity of EMFS to OVX in the upper tail,

TABLE 4 Estimation results for impacts of the OVX changes on the EMFS changes

	0.05	0.10	0.25	0.50	0.75	0.90	0.95	OLS
Panel A								
Constant	−0.0260***	−0.0182***	−0.0096***	−0.0001	0.00970***	0.0192***	0.0257***	−0.0001
ΔOVX_t	0.0912***	0.0870***	0.0826***	0.1030***	0.1240***	0.1680***	0.1940***	0.1338***
ΔEMFS_{t-1}	0.1150*	0.0971**	0.1090***	0.1410***	0.1470***	0.1790***	0.1880***	0.1343***
R^2(%)	2.29	2.88	3.36	4.60	8.69	13.73	17.37	14.56
DW Stat.	–	–	–	–	–	–	–	2.1187
VIF	–	–	–	–	–	–	–	1.00
Panel B								
Constant	−0.0242***	−0.0181***	−0.0092***	−0.0001	0.0089***	0.0181***	0.0244***	−0.0001
ΔOVX_t	0.0139	0.0279**	0.0424***	0.0576***	0.0846***	0.1040***	0.1330***	0.0846***
ΔVIX_t	0.0980***	0.0832***	0.0693***	0.0718***	0.0638***	0.0753***	0.0756***	0.0749***
$\Delta EMFS_{t-1}$	0.1230**	0.1500***	0.1510***	0.1460***	0.1600***	0.1570***	0.1700***	0.1494***
R^2(%)	8.79	8.30	7.75	9.47	13.31	18.84	22.41	22.82
DW Stat.	–	–	–	–	–	–	–	2.2463
VIF	–	–	–	–	–	–	–	1.14

Note: Panel A reports the results for the models specified in Equations (1) and (7). Similarly, Panel B reports the results based on Equations (2) and (8). R^2 denotes the adjusted and pseudo-*R*-squared for OLS and quantile regression models, respectively.

Abbreviations: DW stat., Durbin-Watson test statistic; VIF, variance inflation factor.

***Statistical significance at the 1% level.

**Statistical significance at the 5% level.

*Statistical significance at the 10% level.

similar to the previous case as in Equation (7). The result for the slope equality test is reported in Panel B of Table 5, which rejects the null hypothesis of equality for the several chosen quantiles of reference at the 1% level of significance. Thus, the condition of the heterogeneous impact of OVX holds true even after controlling for the VIX. The inclusion of VIX in the model furthers our observation in at least two ways. First, VIX has significantly positive impacts on the EMFS, suggesting that the U.S. market volatility could be a potential antecedent of EMFS. The impacts of VIX as stressors could transmit to the emerging markets through the channels of equity valuation, which is posited by several studies in the past (see Mensi et al., 2014; Xiao, Hu, et al., 2019). Second, we may observe that the values of R-squared are improved for both OLS and quantile regression models after incorporating VIX to the baseline model. Therefore, controlling for the U.S. market volatility could yield incremental benefits in describing the relationship between EMFS and OVX.

To present the above results in brief, we may conclude that the impact of OVX on EMFS is positive and statistically significant. This finding is consistent with some of the previous studies that examine the impact of OVX upon stock market implied volatilities (see Maghyereh et al., 2016; Xiao, Hu, et al., 2019). However, within the limited knowledge of the authors, none of the previous studies report such an evidence in the context of financial stress. The quantile regression results are in

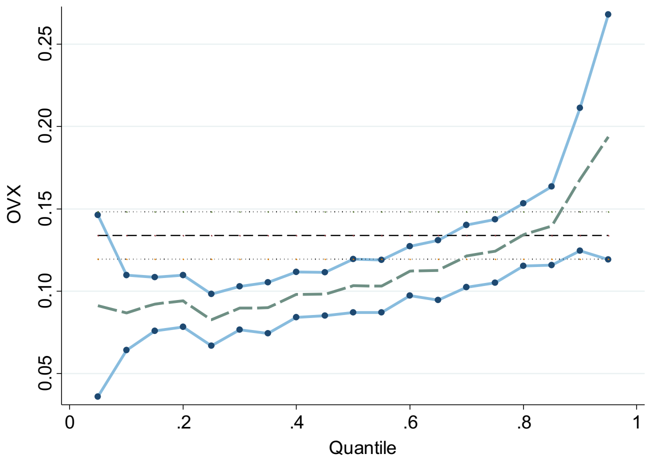

FIGURE 3 OVX coefficient estimates from the quantile regression model specified in Equation (7). The plot depicts the contemporaneous impacts of OVX on EMFS across the quantiles. The olive dashed line denotes point estimates and the two parallel enveloping navy-blue dotted lines signify 95% confidence bands. The horizontal black dashed line estimates the OLS model with black spaced-dotted parallel lines representing 95% confidence bands.

TABLE 5 Quantile slope equality test for the OVX changes

Panel A	**ΔOVX_t**	**0.50–0.95******	**0.25–0.95******	**0.10–0.95******	**0.05–0.95******
		0.50–0.90***	0.25–0.90***	0.10–0.90***	0.05–0.90**
		0.50–0.75**	0.25–0.75***	0.10–0.75**	0.05–0.75
	BP/CW	152.94***			
Panel B	ΔOVX_t	0.50–0.95***	0.25–0.95***	0.10–0.95***	0.05–0.95***
		0.50–0.90***	0.25–0.90***	0.10–0.90***	0.05–0.90***
		0.50–0.75***	0.25–0.75***	0.10–0.75***	0.05–0.75***
	BP/CW	176.59***			

Note: Panel A and B report the results for the quantile slope equality tests for the OVX changes for the models specified in Equations (7) and (8), respectively.
Abbreviation: BP/CW, Breusch-Pagan/Cook-Weisberg test for heteroskedasticity.
***Statistical significance at the 1% level.
**Statistical significance at the 5% level.

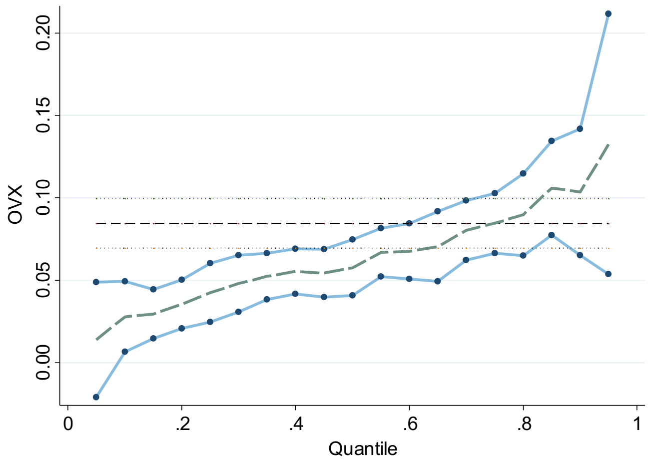

FIGURE 4 OVX coefficient estimates from the quantile regression model specified in Equation (8). The plot depicts the contemporaneous impacts of OVX on EMFS across the quantiles. The olive dashed line denotes point estimates, and the two parallel enveloping navy-blue dotted lines signify 95% confidence bands. The horizontal black dashed line estimates the OLS model with black spaced-dotted parallel lines representing 95% confidence bands.

coherence with the OLS in terms of commonality of direction of impacts. Moreover, our findings also supplement that the impact of the OVX is intense during the phases of high stress (see Figures 3 and 4). Several underlying reasons may be attributed to the phenomenon of higher upper-tail sensitivity of EMFS in response to OVX. For instance, higher level of uncertainties related to oil prices might impede the future production decisions and hence the expected corporate earnings (Maghyereh et al., 2016). Similar interpretations suggesting the adverse effects of oil price uncertainty upon real economic activity and financial sector are also supported by Jo (2014). Bloom (2014) argues that firms are likely to take on more debt as a cheaper source of financing during the recessionary or stressed phases. Such leverage effects precede higher stock return volatilities in anticipation of lower residual earnings for dividend distribution (Bloom, 2014). Extending further, higher and uncertain oil prices could inflate the production costs and the firms may fail to generate adequate earning to serve their existing debts. The delinquent payments to creditors or defaults on debts might damage the firm's image. Consequently, the fall in credit rating of the firms would compel the future debt solicitations costlier than before.

