Commodity and Stock Markets: Dynamic Volatility Spillovers

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ABSTRACT

This paper presents new evidence on the relationship between implied stock and commodity volatility indices, using a systemic approach.

Our results suggest that about 40% of the total variance of the forecast errors is explained by shocks in emerging stock markets, developed stock markets, oil and gold markets during the period from 15 August 2011 - 30 June 2020.

We also found a significant time-varying dependence volatility, with an increase of volatility connectedness during periods of high instability.

KEYWORDS

Implied volatility indices, Dynamic spillovers, Connectedness

1. Introduction

Over the last decades, commodities became an important asset for financial investors. Since the beginning of this century, large inflows of investment capital into commodity markets have raised the issue of their effects on commodity price levels and their volatility. During the same period, trade and financial liberalization have led to an increase in the degree of integration of global stock markets.

Although the increasing degree of market integration, with potential effects on the similarity of price trajectories and market volatilities, the level of returns and risks in each market still seems to be different.

The dynamics of commodity and equity market integration and the effects of spillovers have been an intensive field of study in recent years. Using a wide variety of approaches, many studies have been carried out on the relationships between oil markets and stock markets. Most of this studies present a negative relationship between oil shocks and developed stock markets (e.g., El-Sharif et al., 2005; Abhyankar et al., 2013; Kang et al., 2016), Kilian and Park (2009) show that impact of oil shocks differs significantly on whether they are demand or supply shocks.

The negative relationship between emerging stock markets and oil market is found in Fang and You (2014) and Ghosh and Kanjilal (2016), among others, while Filis and Chatziantoniou (2014) present significant impact differences between oil exporters and importers.

A large body of recent literature has focused on the volatility spillover between oil and financial markets and shows significant time-varying impacts of oil price shocks (see, Arouri et al. (2011); Guesmi and Fattoum (2014); Khalfaoui et al. (2015); Delcoure and Singh (2018); Hammoudeh et al. (2013);Kumar et al. (2012); Sadorsky (2012)).

On the other hand, volatility transmissions between precious metals and stock markets have received less attention and the results are mixed. Maghyereh et al. (2017) on the equity markets of the Gulf Cooperation Council region found an insignificant spillover from gold markets to equity markets, although Pandey and Vipul (2018) recently showed significant volatility spillovers from gold markets to BRICS equity markets.

This study analyses the implied volatility across emerging stock markets, developed stock markets, oil and gold markets using a connectedness measure to measure the dependencies and spillovers effects.

The remaining of the paper is organized as follows: section 2 provides the methodology used; section 3 describes the data; section 4 depicts the main results; finally, section 5 present the main conclusions.

2. Methodology

The empirical analysis follows the dynamic spillover framework developed by Diebold and Yilmaz (2009, 2012) which introduce a measure of connectedness to account for interdependence in financial markets.

The methodology is based on vector autoregressive process (VAR) and the use of forecast error variance decomposition (FEVD) to estimate the connectedness.

Consider a N variable VAR(p) model in the form

$$\boldsymbol{y}_t = \sum_{i=1}^{p} \Phi_i y_{t-i} + \boldsymbol{\varepsilon}_t \quad (1)$$

The moving average representation of VAR(p) is

$$\boldsymbol{y}_t = \sum_{i=0}^{\infty} A_i \boldsymbol{\varepsilon}_{t-i} \tag{2}$$

The H-step-ahed forecast error variance decomposition $\theta_{ij,H}$

$$\theta_{ij,H} = \frac{\sigma_{ii}^{-1} \sum_{h=0}^{H-1} \left(e_i' A_h \Sigma\, e_j\right)^2}{\sum_{h=0}^{H-1} \left(e_i' A_h \Sigma A_h' e_i\right)} \tag{3}$$

Where e_i is a vector equals to one as i-th element and zeros otherwise, σ_{ii} is the standart deviation of the forecast error term, and Σ is the variance matrix for the error vector ε.

