Energy and non–energy commodities: Spillover effects on African stock markets

A. Amendola* M. Boccia† V. Candila‡ G. M. Gallo§

July 14, 2020

Abstract

This paper examines the volatility transmission from energy and metal commodities to six major African exporters' stock markets (Egypt for oil and gold, Nigeria for oil and gas, South Africa for coal and gold, Tunisia for oil, Uganda for gold and Zambia for copper). Modelling commodity volatility with the Double Asymmetric GARCH-MIDAS model with a Student's t-distribution allows to detect the presence of impact and inertial stock market volatility spillovers at different lags and to take into account the leptokurtosis of the commodity series. We then derive the profile of Volatility Impulse Responses of the stock markets to commodity shocks.

Keywords: Volatility spillover, GARCH-MIDAS, African countries, Commodities.

*Dept. of Economics and Statistics, University of Salerno, Italy, alamendola@unisa.it

†Dept. of Economics and Statistics, University of Salerno, Italy, mboccia@unisa.it

‡MEMOTEF Department, Sapienza University of Rome, Italy, vincenzo.candila@uniroma1.it

§Italian Court of Audits (Corte dei conti), and NYU in Florence, Italy, giampiero.gallo@nyu.edu

1 Introduction

Investigating interdependencies across asset classes allows to exploit the benefits of portfolio diversification: in the case of commodity prices and stock markets we have an additional interest also because several economies are dependent on commodity trading, and movements in commodity prices are an important cost component of manufactured goods through energy and raw materials (Silvennoinen and Thorp [1]). Several contributions focus on the interconnections of advanced economies between commodities (for instance, Karanasos et al. [2], Nazlioglu et al. [3]), stock markets (Hou and Li [4], Berg and Vu [5]), currencies (Greenwood-Nimmo et al. [6]) and all their possible interactions (Ildırar and Iscan [7] and Kang et al. [8], among others). More recent is the interest about the volatility spillovers among the stock markets of emerging countries and/or among these latter and developed countries. For instance, Engle et al. [9] analyze volatility spillovers in East Asia surrounding the 1997 crisis, Korkmaz et al. [10] the return and volatility spillovers among six emerging countries (Colombia, Indonesia, Vietnam, Egypt, Turkey, and South Africa). Kim et al. [11] and Neaime [12] investigate the impact of the 2007 financial crisis on five emerging Asian economies and on the Middle East and North Africa stock markets, respectively. However, to the best of our knowledge, the issue of how strong reliance of African emerging economies on commodity exports, whose price volatility may influence these stock markets, has not received adequate attention.

In this paper we examine the volatility spillovers between four energy and metal commodities (Oil, Gas, Gold and Copper) chosen among the top exporting goods of six African countries (Egypt, Nigeria, South Africa, Tunisia, Uganda, Zambia) and the stock markets of these countries. In particular, Egypt, Nigeria and Tunisia mainly export Oil, South Africa has a relevant share of Gas exports, Uganda primarily Gold and Zambia mostly exports Copper.

From an economic viewpoint, our interest is also motivated by the consequences produced on these countries by the increasing trend in commodity prices registered at the beginning of 2000s: a contribution to the development of these export-based economies and a larger foreign investor inflow towards these stock markets (Adjasi and Yartey [13]). According to the statistics reported in the most recent yearbook (Economic Commission for Africa et al. [14]), the African countries here considered in 2018 represent almost one half of the overall African GDP. By the same token, the exchanges considered represent approximately 93% of the total African market capitalization (in 2017) even if they are of limited importance at the world level. In fact, they have no feedback on the global markets fixing the price of these commodities, so it is natural to focus on the unilateral spillovers from a commodity market volatility to a stock exchange. At the same time, there is little, if any, interdependence across markets, so we will not examine spillovers from one country to another.

The literature on volatility spillovers is sizeable and dates back to the early works of Hamao et al. [15], Engle et al. [16], and Lin et al. [17] in an effort to extend the univariate GARCH (Bollerslev [18]) model. So far, different approaches to estimating volatility spillovers have been proposed. For instance, Diebold and Yilmaz [19, 20] consider forecast-error variance decomposition within a vector autoregression as a tool through which a spillover index can be calculated. Another approach falls within the multivariate generalized autoregressive conditional heteroskedasticity [MGARCH] (Bauwens et al. [21]) model. Typically a BEKK (Engle and Kroner [22]) specification is used to estimate the conditional covariance matrices of the involved markets. Subsequently, the volatility impulse response function [VIRF] methodology proposed by Hafner and Herwartz [23] is employed. The VIRF investigates the impact (in terms of size and persistence) of shocks originating in the source of volatility spillover and hitting the (expected) conditional volatility of the recipient. Recently, the MGARCH-VIRF methodology has been applied in different contributions (for instance, Candila and Farace [24], Kang et al. [25]). Rather than relying on estimated conditional variances (and covariances) starting from daily returns, the method suggested by Engle et al. [9] directly considers the conditional expectations of the daily range, in a Multiplicative Error Model [MEM] context (Engle [26] and Engle and Gallo [27]) in order to identify volatility spillovers and VIRF.

Our analysis rests on a methodological approach conceptually divided in three steps. In the first step, the absence/presence of volatility spillover from a source (a commodity) to a recipient (an African stock market index) is tested. In the second step, a bivariate BEKK-MGARCH model is estimated for the relationships source–recipient signalled by the test. In the last step, the VIRF is derived to verify the size and the impact of a shock from the origin to the recipient.

As regards the first step, the absence of shock and volatility relationships can be easily tested through the approach proposed by Chang and McAleer [28]. In the original formulation, the test aims at verifying whether the squared returns (impact) and the estimated volatility (inertia) of another market (origin) has explanatory power for the volatility of the recipient. Chang and McAleer [28] suggest to estimate both these volatilities by considering an extended univariate GARCH specification. This notwithstanding, commodities demand is related to the business cycle and hence its price movements are influenced by some macroeconomic variables [MVs] (e.g. the US Industrial Production index [IndPro], the exchanged volume of commodities, the real exchange rate, the GDP growth, and so forth, as suggested by Chevallier and Ielpo [29], Bapna et al. [30], and Borensztein and Reinhart [31], among others). A problem arising in this context is the discrepancy between the frequency at which the stock market index is observed (i.e., daily) and the frequency of the MV observations (usually, monthly or quarterly). A solution could be to lower the daily frequency of the stock market index to harmonize it with the MV of interest, as done by Diebold and Yilmaz [32], for instance. Another and more recent solution is to mix both the frequencies, by the so-called GARCH-MIDAS (Engle et al. [33]) approach. Recent contributions on this latter approach can be found in Mo et al. [34], Amendola et al. [35] and Conrad and Loch [36], in the univariate framework and in Asgharian et al. [37] and Conrad et al. [38] in the multivariate context. The possible different impact had by positive and negative MV variations on the dependent variable is inserted in Amendola et al. [39], where the filter of the MVs consists of separating the positive and negative MV realizations. In view of its successful contribution in explaining volatility, we take their Double-Asymmetric GARCH-MIDAS [DAGM] model to be implemented in the testing framework of Chang and McAleer [28]. Another contribution of the present paper is that we estimate the DAGM model in a Student's t context, in order to successfully take into account the heavy tails of the commodity returns under investigation. The test employed here highlights that the impact and inertia of Oil influence the stock markets volatility of Egypt, Nigeria, Tunisia and Zambia, Gold that of Uganda and Zambia and Copper affects the volatility of Tunisia, Uganda and Zambia stock markets. Interestingly, among these relationships emerged by the test, some have also an economic interpretation. In fact, the energy and metal commodities having the largest share of exports in Egypt (Oil), Nigeria (Oil), Tunisia (Oil), Uganda (Gold) and Zambia (Copper) are the same commodities influencing these stock markets. Instead, the stock market of South Africa seems to be unaffected by the impact and inertia originating from the commodities considered. This is in line with the findings of Sugimoto et al. [40] where, even though the attention is more on impact spillovers, the authors claim that Gold and Oil commodities modestly affect African stock markets.

