The Impact of the Subprime crisis and The European Debt crisis on the mean and the Volatility Spillovers between the Commodity Market and Moroccan Exchange Rates

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Abstract

This study examined the impact of the Subprime crisis and the European Debt crisis on the mean and the volatility shock transmission between commodity market (Standard & Poor's Goldman Sachs Commodity Index) and Moroccan Exchange rates (Euro to Moroccan Dirham, and United States dollar to Moroccan Dirham). We used daily returns from 15 October 2005 until 31 December 2014 as the primary sample. Then we divided this sample into four subsamples, (after & before) the subprime crisis, and (before & after) the debt crisis. To investigate the changes in the mean and volatility spillovers among Standard & Poor's Goldman Sachs Commodity Index, Euro to Moroccan Dirham Exchange rate, and United States dollar to Moroccan Dirham Exchange rate. We used bivariate Generalized Autoregressive Conditional Heteroscedasticity models as diagonal VECH, diagonal BEKK, and Constant Conditional Correlation model. The empirical results indicated that after the subprime crisis, the relationship between Standard & Poor's Goldman Sachs Commodity Index and United States dollar to Moroccan Dirham Exchange rate is weakened in mean spillovers. Besides, the results also suggested that the relationship between Euro to Moroccan Dirham rates and Standard & Poor's Goldman Sachs Commodity Index grew stronger in terms of volatility transmission. However, after the European debt crisis, the linkage between Standard & Poor's Goldman Sachs Commodity Index and United States dollar to Moroccan Dirham grew more potent in both mean and volatility spillovers. With little budgetary space, especially for net oil importing nations like Morocco, a longer period of higher prices might lead to a scarcity of investments, forcing them to borrow. These results will be of use to the policy authorities in understanding how the movement of the commodity market can influence Moroccan exchange rates and how the occurrence of a crisis can change this influence.

Keywords: the Subprime Crisis; the Debt crisis; bivariate GARCH models; mean and volatility spillovers; Commodity market; Exchange rates

JEL classification: C32; F31; G38

INTRODUCTION

International financial markets are more connected than ever before, because of economic globalization and the growing trend of financial integration. Many writers (Bekaert & Harvey, 1997) have claimed that economic system openness can improve international financial linkages and stock market correlation. Strong linkages between various markets across the world can minimize local market isolation, improve the capacity to respond quickly to news from other markets, and reduce the advantage of international diversity, particularly during times of crisis.

Morocco has historically been a net importer of coal, oil, natural gas, and electricity, to the point that the country's energy industry is dominated by fossil fuels, which account for virtually all of the country's primary energy consumption in 2018 (oil 60.2 percent, coal 24 percent, and gas 4.5 percent)[1]. Morocco is also a key source of minerals, particularly phosphates, since it has an estimated 77 percent of the world's total phosphate deposits and is the world's largest exporter[2]. Actually, Morocco has begun to adjust its currency liberalization strategy. Thus, the study of the impact of the two different crises on the mean and volatility spillovers between Moroccan Exchange rates and a general commodity index is crucial.

The mean and volatility choc transmissions between the currency and commodities markets have been the subject of several research. For example, (Antonakakis, Nikolaos & Kizys, Renatas, 2015) investigates the spillover relationship between gold, silver, platinum, and the CHF/USD and GBP/USD exchange rates. (Katusiime, 2018) studied at the spillover effects between oil prices, food prices, and the UGX/USD exchange rate, and both studies found that the global financial crisis had an impact on the spillover effects. However, there were a few gaps in the literature that we discovered. To begin with, there are no empirical studies showing the spillover impact between Moroccan exchange rates and worldwide commodity indexes. Second, (Antonakakis, Nikolaos & Kizys, Renatas, 2015) and Katusiime (2018) looked at the impact of the subprime mortgage crisis and considered a long sample (over 20 years). There is, however, no empirical study that looks at the immediate impact of both the subprime and European debt crises in the short term (1 year span). Such analysis would be crucial to investors,

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[1] Data and statistics - Morocco : Balances 2018, International Energy Agency
https://www.iea.org/data-and-statistics/data-tables?country=MOROCCO&energy=Balances&year=2018
[2] Oxford business group
https://oxfordbusinessgroup.com/overview/new-tricks-having-traditionally-relied-phosphates-industry-mining-sector-diversifying

government, financial institutions, and portfolio managers alike. It will enable them to design appropriate hedging strategies and devise market policies.

In a brief preview of our results, we find the nature of spillovers to differ across the subprime crisis and the debt crisis. The impact of the subprime crisis on the mean spillover has severed the influence of the lagged return of USD/MAD on the S&P GSCI returns. However, it strengthens the volatility spillover between EUR/MAD and S&P GSCI. In addition, The Debt Crisis boosts the mean and volatility spillovers between USD/MAD and S&P GSCI returns in both ways.

The rest of the paper is organized as follows. Section 1 a brief Literature Review, Section 2 represent the Econometric Methodology in this paper, Section 3 shows and analyzes the empirical findings, and Section 4 summarizes the study and concludes with some general remarks.