In order to bounded the spillover index between zero and one, Diebold and Yilmaz (2012) standartize the variance decomposition by

$$\tilde{\theta}_{ij,H} = \frac{\theta_{ij,H}}{\sum_{j=1}^{N} \theta_{ij,H}} \tag{4}$$

The connectedness measure is then given by:

$$C^H = \frac{1}{N} \sum_{\substack{i,j=1 \\ i \neq j}} \tilde{\theta}_{ij,H} \tag{5}$$

To show the influence of one variable into the system connectedness, or the volatility spillover from the variable i to all other variables j, we have

$$C_{i\rightarrow \cdot}^H = \frac{\sum_{\substack{i,j=1 \\ i \neq j}} \tilde{\theta}_{ji,H}}{\sum_{j=1} \tilde{\theta}_{ji,H}} \sum_{i=1}^{K} \theta_{ij}^H \quad ,\mathrm{j} \neq \mathrm{i} \tag{6}$$

The directional spillover received by market i from all other markets j

$$C_{i\leftarrow \cdot}^H = \sum_{j=1}^{K} \theta_{ij}^H \quad ,\mathrm{j} \neq \mathrm{i} \tag{7}$$

The net directional connectedness (NDC) is the difference between the shocks transmitted to all other markets and received from all other markets:

$$C_i^H = C_{i\rightarrow \cdot}^H - C_{i\leftarrow \cdot}^H \tag{8}$$

3. Data Description and Preliminary Analysis

We use daily frequency data on four volatility indices from August 15 2011 to June 30 2020, collected from the Thomson Reuters DataStream.

The implied volatility indices used are the volatility of the oil price (OVX), the volatility of the gold price (GVZ), the emerging markets' implied equity volatility index (VXEEM), which measures volatility in emerging markets and the developed equity market volatility index (VXEFA). All series are calculated by the Chicago Board Options Exchange (CBOE).

The CBOE Crude Oil ETF Volatility Index (OVX) a measure of the market's expectation of 30-day volatility of crude oil prices United States Oil Fund (USO) and the USO is a commodity Exchange Traded Fund (ETF) that replicate the returns of the WTI price using futures contracts.

The CBOE Gold exchange-traded fund (ETF) Volatility Index (GVZ), the measure of market's expectation of 30-day volatility of gold prices, which based on the bid and ask prices of the SPDR Gold Shares.

VXEFA for developed equity markets excluding the United States is computed from options traded on the underlying iShares MSCI EAFE ETF and provides exposure to 24 developed markets. The Emerging Market Volatility (VXEEM) is calculated from options traded on the iShares MSCI EMs ETF and provides exposure to 26 Emerging Markets.

All data are expressed in first-differenced natural logs.

Table 1 presents the descriptive statistics on the four implied volatility indices and table 2 reports a simple correlation matrix between these variables.

Table 1. Descriptive statistics

	N	mean	sd	skewness	kurtosis	min	max
gvz	2049	16.71	5.450	1.400	5.860	8.880	48.98
ovx	2049	36.10	21.50	5.060	41.85	14.50	325.1
vxeem	2049	23.29	8.140	2.600	13.90	13.28	92.46
vxefa	2049	18.39	8.440	2.210	9.600	7.770	75.17

Table 2. Correlation matrix

	gvz	ovx	vxeem	vxefa
gvz	1			
ovx	0.395***	1		
vxeem	0.728***	0.568***	1	
vxefa	0.747***	0.538***	0.911***	1

Among all volatility indices, the ovx has the highest mean and the highest standard deviation, while the gvz has the lowest mean and also the lowest standard deviation.

The correlation matrix shows that during the sample period the volatility of equity markets shows a high level of interconnection and that the lowest correlation is between oil volatility and gold volatility.

4. Empirical Results

4.1 - Static Volatility Connectedness Analysis

Table 3 reports the full-sample connectedness results of a ten-period ahead forecasting horizon for variance decomposition based on six implied volatility series VAR. Bayesian Information Criteria (BIC) are used to choose lag length. All results are based on vector autoregressions of order 2 and generalized variance decompositions of 10-day ahead volatility forecast errors.