Christoffersen and Pan (2018) highlight another dimension to the relationship by suggesting that higher oil-related uncertainties might lead funding constraints to the market speculators discouraging financial activities. The credit availabilities to the market may freeze if the lenders perceive greater counterparty risks. The periods of higher financial stress are often characterized by increased uncertainties about fundamental values of financial assets and information asymmetries (Das, Bhatia, et al. 2018; Das, Kumar, et al., 2018; Hakkio and Keeton, 2009; Illing and Liu, 2006; Monin, 2019). Thus, the lenders might evaluate risks with a pessimistic approach in response to oil uncertainties during high-stress periods constraining the availability of loanable funds. A constrained investment environment might incentivize the investment managers to herd on investment choices. Since mimicking investment, behaviour assures that a manager will not underperform to his peers (Rajan, 2006). Such collective behaviour might move the asset prices away from their fundamentals deepening the roots of financial fragility (Bikhchandani et al., 1998; Chauhan et al., 2019; Rajan, 2006). This channel of financial stress, routed through oil uncertainties, could be more impactful in the context of emerging markets given their higher oil dependencies (Basher

TABLE 6 Estimation results for testing lagged impacts of the OVX changes on the EMFS changes

	0.05	0.10	0.25	0.50	0.75	0.90	0.95	OLS
Constant	−0.0234***	−0.0175***	−0.0093***	0.0003	0.0088***	0.0181***	0.0251***	0.0001
ΔOVX_t	0.0346	0.0352**	0.0595***	0.0681***	0.0858***	0.1070***	0.1370***	0.0889***
ΔOVX_{t-1}	0.0421**	0.0649***	0.0647***	0.0542***	0.0513***	0.0622***	0.0740***	0.0605***
ΔOVX_{t-2}	−0.0094	0.0110	0.0204**	0.0257***	0.0209**	0.0416***	0.0376*	0.0240***
ΔOVX_{t-3}	−0.0171	−0.0084	−0.0022	0.0147*	0.0205**	0.0416***	0.0604***	0.0166**
ΔOVX_{t-4}	−0.0100	0.0042	0.0137	0.0004	0.0161*	0.0292***	0.0338**	0.0114
ΔOVX_{t-5}	−0.0142	0.0072	0.0027	0.0159**	0.0150**	0.0148	0.0101	0.0147**
ΔOVX_{t-6}	−0.0084	−0.0113	−0.0044	0.0129	0.0209***	0.0178	0.0367	0.0121*
ΔOVX_{t-7}	−0.0042	−0.0123	−0.0083	−0.0074	−0.0001	0.0002	0.0070	−0.0041
ΔOVX_{t-8}	−0.0369*	−0.0099	0.0032	0.0113	0.0059	0.0110	0.0200	0.0048
ΔVIX_t	0.0946***	0.0852***	0.0632***	0.0683***	0.0630***	0.0766***	0.0853***	0.0755***
$\Delta EMFS_{t-1}$	0.0819	0.0889**	0.0611*	0.0862***	0.0795***	0.0598	0.0707	0.079***
H_0: $\beta_0 = \beta_1$	0.07	2.42	0.12	1.08	4.07**	3.68*	4.40**	7.59***
R^2(%)	10.01	10.14	9.59	10.88	14.88	20.60	24.97	25.19
DW Stat.	–	–	–	–	–	–	–	2.1401
VIF	–	–	–	–	–	–	–	1.09

Note: The table reports the results for the models specified in Equations (3) and (9). H_0: $\beta_0 = \beta_1$ is the null hypothesis of the Wald test for assessing the difference between the estimates of OVX at the lag 0 and at the lag 1. R^2 denotes the adjusted and pseudo R-squared for OLS and quantile regression models, respectively.

***Statistical significance at the 1% level.

**Statistical significance at the 5% level.

*Statistical significance at the 10% level.

and Sadorsky, 2006; Das and Kannadhasan, 2020) coupled up with poor governance, information asymmetry and disclosure quality (Chauhan et al., 2016; Patel et al., 2002; Tang et al., 2013). Therefore, the stronger responses to oil volatilities may be realized during the window periods of high stress.

5.2 | Lagged impacts of OVX on EMFS

Next, we test the gradual information diffusion hypothesis by assessing the lagged impacts of OVX upon EMFS. The existing studies state that the presence of gradual diffusion of information may be affirmed only when the following conditions are satisfied: (a) the magnitude of lagged OVX impacts on EMFS should correspond or exceed the magnitude of contemporaneous OVX impacts and, (b) the impacts of OVX are should peak in the initial lags and then decay with increasing lag sizes (see Driesprong et al., 2008; Lu and Jacobsen, 2016; Xiao, Hu, et al., 2019). Thus, in congruence with the stated conditions, we estimate the models specified in Equations (3) and (9).

Table 6 exhibits the estimated output based on Equations (3) and (9). Additionally, Figure 5 illustrates the lagged impacts of OVX upon EMFS at different lag sizes (lags 1–8) by plotting the coefficients obtained from estimating Equation (9). The OLS results show that in addition to the contemporaneous coefficient (lag 0), the lagged coefficients are significantly positive for all lags except lags 4, 7 and 8. In comparison to lag 0, the coefficients are weaker at the lag 1 and other subsequent lags. To validate whether there is a significant difference in the estimates of OVX at the lags 1 and 0, we perform the Wald test for the following null hypothesis: $\beta_0 = \beta_1$. The result of the Wald test fails to accept the null hypothesis of equality and suggests statistically significant differences in contemporaneous and lagged estimates of OVX. Thus, the results do not strictly adhere to the predefined conditions necessary to conclude in favour of gradual information diffusion hypothesis. We also observe some interesting inferences from the quantile regression results. Similar to the contemporaneous OVX coefficients, the coefficients at the first lag is significantly positive across all the quantiles of EMFS. However, we may further note that the lag 1 coefficients are greater than lag 0 at the lower tail, that is, 0.05 to 0.25 quantiles. At quantile 0.50 the lag 0 OVX coefficient is marginally higher than lag 1. In the upper tail (quantiles 0.75 to 0.95), the lag 0 exceed the values of lag 1 OVX coefficients. Besides, the magnitude of impact tends to decay for all