After having estimated the BEKK specification for each of the previous ten relationships, the VIRF is used as a tool to describe the response of the stock market index to shocks occurring in the commodity markets. The analysis in this step is restricted to the relationships where all the estimated coefficients are found significant. The most relevant effects take place after negative daily returns for Copper, when the volatility of Uganda and Zambia increases up to 2% the day after the shock, while the persistence of these volatility shocks vanishes after approximately 50 days.

The rest of the paper is organized as follows. Section 2 presents the three-step analysis. Section 3 details the results. Conclusions follow.

2 Methodology

Throughout the paper, the series i and j indicate respectively the receiver and the origin of the volatility spillover. Moreover, we adopt the expression "$j \to i$" to denote the occurrence of a volatility spillover from j to i. Adopting a standard notation, $y_{v,t}$ represents the log-returns (close-to-close) of the series v at time t, usually a day, that is: $y_{v,t} = \log(P_{v,t}) - \log(P_{v,t-1})$. Furthermore, we assume that:

$$y_{v,t} = E\left(y_{v,t}|I_{t-1}\right) + \varepsilon_{v,t}, \quad \text{with } v = i, j, \tag{1}$$

where $E\left(y_{v,t}|I_{t-1}\right)$ represents the expected return conditional on the information set I_{t-1}, and $\varepsilon_{v,t}$ is the heteroskedastic error term, such that

$$\varepsilon_{v,t} = h_{v,t} z_t, \tag{2}$$

where z_t is a random sequence of i.i.d. distributed variables with mean zero and unit variance and $h_{v,t}$ is the conditional standard deviation for series v. The GARCH specification to model the conditional variance $h^2_{v,t}$ for the series v is:

$$h^2_{v,t} = w_v + \alpha_v \varepsilon^2_{v,t-1} + \beta_v h^2_{v,t-1}, \tag{3}$$

where w_v is the constant and α_v and β_v are the so-called ARCH and GARCH parameters, respectively. In order to test the volatility spillover from commodity j (origin) to series i (recipient), Chang and McAleer [28] proposed to add lagged squared returns and variances of series j to Eq. (3), which, when series i and j are simultaneously included, becomes:

$$h^2_{i,t} = w_i + \alpha_i \varepsilon^2_{i,t-1} + \beta_i h^2_{i,t-1} + \alpha_j \varepsilon^2_{j,t-1} + \beta_j h^2_{j,t-1}. \tag{4}$$

In this formulation, α_j represents the effect of a shock or impact spillover from series j to series i, while β_j represents the effect of a volatility or inertial spillover. Some possible extensions, which will not be covered in this paper, include bidirectional (that is, $j \rightarrow i$ and $i \rightarrow j$), contemporaneous ($j \rightarrow i$, with both the series are at time t) and non-causal relationships ($j \rightarrow i$, with j at time $t+1$ influences i at time t).

The null of no (shock and inertial) volatility spillover, alternatively defined as Granger non-causality (Granger [41]), is:

$$H_0 : \alpha_j = \beta_j = 0. \tag{5}$$

The test in (5) can be easily carried out through a Likelihood Ratio [LR] approach, where the log-likelihood of the unrestricted model (Eq. (4), with parameter space $\Theta^{UNR} = \left\{w_i, \alpha_i, \beta_i, \alpha_j, \beta_j\right\}$) is compared to that of the restricted one (as expressed by Eq. (3), with $v = i$ and $\Theta^R = \{w_i, \alpha_i, \beta_i\}$).

According to Eq. (4), currently the LR test would only allow for impact and inertial spillovers originating in series j at time $t-1$ and having some effects on series i at time t. However, such configuration may lead also to some spurious interdependencies. The evaluation of volatility spillover existence from j to i would be much more strengthened if the null was rejected independently of the lagged periods $t-l$, with $l = \{1,2,3\}$, for instance. Hence, we change Eq. (4) to:

$$h^2_{i,t} = w_i + \alpha_i \varepsilon^2_{i,t-1} + \beta_i h^2_{i,t-1} + \alpha_j \varepsilon^2_{j,t-l} + \beta_j h^2_{j,t-l}, \quad \text{with } l = \{1,2,3\}. \tag{6}$$

Therefore, the LR test is based on the comparison between the log-likelihoods of the unrestricted (Eq. (6)) and restricted (Eq. (3)) models.

Finally, we adopt the following definition [Def.] to qualify the existence of a volatility spillover:

Definition 1 *A commodity j transfers impact and inertial spillovers to country i, that is $j \rightarrow i$, if and only if the null of the LR test in (5), on the basis of the restricted model in (3) and the unrestricted model in (6), with $l = \{1,2\}$, $l = \{2,3\}$, or alternatively $l = \{1,2,3\}$, is rejected at the 1% significance level.*

Therefore, the previous definition assumes that $j \rightarrow i$ only if at least two LR tests are rejected at the 1% significance level, with the unrestricted model that includes (again, at least) two consecutive (lagged) periods for the commodity impact and inertia.

In this contribution, we estimate the volatility of the commodity j taking into account the fact that some MVs may drive, asymmetrically, its volatility. Then, we adopt a DAGM expression for $h_{j,t}$, assuming a multiplicative decomposition of the conditional variance of the originator, $h^2_{j,t}$, in Eq. (2), in a short- and long-run component, such that:

$$h^2_{j,t} = \tau_{j,m} g_{j,t,m}, \tag{7}$$

where $g_{j,t,m}$ indicates the short-run component of the series j for day t of the period m, and $\tau_{j,m}$ the corresponding long-run component, which in this configuration varies at a monthly frequency m, with $m = 1, \cdots, M$, given that we will use monthly observations for the MVs. Furthermore, let D_m be the number of days included in month m. The total number of daily observations is $T = \sum_{m=1}^{M} D_m$.

The short-run component $g_{j,t,m}$ follows a unit mean-reverting GARCH(1,1), that is:

$$g_{j,t,m} = (1 - \alpha_{j,s} - \beta_{j,s} - \gamma_{j,s}/2) + \left(\alpha_{j,s} + \gamma_{j,s} \cdot \mathbb{1}_{\left(\varepsilon_{j,t-1,m} < 0\right)}\right) \frac{\left(\varepsilon_{j,t-1,m}\right)^2}{\tau_t} + \beta g_{j,t-1,m}, \tag{8}$$

where the suffix "s" stands for short-run and is used to distinguish the α and β parameters in Eq. (8) from those in Eq. (6). In addition to $\alpha_{j,s}$, we include also $\gamma_{j,s}$, which is the term associated with negative lagged innovation $\varepsilon_{j,t-1,m}$, with $\mathbb{1}_{(.)}$ being an indicator function that assumes value one if the argument is true. In order to ensure the positivity of short-run component, the following constraints are set: $\alpha_{j,s} \geq 0$, $\beta_{j,s} \geq 0$ and $\alpha_{j,s} + \beta_{j,s} + \gamma_{j,s}/2 < 1$.

The long-run component in Eq. (7) is defined as:

$$\tau_{j,m} = exp\left(\phi_j + \theta_j^+ \sum_{k=1}^{K} \delta_k(\omega_{j,2}^+) MV_{m-k} \mathbb{1}_{(MV_{m-k} \geq 0)} + \theta_j^- \sum_{k=1}^{K} \delta_k(\omega_{j,2}^-) MV_{m-k} \mathbb{1}_{(MV_{m-k} < 0)}\right), \tag{9}$$

where θ_j^+ and θ_j^- respectively represent the *sign–specific* parameters associated with positive and negative K lagged MV variations, each of which are weighed (through $\delta_k(\omega_2^+)$ and $\delta_k(\omega_2^-)$) according to a proper weighting function. As in other works concerning the GARCH-MIDAS, we opt for the Beta function as the weighting function, which has the following general formulation:

$$\delta_k(\omega) = \frac{(k/K)^{\omega_1 - 1}(1 - k/K)^{\omega_2 - 1}}{\sum_{j=1}^{K}(j/K)^{\omega_1 - 1}(1 - j/K)^{\omega_2 - 1}}. \tag{10}$$

with $\sum_{k=1}^{K} \delta_k(\omega) = 1$ and the constraint that $\omega_1 < \omega_2$, which allows for a larger importance on more recent observations. Moreover, we impose $\omega_1 = 1$, in order to have a monotonically decreasing weighting scheme.