I.   Literature Review

The literature comprises many alternative frameworks of ARCH and GARCH models (Bollerslev, 1986, 1990; Bollerslev, Engle and Wooldridge, 1988; Engle & Kroner, 1995; Engle et al., 1987; Engle, 1982, 2002; Glosten et al., 1993). GARCH models are now commonly used to model and analyze changes in the volatility of financial assets (Choudhry, 1996; Hamao et al., 1990; Kanas, 1998; Lin et al., 1994; Ng, 2000; Susmel & Engle, 1994). As a result, a growing body of empirical literature studies the transmission of mean and volatility. Most researchers find that:

1.   Significant co-movements are observed in world stock markets

2.   Returns, correlations, and volatility spillovers across stock markets rise in times of financial crisis

The empirical literature on the mean and the volatility spillovers primarily began by examining spillovers across markets trading the same asset class. Indeed, much of the literature began with an analysis of exchange rate volatility following the events surrounding developments in the European Monetary System in the late 80s the early 90s (Artis & Taylor, 1988; Rose & Svensson, 1994). (Engle et al., 1990) addresses The possible transmission of volatility between markets. He uses daily observations on US dollar exchange rates and finds evidence of volatility spillovers across different market locations. (Laopodis, 1998) reports significant volatility spillovers among a range of Deutschemark exchange rates before

Germany's reunification while also noting asymmetric spillover effects, whereby a bad news spillover has a more significant impact than a comparable good news one.

Following the analysis of exchange rate spillovers, researchers examined stock markets for the presence of similar effects. (Bonfiglioli & Favero, 2005) detect no long-term interdependence between German and US stock markets; however, short-term fluctuations of US share prices spillover to German ones. (Caporale et al., 2006) find evidence of volatility spillovers in all cases for US, European, Japanese, and Southeast Asian daily stock market returns. In turn, (Beirne et al., 2013) identify volatility spillovers from mature to emerging stock markets. Besides, researchers focused on analyzing volatility transmission between emerging markets concerning the increase in their degree of financial integration after the liberalization process (Bensafta & Samedo, 2011; Karolyi, 1995; Kearney, 2000; Leachman & Francis, 1996).

A characteristic expansion is to analyze the relationship between stock returns and exchange rates with early examinations (Smith 1992). (Kanas, 2000) examinations interdependencies between exchange rate and stock return volatilities for six industrialized nations. Proof of such spillovers emerging from stock return to stock return to exchange rate return variations is reported in five countries (the US, the UK, Japan, France, and Canada, the leading case being Germany).

Regarding commodity markets, a significant part of the literature analyses the oil market. (Huang et al., 1996; Jones & Kaul, 1996), they are the first to study The connection between oil value shocks and financial markets. The outcomes from this exploration show that oil value shocks influence stock returns over a scope of markets, including the US, Canada, the UK, and Japan. Also, (Park & Ratti, 2008) report a significant impact of oil value shocks on stock returns for the US and 13 European nations.

Nandelenga and Simpasa (2020) investigate the dependency between oil price and exchange rate for two group of emerging countries, net exporters: Nigeria, Angola, Ghana, Algeria, Venezuela, Brazil, Mexico, Argentina and Saudi Arabia, and net importers: Mozambique, Kenya, Egypt, Zambia, South Africa, Botswana, Thailand, Malaysia, Poland, New Zealand, South Korea. Their findings demonstrate that heterogeneous dependence exists for both net oil exporters and net oil importers, as well as for different types of currency rates and nation classifications. Their findings also demonstrate that following the global financial crisis, a rise (reduction) in oil prices in a net oil exporting (importing) nation is related with an

appreciation (depreciation) of the domestic currency versus the US dollar, as well as a considerable increase in dependency. There is no empirical study that examines the influence of various crises on the return and volatility spillovers between the commodities market and Moroccan exchange rates. Thus, this is where we want to contribute.

II.   Econometric Methodology

We began with the ARCH LM Test to justify the model choice to examine the impact of the Subprime Crisis and the European Debt crisis on the return and volatility spillovers between the commodity market and Moroccan Exchange rate. Then we identify breaking dates using a uni root test with a breakpoint. We constructed specific models for each sample. Finally, we conducted Portmanteau Test on residuals for residual diagnostics and Wald Test to check spillover effects.

2.1.   Unit Root Testing with a Breakpoint

(Perron, 1989) considered four models for data with a one-time break. For non-trending data, we have a model with (O) a one-time change in level; for trending data, let model (A) represent a change in level, model (B) a change in trend and level, and model (C) a change in trend.

In addition, he considers two versions of the four models which differ in their treatment of the break dynamics: the innovational outlier (IO) model assumes that the break materializes gradually, with the breaks following the same dynamics as the innovations, while the additive outlier (AO) model suppose the breaks happen instantly. the null Hypothesis of The tests proposed here evaluate that the data follow a unit root process, possibly with a break, versus a trend stationary with break alternative

In our case of study, we will only test for a one-time break in both level and trend for trending data, and with both versions, the innovational outlier (IO) and the additive outlier (AO)

2.2.   Conditional Mean, Covariance, and Variance Equations

To examine the mean and volatility spillovers between the commodity market and the Moroccan Exchange rate, we utilize three multivariate VAR-GARCH models. Namely, VAR-DBEKK, developed by (Engle & Kroner, 1995), permits the explicit and dynamic parameterization of conditional covariances. It reduces the number of parameters computed by restricting the parameter matrices to be diagonal and reducing the difficulty with VECH by

ensuring that the conditional covariance matrix is always positive definite. The second models are VAR-DVEC developed by (Bollerslev, Engle, and Wooldridge, 1988) because the unrestricted VECH model, in the simplest case of two assets, contain 21 parameters. Estimating the unrestricted VECH model can quickly become infeasible as the number of assets employed in the model increases. The third models are the VAR-CCC models, known as The constant correlation model developed by (Bollerslev, 1990), in which the conditional correlations are constant. Thus, the conditional covariance are proportional to the product of the corresponding conditional standard deviations. We have also chosen these models, because in general, the generalized autoregressive conditional heteroscedasticity (GARCH) has been employed in a number of empirical work (Wu et al., 2012). The GARCH model accounts for volatility spillover and nonlinearities, empirical results have demonstrated that the dependence between oil price and exchange rate may be characterized by a nonlinear and asymmetric relationship.