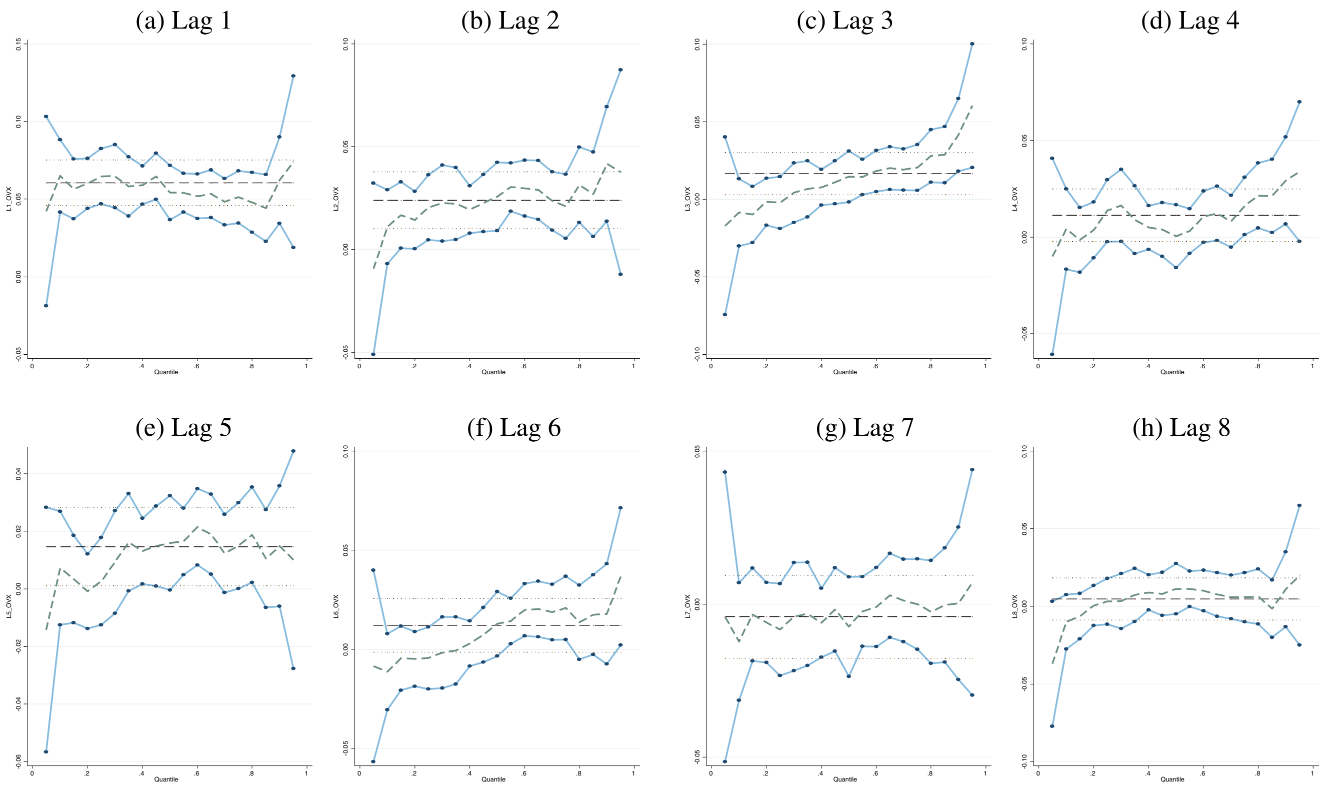

FIGURE 5 Lagged OVX coefficient estimates from the quantile regression model specified in Equation (9). The plot depicts the lagged impacts of OVX on EMFS across the quantiles. The olive dashed line denotes point estimates, and the two parallel enveloping navy-blue dotted lines signify 95% confidence bands. The horizontal black dashed line estimates the OLS model with black spaced-dotted parallel lines representing 95% confidence bands.

subsequent lags after the lag 1, with only marginal exception at quantile 0.95. The Wald test results support these empirical findings. We fail to reject $\beta_0 = \beta_1$, which signify similarity in the estimates of OVX at the lags 1 and 0 for the quantiles 0.05–0.50. Whereas, we fail to accept $\beta_0 = \beta_1$ in the case of upper quantiles (0.75–0.95). Overall, the results fail to convincingly fulfil the gradual information diffusion conditions stated earlier and thus, the results are not in strong support of the hypothesis.

We further resort to the values of R-squared to test the gradual information diffusion hypothesis following the previous studies (see Driesprong et al., 2008; Lu and Jacobsen, 2016; Xiao, Hu, et al., 2019). Figure 6 plots the R-squared values obtained by executing individual regression models similarly specified in Equations (3) and (9) at the lags 1 to 8. In the case of the OLS regression, it is clearly evident that the highest explanatory power exists at the first lag. The explanatory ability, however, declines gradually for the subsequent lagged trading days. The plot of R-squared values derived from the quantile regression models depicts qualitatively similar implications. Though some instances of sudden rise in explanatory power at the eighth lag can be observed for quantiles 0.05, 0.75 and 0.95, importantly the explanatory power remains the highest for the lag 1. Therefore, our results are inconsistent with Driesprong et al. (2008) and Lu and Jacobsen (2016) as their study supports stronger effects at higher lags. Instead, our results are somewhat coherent with Xiao, Hu, et al., 2019, who also opine stronger effects at initial lags (and weaker effects at higher lags). Thus, the conclusions based on R-squared measure even fail to support the gradual information diffusion hypothesis strongly.

Thus, to synopsize the results, we find that the lagged OVX impacts on EMFS are positive and statistically significant mainly at the first lag. It appears that the relationship is transient and primarily sustained in the short-run. Similar findings are offered in the case of equity index implied volatilities concerning OVX in the previous studies (see Badshah et al., 2018; Xiao, Hu, et al., 2019). We must account that the implied volatility indexes contain additional information relating to the market's future expectations and thus can better predict asset price volatilities (Kenourgios, 2014; Luo and Qin, 2017). Additionally, the EMFS is also a forward-looking index, which is capable of predicting the future economic activities (Monin, 2019). Thus, the information carried by OVX could quickly transmit to the EMFS through the asset

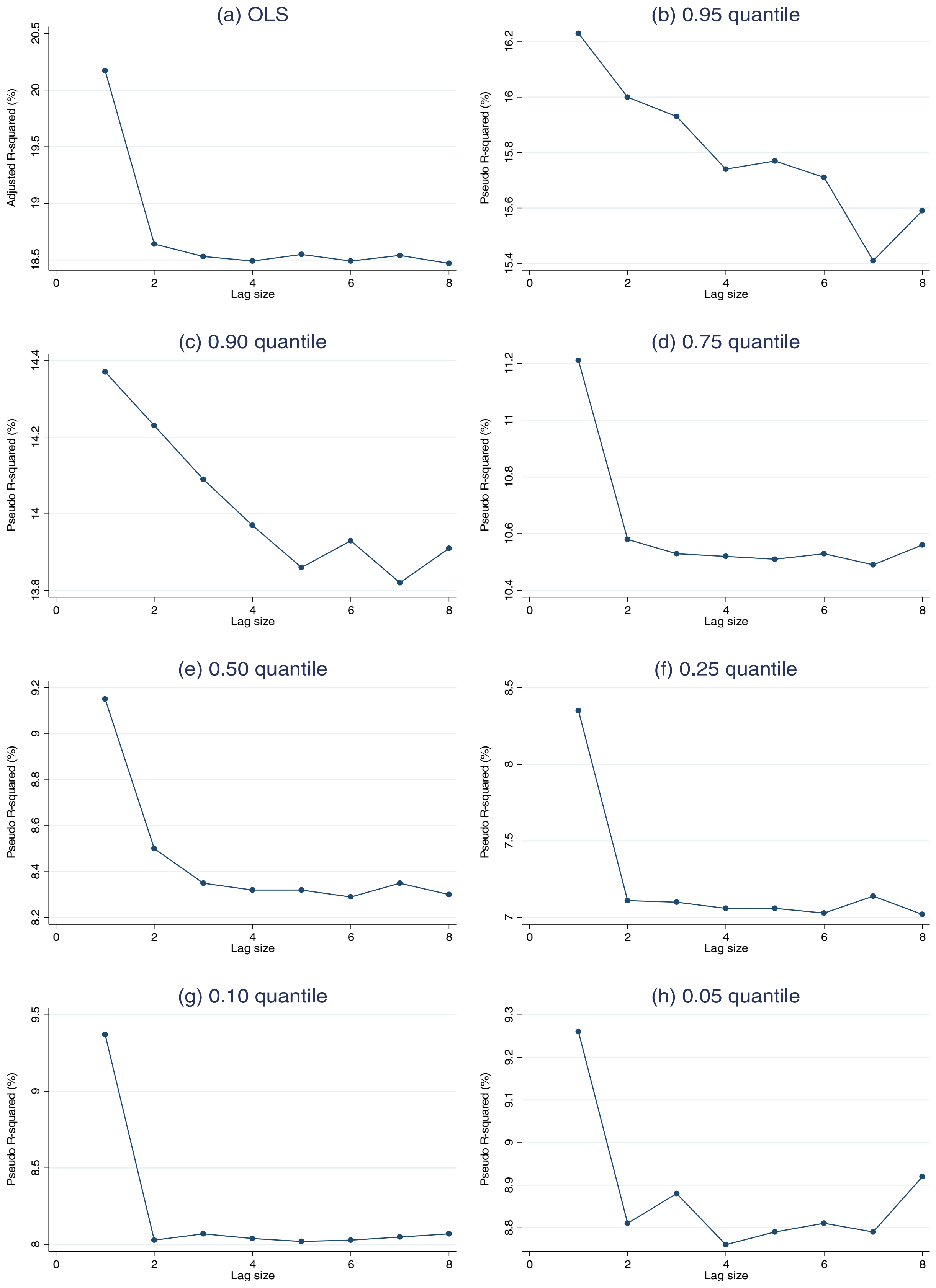

FIGURE 6 Plot of R-squared from regression models specified in Equations (3) and (9) at the lags 1 to 8

price volatility channel (Xiao, Hu, et al., 2019). Accordingly, the market participants may evaluate the future market outlook contained in the OVX, thereby lessening delayed responses. Moreover, with the advent of financialization, the linkages between oil and financial markets are more intensified than before, primarily through volatility connectedness (Antonakakis et al., 2020; Maghyereh et al., 2016).