Table 3. Volatility spillover for full sample

	gvz	ovx	vxeem	vxefa	From others	NDC
gvz	65,23	6,51	15,47	12,80	34,77	-6,84
ovx	5,40	71,55	14,45	8,60	28,45	-1,79
vxeem	12,12	11,27	50,87	25,74	49,13	10,44
vxefa	10,41	8,88	29,65	51,05	48,95	-1,81
To others	27,93	26,66	59,57	47,14		

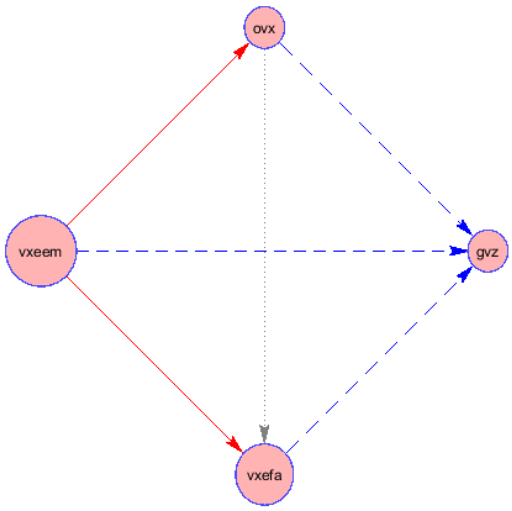
Note: From others - directional spillover indices measure spillovers from all indexes j to index i; Contribution to others - directional spillover indices measure spillovers from index i to all indexes j; NDC refers to net directional connectedness, which reports the difference between To and From for each variable. The total connectedness is 40.32 p.c..

The amount of spillover effects in this four variable VAR system, measure by the total connectedness of volatilities is around 40%.

The oil and gold (commodities) respond more to shocks received from the system than their shocks contribute to. The oil volatility contributes only 26,66% to the total variation in the system and the system contributes 28,45% to the oil volatility. The same pattern of negative net connectedness relative to the system can be observed for the gold.

The Emerging and Developed Stock Markets volatilities present higher explanatory (impact) power to Commodities shocks face to what commodities shocks con explain them.

Fig. 1: Figure presents the pairwise net directional connectedness.



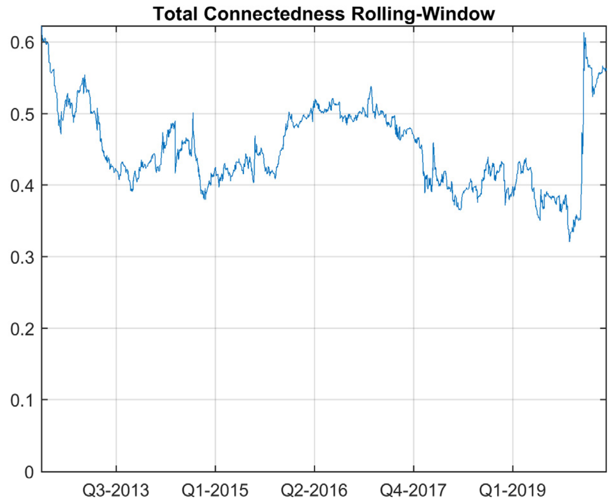
The figure 1 shows how the system is connected variable to variable. An arrow from variable i to variable j correspond to a net directional connectedness between the indices. Solid line arrows connect system members with the highest total net directional connectedness whereas dash and dot line arrows connect the lowest total net directional connectedness.

The commodities markets are net receivers of shocks from each others and mainly from stock markets. Stock markets contribute more than they receive from all others markets. This result can be seen as an evidence of a high level of impact of equity markets on commodity markets.

4.2 - Dynamic Volatility Connectedness Analysis

Fig. 2 plots the total volatility spillover index using a rolling-window of 250-days and a 10-days horizon.

Fig. 2: Total spillover: Spillovers from volatility over the sampling period spanning from September 2012 to June 2020.



The rolling window estimates show how much the degree of volatility spillover vary over time. The fluctuations in the spillover index estimates suggest the time-varying behavior of volatility spillovers. During the sub-period spillovers from volatility are on average 45%, but the connectedness in the system changed over time, ranging from a high of 61% (March 2020) to a low of 32,0% (December 2019).

The results also show a decrease for the connectedness until end of 2004 followed by a positive trend to the mid of 2017. The connectedness reduces to their minimum at the end of 2019 and increases significantly during pandemic crisis of 2020.

The significant increase of total connectedness level around March 2020 and their high level until the end of sample reflects a significant increase of contribution of all variables to the system with particular impact of oil and emerging markets that shows a high persistence.