Let $r_t = (r_{1t},...,r_{Nt})'$ be a vector of returns of N number of assets at time index t = (1, 2,…, T) The set of information available at time t is denoted by $\mathfrak{I}_t$ We assume that the dynamic multivariate assets return r_t can be adequately represented by a vector autoregression of order p conditional on the information set $\mathfrak{I}_{t-1}$ as:

$$r_t | \mathfrak{I}_{t-1} = \Phi_0 + \sum_{l=1}^{p} \Phi(l) r_{t-l} + \varepsilon_t \quad \textbf{(1)}$$

Where, $E(r_t | \mathfrak{I}_{t-1}) = \Phi_0 + \sum_{l=1}^{p} \Phi(l) r_{t-l} = \mu_t$ and $\Phi(l) = (\Phi_{ij}(l))$ is The N x N coefficient matrix of the lagged dependent variable of the mean model. The N × 1 intercept vector is denoted by Φ_0 and $\varepsilon_t | \mathfrak{I}_{t-1} = H_t^{0.5} \zeta_t$, where $\zeta_t = (\zeta_{1t},...,\zeta_{Nt})'$ is the independent and identically distributed (iid) random vectors of order N × 1 with $E(\zeta_t) = 0$ and $E(\zeta_t \zeta_t') = I_N$ where I_N is an Identity matrix of order N × N. The symmetric conditional variance-covariance matrix H_t of order N × N is defined as follows:

$$H_t = E(\varepsilon_t \varepsilon_t' | \mathfrak{I}_{t-1}) = E\left[(r_t - E(r_t))(r_t - E(r_t))' | \mathfrak{I}_{t-1} \right] \quad \textbf{(2)}$$

Model (1) with (2) can be written more compactly as $r_t | \mathfrak{I}_{t-1} \sim D(\mu_t, H_t)$, where $D(.,.)$ is some specified probability distribution. Or, equivalently as $\varepsilon_t | \mathfrak{I}_{t-1} \sim D(0, H_t)$. Various parameterizations for H_t have been proposed in the literature, for example, (Bollerslev et al.,

1988), (Engle, 2002) and (Tse & Tusi, 2012), among others. Therefore, our model of return and volatility of returns takes the following form.

- **Return Equations**

$$r_t|\Im_{t-1} = \Phi_0 + \sum_{l=1}^{p} \Phi(l)r_{t-l} + \varepsilon_t, \ \varepsilon_t \mid \Im_{t-1} \sim D(0, H_t) \quad \textbf{(3)}$$

Where Φ_0 is the intercept vector and $\Phi(l)$ is the coefficient matrix of the auto regression of lag order l for the mean Equation.

In our case of study, the Return Equation (3) becomes:

$$\begin{pmatrix} r_{i,t} \\ r_{j,t} \end{pmatrix}_{|\Im_{t-1}} = \begin{pmatrix} \Phi_{0,i} \\ \Phi_{0,j} \end{pmatrix} + \sum_{l=1}^{p} \begin{pmatrix} \Phi_{i,i}(l) & \Phi_{i,j}(l) \\ \Phi_{j,i}(l) & \Phi_{j,j}(l) \end{pmatrix} \begin{pmatrix} r_{i,t-l} \\ r_{j,t-l} \end{pmatrix} + \begin{pmatrix} \varepsilon_{i,t} \\ \varepsilon_{j,t} \end{pmatrix} \quad \textbf{(4)}$$

Let :

$$\Phi_{1,1}(l) = \phi_1(l) + \alpha(l)$$
$$\Phi_{i,i}(l) = \phi_i(l) + \alpha(l)$$
$$\Phi_{1,i}(l) = \phi_i(l)$$
$$\Phi_{i,1}(l) = \phi_1(l)$$

Eq (4) Becomes:

$$\begin{pmatrix} r_{i,t} \\ r_{j,t} \end{pmatrix}_{|\Im_{t-1}} = \begin{pmatrix} \Phi_{0,i} \\ \Phi_{0,j} \end{pmatrix} + \sum_{l=1}^{p} \begin{pmatrix} \phi_1(l) + \alpha(l) & \phi_i(l) \\ \phi_1(l) & \phi_i(l) + \alpha(l) \end{pmatrix} \begin{pmatrix} r_{i,t-l} \\ r_{j,t-l} \end{pmatrix} + \begin{pmatrix} \varepsilon_{i,t} \\ \varepsilon_{j,t} \end{pmatrix} \textbf{(5)}$$

Where 1 refers to S&P GSCI, (2) refers to EUR/MAD, 3 to USD/MAD, and i = 2; 3

Note: *for S& P GSCI-EUR/MAD during Sample 3. We will use Eq(5) to model* $(dr_{1,t}, dr_{2,t})$ *instead of* $(r_{1,t}, r_{2,t})$ *where* $dr_{i,t} = r_{i,t} - r_{i,t-1}$

- **DBEKK Variance Covariance model:**

$$H_t \mid \Im_{t-1} = MM' + A\varepsilon_{t-1}\varepsilon'_{t-1}A' + BH_{t-1}B' \quad \textbf{(6)}$$

M is a N × N lower triangular matrix such that MM' is a symmetric and positive definite matrix containing the intercepts parameters of the conditional volatility model (6). The matrices $A = (A_{ij})$, $B = (B_{ij})$ for i,j=1,2,…,N are each N × N matrices of short-run and long-run weight parameters, respectively. Model (6) is generally known as the Full BEKK model (Engle & Kroner, 1995).