Interestingly, we further notice that the magnitude of the lagged OVX coefficients are more substantial than the contemporaneous in the lower quantiles. Whereas, in the higher quantiles, the trend is reversed as the magnitude of the lagged OVX coefficients turns weaker in comparison to contemporaneous coefficients. Therefore, we may conclude that when the financial stress levels are low, the delayed response to OVX is comparatively stronger. The lower financial stress levels imply financial stability; under such circumstances, the markets might under-react and take more time to assimilate new information to the system. Conversely, higher financial stress is often associated with lower business confidence levels. Thus, markets might over-react to the arrival of new information, and the adverse effects are likely to be realized quickly. Lastly, Table 7 exhibits the results for the slope equality test of the contemporaneous and the first lagged OVX impacts upon EMFS. In the case of contemporaneous OVX coefficients, we can observe inequalities of the slopes. Nevertheless, in the case of the first lag OVX impacts upon EMFS, we fail to find any statistically significant evidence of heterogeneity. It implies that the impact of OVX in the lower or middle quantiles do not significantly different than the effects realized in the higher quantiles. Thus, the results broadly validate that the direction and magnitude of contemporaneous OVX

TABLE 7 Quantile slope equality test for the OVX changes at the lags 0 and 1

ΔOVX_t	0.50–0.95***	0.25–0.95***	0.10–0.95***	0.05–0.95***
	0.50–0.90**	0.25–0.90**	0.10–0.90***	0.05–0.90***
	0.50–0.75	0.25–0.75*	0.10–0.75***	0.05–0.75**
ΔOVX_{t-1}	0.50–0.95	0.25–0.95	0.10–0.95	0.05–0.95
	0.50–0.90	0.25–0.90	0.10–0.90	0.05–0.90
	0.50–0.75	0.25–0.75	0.10–0.75	0.05–0.75
BP/CW	244.39***			

Note: The table reports the results for quantile slope equality tests for the OVX changes at the lags 0 and 1 for the models specified in Equations (9).

Abbreviation: BP/CW denotes Breusch-Pagan/Cook-Weisberg test for heteroskedasticity.

***Statistical significance at the 1% level.

**Statistical significance at the 5% level.

*Statistical significance at the 10% level.

TABLE 8 Estimation results for testing asymmetric impacts of the OVX changes on the EMFS changes

	0.05	0.10	0.25	0.50	0.75	0.90	0.95	OLS
Constant	−0.0244***	−0.0183***	−0.0108***	−0.0029***	0.0054***	0.0136***	0.0190***	−0.0028***
ΔOVX_t^+	0.0276	0.0392*	0.0989***	0.1500***	0.1910***	0.2620***	0.3230***	0.1518***
ΔOVX_t^-	0.0031	0.0195	−0.0072	−0.0299**	−0.0166	0.0087	−0.0072	−0.0109
ΔVIX_t	0.0975***	0.0828***	0.0653***	0.0691***	0.0645***	0.0654***	0.0890***	0.0741***
$\Delta EMFS_{t-1}$	0.1230**	0.1440***	0.1320***	0.1250***	0.1410***	0.1640***	0.1400***	0.1369***
H_0: $\beta_1 = \beta_2$	0.19	0.24	13.84***	57.83***	104.69***	22.00***	19.38***	68.95***
R^2(%)	8.83	8.36	8.35	11.09	15.66	21.95	26.34	25.14
DW Stat.	–	–	–	–	–	–	–	2.2372
VIF	–	–	–	–	–	–	–	1.16

Note: The table reports the results for the models specified in Equations (4) and (10). H_0: $\beta_0 = \beta_1$ is the null hypothesis of the Wald test for assessing the difference between the estimates of positive and negative OVX changes. R^2 denotes the adjusted and pseudo-R-squared for OLS and quantile regression models, respectively.

***Statistical significance at the 1% level.

**Statistical significance at the 5% level.

*Statistical significance at the 10% level.

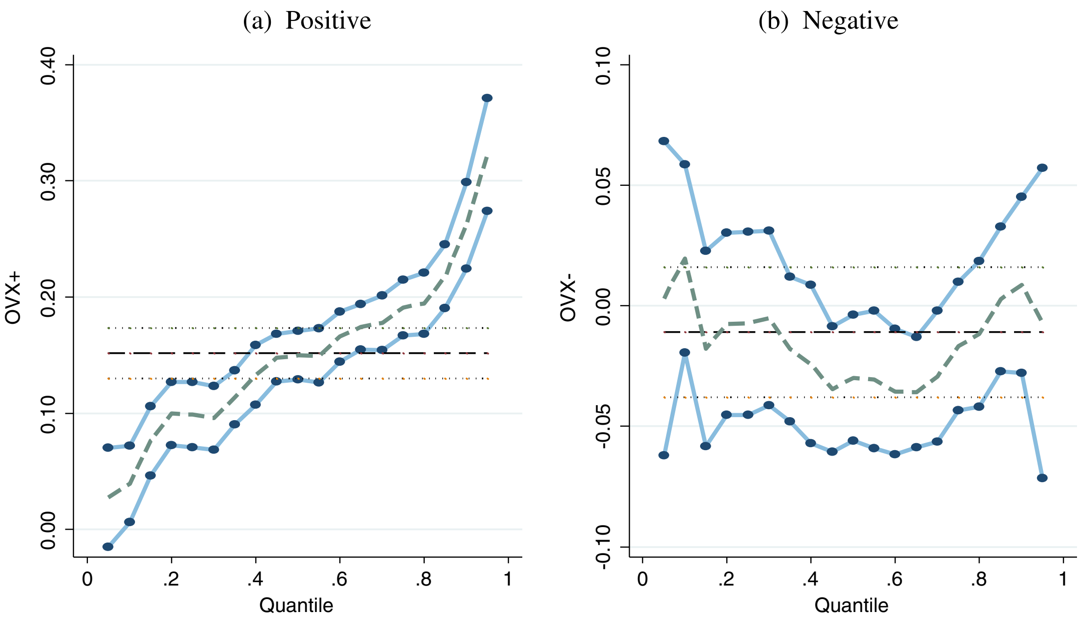

FIGURE 7 Positive and negative OVX coefficient estimates from the quantile regression model specified in Equation (10). The plot depicts the positive and negative impacts of OVX on EMFS across the quantiles. The olive dashed line denotes point estimates, and the two parallel enveloping navy-blue dotted lines signify 95% confidence bands. The horizontal black dashed line estimates the OLS model with black spaced-dotted parallel lines representing 95% confidence bands.

TABLE 9 Quantile slope equality test for the positive and negative OVX changes

ΔOVX_t^+	**0.50–0.95***	**0.25–0.95***	**0.10–0.95***	**0.05–0.95***
	0.50–0.90***	0.25–0.90***	0.10–0.90***	0.05–0.90***
	0.50–0.75**	0.25–0.75***	0.10–0.75***	0.05–0.75***
ΔOVX_t^-	0.50–0.95	0.25–0.95	0.10–0.95	0.05–0.95
	0.50–0.90	0.25–0.90	0.10–0.90	0.05–0.90
	0.50–0.75	0.25–0.75	0.10–0.75	0.05–0.75
BP/CW	282.92***			

Note: The table reports the results for quantile slope equality tests for the positive and negative OVX changes for the models specified in Equations (10).
Abbreviation: P/CW denotes Breusch-Pagan/Cook-Weisberg test for heteroskedasticity.
***Statistical significance at the 1% level.

impacts remain nearly robust even after considering the lagged effects.

5.3 | Asymmetric impacts of OVX on EMFS

Finally, we examine the asymmetric effects of the OVX on EMFS basing upon the models specified in Equations (4) and (10). The estimated results are exhibited in Table 8. The OLS regression result shows that while the coefficient for the positive OVX changes is positive and significant at the 1% level, the negative OVX coefficient remains insignificant statistically. The result suggests that the EMFS is mainly driven by rising oil uncertainties than otherwise. Further, we find that the Wald test rejects the null hypothesis of equality for the positive and negative OVX estimates (see column 9, row 7). It indicates the existence of asymmetry in the average association between OVX and EMFS.