Figures 3 to 6 show the contribution of each variable and the system's contribution to each variable.

Fig. 3: Rolling-windows of GVZ, From/To/Net Spillovers

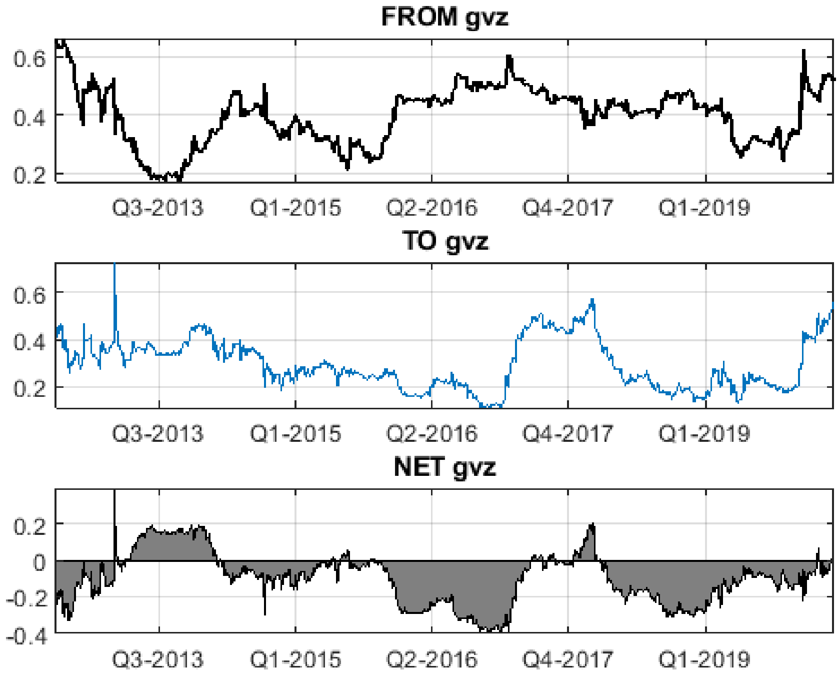


Fig. 4: Rolling-windows of OVX, From/To/Net Spillovers

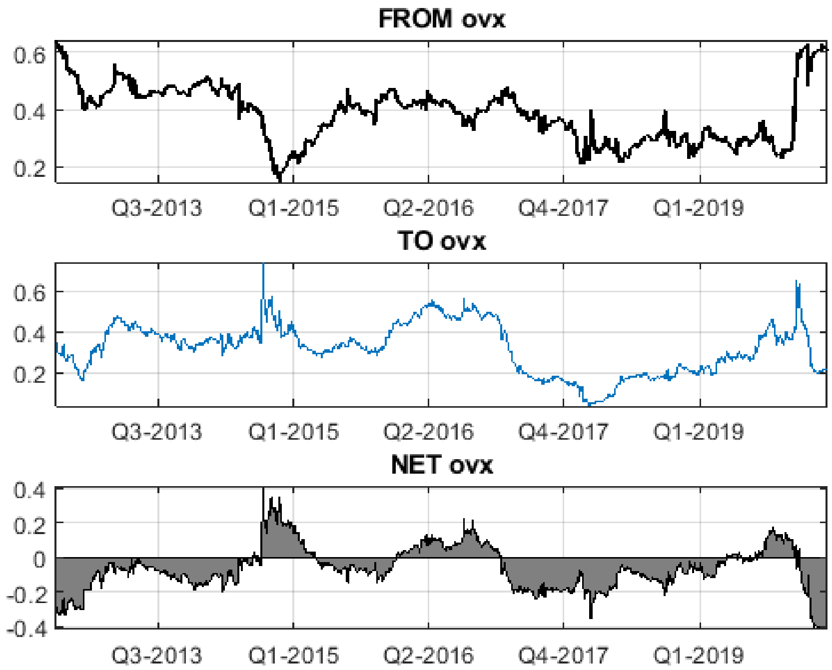


Fig. 5: Rolling-windows of VXEFA, From/To/Net Spillovers

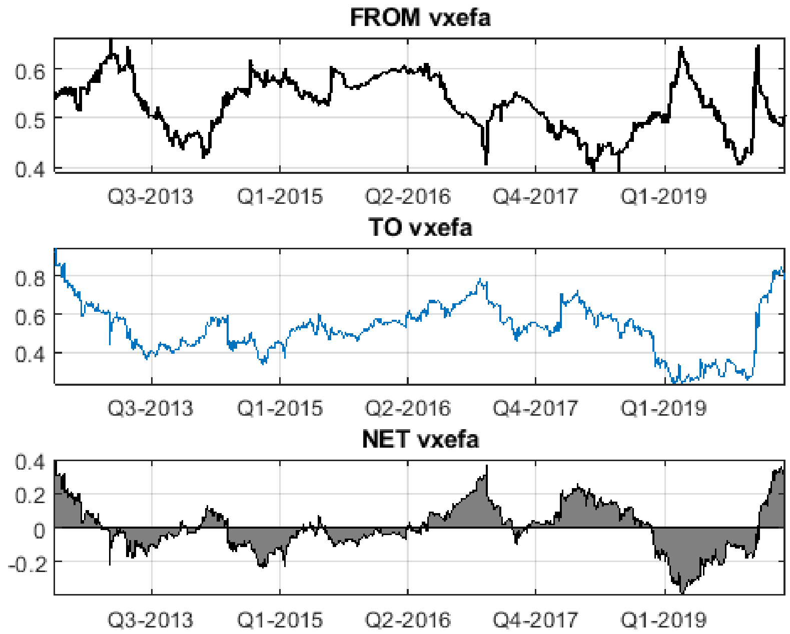
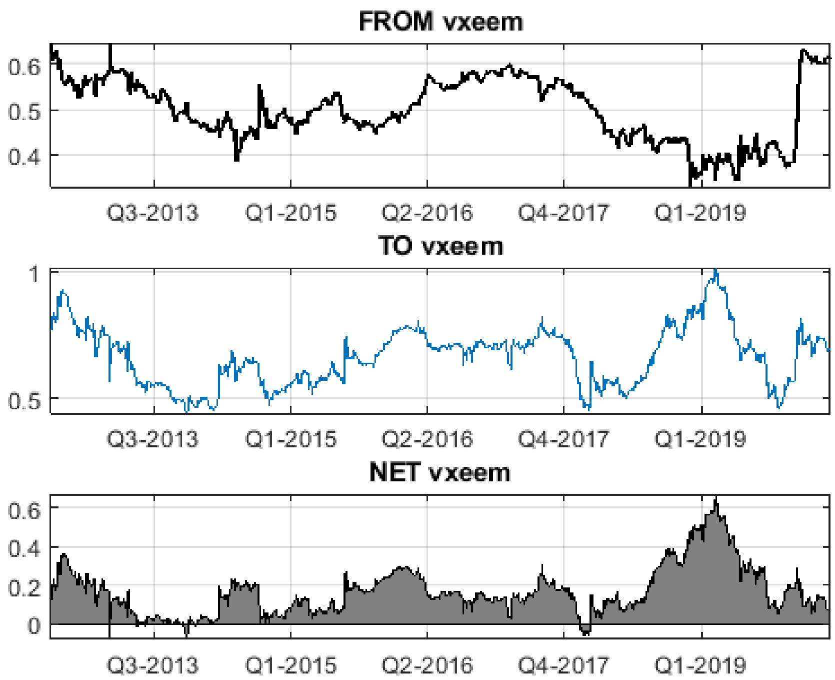


Fig. 6: Rolling-windows of VXEEM, From/To/Net Spillovers



5. Conclusions

In this paper, we perform the analysis the interaction of equity and two main commodities, the gold and oil. Using the connectedness index based on a VAR approach, we measure how each of elements of a system is affected by the system's dynamics and to contribute to the system.

Our results show a significant connectedness among the four implied volatility indices around 40% over the full period analysed. The volatility connected presents significant variation over time with particular surge in periods of great instability. Finally, our results suggest that the contribution of emerging market volatility shocks to commodity market volatility and developed equity market volatility is greater than the reverse.

The evidence presented in the paper about the volatility transmission are useful to portfolio managing as well as among other to policy-makers.

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