In model (6), if the matrices A and B are diagonal, we get a diagonal BEKK (DBEKK). We will treat model (6) as the DBEKK model with diagonal A and B matrices. So model (6) is our DBEKK model of conditional volatility.

- **DVEC Variance-Covariance Model:**

Suppose $\varepsilon_t = (\varepsilon_{1t},...,\varepsilon_{Nt})$ such that $E(\varepsilon_t) = 0$ and $E(\varepsilon_t \varepsilon_t' \mid \Im_{t-1}) = H_t$ where H_t is positive definite and $\varepsilon_t = H_t^{0.5} \zeta_t$ with $\zeta_t \sim i.i.d.(0, I_N)$. $\Im_{t-1}$ Contains past market information up to time t − 1. The conditional variance equation (VECH model), as suggested by (Bollerslev et al., 1988) is defined as:

$$vech(H_t) = C + \sum_{k=1}^{q} A_k vech(\varepsilon_{t-k} \varepsilon_{t-k}') + \sum_{k=1}^{p} B_k vech(H_{t-k}) \quad \text{(7)}$$

where each denotes the half vectorization operator. The $A_k = (A_{ij,k})$ and $B_k = (B_{ij,k})$ are coefficient matrices with N(N + 1)/2 are coefficient matrices with C is an (N(N + 1)/2) × 1 intercept vector with positive elements. In the VECH specification, every conditional variance and covariance is a linear function of all previous conditional variance and covariance (Terasvirta, Tjostheim & Granger, 2010). The DVECH(1,1) model is given by:

$$H_t = C + A \circ (\varepsilon_{t-1} \varepsilon_{t-1}') + B \circ H_{t-1} \quad \text{(8)}$$

With ∘ as he Hadamard product. The C, A, and B are N × N symmetric matrices, and It assumes that A and B in Eq(8) are diagonal. The Equation can be written as:

$$h_{ij,t} = c_{ij} + A_{ij} \varepsilon_{i,t-1} \varepsilon_{j,t-1} + B_{ij} h_{ij,t-1} \quad \text{(9)}$$

- **CCC Variance-Covariance model:**

The constant correlation model is derived by (Bollerslev, 1990) in which the conditional correlations are constant. Thus the conditional covariances are proportional to the product of

the corresponding conditional standard deviations. The Conditional Variance-Covariance Equations are given by:

For i=1,…,N

$$h_{ii,t} = c_i + A_i \varepsilon_{i,t-1}^2 + B_i h_{ii,t-1} \quad \textbf{(10)}$$

For i≠j and i,j=1,2,…,N

$$h_{ij,t} = \rho_{ij} \sqrt{h_{ii,t} h_{jj,t}} \quad \textbf{(11)}$$

Where $\varepsilon_t = (\varepsilon_{1t},...,\varepsilon_{Nt})'$ such that $E(\varepsilon_t) = 0$ and $E(\varepsilon_t \varepsilon_t' \mid \mathfrak{I}_{t-1}) = H_t$, $\mathfrak{I}_{t-1}$ contains past market data up to time t − 1. Note that the conditional covariance matrix $H_t = (h_{ij,t})$ is almost surely positive for all t. c_i, A_i, B_i, and ρ_{ij} the (CCC) parameters are estimated.

- **Estimation Method**

The Conditional Mean-Variance system can be estimated jointly under the assumption of conditional normality. The parameters of the multivariate VAR-GARCH models of any of the above specifications can be estimated by maximizing the log-likelihood function.

$$l(\theta) = -\frac{TN}{2} \log(2\Pi) - \frac{1}{2} \sum_{t=1}^{T} (\log |H_t| + \varepsilon_t' H_t^{-1} \varepsilon_t) \quad \textbf{(12)}$$

Where θ denotes all the unknown parameters to be estimated, N is the number of assets and T is the number of observations and all other notation is as above. The maximum-likelihood estimate θ is asymptotically normal, and thus traditional procedures for statistical inference are applicable.

2.3. Residual Diagnostic

(Box & Pierce, 1970) portmanteau statistics have been used as the benchmark for detecting model inadequacy in multivariate conditional heteroscedasticity models. This Test is based on cross products of the standardized residuals often provides a useful diagnostic.

Denoting $\hat{\varepsilon}_t = (\hat{\varepsilon}_{t1},...,\hat{\varepsilon}_{tk})'$ and the elements of $\hat{\sum}_t$ by $\hat{\sigma}_{ij,t}$, we define i-th standardized residuals at time t as

$$\tau_{it} = \frac{\hat{\varepsilon}_{it}}{\sqrt{\hat{\sigma}_{iit}}}$$

Let $\hat{\rho}_{ij,t}$ be the estimated conditional correlation coefficient defined by $\hat{\rho}_{ij,t} = \frac{\hat{\sigma}_{ijt}}{\sqrt{\hat{\sigma}_{iit}\hat{\sigma}_{jjt}}}$; we consider $C_{ij,t}$ defined by

$$C_{ij,t} = \begin{cases} \tau_{it}^2 - 1 & i = j \\ \tau_{it}\tau_{jt} & i \neq j \end{cases}$$