Wanting to consider a greater density in the tails of the conditional distribution of the commodity series, instead of considering that the log-returns of j are conditionally normally distributed, we assume that they follow a Student's t-distribution (Bollerslev [42]), with $df > 2$ degrees of freedom, that is:

$$\varepsilon_{j,t,m} | I_{t-1,m} \sim f_{df}\left(\varepsilon_{j,t,m} | I_{t-1,m}\right), \tag{11}$$

where f_{df} is the (conditional) density function for $\varepsilon_{j,t,m}$, defined as:

$$\begin{aligned} f_{df}\left(\varepsilon_{j,t,m} | I_{t-1,m}\right) \quad = \quad & \Gamma\left(\frac{df+1}{2}\right)\Gamma\left(\frac{df}{2}\right)^{-1}\left((df-2)\, h_{j,t}^2\right)^{-1/2} \times \\ & \left(1 + \frac{\varepsilon_{j,t,m}^2}{h_{j,t}^2\,(df-2)}\right)^{-(df+1)/2}. \end{aligned} \tag{12}$$

The parameters to estimate included in the parameter space of the DAGM plus the degrees of freedom df, $\Theta^{DAGM} = \left\{\alpha_{j,s}, \beta_{j,s}, \gamma_{j,s}, \phi_j, \theta_j^+, \omega_{j,2}^+, \theta_j^-, \omega_{j,2}^-, df\right\}$, can be easily obtained maximizing the following log-likelihood:

$$\mathscr{L}(\Theta^{DAGM};j)=\sum_{m=1}^{M}\left\{\sum_{t=1}^{D_m}\left[\log\left(f_{df}\left(\varepsilon_{j,t,m}|I_{t-1,m}\right)\right)\right]\right\}. \tag{13}$$

Now, let us assume that between the series i and j some volatility spillovers hold according to Def. 1. In order to further analyse these interdependencies, we adopt the VIRF methodology proposed by Hafner and Herwartz [23], which makes use of the conditional covariance matrix, labelled as H_t, derived using the BEKK model. Let $\boldsymbol{\varepsilon}_t$ be a 2×1 vector of daily-log returns (if $E\left(y_{v,t}|I_{t-1}\right)=0$, for $v=i,j$) or residuals, such that:

$$\boldsymbol{\varepsilon}_t=H_t^{1/2}\boldsymbol{z}_t,\quad t=1,\ldots,T, \tag{14}$$

where the random vector $\boldsymbol{z}_t$ is assumed to have zero means ($E(\boldsymbol{z}_t)=\mathbf{0}$) and that $E\left(\boldsymbol{z}_t\boldsymbol{z}_t^{'}\right)=I_2$, an identity matrix of order 2. Furthermore, $\boldsymbol{z}_t$ is assumed to follow a multivariate normal distribution. In the BEKK(1,1) representation, H_t is obtained as follows:

$$H_t=CC^{'}+A\boldsymbol{\varepsilon}_t\boldsymbol{\varepsilon}_t^{'}A^{'}+GH_{t-1}G^{'}, \tag{15}$$

with C being a lower triangular matrix and A and B having both dimension 2×2. The dynamic structure of a BEKK(1,1) is:

$$\begin{aligned}\begin{bmatrix}H_{ii,t} & H_{ij,t}\\ H_{ji,t} & H_{jj,t}\end{bmatrix}&=\begin{bmatrix}C_{ii} & 0\\ C_{ji} & C_{jj}\end{bmatrix}\begin{bmatrix}C_{ii} & C_{ji}\\ 0 & C_{jj}\end{bmatrix}+\\ &+\begin{bmatrix}A_{ii} & A_{ij}\\ A_{ji} & A_{jj}\end{bmatrix}\begin{bmatrix}\varepsilon_{ii,t-1}^2 & \varepsilon_{i,t-1}\varepsilon_{j,t-1}\\ \varepsilon_{j,t-1}\varepsilon_{i,t-1} & \varepsilon_{jj,t-1}^2\end{bmatrix}\begin{bmatrix}A_{ii} & A_{ji}\\ A_{ij} & A_{jj}\end{bmatrix}+\\ &+\begin{bmatrix}G_{ii} & G_{ij}\\ G_{ji} & G_{jj}\end{bmatrix}\begin{bmatrix}H_{ii,t-1} & H_{ij,t-1}\\ H_{ji,t-1} & H_{jj,t-1}\end{bmatrix}\begin{bmatrix}G_{ii} & G_{ji}\\ G_{ij} & G_{jj}\end{bmatrix},\end{aligned}$$

with H_{ii}, H_{jj}, and H_{ij} representing the conditional variances for series i, j and their conditional covariance at time t, respectively. The coefficients A_{ij} and A_{ji} capture the "impact" component of spillovers, while G_{ij} and G_{ji} apply to the "inertial" component for lagged covariances. Because of the linkage of interest is only from series j to series

i, we only pay attention to the coefficients A_{ij} and G_{ij}, which contribute to determine $H_{ii,t}$ by the following formulation:

$$\begin{aligned} H_{ii,t} =& C_{ii}^2 + A_{ii}^2\varepsilon_{i,t-1}^2 + 2A_{ii}A_{ij}\varepsilon_{i,t-1}\varepsilon_{j,t-1} + A_{ij}^2\varepsilon_{j,t-1}^2 + \\ & G_{ii}^2 H_{ii,t-1} + G_{ii}G_{ij}H_{ij,t-1} + G_{ij}^2 H_{jj,t-1}. \end{aligned} \tag{16}$$

In the last step of our analysis we assume that some shocks, denoted by $\boldsymbol{s}_t$, perturb the matrix H_t. Therefore, $\boldsymbol{s}_t$ is an unpredictable vector of shocks occurring at time t and affecting the future realizations of H_t. The VIRF methodology consists of evaluating the conditional expectation of H_t with and without the shock $\boldsymbol{s}_t$.

In order to identify the VIRF, the *vech* representation of the model in Eq. (15) is used:

$$vech\,(H_t) = vech\,(C) + R \cdot vech\left(\boldsymbol{\varepsilon}_t \boldsymbol{\varepsilon}_t^{'}\right) + F \cdot vech\,(H_{t-1})\,, \tag{17}$$

where $vech\,(\cdot)$ is the operator stacking the lower fraction of an $N \times N$ matrix into an $N^* = N(N+1)/2$ dimensional vector, and R and F are the matrices with $(N^*)^2$ elements. $E\left[vech\,(H_t|I_{t-1})\right]$ represents the baseline scenario, where no shocks are happened. The h-step-ahead VIR is given by:

$$V_h\,(\boldsymbol{z}_t) = E\left[vech\,(H_{t+h}|\boldsymbol{s}_t, I_{t-1})\right] - E\left[vech\,(H_{t+h}|I_{t-1})\right]. \tag{18}$$

In Eq. (18), the VIRF is obtained comparing the h-step-ahead expected conditional covariance matrix, once the shock at time t is occurred, to the baseline scenario. In this work, we only assume that the shock concerns the series j. Following the *vech* representation used in Eq. (17), the one-step-ahead VIRF is:

$$V_1\,(\boldsymbol{s}_t) = R \cdot \left\{ vech\left(H_t^{1/2}\boldsymbol{s}_t\boldsymbol{s}_t^{'}H_t^{1/2}\right) - vech(H_t) \right\}, \tag{19}$$

with $\boldsymbol{s}_t$ as:

$$\boldsymbol{s}_t = H_t^{-1/2}\boldsymbol{\varepsilon}_t, \tag{20}$$

and $H_t^{-1/2}$ coming out from the Jordan decomposition of the conditional covariance matrix:

$$H_t^{1/2} = \Gamma_t \Lambda_t^{1/2} \Gamma_t^{'}, \tag{21}$$

where Λ_t is a diagonal matrix containing the eigenvalues of H_t, and Γ_t is a 2×2 matrix of the corresponding eigenvectors.