From the perspective of the quantile regression results, we observe that for the positive OVX changes have a significantly positive impact on EMFS across all the quantiles. The extreme lower quantile (0.05) being the only exception. Moreover, the impacts gradually turn stronger in the upper quantiles. This phenomenon can be better understood by referring to Figure 7 (a). In the case of negative OVX changes, the coefficients majorly remain statistically insignificant, with the only exception being the median quantile. Additionally, some higher upper-tail sensitivity can also be observed in the case of negative OVX coefficients. Nevertheless, such upper-tail behaviour is weaker in magnitude in comparison to the positive OVX changes (see Figure 7 (b)). The Wald test coefficients for equality of positive and negative OVX estimates rejects the hypothesis of equality for the quantiles from 0.25 to 0.95. The lower quantiles of 0.05 and 0.10 depict the absence of asymmetric responses of EMFS concerning positive and negative OVX changes. Lastly, the results of the slope equality test reported in Table 9 shows that the null hypothesis of equality is rejected for positive OVX changes across all the reported quantile-combinations. Whereas, we fail to reject the null hypothesis of equality in the case of negative OVX changes. These results satisfy the inferences drawn from Figure 7, which suggests stronger upper-tail behaviour for positive OVX changes.

To summarize, we find asymmetric impacts of positive and negative OVX changes upon EMFS using both OLS and quantile regression frameworks. The impacts are significantly positive for the positive OVX changes meaning that rising OVX would drive up the stress in the financial markets. This finding is somewhat intuitive as the previous studies posit that oil-related uncertainties dampen the future economic activities (Das, Bhatia, et al., 2018; Das, Kumar, et al., 2018; Diaz et al., 2016; Jo, 2014). The market participants may perceive the rising uncertainties concerning oil prices as the forerunner of future fall in economic activities. In anticipation of economic downfall, the market participants may over-react to rising oil uncertainties. Further, the over-reactions tend to intensify when there is existing fragility in the financial system. As we can observe in Figure 7 (a) the magnitude of positive OVX impact is higher in the upper quantiles. Thus, under conditions of high stress, the market participants assign a higher degree of apprehensions regarding the future economic outlook (Zhu et al., 2016). In the case of negative OVX changes signifying lower oil uncertainties, the responses of EMFS is mostly insignificant. You et al. (2017) contend that the growth potentials of the prospering economies may neutralize the adverse effects of oil markets. Such adverse effects may weaken further when the oil uncertainties are low. Moreover, in a state of lower uncertainty coupled up with economic prosperity, the firms tend to trade actively with lower information asymmetries. Therefore, the market participants are optimist about the future business conditions, and the public policy is well-defined (Bloom, 2014). The combination of all these factors may be attributed to the minimization of negative OVX impacts upon EMFS.

6 | ROBUSTNESS RESULTS

In this section we test the robustness of our findings in two different ways. First, instead of considering VIX, we use the financial stress index of the US (USFS) and other advanced economies[13] (OAEFS). Second, we replace the dependent variable EMFS with the CBOE emerging market implied volatility index (VXEEM), to test the impacts of OVX upon equity market volatility in the emerging markets.

6.1 | Do the baseline results remain robust when the VIX is replaced by the financial stress indexes of the US and other advanced economies?

The financial market fragility of the developed world is often a crucial source of stress to the emerging markets (Das et al., 2019). Thus, we replace VIX and consider the USFS and OAEFS individually as another measure of developed market instability. We are specifically interested in verifying whether the impacts of OVX upon EMFS remain similar when the developed market stress indexes are controlled. Thus, we re-estimate Equations (2) and (8) by replacing VIX as the control variable. Table 10 exhibits the result for the impacts of OVX upon EMFS while controlling for USFS. The OLS model reveals that the results are qualitatively similar. Notably, the explanatory power of this model is improved, as suggested by the *R*-squared, in comparison to the baseline results. Another interesting fact is that after controlling for USFS the magnitude of the OVX coefficient is reduced marginally. Notably, the direction of the relationship and statistical significance is consistent. In the case of the quantile regression model, the coefficients of OVX are not significant at the lower quantiles. Nonetheless, the OVX turns significant in the median and higher quantiles. Further, the higher sensitivity in the upper quantiles also holds in this case. The R-squared also increases in tandem with the rising quantiles, implying better explanatory ability of the model when the level of stress is high. Table 11 reports the result considering OAEFS. The OLS model results are coherent with the baseline results. However, it is interesting to note that this model outperforms all previous models in terms of explanatory power designated by the R-squared (43.21%). The quantile regression model results conform to all the characteristics of the relationship, as observed previously. Thus, we conclude that our baseline findings are robust when the developed market stress indexes replace VIX.

6.2 | Does OVX impact the emerging equity market volatility in a similar manner?

As an alternative robustness check, we consider the CBOE emerging equity market implied volatility index (quoted as VXEEM) as another proxy of financial market instability. A plethora of recent studies examine the volatility relationship between oil and equity markets using the implied volatility indexes (see Dutta, 2018; Maghyereh et al., 2016; Xiao, Hu, et al., 2019). We estimate Equations (2) and (8) by replacing the dependent variable by VXEEM. The results are reported in Table 12. The OLS model shows that OVX coefficient is positive and significant at the 1% level, which is consistent with the previous results. Additionally, the explanatory ability of the model is better than all previous models with an R-squared statistic of 64.11%. Besides, the quantile regression model results also illustrate similar results. All the coefficients of OVX is positive and significant at the 1% level with higher magnitude at the upper quantiles. Furthermore, the R-squared values of the quantile regression model improve with higher

TABLE 10 Estimation results for impacts of the OVX changes on the EMFS changes with the U.S. financial stress as control

	0.05	0.10	0.25	0.50	0.75	0.90	0.95	OLS
Constant	−0.0220***	−0.0163***	−0.0081***	0.0001	0.0082***	0.0160***	0.0220***	0.0001
ΔOVX_t	−0.0106	0.0049	0.0137	0.0195**	0.0414***	0.0812***	0.0950***	0.0460***
$\Delta USFS_t$	0.1150***	0.1070***	0.0993***	0.1040***	0.1040***	0.0998***	0.1040***	0.1010***
$\Delta EMFS_{t-1}$	0.0853*	0.1130***	0.1090***	0.1160***	0.1370***	0.1680***	0.1610***	0.1320***
$R^2(\%)$	16.50	16.08	16.33	19.04	22.58	27.21	30.28	36.83
DW Stat.	–	–	–	–	–	–	–	2.3511
VIF	–	–	–	–	–	–	–	1.17

Note: The table reports the results based on Equations (2) and (8), with the U.S. financial stress as a control instead of VIX. R^2 denotes the adjusted and pseudo-R-squared for OLS and quantile regression models, respectively.
Abbreviation: DW stat., Durbin-Watson test statistic; VIF, variance inflation factor.
***Statistical significance at the 1% level.
**Statistical significance at the 5% level.
*Statistical significance at the 10% level.

TABLE 11 Estimation results for impacts of the OVX changes on the EMFS changes with other advanced economy's financial stress as control

	0.05	0.10	0.25	0.50	0.75	0.90	0.95	OLS
Constant	−0.0207***	−0.0148***	−0.0071***	0.0002	0.0074***	0.0153***	0.0205***	0.0001
ΔOVX_t	0.0015	0.0268***	0.0275***	0.0406***	0.0500***	0.0775***	0.1020***	0.0578***
$\Delta OAEFS_t$	0.0997***	0.0890***	0.0933***	0.0965***	0.0962***	0.0955***	0.0896***	0.0933***
$\Delta EMFS_{t-1}$	0.0334	0.0434	0.0460**	0.0282	0.0443*	0.0671**	0.0897**	0.0377**
$R^2(\%)$	17.86	19.51	21.92	23.90	27.37	32.07	34.57	43.21
DW Stat.	–	–	–	–	–	–	–	2.0631
VIF	–	–	–	–	–	–	–	1.12

Note: The table reports the results based on Equations (2) and (8), with other advanced economies' financial stress as a control instead of VIX. R^2 denotes the adjusted and pseudo-R-squared for OLS and quantile regression models, respectively.
Abbreviation: DW, Durbin-Watson test statistic; VIF, variance inflation factor.
***Statistical significance at the 1% level.
**Statistical significance at the 5% level.
*Statistical significance at the 10% level.