For i,j=1,2,…,k When the constant-correlation or the no-correlation models are estimated $\hat{\rho}_{ij,t}$, is a constant with respect to t. Under correct model specification, $C_{ij,t}$ is asymptotically serially uncorrelated and $E(C_{ij,t} | \Phi_{t-1}) \to 0$ as $n \to \infty$. Thus, a diagnostic can be constructed based on the Box-Pierce statistic of the squared lag autocorrelation coefficient $C_{ij,t}$. Specifically, we denote r_{hij} as the lag-h autocorrelation coefficient of $C_{ij,t}$ and define

$$Q(i,j;m) = n\sum_{h=1}^{m} r_{hij}^2$$

If the multivariate conditional heteroscedasticity model fits the data, $C_{ij,t}$ should be serially uncorrelated for i and j. An excessive value of Q would suggest model inadequacy. The Test has been widely used in the empirical literature for diagnosing both univariate and multivariate conditional heteroscedasticity models (Tse et al., 1999).

2.4. Wald Test

This Test is based on unrestricted regression. The Wald statistic calculates how close the unrestricted estimates come to fulfilling the restrictions under the null Hypothesis. If the restrictions are true, then the unrestricted estimates should come close to fulfilling the restrictions.

Refer to Return Equation (5) in Section 2.2. To test Return Spillovers between Commodity Market and Moroccan Exchange Rate. The following hypotheses can be tested by using Wald Test:

- **Return Spillovers from S&P GSCI to EUR/MAD or from S&P GSCI to USD/MAD**

$$H_1^0 : \phi_1 = 0$$

- **Return Spillovers from EUR/MAD to S&P GSCI or from USD/MAD to S&P GSCI**

$$H_2^0 : \phi_i = 0$$

Refer to the multivariate volatility model for (N = 2) of Section 2.2. The following hypotheses are of interest to test the volatility spillover effects between commodity market and Moroccan Exchange Rate by Wald Test. The following hypotheses can be tested.

- **Volatility Spillovers between S&P GSCI and EUR/MAD or between S&P GSCI and USD/MAD**

H_3^0 (For DVEC model):A12 = B12 = 0

H_3^0 (For DBEKK model):A11 × A22 = B11 × B22 = 0

H_3^0 (For CCC model): $\rho_{12} = 0$

- **Spillovers between S&P GSCI and EUR/MAD or between S&P GSCI and USD/MAD**

$H_4^0 : H_1^0, H_2^0, H_3^0$ Are true

III.   Results and Discussions

3.1.   Data, Descriptive Statistics and Unit root test with break one point

- **Data**

We used the commodity index, the S&P GSCI, and utilized the Exchange rates EUR/MAD & USD/MAD. We chose a general commodity index as Morocco has a range of natural resources; this includes oil, natural gas, although Morocco is a net importer of both. Moreover, Morocco produces a wide range of minerals, including phosphates, silver, gold, zinc, manganese, tungsten, tin titanium, zinc, antimony, iron, copper, and cobalt. The data is collected over the sample period from 15 October 2005 until 31 December 2014 from DataStream, giving 2589-time series observations. Continuously compounded daily returns are calculated based on the following logarithmic filter:

$$r_{i,t} = Ln(\frac{P_{i,t}}{P_{i,t-1}})$$

Where $r_{i,t}$ and $P_{i,t}$ represent percentage daily returns and opening index/exchange rate i prices at day t, respectively. To compensate for the missing data values in S&P CGSI is smoothened out by filling the missing data by the close price of the day before ($P_{i,t-1}(close)$).

- **Descriptive Statistics**

Table 1. Descriptive statistics from 15/10/2005 to 31/12/2014

Descriptive statistics	S&P GSCI returns	EUR/MAD returns	USD/MAD returns
Mean	0.011588	-0.000828	0.004626
Median	0.076670	0.000000	-0.003609
MAX	11.07047	3.393901	2.831520
MIN	-13.90054	-2.106613	-3.313822
Standard Deviation	1.534337	0.363574	0.490074
Skewness	-0.410634	0.342634	-0.139613
Kurtosis	9.028105	9.543665	6.756052
Jarque Berra	3992.727	4669.817	1530.304
(Prob.)	0.000000	0.000000	0.000000
Q(20)	54.287	137.72	71.374

(Prob.)	0.000	0.000	0.000
ADF Test	-55.16171	-62.16644	-57.13515
(Prob.)	0.0001	0.0001	0.0001
PP Test	-55.15562	-62.21278	-57.30871
(Prob.)	0.0001	0.0001	0.0001
ARCH LM Test F-stat	226.2592	120.7368	174.3409
(Prob.)	0.0000	0.0000	0.0000
ARCH LM Test Obs*R	208.2165	115.4404	163.4560
(Prob.)	0.0000	0.0000	0.0000

[a] Q(20) is the Ljung-Box for serial correlation in the residuals.

[b] The critical values for the ADF and PP test are -3.432 and -2.863, for 1% and 5%, respectively.

[c] to test the null Hypothesis of no ARCH effect up to order 9 in the residuals, we specified a regression of the squared residuals on a constant and lagged squared residuals up to 9.

The characteristics of our data set are presented in (Table 1). GSCI S&P offered on average the highest return (11.07%) compared to the two Exchange rates that were only provided (3.39% for EUR/MAD and 2.83% for USD/MAD). Besides, GSCI S&P showed comparatively higher risk (Std.Dev 1.534) than the Exchange rates (Std.Dev 0.363 for EUR/MAD and Std.Dev 0.490 for USD/MAD).

The results in (Table 1) also suggest the existence of non-normality and fat tails.

The Jarque-Bera Lagrange Multiplier Test rejected the null Hypothesis that the data were normally distributed.