Finally, for $h \geq 2$, the VIR becomes:

$$V_h(\boldsymbol{s}_t) = (R+F) \cdot V_{h-1}(\boldsymbol{s}_t). \tag{22}$$

3 Empirical analysis

Daily data on African stock markets and the considered commodities were collected from the Eikon Thomson Reuters provider. The sample period slightly changes across the series, depending on the availability of the prices, spanning at a minimum from August 2004 to January 2019 (Uganda), while at its longest it goes from September 1999 to January 2019. The quotations synthesized in the African stock market indexes are expressed in their local currency, whereas all the commodities are in United States dollars ($). The chosen index for the Egyptian stock market is EGX 30, which is a weighed index of the top 30 most highly capitalized and liquid stocks listed on that exchange. As regards the Nigerian stock market, we consider the NGSE all share index, which reports the movements of all the listed equities. FTSE/JSE all share index is the chosen capitalization-weighted index of the South Africa Stock Exchange, whose constituents include up to the top 99% of all the listed equities in that exchange. With reference to the Tunisian market index, we opt for TUNINDEX, which is a capitalization-weighted index. Uganda Stock Exchange and Lusaka Stock Exchange all share indexes are the chosen market indexes for Uganda and Zambia, respectively made up of 17 and 24 listed companies. Oil, Gas, Gold and Copper commodities considered here are futures contracts exchanged in the New York Mercantile Exchange.

As mentioned earlier, the criterion to choose the commodities was their weight as export shares in these emerging countries, according to the most recent statistics provided by World Integrated Trade Solution database of the World Bank. For instance, in 2017 Nigeria exported over $ 36 billion in Oil while the global amount of its exports was about $ 44.5 billion.

Tables 1 and 2 synthesize some summary statistics related to the daily returns for African stock markets and commodities, respectively. All series are not symmetric and have a high skewness and kurtosis.

Table 1: Emerging African stock market daily log–returns statistics

Country	Index	Time-span	Obs.	Mean	Stand. Dev.	Skewness	Kurtosis[a]	Top Comm. Export[b]
Egypt	EGX 30	1999-09-01 / 2019-01-28	4731	0.061	1.694	−0.353	8.438	Petroleum, Gold
Nigeria	NGSE	1999-09-01 / 2019-01-28	4812	0.038	0.986	0.096	3.296	Petroleum, Natural Gas
South Africa	FTSE/JSE	1999-09-01 / 2019-01-28	4855	0.043	1.192	−0.172	3.539	Coal, Gold
Tunisia	TUNINDEX	1999-09-01 / 2019-01-28	4795	0.042	0.520	−0.071	7.499	Petroleum
Uganda	USE	2004-08-03 / 2019-01-15	2682	0.056	1.484	0.109	6.017	Coffee, Gold
Zambia	LUSE	1999-09-01 / 2019-01-28	4707	0.067	1.066	0.308	8.702	Copper

Percentage scale.
[a] The reported value is the excess kurtosis.
[b] The column shows the top two commodities, if available, exported by the country according to the World Integrated Trade Solution database.

Table 2: Energy and metal commodities daily log–returns

Commodity	Index	Time-span	Obs.	Mean	Stand. Dev.	Skewness	Kurtosis[a]
Oil	CLc1	1999-09-01 / 2019-01-28	4870	0.018	2.382	−0.133	3.928
Gas	NGc1	2000-01-04 / 2019-01-28	4788	0.006	3.409	0.485	5.617
Gold	GCc1	1999-09-01 / 2019-01-28	4870	0.034	1.070	−0.128	2.431
Copper	HGc1	1999-09-01 / 2019-01-28	4878	0.025	1.721	−0.174	4.346

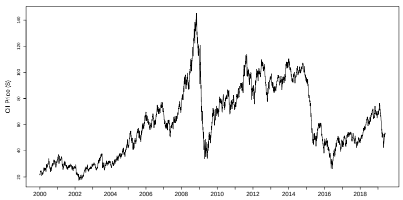
Percentage scale.
[a] The reported value is the excess kurtosis.

The patterns of the four commodity prices are shown in Figure 1. The most notable feature in the Oil commodity is the surge of the period 2007-2008, culminated in a sharp decrease. The other energy commodity, Gas, has a similar pattern with respect to that of Oil. This is in line with the assumption that both the series are interconnected, largely documented in literature (see, for instance, Hartley et al. [43] and Villar and Joutz [44], among others). As regards the behavior of the metal commodities analyzed here, Gold price seems to have an increasing trend from the beginning of the sample period up to 2011, while Copper, even if with less variations, has more than one discernible dynamic pattern. Consistent with these dynamics is the work of Rossen [45], where the author claims that the co-movements are not properly a feature of metal commodities.

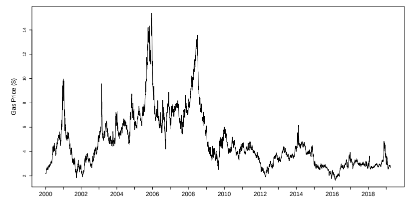
For the sake of completeness, in Figure 2 we report the time series of the stock market indices which we have considered.

Step 1

Our first step consists of applying the volatility spillover test between series j and series i. As mentioned above, the volatility of the commodity series j has been estimated by means of the DAGM model, with a Student's t-distribution for the innovation term. The connections between the economic factors and commodity volatilities has been recently investigated by Prokopczuk et al. [46]. The description of the MVs used in this work, all taken in the first differences, influencing each single series j is provided in Table 3.

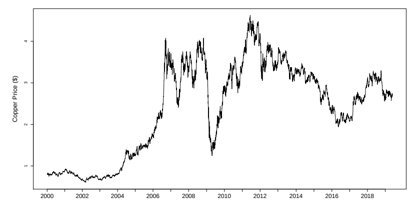


(a) Oil



(b) Gas

(c) Gold



(d) Copper

Figure 1: Commodity prices

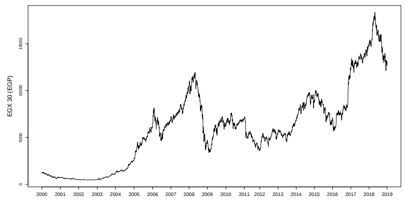
All the MVs have been obtained from the Federal Reserve Economic Data [FRED] site. Notably, Table 3 reports also a Granger Causality test for different (monthly) lagged period of the MV influencing the (monthly) aggregated volatility of series j. The null of absence of Granger Causality has been almost always largely rejected.

Table 3: Macroeconomic variables influencing commodities

Macroec. variable	Index	Commodity influenced	Granger Test[a]	Source
Industrial Production: Crude oil	IPG211111CS	Oil	$l=1$, 2.10 $l=6$, 5.30*** $l=12$, 3.16***	Mo et al. [34] Karali and Ramirez [47] Karali and Power [48]
Industrial Production: Natural gas	IPG2212S	Gas	$l=1$, 3.27* $l=6$, 1.56 $l=12$, 1.59*	Karali and Ramirez [47] Karali and Power [48]
Gross Domestic Product (GDP): Normalized for the United States	USALORSGPNOSTSAM	Gold	$l=1$, 7.47*** $l=6$, 3.82*** $l=12$, 2.53***	Mo et al. [34] Bapna et al. [30]
Industrial Production	INDPRO	Copper	$l=1$, 0.41 $l=6$, 4.77*** $l=12$, 4.22***	Mo et al. [34] Slade and Thille [49]

[a] The column reports the F-statistics of the Granger Causality test, aiming at verifying if the variables in the first column Granger causes the volatility of the variables in the third column, with three different lags l. Being the macroeconomic variable observed monthly, the monthly aggregated volatility is considered. The tests cover the period January 2001 - December 2018. *, ** and *** denote significance at the 10%, 5% and 1% levels, respectively.