TABLE 12 Estimation results for impacts of the OVX changes on the VXEEM changes

	0.05	0.10	0.25	0.50	0.75	0.90	0.95	OLS
Constant	−0.0556***	−0.0418***	−0.0217***	−0.0014	0.0212***	0.0451***	0.0612***	−0.0001
ΔOVX_t	0.1610***	0.1560***	0.1390***	0.1700***	0.2050***	0.2490***	0.3230***	0.2143***
ΔVIX_t	0.5140***	0.5260***	0.5520***	0.5530***	0.5930***	0.6010***	0.6280***	0.5607***
$\Delta VXEEM_{t-1}$	−0.0106	−0.0007	−0.0060	−0.0153	−0.0153	−0.0380	0.0063	−0.0225*
R^2(%)	35.31	35.51	35.91	38.14	41.27	45.01	47.83	64.11
DW Stat.	–	–	–	–	–	–	–	2.2550
VIF	–	–	–	–	–	–	–	1.14

Note: The table reports the results based on Equations (2) and (8), with dependent variable VXEEM instead of EMFS. R^2 denotes the adjusted and pseudo-*R*-squared for OLS and quantile regression models, respectively.
Abbreviation: DW stat., Durbin-Watson test statistic; VIF, variance inflation factor.
***Statistical significance at the 1% level.
*Statistical significance at the 10% level.

quantiles suggesting better explanatory capability at the higher quantiles. Thus, overall, the results are principally similar to the baseline findings. Hence, we find our results are robust even with consideration of alternative variables.

7 | FURTHER ANALYSIS

7.1 | Which global categorical stress indicator drives EMFS the most given oil uncertainties?

Lastly, we further our analysis by investigating which global categorical stress indicator drives EMFS the most. Illing and Liu (2006) suggest that the overall financial stress is sourced from several categories of the financial market system. Thus, it is interesting to identify the category of financial stress that is mostly correlated with EMFS. Further, it is also important to decipher how oil market uncertainty plays a role in driving correlations between EMFS and categorical stress indicators (CSI). The OFR provides five global CSI: (a) credit, (b) equity valuation, (c) safe assets, (d) funding and (e) volatility. The nature of stress indicated by each of the categories is briefly explained in Table 13.

We compute 22-trading-day rolling correlations[14] between EMFS and each of the categorical indicators. The mean of the correlations is exhibited in the form of bar-chart in Figure 8. We observe the highest mean correlation of EMFS with the Credit market stress, followed by Equity Valuation and Volatility stress indicators. Further, the stress related to safe assets is least correlated with EMFS. The higher correlation of EMFS with credit-related stress is somewhat conceivable since most of the emerging markets follow the tightening of monetary policy as a measure to combat inflationary pressures.[15] Since the oil price movements are often considered as the forerunner of inflation (Cologni and Manera, 2008), the primary oil impacts may be realized on the credit markets followed by the equity and other asset markets. In other words, the lack of credit availability is expected to reduce investments and hence the corporate earnings. The expectation of lower future earnings may suppress the intrinsic values of equity, leading to volatile market prices.

Additionally, it is essential to understand how the correlations between EMFS and categorical stress indicators vary given the OVX. We are specifically interested in investigating the expectation of EMFS given the CSI, that is, $E(EMFS_t|CSI_t)$ and in the presence of oil uncertainties. We assume that the oil volatility has a first-order impact on the global CSI, forming second-order impacts on the EMFS -a similar proposition to Illing and Liu (2006). Hence, we examine the impacts of CSI to EMFS using the following regression models, partially adapted from Connolly et al. (2005):

$$\Delta EMFS_t = \alpha + \beta \Delta \mathrm{Credit}_t + \delta(\Delta \mathrm{Credit}_t * \Delta OVX_t) + \rho \mathrm{RC}_t + \gamma \Delta VIX_t + \varepsilon_t \tag{11a}$$

$$\Delta EMFS_t = \alpha + \beta \Delta EV_t + \delta(\Delta EV_t * \Delta OVX_t) + \rho \mathrm{RC}_t + \gamma \Delta VIX_t + \varepsilon_t \tag{11b}$$

$$\Delta EMFS_t = \alpha + \beta \Delta \mathrm{SA}_t + \delta(\Delta SA_t * \Delta OVX_t) + \rho \mathrm{RC}_t + \gamma \Delta VIX_t + \varepsilon_t \tag{11c}$$

TABLE 13 Definitions of categorical stress indicators given by Office of Financial Research

Category	Definition
Credit	"Contains measures of credit spreads, which represent the difference in borrowing costs for firms of different creditworthiness. In times of stress, credit spreads may widen when default risk increases or credit market functioning is disrupted. Wider spreads may indicate that investors are less willing to hold debt, increasing costs for borrowers to get funding."
Equity Valuation	"Contains stock valuations from several stock market indexes, which reflect investor confidence and risk appetite. In times of stress, stock values may fall if investors become less willing to hold risky assets."
Funding	"Contains measures related to how easily financial institutions can fund their activities. In times of stress, funding markets can freeze if participants perceive greater counterparty credit risk or liquidity risk."
Safe Asset	"Contains valuation measures of assets that are considered stores of value or have stable and predictable cash flows. In times of stress, higher valuations of safe assets may indicate that investors are migrating from risky or illiquid assets into safer holdings."
Volatility	"Contains measures of implied and realized volatility from equity, credit, currency, and commodity markets. In times of stress, rising uncertainty about asset values or investor behaviour can lead to higher volatility."

Note: The table defines the categorical stress indicators given by the Office of Financial Research. Available at: https://www.financialresearch.gov/financial-stress-index/.

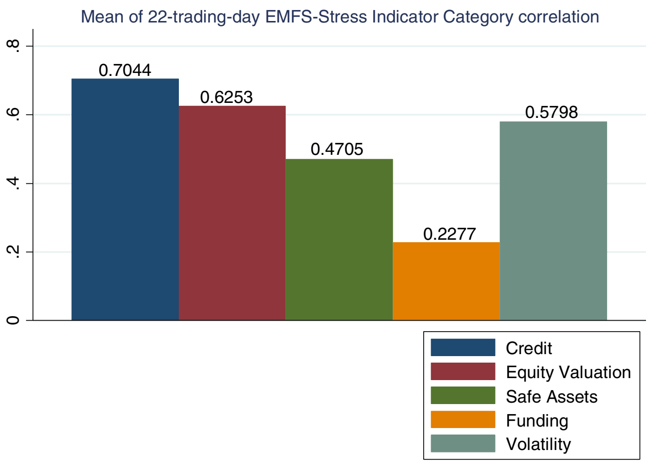

FIGURE 8 Average 22-trading-day correlations between EMFS and global stress indicator categories

$$\Delta EMFS_t = \alpha + \beta \Delta \text{Funding}_t + \delta(\Delta \text{Funding}_t * \Delta OVX_t) + \rho \text{RC}_t + \gamma \Delta VIX_t + \varepsilon_t \tag{11d}$$

$$\Delta EMFS_t = \alpha + \beta \Delta \text{Volatility}_t + \delta(\Delta \text{Volatility}_t * \Delta OVX_t) + \rho \text{RC}_t + \gamma \Delta VIX_t + \varepsilon_t \tag{11e}$$

where EV and SA denote Equity Valuation and Safe Assets stress indicators, respectively. RC_t is the 22-trading-day rolling correlation used to control the past correlation trends between EMFS and respective CSI. The primary coefficient of our interest is δ, which shows how the CSI to EMFS relation varies with OVX. It is essential to note that the EMFS and CSI are endogenous variables in the economy and both are jointly determined. Therefore, our investigation is not intended to imply economic causality rather to verify the co-movement dynamics. Further, it is also worth investigating how the δ coefficients vary over across the different quantiles. Thus, the OLS models specified in Equation (11a)–(11e) are estimated in the quantile regression form as below:

$$q_{\Delta EMFS_t}(\tau|x) = \alpha(\tau) + \beta(\tau)\Delta \text{Credit}_t + \delta(\tau)(\Delta \text{Credit}_t * \Delta OVX_t) + \rho(\tau)\text{RC}_t + \gamma(\tau)\Delta VIX_t + \varepsilon_t \tag{12a}$$