The Ljung-Box statistics detected significant autocorrelation in all cases.

The stationarity of the return series is tested based on the ADF and PP unit root tests. The Null Hypothesis of a unit root is rejected, indicating that the return series under study are stationary processes. In addition, the LM test for ARCH effects is estimated to justify the choice of the GARCH model structure. The relevant F-statistics and Engle's LM tests were significant in all return series, supporting the presence of ARCH effects and the choice of GARCH as an appropriate model for this study.

- **Unit root test with break one point**

i. To identify both structural and tendency changes that occur gradually, we used the additive Outlier (AO) model. The results in (Table 2) showed that a structural change

occurred for both tendency and mean on 16 October 2008, which match approximately the Subprim's Crash

ii.   To identify both structural and tendency changes that occur immediately, we used The Innovational Outlier (IO) model. The results in (Table 2) show that a structural change occurred for both tendencies and mean on 05 September 2011, which match approximately with the European Debt Crisis.

Table 2. Unit Root Test with one Breakpoint for two versions AO & IO

	Test OutPut		
Versions	**Break Date**	**t-Statistic**	***Prob.***
Additive outlier	16 October 2008	-55.83523	< 0.01
Innovational Outlier	05 September 2011	-56.22589	< 0.01

- **Conclusion**

We wanted to study the immediate impact of those two crises on the spillover effect between commodity index S&P GSCI and the two exchanges EUR/MAD and USD/MAD. Thus, we have to split the data set into four samples (after & before) subprime crisis and (after & before) Greece crises (known as Debt Crisis).

1.   sample 1: From 16 October 2007 to 15 October 2008

2.   sample 2: From 16 October 2008 to 16 October 2009

3.   sample 3: From 05 September 2010 to 04 September 2011

4.   sample 4: From 05 September 2011 to 05 September 2012

3.2.   Discussion of the empirical results

As the study focuses on the impact of the subprime crisis & The European debt crisis on the mean and the volatility spillover effect between commodity market(S&P GSCI) and Moroccan Exchange Rate (EUR/MAD & USD/MAD), Eight VAR-GARCH bivariate models

were estimated using Eviews program version 10. Each model was calibrated with daily S&P GSCI returns and an Exchange Rate for the four samples.

3.2.1. *Impact of the Subprime crisis and The European debt crisis on the Mean and Volatility spillover between S&P GSCI and EURO/MAD*

- **Mean Spillovers**

   Table 3.   Coefficient estimation for the mean system (S&P GSCI– EUR/MAD)

	Samples			
Coefficients	Before Subprime	After Subprime	Before Debt crisis	After Debt crisis
$\Phi_{0,1}$	-0.116036	0.117972	-0.015580	0.019190
$\Phi_{0,2}$	0.023326*	0.013058	-0.004973	-
$\alpha(1)$	-0.144385***	-	-0.719402***	-0.014163
$\alpha(2)$	0.073954**	-	-0.641814***	0.121579**
$\alpha(3)$	-	-	-0.396467***	-0.155544***
$\alpha(4)$	-	-	-0.218179***	-
$\varphi_1(1)$	0.020374***	0.020308***	-	-0.005129
$\varphi_2(1)$	-0.302766***	-0.327927***	-0.429737***	-0.500089***
$\varphi_2(2)$	-0.181777***	-	-	-0.289451***
$\varphi_2(6)$	-	-	0.040822	-

[a] *significant at the level of 10%, **significant at the level of 5%, ***significant at the level of 1%

For own mean spillovers, The results from (Table 3) showed that($\varphi1(1)$, $\varphi2(1)$, $\varphi2(2)$, $\alpha(1)$ and $\alpha(2)$) were statistically significant, suggesting that both S&P GSCI and EUR/MAD returns before Subprime crisis depended on their first and second lags, however, after the Subprime crisis, they only depended on their first lag, since only ($\varphi1(1)$ and $\varphi2(1)$)were statistically significant.

Also, the results showed that before the Debt crisis, the Equation (dr1,t-dr2,t) depended on its first four lags ((1) refers to S& P GSCI and (2) refers to EUR/MAD) since ($\alpha(1)$, $\alpha(2)$,

α(3), α(4) and φ2(1)) were statistically significant. Moreover, the results from Table 3 also indicated that after the Debt crisis, both S&P GSCI and EUR/MAD returns depended on their tree first lags since (α(2), α(3), φ2(1) and φ2(2)) were statistically significant.

For cross-mean spillovers, the results from Table 3 indicated that before the Subprime crisis, EUR/MAD returns were influenced by S&P GSCI return's first lag since (φ1(1)) was statistically significant. However, S&P GSCI returns were influenced by EUR/MAD return's first and second lags since (φ2(1) and φ2(2)) were both statistically significant. Besides, after the Subprime Crisis, the cross means spillovers were still relatively the same as before, Indicating that the Subprime crisis did not impact cross-mean shock transmission.

The results from (Table 3) also indicated that Before the Debt crisis, S&P GSCI returns were influenced by EUR/MAD return's first lag since (φ2(1)) was the only statistically significant parameter. Also, after the Debt crisis, the results showed that (φ2(1) and φ2(2)) were statistically, meaning that the European Debt crisis did not have a significant impact on the cross mean spillovers between S&P GSCI and EUR/MAD.