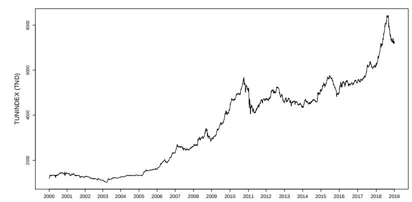
The DAGM estimates with some residuals diagnostics are reported in Table 4. Looking at the DAGM estimates, the intuition that positive and negative MVs variations may have different impact on the volatility of the commodity variable is confirmed: in some cases, only positive MV variations have an effect, in some others



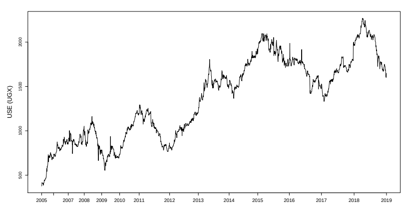
(a) Egypt

(b) Nigeria

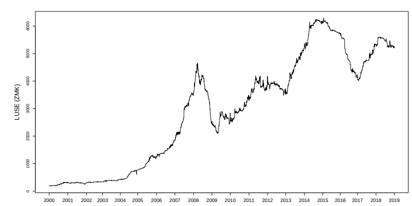
(c) South Africa



(d) Tunisia



(e) Uganda



(f) Zambia

Figure 2: African stock market prices

the opposite occurs. One of the main contribution of this work, the estimation of the DAGM with a Student's t-distribution, leads to a plausible and statistically significant set of degrees of freedom for all the commodities returns. More importantly, the performances of the DAGM models are always statistically superior than that of the standard GARCH-MIDAS [GM] model, according to the Diebold and Mariano [50] test. In order to fairly compare the two models, also the GM has been estimated with a Student's t-distribution. The DAGM models have also a better fit than the GM model, in terms of the Akaike Information Criterion [AIC]. Also the residual diagnostics are generally good, as shown in the last six rows of Table 4. In particular, the p-values of the Ljung-Box and Lagrange Multiplier (Engle [51]) tests for conditional heteroskedasticity are reported, with respect to different lags. Independently of the lag considered, the squared standardized residuals appear homoskedastic.

Table 4: DAGM estimates of commodity volatilities

	Oil	**Gas**	**Gold**	**Copper**
α	0.019^{***}	0.073^{***}	0.036	0.025^{***}
	(0.007)	(0.013)	(0.029)	(0.009)
β	0.948^{***}	0.92^{***}	0.97^{***}	0.966^{***}
	(0.009)	(0.01)	(0.044)	(0.013)
γ	0.05^{***}	-0.022	-0.012	0.014
	(0.011)	(0.016)	(0.019)	(0.017)
ϕ	-7.459^{***}	-6.261^{***}	-63.321	-12.864^{***}
	(0.312)	(0.244)	(182.997)	(0.679)
θ^{+}	-0.325^{**}	-0.06	2.439^{***}	-0.183
	(0.15)	(0.039)	(0.214)	(0.65)
ω_2^{+}	1.68^{***}	2.541^{***}	1.813^{***}	2.248
	(0.331)	(0.681)	(0.131)	(119.086)
θ^{-}	-0.068	0.187^{***}	2.713	0.36^{**}
	(0.223)	(0.063)	(182.091)	(0.148)
ω_2^{-}	1.484	2.081^{***}	15.78^{***}	21.992^{***}
	(5.859)	(0.181)	(0.001)	(0.081)
df	9.428^{***}	6.69^{***}	6.55^{***}	6.407^{***}
	(0.744)	(1.001)	(1.517)	(2.134)
DM	-6.7^{***}	-5.348^{***}	-4.569^{***}	-2.044^{**}
AIC-DAGM	-27990.976	-24079.069	-29118.895	-25142.896
AIC-GM	-27512.802	-23801.056	-28723.911	-25140.895
LB_5	0.505	0.892	0.019	0.029
LB_{10}	0.435	0.719	0.151	0.169
LB_{20}	0.562	0.865	0.448	0.495
LM_5	0.51	0.879	0.018	0.036
LM_{10}	0.431	0.702	0.153	0.197
LM_{20}	0.497	0.855	0.428	0.516

Notes: Newey-West (HAC) standard errors are in parentheses. The additional volatility determinants are shown in Table 3. df is the Student's t degrees of freedom. *, ** and *** denote significance at the 10%, 5% and 1% levels, respectively. DM stands for the Diebold-Mariano two-tailed test statistics, whose null is of equal predictive forecasting ability between the DAGM and the competing model, the GARCH-MIDAS [GM]. If the test statistic is negative, it means that the DAGM outperforms the competing model. LB_l represents the p-values of the Ljung-Box test at l lag, applied on squared standardized residuals. LM_l represents the p-values of the Lagrange Multiplier (Engle [51]) test for conditional heteroskedasticity with l lags, always applied on the squared standardized residuals.

The p–values of the LR test concerning the presence of volatility spillovers are reported in Table 5. As a result, Oil transfers impact and inertial spillovers to Egypt, Nigeria, Tunisia and Zambia (that is, Oil → Egypt, Oil → Nigeria, Oil → Tunisia and Oil → Zambia). Moreover, we find that Gas → Zambia, Gold → Uganda and Gold → Zambia, and finally, Copper influences the stock markets of Tunisia, Uganda and Zambia. South Africa is the only county considered that does not receive spillovers from any of the considered commodities, according to Def. 1.

Table 5: P-values of the volatility spillover test

Country	**Lag**	**Oil**	**Gas**	**Gold**	**Copper**
Egypt	$t-1$	0.001	0.990	0.052	0.000
	$t-2$	0.005	1.000	0.037	0.141
	$t-3$	0.001	0.997	0.048	0.767
Nigeria	$t-1$	0.004	0.637	0.961	0.827
	$t-2$	0.000	0.428	0.358	0.763
	$t-3$	0.006	0.644	0.379	0.904
South Africa	$t-1$	0.097	1.000	0.812	0.453
	$t-2$	0.399	0.834	0.673	0.673
	$t-3$	0.567	1.000	0.057	0.567
Tunisia	$t-1$	0.000	0.691	0.359	0.000
	$t-2$	0.000	0.558	0.215	0.000
	$t-3$	0.000	0.447	0.257	0.470
Uganda	$t-1$	0.273	0.441	0.000	0.153
	$t-2$	0.250	0.469	0.000	0.000
	$t-3$	0.544	0.430	0.014	0.000
Zambia	$t-1$	0.000	0.000	0.000	0.000
	$t-2$	0.000	0.000	0.000	0.000
	$t-3$	0.000	0.000	0.000	0.000

Notes: The table presents the p-values of the LR test to detect the impact and inertial spillover originating from commodity j (Oil, Gas, Gold or Copper) and transferring to country i (first column), for different lagged periods (second column). Dark, medium-dark, and light shades of gray denote significance at the 1%, 5%, and 10% levels, respectively.

Step 2

Having established which commodity originated a impact and inertial spillover towards a African country, we focus on the size and persistence of such a spillover by using the VIRF. The VIRF requires an estimate of the conditional covariance matrix, obtained in this step by means of the BEKK model, whose estimates for the ten relationships highlighted before are reported in Table 6. Some interesting points emerge. First, there is some evidence of bidirectional, impact and inertial spillovers: this happens for the relationships Oil and Tunisia and Zambia, Copper and Tunisia, Uganda and Zambia, because of the jointly significance of the coefficients A_{ij}, A_{ji}, G_{ij} and G_{ji}. However, we only explore the issues with the direction $j \rightarrow i$, for the reasons explained above, while we assume that these bi-directional relationships may be due to some spurious interdependencies. Second, some impact spillovers are found: from Oil to Tunisia and Zambia, from Copper to Tunisia, Uganda and Zambia, because of the significance of the A_{ij} parameters. A third aspect to underline is the presence of inertial spillovers from Oil to Tunisia and Zambia, from Copper to Tunisia, Uganda and Zambia and finally from Gold to Zambia. This derives from the high significance of the coefficient G_{ij} for the previous relationships. In summary, the BEKK analysis allows to disentangle the impact and inertial spillovers of the commodity j towards country i.