$$q_{\Delta EMFS_t}(\tau|x) = \alpha(\tau) + \beta(\tau)\Delta EV_t + \delta(\tau)(\Delta EV_t * \Delta OVX_t) + \rho(\tau)\text{RC}_t + \gamma(\tau)\Delta VIX_t + \varepsilon_t \tag{12b}$$

$$q_{\Delta EMFS_t}(\tau|x) = \alpha(\tau) + \beta(\tau)\Delta SA_t + \delta(\tau)(\Delta SA_t * \Delta OVX_t) + \rho(\tau)\text{RC}_t + \gamma(\tau)\Delta VIX_t + \varepsilon_t \tag{12c}$$

$$q_{\Delta \text{EMFS}_t}(\tau|\text{x}) = \alpha(\tau) + \beta(\tau)\Delta \text{Funding}_t + \delta(\tau)(\Delta \text{Funding}_t * \Delta \text{OVX}_t) + \rho(\tau)\text{RC}_t + \gamma(\tau)\Delta \text{VIX}_t + \varepsilon_t \tag{12d}$$

$$q_{\Delta \text{EMFS}_t}(\tau|\text{x}) = \alpha(\tau) + \beta(\tau)\Delta \text{Volatility}_t + \delta(\tau)(\Delta \text{Volatility}_t * \Delta \text{OVX}_t) + \rho(\tau)\text{RC}_t + \gamma(\tau)\Delta \text{VIX}_t + \varepsilon_t \tag{12e}$$

TABLE 14 Estimation results for impacts of the CSI with OVX changes on the EMFS changes

	0.05	0.10	0.25	0.50	0.75	0.90	0.95	OLS
Panel A: Credit								
Constant	−0.0172***	−0.0141***	−0.0087***	−0.0020**	0.0040***	0.0083***	0.0105***	−0.0028**
$\Delta Credit_t$	0.4540***	0.4970***	0.5010***	0.5060***	0.4940***	0.4700***	0.4780***	0.4170***
$\Delta Credit_t * \Delta OVX_t$	−0.3790	−0.3030	0.2110	0.940***	1.353***	1.500***	2.713***	1.1250***
ρRC_t	−0.0007	0.0028	0.0038**	0.0030**	0.0027*	0.0054***	0.0076**	0.0035**
ΔVIX_t	0.0400***	0.0358***	0.0264***	0.0224***	0.0245***	0.0291***	0.0313***	0.0358***
$R^2(\%)$	25.99	28.85	32.02	35.53	38.03	40.42	40.79	50.63
DW Stat.	–	–	–	–	–	–	–	1.9842
VIF	–	–	–	–	–	–	–	1.13
Panel B: Equity valuation								
Constant	−0.0217***	−0.0159***	−0.0075***	−0.0010	0.0058***	0.0133***	0.0170***	−0.0013
Δ Equity Valuation$_t$	0.2440***	0.2400***	0.2480***	0.2440***	0.2480***	0.2650***	0.2390***	0.2490***
Δ Equity Valuation$_t$ $*\Delta OVX_t$	−0.5770	−0.2430	0.2570**	0.5620***	0.6610***	1.1470***	1.2250***	0.4420***
ρRC_t	0.0029	0.0021	0.0006	0.0011	0.0014	0.0005	0.0029	0.0014
ΔVIX_t	0.0071	−0.0038	−0.0145***	−0.0113**	−0.0057	−0.0120	−0.0018	−0.0080
$R^2(\%)$	19.60	20.72	23.30	25.70	28.75	32.44	34.60	43.63
DW Stat.	–	–	–	–	–	–	–	2.0345
VIF	–	–	–	–	–	–	–	1.37
Panel C: Safe assets								
Constant	−0.0222***	−0.0170***	−0.0094***	−0.0018*	0.0069***	0.0156***	0.0227***	−0.0008
ΔSafe Assets$_t$	0.2590***	0.2630***	0.2960***	0.3060***	0.2730***	0.2840***	0.2820***	0.2870***
ΔSafe Assets$_t$ $*\Delta OVX_t$	−0.3810	−0.2660	0.9660	1.4870***	1.7830***	1.9530***	1.6160**	1.0300***
ρRC_t	−0.0017	0.0021	0.0022	0.0021	0.0011	0.0005	0.0022	0.0010
ΔVIX_t	0.0746***	0.0639***	0.0417***	0.0421***	0.0564***	0.0597***	0.0819***	0.0591***
$R^2(\%)$	12.54	12.63	14.98	15.97	18.36	19.39	20.61	28.50
DW Stat.	–	–	–	–	–	–	–	1.8292
VIF	–	–	–	–	–	–	–	1.11
Panel D: Funding								
Constant	−0.0240***	−0.0175***	−0.0090***	−0.0007*	0.0080***	0.0186***	0.0253***	−0.0001
$\Delta Funding_t$	0.1530***	0.1140***	0.1410***	0.1360***	0.1270***	0.1500***	0.1790***	0.1460***
$\Delta Funding_t * \Delta OVX_t$	0.3650	0.5560	0.5840**	0.5790**	1.1000***	1.4120**	2.2550***	0.7820***
ρRC_t	−0.0011	−0.0006	−0.0003	0.0009	0.0011	−0.0031	−0.0034	−0.0007
ΔVIX_t	0.0955***	0.0881***	0.0685***	0.0659***	0.0721***	0.0959***	0.0856***	0.0812***
$R^2(\%)$	10.05	9.45	9.23	10.86	12.73	16.20	19.21	22.47
DW Stat.	–	–	–	–	–	–	–	1.9397
VIF	–	–	–	–	–	–	–	1.05
Panel E: Volatility								
Constant	−0.0166***	−0.0119***	−0.0075***	−0.0017*	0.0049***	0.0109***	0.0141***	−0.0008
$\Delta Volatility_t$	0.1140***	0.1050***	0.0988***	0.1020***	0.0985***	0.1030***	0.1040***	0.1040***
$\Delta Volatility_t * \Delta OVX_t$	−0.0526	−0.0548	0.0210	0.2260**	0.4630***	0.5170***	0.5640***	0.1420***
ρRC_t	−0.0084*	−0.0068**	−0.0008	0.0023	0.0036**	0.0061***	0.0083**	0.0007

TABLE 14 (Continued)

	0.05	0.10	0.25	0.50	0.75	0.90	0.95	OLS
ΔVIX_t	−0.0207	−0.0178*	−0.0235***	−0.0268***	−0.0272***	−0.0324***	−0.0221	−0.0308***
R^2(%)	20.05	19.23	18.82	20.93	25.97	32.59	36.38	41.71
DW Stat.	–	–	–	–	–	–	–	1.9675
VIF	–	–	–	–	–	–	–	1.67

Note: The table reports the results based on Equations (11a)–(11e) and (12a)–(12e) for OLS and quantile regression, respectively. R^2 denotes the adjusted and pseudo-*R*-squared for OLS and quantile regression models, respectively.

Abbreviations: DW stat., Durbin-Watson test statistic; VIF, variance inflation factor.

***Statistical significance at the 1% level.

**Statistical significance at the 5% level.

*Statistical significance at the 10% level.

Table 14 reports the results for Equation (11a)–(11e) (for OLS) and Equation (12a)–(12e) (for quantile regression). The OLS results show that all the CSI are positive and significant at the 1% level. Interestingly, when the CSI is interacted with OVX, the magnitude of the coefficients (δ) exceeds the standalone CSI coefficients (β). It implies that the joint impact of OVX and CSI is more influential than the individual CSI. In other words, the co-movement between EMFS and CSI is stronger in the presence of oil market uncertainties. Moreover, all the δ coefficients are significant at the 1% level. The highest magnitude of δ is observed for credit market stress, followed by equity valuation and volatility indicators. This result is consistent with the mean correlation values exhibited in Figure 8. The *R*-squared coefficients also show that the model incorporating Credit stress has the maximum explanatory power. Thus, the results confirm that EMFS is majorly driven by Credit market stress, followed by equity and other asset volatility channels. The results of the quantile regression model are fairly consistent with the OLS model. Nevertheless, it complements to the dynamics of the relationship by indicating that mostly the δ coefficients are significant at the upper quantiles. In addition, the magnitude of the coefficients is relatively higher at the upper quantiles and are the R-squared values. It suggests that the EMFS is better predicted when the stress levels are high. The phenomenon of upper-tail sensitivity is consistent with our all previous findings.