- **Volatility Spillover**

Table 4. Coefficient estimation for the volatility models (S&P GSCI-EUR/MAD)

Coefficients	Samples			
	Before Subprime	After Subprime	Before Debt Crisis	After Debt Crisis
Model Type	DVEC	DVEC	DVEC	DVEC
C_{11}	-0.036299***	-0.009872	0.870467**	0.044792
C_{12}	0.051048*	-0.002216**	0.074423	0.011398*
C_{22}	0.045239***	0.000334	0.036079**	0.040593
A_{11}	-0.023084	0.023251**	0.213781*	0.057830*
A_{12}	-0.078592	-0.017839***	0.201113**	0.087842**
A_{22}	1.043652***	-0.034944***	0.139028**	-0.051738

B_{11}	1.041258***	0.973930***	0.433995*	0.902635***
B_{12}	0.466000	1.033934***	-0.365902	0.722221***
B_{22}	-0.062758	1.027969***	0.302912	0.085039
Log Likelihood	-562.8677	-589.8459	-422.1217	-332.4781
Avg. Log Lh	-1.090829	-1.129973	-0.917656	-0.644337

[a] *significant at the level of 10%, **significant at the level of 5%, ***significant at the level of 1%

For own-volatility spillovers (ARCH effects) before the Subprime crisis, only A22 was statistically significant, suggesting that EUR/MAD returns were influenced by its past errors. However, after the Subprime crisis, A11 and A22 were statistically significant, suggesting that both EUR/MAD and S&P GSCI returns were influenced by their past errors (see Table 4).

Table 4 also showed that Before the Debt crisis, A11 and A22 were still both statistically significant. However, only A11 was still significant after the Debt crisis, suggesting that only S&P GSCI was influenced by its past errors. We can safely assume that the Debt crisis reduced EUR/MAD past errors influences.

As for cross-volatility effects for all the periods except for the sample before the subprime, A12 was statistically significant, suggesting that both markets were influenced by the past innovations of the other market (see Table 4), and we can safely assume that the subprime crisis strengthened cross volatility link between S&P GSCI and EUR/MAD. Nevertheless, The Debt crisis did not affect this link between S&P GSCI and EUR/MAD

The Lagged own-volatility persistence (GARCH effects) before the Subprime crisis, only B11 was statistically significant, indicating that only S&P GSCI returns were influenced by its own lagged volatility. Moreover, after the Subprime crisis, B11 and B22 were significant, suggesting that both S&P GSCI returns and EUR/MAD returns were influenced by their own lagged volatility (see Table 4).

Table 4 also indicated that Before the Debt crisis (B11 = 0.433995) was statistically significant at 10%. However, after the Debt crisis (B11 = 0.902635) was statistically significant at 1%, which means that the Debt crisis caused an increase in S&P GSCI's own volatility persistence.

For the cross-volatility persistence, before the Subprime crisis and before the Debt crisis, The results from Table 4 showed that there was no volatility shock transmission between S&P GSCI and EUR/MAD since B12 was not significant during those two periods. However,

after the Subprime crisis and after the Debt crisis, B12 became statistically significant, indicating a volatility shock transmission between these two markets. Thus, we can safely assume that these two crises caused a short-term increase in Linkage between S&P GSCI and EUR/MAD regarding cross volatility persistence.

3.2.2. *Impact of the Subprime crisis and European Debt crisis on Mean and Volatility spillover* between S&P GSCI and USD/MAD

- **Mean Spillover**

Table 5.   Coefficient estimation for the mean systems (S&P GSCI USD/MAD)

Coefficients	Samples			
	Before Subprime	After Subprime	Before debt crisis	After debt crisis
$\Phi_{0,1}$	0.026540	0.142622	0.187926**	0.000334
$\Phi_{0,3}$	-0.014606	-0.064174	-0.035740	0.015874
$\alpha(1)$	-0.050927***	-	-	-0.096370**
$\varphi_1(1)$	-0.095178***	-0.048235***	-	-
$\varphi_1(4)$	-	-	-	0.053696***
$\varphi_3(1)$	-0.192520***	-	-	-
$\varphi_3(2)$	-	-	-	-0.063918
$\varphi_3(5)$	-	-	-	0.090588**
$\varphi_3(8)$	-	-	-	-0.098490**

a *significant at the level of 10%, **significant at the level of 5%, ***significant at the level of 1%

For the own mean spillovers, The results from Table 5 showed that before the Subprime crisis, ($\alpha(1)$, $\varphi_1(1)$, and $\varphi_3(1)$) were statistically significant, Indicating that both S&P GSCI and USD/MAD returns depended on their first lags. However, after the Subprime crisis, only S&P GSCI return depended on its first lag since $\varphi_1(1)$ was significant.

The results also showed that before the Debt crisis, there were no own mean spillovers. However, after the Debt crisis, S&P GSCI returns depended on its first and firth lags, in addition, USD/MAD Exchange return depended on it first, fifth, and eight lags, since ($\alpha(1)$, $\varphi_1(4)$, $\varphi_3(5)$ and $\varphi_3(8)$) were statistically significant.

The cross-mean spillovers, the results from Table 5 showed that before the Subprime crisis, ($\varphi1(1)$ and $\varphi3(l)$) were statistically significant, indicating that there was a bi-directional link between S&P GSCI and USD/MAD returns in terms of the cross mean spillovers. However, after the Subprime crisis, USD/MAD returns were influenced by the first lag of S&P GSCI since ($\varphi1(l)$) is statistically significant.

The results also showed that before Debt Crisis, there were no cross-mean spillovers. However, after the Debt crisis, ($\varphi1(4)$) was statistically significant, indicating that the Fourth lag of S&P GSCI influenced USD/MAD returns, besides ($\varphi3(5)$ and $\varphi3(8)$) were also significant, indicating that S&P GSCI returns were influenced by the fifth and the eight lags of USD/MAD returns.