Table 6: BEKK estimates

j (source) i (recipient)	Oil Egypt	Oil Nigeria	Oil Tunisia	Copper Tunisia	Gold Uganda	Copper Uganda	Oil Zambia	Gas Zambia	Gold Zambia	Copper Zambia
C_{ii}	0.454^{***}	0.376^{***}	0.188^{***}	0.263^{***}	0.099^{***}	0.326^{***}	0.780^{***}	0.052^{***}	0.176^{***}	0.468^{***}
	(0.041)	(0.023)	(0.010)	(0.013)	(0.026)	(0.011)	(0.024)	(0.008)	(0.012)	(0.018)
C_{ji}	0.000	0.000	0.000	-0.001	0.010^{***}	0.006^{***}	0.000^{*}	0.001	0.009^{***}	0.001^{***}
	(0.001)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.000)	(0.002)	(0.000)	(0.000)
C_{jj}	-0.005^{***}	0.004^{***}	0.003^{**}	0.000	0.003	0.000	0.003^{***}	0.008^{***}	-0.001	0.000
	(0.001)	(0.000)	(0.001)	(0.000)	(0.002)	(0.001)	(0.000)	(0.001)	(0.001)	(0.000)
A_{ii}	0.390^{***}	-0.562^{***}	-0.480^{***}	-0.537^{***}	0.280^{***}	0.274^{***}	0.502^{***}	-0.218^{***}	0.232^{***}	-0.387^{***}
	(0.023)	(0.025)	(0.021)	(0.012)	(0.021)	(0.006)	(0.023)	(0.011)	(0.002)	(0.016)
A_{ji}	7.379^{***}	-1.126	1.077^{***}	-3.302^{***}	-22.697^{***}	16.116^{***}	-2.043^{**}	1.757^{***}	-4.977^{***}	-6.076^{***}
	(1.459)	(0.705)	(0.298)	(0.436)	(2.420)	(1.362)	(0.998)	(0.312)	(0.981)	(1.078)
A_{ij}	0.000	-0.001^{*}	0.001^{***}	-0.002^{***}	0.000	-0.001^{**}	0.001^{***}	0.000	0.000	-0.003^{***}
	(0.000)	(0.000)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
A_{jj}	0.312^{***}	0.288^{***}	0.284^{***}	0.281^{***}	0.217^{***}	0.269^{***}	0.301^{***}	-0.357^{***}	-0.314^{***}	0.278^{***}
	(0.013)	(0.011)	(0.009)	(0.013)	(0.039)	(0.014)	(0.011)	(0.014)	(0.025)	(0.016)
G_{ii}	-0.872^{***}	0.742^{***}	0.808^{***}	-0.664^{***}	0.947^{***}	-0.857^{***}	-0.506^{***}	0.974^{***}	0.955^{***}	0.791^{***}
	(0.017)	(0.026)	(0.017)	(0.025)	(0.007)	(0.011)	(0.032)	(0.003)	(0.001)	(0.013)
G_{ji}	3.982	-0.125	-0.829^{***}	-3.191^{***}	4.514^{***}	26.973^{***}	-0.748	-1.183	-13.348^{***}	5.090^{***}
	(3.957)	(0.369)	(0.073)	(0.373)	(1.097)	(2.473)	(0.830)	(1.007)	(0.536)	(0.498)
G_{ij}	0.000	0.000	0.002^{***}	0.003^{***}	0.000	0.005^{***}	0.001^{***}	-0.001	-0.002^{***}	-0.003^{***}
	(0.001)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)
G_{jj}	0.927^{***}	0.942^{***}	0.946^{***}	-0.955^{***}	0.006	0.773^{***}	-0.945^{***}	-0.910^{***}	-0.349^{***}	0.942^{***}
	(0.007)	(0.005)	(0.009)	(0.003)	(0.019)	(0.023)	(0.005)	(0.008)	(0.056)	(0.005)

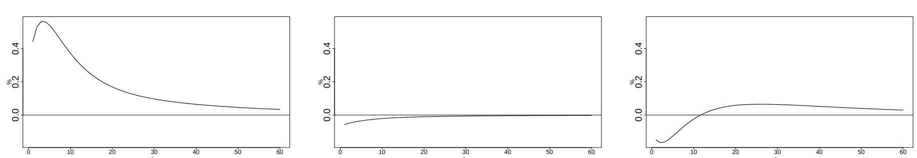
Notes: Standard errors are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Step 3

The last step of our analysis consists of investigating the response of volatility to a given shock in the series of the commodity. This step employs the VIRF methodology and is focused only on the relationships underlined in Table 5 in which both the impact and the inertial spillovers are significant. As described above, this happens for the relationships Oil $\rightarrow$ Tunisia, Copper $\rightarrow$ Tunisia, Copper $\rightarrow$ Uganda, Oil $\rightarrow$ Zambia and Copper $\rightarrow$ Zambia. For each of the previous relationships, we report the volatility impulse responses for three situations. The first situation consists of a calm period, where the commodity log-returns is close to its mean. The second and the third situations occur when the commodity log-return exhibits its minimum and maximum value. We call these situations t_c, t_n, and t_p, where the suffixes c, p, and n stand for “calm”, “negative”, and “positive” periods. We report all the results relatively to the estimated conditional volatility at the date of the shock. Thus, all the following results are expressed in percentage.

Oil $\rightarrow$ Tunisia

The consequences of Oil shocks to Tunisia stock market are illustrated in Figure 3. A negative shock (Figure 3a) has a larger persistence (more than 60 days) and a larger impact (more than 0.4% bigger volatility) than what happens in case of positive shock. As expected, relatively to these two circumstances, the effect of no shock on the Tunisia stock markets is negligible.

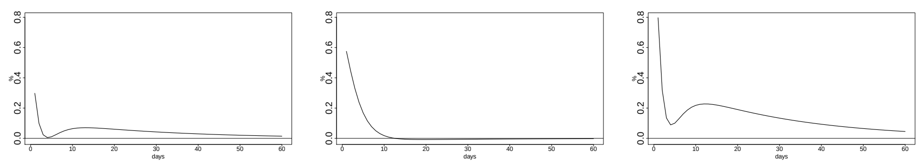


(a) $t_n = 2001\text{-}09\text{-}24$ (b) $t_c = 1999\text{-}10\text{-}20$ (c) $t_p = 2008\text{-}12\text{-}22$

Figure 3: Volatility Impulse Response from Oil to Tunisia

Copper → Tunisia

Three main points can be highlighted in Figure 4. First, after both a Copper price increase and decrease, the volatility of Tunisia's stock market increases. Second, a positive shock in the Copper market lets higher the Tunisia's stock market volatility (up to 0.8% larger) than a negative shock (up to 0.3% larger). Third, the stock market volatility of Tunisia increases and sharply decreases (the effect cancels after 10 days) if the Copper price is invariant.

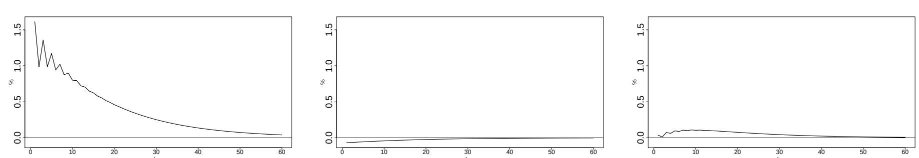


(a) $t_n = 2008\text{-}10\text{-}10$ (b) $t_c = 1999\text{-}11\text{-}17$ (c) $t_p = 2008\text{-}10\text{-}29$

Figure 4: Volatility Impulse Response from Copper to Tunisia

Copper → Uganda

Figure 5 illustrates the volatility responses of Uganda's stock market after a given shock in Copper prices. The greatest impact takes place when a negative shock occurs in Copper prices. In this case, the volatility is expected to increase up to 1.5% (the day after the shock). Instead, calm and positive periods let the stock market volatility invariant.