8 | CONCLUSION

The crucial role of oil in predicting financial stress is well-conceived in past literature; however, the empirical validation of the relationship is scarce. In this study, we add to the existing literature by examining the relationship between financial stress and oil price uncertainty (OVX). Moreover, we also focus on the case of emerging markets given their higher oil-dependence, which is limited in the existing literature. Thus, we examine the relational dynamics between OVX and EMFS by resorting to a quantile regression framework. Further, we also test for the existence of gradual information diffusion hypothesis by exploring the lagged association between OVX and EMFS. Lastly, we also investigate the asymmetric responses of EMFS concerning high or low OVX changes.

The empirical findings are presented in four segments. The first segment shows some preliminary results. We primarily observe that OVX annexes additional information as compared to oil returns and realized volatilities. Thus, OVX is a better predictor of EMFS as compared to other traditional measures of oil price movements. Further, we also test for the Granger causalities and find that the causalities mainly run from OVX to EMFS and not the other way around. The second segment presents the main results. The results show that the impact of OVX upon EMFS is positively significant across quantiles. Additionally, such impacts become stronger in the upper quantiles. These results are consistent and robust even after considering VIX as a control. It implies that the financial sector as a whole is more sensitive to oil market volatilities when the current stress levels are high. Next, we test the lagged relationship between OVX and EMFS to validate the presence (or absence) of the gradual information diffusion hypothesis. We find that the impacts of OVX at the lower quantiles (0.05–0.25) is significant mainly at the lag 1. The coefficients become weaker or statistically insignificant in the subsequent lags. However, the lagged coefficients at the lag 1 are stronger than the contemporaneous coefficients (lag 0). It essentially means that when the market stress is low, the impacts of the OVX is realized with a lag. In the case of intermediate to higher quantiles (0.50–0.95) the contemporaneous coefficients are stronger than lagged coefficients. Such a finding signifies that when the stress levels are on the higher end, the financial markets quickly assimilate the oil-related information. Furthermore, the lagged coefficients tend to become weaker or insignificant with increasing lag sizes. Therefore, the results do not strongly conform to the gradual information diffusion hypothesis as the relationship is transient. The results for the asymmetric impacts confirm that only positive impulse in the OVX drives the EMFS. The negative OVX changes mostly stand insignificant, statistically implying limited predictive abilities.

In the third segment, we test the robustness of our main empirical findings. As a measure of testing robustness, we first substitute the baseline control variable VIX with the developed market stress indicators, that is, USFS and OAEFS individually. The results of these two models incorporating USFS and OAEFS separately confirm that the baseline results are robust. The key findings remain qualitatively similar. In the second part, we substitute the dependent variable EMFS with an alternative measure of emerging market stress, that is, CBOE VXEEM. Again, in this case the results are similar indicating that the principal findings are robust. In the fourth segment, we investigate which of the CSI impacts the EMFS the most both individually as well as when interacted with the OVX. The results confirm that all the CSI standalone and with OVX interaction is mostly positive and significant at the 1% level. Nevertheless, in terms of the magnitude of such impacts, credit market stress appears to be the crucial driver of EMFS, followed by the measures of equity valuation and volatility stress.

We believe that these results have certain relevant implications for the market participants to take informed managerial decisions. From the perspective of the investors, they can leverage the information content in OVX rather than realized oil prices or volatilities to anticipate the upcoming instabilities in the financial markets. Thus, from the risk management perspective, they can shift their investments from the assets with higher oil exposure to the relatively safer assets. Moreover, as we find that when the stress levels are low, the oil-related information is absorbed in the market with a lag. Whereas, when the stress levels are high, the markets are more reactive initially; however, such impacts fade away subsequently. Thus, the investors in tradable assets such as equities should not fall in the trap of panic-selling as the OVX impacts appear transient. The policymakers, on the other hand, have a crucial role to play by regulating the credit markets to minimize the adverse impacts of oil price uncertainties. The greater institutional regulations might prevent the firms from the problems of credit inadequacies. Thus, the firms may allocate its resources to produce the output matching the current demands in the market in the most efficient manner. Therefore, the respective administrative authorities of the emerging markets should adopt policy measures for stabilization of oil-related fears. This will ensure smoother functioning of the financial sector. As a future course of study, the scholars may attempt to examine how the OVX impacts the financial stress across the oil-importing and exporting emerging markets. It would further enhance our understanding of the role of oil uncertainties to predict financial stress across the two heterogeneous sub-groups within the universe of emerging markets.

ENDNOTES

[1] The instability of future earnings is a source of concern to the lenders since it is difficult to ascertain the true quality of the borrowers. Such asymmetries of information could drive the borrowing costs as the lender's risk premium component, further dampening economic activities.

[2] Wan and Kao (2015) argue that on account of financialization of commodities, the prices of oil may be influenced beyond the fundamental supply–demand structure. Rather, changes in the financial market conditions may also play a crucial role in determination of oil prices. An emerging stream of literature focusses upon the co-movement of equity and commodity markets with focus on oil to empirically validate the notion of financialization (see Bianchi et al., 2020; Buyuksahin and Harris, 2011; Büyükşahin and Robe, 2014; Kilian and Murphy, 2014). The findings of majority of these studies support the presence of speculative motive of investors in commodity markets during the financial crisis.

[3] The specification of our regression models is closely follow Xiao, Hu, et al. (2019). Further, at the recommendation of the reviewer we have also reported some alternative models reported in Table A1 of the online appendix. The results remain robust and qualitatively similar.

[4] At the recommendation of the anonymous reviewer, we have also looked that "how important is OVX in influencing EMFS over VIX?". Using the encompassing test suggested by Chong and Hendry (1986) we find that OVX appears to be a better predictor for EMFS when compared to VIX. The full results are available in Table A2 of the online appendix.

[5] The series of all implied volatility indexes used in this study is sourced from FRED Economic Data, St. Louis Fed.

[6] The further details regarding the definition and construction procedure of these stress indications, the readers may refer the website of the OFR, available here: https://www.financialresearch.gov/financial-stress-index/.

[7] Nazlioglu et al. (2015) use Cleveland Financial Stress Index (CFSI) to proxy for financial stress this index was available at daily frequency, however, the index was discontinued in May, 2016.

[8] The data for EMFS and OVX are available from January 3, 2000 and May 10, 2007, respectively. However, in Section 6 we also use the CBOE emerging markets volatility index (VXEEM) as an alternative measure of financial stress to test the robustness of our baseline findings. The data for VXEEM are published since March 16, 2011. Therefore, we start the sample for our study onset this date to maintain consistency and comparability of the empirical results.

[9] We follow the data transformation approach similar to Reboredo and Uddin (2016) for empirical analysis.

[10] We also present a scatterplot between EMFS and OVX in the online appendix at the recommendation of the anonymous reviewer. This graph aids to comprehend the relationship visually. It can be inferred that outliers tend to increase under the condition of higher EMFS and OVX, which is expected as the markets become jittery under conditions of high financial stress and oil market volatility. Additionally, the linear prediction in the graph indicates a prima facie positive relationship between these variables.

[11] The data are obtained from the website of the U.S. Energy Information Administration (EIA). The price data are converted into returns using the first logged differences. The descriptive statistics and unit root test results of all the additional variables used in preliminary, robustness and additional tests are available upon request.

[12] We do not provide the detailed methodological expression for the spectral Granger causality test for brevity. The interested readers may refer to Breitung and Candelon (2006) for a detailed discussion on methodology.

[13] The other advanced economies mainly include Japan and the Eurozone.

[14] We use a similar methodological approach to Connolly et al. (2005).

[15] David Petitcolin, "Credit potentials gives emerging markets the edge", Euromoney, December 17, 2012, accessed October 10, 2020 22:26 hours. Available at: https://www.euromoney.com/article/b12kjfvlqwt37m/credit-potential-gives-emerging-markets-the-edge.

DATA AVAILABILITY STATEMENT

Data available on request from the authors

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