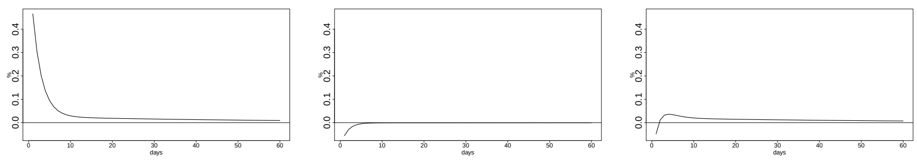


(a) $t_n = 2008\text{-}10\text{-}30$ (b) $t_c = 2005\text{-}06\text{-}23$ (c) $t_p = 2006\text{-}05\text{-}23$

Figure 5: Volatility Impulse Response from Copper to Uganda

Oil → Zambia

In Figure 6 the VIRs of Oil on the Zambia's stock market are illustrated. In the left plot, describing the results on the stock market volatility of a negative shock in Oil prices, the volatility increases up to 0.4%, while the effect cancels after 30 days, approximately. Not surprisingly, the effects of a calm and positive periods in the Oil prices are much less evident.

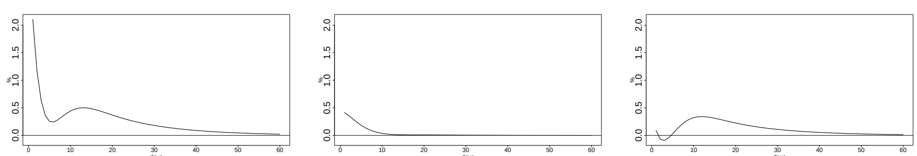


(a) $t_n = 2001\text{-}09\text{-}24$ (b) $t_c = 1999\text{-}10\text{-}20$ (c) $t_p = 2008\text{-}12\text{-}22$

Figure 6: Volatility Impulse Response from Oil to Zambia

Copper → Zambia

As highlighted in Table 1, Copper is the main exported good by Zambia. This maybe justify the size of a negative shock in the Copper prices and affecting the Zambia's stock market. In this case, the stock market volatility of Zambia increases up to 2%, with a persistence of over 50 days, while the effects after the other two types of shocks appear negligible, as highlighted in Figure 7.



(a) $t_n = 2008\text{-}10\text{-}10$ (b) $t_c = 1999\text{-}10\text{-}21$ (c) $t_p = 2008\text{-}10\text{-}29$

Figure 7: Volatility Impulse Response from Copper to Zambia

4 Conclusion

In this paper we have addressed a rarely investigated issue, that is, the dependence of the most important African stock markets (Egypt, Nigeria, South Africa, Tunisia, Uganda and Zambia) upon the price fluctuations of energy and metal commodity markets (Oil, Gas, Gold and Copper). The idea is that for countries in which commodity exports are a relevant share of their trade, economic activity as reflected in the variations in quoted stock prices will depend on what commodity price volatility is. The reverse is not arguable given the tiny importance of these markets in the global allocation of resources. The paper is hence empirically motivated in its effort to ascertain which bilateral links are relevant in defining channels of transmission.

We build a methodology to address this research question. Our approach moves within the GARCH framework and has a pre-testing phase where an extended GARCH specification of a stock market conditional variance includes the possibility of additional explanatory power coming from the most recent lagged squared (log-)returns (what we call impact) and conditional variance (what we call inertia) from a single commodity. Given the complex interactions at work in global portfolio allocations and in demand/supply of a commodity, chances are that even commodities that are not directly among the natural resources exported by a country may affect stock markets. To be noted as a relevant original contribution is the adoption of the DAGM model for the commodity volatility which gives us the opportunity to introduce some information about macroeconomic variables observed at world level driving a low-frequency component of volatility reacting to different phases of the business cycle. Another methodological innovation of this paper is the estimation of the DAGM model in a Student's t framework, in order to take into account the leptokurtosis of the commodity (log-)returns.

The first step has highlighted ten significant relationships originating from the four energy and metal commodities and affecting the African Stock markets: Oil affects the stock markets of Egypt, Nigeria, Tunisia and Zambia, Gold those of Uganda and Zambia, Copper those of Tunisia, Uganda and Zambia and finally Gas affects the stock market of Zambia. Therefore, two points can be underlined. First, the stock market of Zambia is the most vulnerable market to commodity price variations among the considered emerging countries. Second, countries with the largest share of exports given by a commodity have a stock market whose volatility is also influenced by that commodity. This happens for: (i) the stock markets of Egypt, Nigeria and Tunisia, which mainly export Oil and whose stock markets depend on the impact and the inertia of this commodity (ii) the stock market of Uganda, whose volatility depends also on the variations of Gold prices, which is one of the main exporting good of that country; (iii) the stock market of Zambia, whose exports are mainly based on Copper, is in turn influenced by Copper impact and inertia.

In the next phase, a bivariate BEKK–MGARCH model for a pair of commodity and relevant market isolated under the first step has estimated. By means of this set of BEKK models, the commodity impact and inertial spillovers towards the country stock market's volatility have taken into account. And, only the significant relationships are considered in order to address the last step of our analysis, consisting of the analysis of the VIRF. These relationships are: Oil – Tunisia, Copper – Tunisia, Copper – Uganda, Oil – Zambia and Copper – Zambia. The VIRF defines the profile of the convergence of the conditional volatility to the unconditional level, following an impulse - in this case a shock applied to the commodity to trace its trajectory into the volatility of the national stock market: we have presented different profiles according to a characterization of starting conditions in the market which may change according to whether the market goes through a phase of tranquillity or turbulence. We have seen the most interesting profiles as those Volatility Impulse Responses where non monotonicity and slower convergence to the long run equilibrium level were detected. In particular, turbulence periods occurring today in the commodity prices tend to increase the tomorrow stock market volatility.

A word is in order about the fact that focusing the attention on emerging markets is often frustrated by reduced data availability and/or data quality. This is truly unfortunate because economic development is also the result of how institutions work and the desire for quantitative research to offer some policy options. In this respect, the unavailability of the *intra-daily quartet* Open–High–Low–Close for these major African stock markets keeps us away from being able to apply a volatility spillover analysis in the vein of Engle et al. [9] on a direct measure of volatility such as the daily range.

References

[1] A. Silvennoinen and S. Thorp, "Financialization, crisis and commodity correlation dynamics," *Journal of International Financial Markets, Institutions and Money*, vol. 24, pp. 42–65, 2013.

[2] M. Karanasos, F. M. Ali, Z. Margaronis, and R. Nath, "Modelling time varying

volatility spillovers and conditional correlations across commodity metal futures," *International Review of Financial Analysis*, vol. 57, pp. 246–256, 2018.

[3] S. Nazlioglu, C. Erdem, and U. Soytas, "Volatility spillover between oil and agricultural commodity markets," *Energy Economics*, vol. 36, pp. 658–665, 2013.

[4] Y. G. Hou and S. Li, "Volatility and skewness spillover between stock index and stock index futures markets during a crash period: New evidence from China," *International Review of Economics & Finance*, vol. 66, pp. 166–188, 2020.

[5] K. A. Berg and N. T. Vu, "International spillovers of US financial volatility," *Journal of International Money and Finance*, vol. 97, pp. 19–34, 2019.

[6] M. Greenwood-Nimmo, V. H. Nguyen, and B. Rafferty, "Risk and return spillovers among the G10 currencies," *Journal of Financial Markets*, vol. 31, pp. 43–62, 2016.

[7] M. Ildırar and E. Iscan, "The interaction between stock prices and commodity prices: Eastern Europe and Central Asia case," *International Journal of Economics and Finance Studies*, vol. 8, no. 2, pp. 94–106, 2016.

[8] W. Kang, R. A. Ratti, and K. H. Yoon, "The impact of oil price shocks on the stock market return and volatility relationship," *Journal of International Financial Markets, Institutions and Money*, vol. 34, pp. 41–54, 2015.

[9] R. F. Engle, G. M. Gallo, and M. Velucchi, "Volatility spillovers in East Asian financial markets: a MEM–based approach," *Review of Economics and Statistics*, vol. 94, no. 1, pp. 222–223, 2012.

[10] T. Korkmaz, E. İ. Çevik, and E. Atukeren, "Return and volatility spillovers among CIVETS stock markets," *Emerging Markets Review*, vol. 13, no. 2, pp. 230–252, 2012.

[11] B.-H. Kim, H. Kim, and B.-S. Lee, "Spillover effects of the US financial crisis on financial markets in emerging Asian countries," *International Review of Economics & Finance*, vol. 39, pp. 192–210, 2015.

[12] S. Neaime, "The global financial crisis, financial linkages and correlations in returns and volatilities in emerging MENA stock markets," *Emerging Markets Review*, vol. 13, no. 3, pp. 268–282, 2012.

[13] C. K. Adjasi and C. A. Yartey, "Stock market development in Sub-Saharan Africa: critical issues and challenges," International Monetary Fund (IMF) Working Paper 209, 2007.

[14] Economic Commission for Africa et al., *African Statistical Yearbook 2018*, 2018.

[15] Y. Hamao, R. W. Masulis, and V. Ng, "Correlations in price changes and volatility across international stock markets," *The Review of Financial Studies*, vol. 3, no. 2, pp. 281–307, 1990.

[16] R. F. Engle, T. Ito, and W. L. Lin, "Meteor showers or heat waves? Heteroskedastic intra daily volatility in the foreign exchange market," *Econometrica*, vol. 58, pp. 1749–78, 1990.

[17] W.-L. Lin, R. F. Engle, and T. Ito, "Do bulls and bears move across borders? International transmission of stock returns and volatility," *Review of Financial Studies*, vol. 7, no. 3, pp. 507–538, 1994.

[18] T. Bollerslev, "Generalized autoregressive conditional heteroskedasticity," *Journal of Econometrics*, vol. 31, pp. 307–327, 1986.

[19] F. X. Diebold and K. Yilmaz, "Measuring financial asset return and volatility spillovers, with application to global equity markets," *The Economic Journal*, vol. 119, no. 534, pp. 158–171, 2009.

[20] ——, "Better to give than to receive: Predictive directional measurement of volatility spillovers," *International Journal of Forecasting*, vol. 28, no. 1, pp. 57–66, 2012.

[21] L. Bauwens, S. Laurent, and J. V. K. Rombouts, "Multivariate GARCH models: a survey," *Journal of Applied Econometrics*, vol. 21, pp. 79–109, 2006.

[22] R. F. Engle and F. K. Kroner, "Multivariate simultaneous generalized ARCH," *Econometric Theory*, vol. 11, pp. 122–150, 1995.

[23] C. M. Hafner and H. Herwartz, “Volatility impulse responses for multivariate GARCH models: An exchange rate illustration,” *Journal of International Money and Finance*, vol. 25, no. 5, pp. 719–740, 2006.

[24] V. Candila and S. Farace, “On the volatility spillover between agricultural commodities and Latin American stock markets,” *Risks*, vol. 6, no. 4, pp. 1–16, 2018.

[25] S. H. Kang, H.-U. Ko, and S.-M. Yoon, “Contagion effects and volatility impulse responses between US and Asian stock markets,” *Korea and the World Economy*, vol. 18, no. 2, pp. 111–130, 2017.

[26] R. F. Engle, “New frontiers for ARCH models,” *Journal of Applied Econometrics*, vol. 17, pp. 425–446, 2002.

[27] R. F. Engle and G. M. Gallo, “A multiple indicators model for volatility using intra-daily data,” *Journal of Econometrics*, vol. 131, pp. 3–27, 2006.

[28] C.-L. Chang and M. McAleer, “A simple test for causality in volatility,” *Econometrics*, vol. 5, no. 1, pp. 1–5, 2017.

[29] J. Chevallier and F. Ielpo, “Cross-market linkages between commodities, stocks and bonds,” *Applied Economics Letters*, vol. 20, no. 10, pp. 1008–1018, 2013.

[30] I. Bapna, V. Sood, N. K. Totala, and H. S. Saluja, “Dynamics of macroeconomic variables affecting price innovation in gold: a relationship analysis,” *Pacific Business Review International*, vol. 5, no. 1, pp. 1–10, 2012.

[31] E. Borensztein and C. M. Reinhart, “The macroeconomic determinants of commodity prices,” *IMF Staff Papers*, vol. 41, no. 2, pp. 236–261, 1994.

[32] F. X. Diebold and K. Yilmaz, “Macroeconomic volatility and stock market volatility, worldwide,” National Bureau of Economic Research, Working Paper 14269, 2008.

[33] R. F. Engle, E. Ghysels, and B. Sohn, “Stock market volatility and macroeconomic fundamentals,” *Review of Economics and Statistics*, vol. 95, no. 3, pp. 776–797, 2013.

[34] D. Mo, R. Gupta, B. Li, and T. Singh, "The macroeconomic determinants of commodity futures volatility: Evidence from Chinese and Indian markets," *Economic Modelling*, vol. 70, pp. 543–560, 2018.

[35] A. Amendola, V. Candila, and A. Scognamillo, "On the influence of US monetary policy on crude oil price volatility," *Empirical Economics*, vol. 52, no. 1, pp. 155–178, 2017.

[36] C. Conrad and K. Loch, "Anticipating long-term stock market volatility," *Journal of Applied Econometrics*, vol. 30, no. 7, pp. 1090–1114, 2015.

[37] H. Asgharian, C. Christiansen, and A. J. Hou, "Macro-finance determinants of the long-run stock–bond correlation: The DCC-MIDAS specification," *Journal of Financial Econometrics*, vol. 14, pp. 617–642, 2015.

[38] C. Conrad, K. Loch, and D. Rittler, "On the macroeconomic determinants of long-term volatilities and correlations in U.S. stock and crude oil markets," *Journal of Empirical Finance*, vol. 29, pp. 26–40, 2014.

[39] A. Amendola, V. Candila, and G. M. Gallo, "On the asymmetric impact of macro–variables on volatility," *Economic Modelling*, vol. 76, pp. 135–152, 2019.

[40] K. Sugimoto, T. Matsuki, and Y. Yoshida, "The global financial crisis: An analysis of the spillover effects on African stock markets," *Emerging Markets Review*, vol. 21, pp. 201–233, 2014.

[41] C. W. J. Granger, "Investigating causal relations by econometric models and cross-spectral methods," *Econometrica*, vol. 37, no. 3, pp. 424–438, 1969.

[42] T. Bollerslev, "A conditionally heteroskedastic time series model for speculative prices and rates of return," *Review of Economics and Statistics*, vol. 69, no. 3, pp. 542–547, 1987.

[43] P. R. Hartley, K. B. Medlock III, and J. E. Rosthal, "The relationship of natural gas to oil prices," *The Energy Journal*, vol. 29, no. 3, p. 47, 2008.

[44] J. A. Villar and F. L. Joutz, "The relationship between crude oil and natural gas prices," *Energy Information Administration, Office of Oil and Gas*, pp. 1–43, 2006.

[45] A. Rossen, “What are metal prices like? Co-movement, price cycles and long-run trends,” *Resources Policy*, vol. 45, pp. 255–276, 2015.

[46] M. Prokopczuk, A. Stancu, and L. Symeonidis, “The economic drivers of commodity market volatility,” *Journal of International Money and Finance*, vol. 98, pp. 1–13, 2019.

[47] B. Karali and O. A. Ramirez, “Macro determinants of volatility and volatility spillover in energy markets,” *Energy Economics*, vol. 46, pp. 413–421, 2014.

[48] B. Karali and G. J. Power, “Short- and Long-Run Determinants of Commodity Price Volatility,” *American Journal of Agricultural Economics*, vol. 95, no. 3, pp. 724–738, 2013.

[49] M. E. Slade and H. Thille, “Commodity spot prices: An exploratory assessment of market structure and forward-trading effects,” *Economica*, vol. 73, no. 290, pp. 229–256, 2006.

[50] F. X. Diebold and R. S. Mariano, “Comparing predictive accuracy,” *Journal of Business & Economic Statistics*, vol. 13, no. 3, pp. 253–263, 1995.

[51] R. F. Engle, “Autoregressive conditional heteroscedasticity with estimates of the variance of United Kingdom inflation,” *Econometrica*, vol. 50, pp. 987–1007, 1982.