Overall, the two crises enhanced the link between the commodities market and Moroccan exchange rates. As a result, Moroccan exchange rates are becoming more integrated. This was in line with most research on the impact of the global financial crisis on interdependencies between commodities market and currency rate. The most recent article is written by Nandelenga and Simpasa(2020), they found that there is a significant increase in degree of dependence after the global financial crisis between crude Oil and emerging countries both net exporters and net importers of crude Oil. However, our study goes on to say that, various crises have distinct spillover consequences. The subprime crisis, for example, enhanced the correlation between EUR/MAD and commodity indexes, whereas the debt crisis strengthened the link between USD/MAD and commodities. The fact that investors, risk managers, and speculators prefer to swing between commodities and other exchange rates, except for the currency of the crisis cause, might explain these outcomes.

- **Volatility spillover**

Table 6. Coefficient estimation for the volatility models (S&P GSCI-USD/MAD)

Coefficients	Samples			
	Before Subprime	After Subprime	Before Debt Crisis	After Debt Crisis
Model Type	CCC	CCC	DBEKK	DVEC
C_{11}	-	-	0.677494**	0.064575
C_{12}	-	-	-0.240744	-0.009131**
C_{22}	-	-	0.370225**	-0.000957

A_{11}	-	-	0.394193***	0.009391
A_{12}	-	-	-	-0.024602***
A_{22}	-	-	-0.156380	-0.032671***
B_{11}	-	-	0.698154***	0.938988***
B_{12}	-	-	-	0.988794***
B_{22}	-	-	0.142643	1.030562***
C_1	0.025107*	-0.003682	-	-
C_2	0.001307	-0.004398*	-	-
A_1	-0.021616***	0.027980**	-	-
A_2	-0.036166**	0.012009	-	-
B_1	1.022706***	0.969620***	-	-
B_2	1.041923***	0.989830***	-	-
ρ_{12}	-0.353264***	-0.308848***	-	-
Log Likelihood	-741.7356	-883.2195	-626.7182	-558.0238
Avg.Lh	-1.426415	-1.691991	-1.300245	-1.098472

[a] *significant at the level of 10%, **significant at the level of 5%, ***significant at the level of 1%

[b] For DBEKK model let $C=MM'$

For own-volatility spillovers (ARCH effect), before the Subprime crisis, both S&P GSCI and USD/MAD Exchange returns were influenced by their past errors since A_1 and A_2 from the CCC model were both statistically significant. However, only A_1 from the CCC model was significant after the Subprime crisis, indicating that only S&P GSCI returns were influenced by their past errors (see Table 6).

The results from Table 6 Also showed that before the Debt crisis, A_{11} from the DBEKK model was statistically significant, indicating that only S&P GSCI returns were influenced by their past errors. In contrast, after the Debt crisis, A_{22} From DVEC Model became significant, suggesting that only USD/MAD Exchange returns were influenced by their past.

As for cross-volatility spillover effects, these effects were not captured before and after the Subprime crisis since S&P GSCI-USD/MAD in these periods were modeled by the CCC model.

Before the Debt crisis, these effects were captured by A11 × A22 since this period was modeled by the DBEKK model, where A11 was statistically significant while A22 was not. We conducted a Wald test (see Table 8), the results indicate that we could not reject A11 × A22 = 0, showing no cross volatility effects. However, after the Debt crisis, these effects are captured by A12 using the DVEC model, which was statistically significant, suggested that there were cross volatility spillovers (see Table 6).

As for The Lagged own-volatility persistence (GARCH effects), the results from Table 6 also showed that the Subprime crisis did not significantly impact these effects since B1 and B2 From the CCC model were statistically significant after and before the Subprime crisis. It also indicates that both S&P GSCI and USD/MAD were influenced by their own lagged volatility.

Before the Debt crisis, these effects were captured by B_{11}^2 and B_{22}^2 (see DBEKK parametrization). Table 6 also showed that only B_{11} was statistically significant, indicating that only S&P GSCI was influenced by its past volatility. Moreover, after the Debt crisis, these effects were captured by (B_{11} and B_{22}) from the DVEC model B_{11} . They were both statistically significant, indicating that both S&P GSCI and USD/MAD were influenced by their own lagged volatility.

For the cross-volatility persistence, the subprime crisis did not have a significant impact on these effects since ρ_{12} was statistically significant in both periods (before & after the Subprime crisis).

Before the Debt crisis, these effects were captured by B11 × B22 (see DBEKK parametrization). The results from Table 6 showed that B11 was statistically significant, but B22 was not. We conducted a Wald test to test H0: B11 x B22 = 0, and the results rejected the null Hypothesis, indicating no cross volatility persistence between S&P GSCI and USD/MAD. However, after the Debt crisis, these effects were captured by (B12) from DVEC Model, B12 was statistically significant, indicating that there was cross volatility persistence between S&P GSCI and USD/MAD.

Overall, the subprime crisis only reduced the Own volatility spillover for USD/MAD. Nevertheless, the Debt crisis had strengthened cross volatility and cross volatility persistence between S&P GSCI and USD/MAD.

3.3. Residual Diagnostic and Wald Test

Finally, the portmanteau Test using Standard Residuals showed no evidence of auto-correlation in the standardized residuals (Table 7 & 8). The conditional mean return equations were correctly specified, and Table 9 confirmed the spillover effects discussed above.

Table 7. Portmanteau Test using Standard Residuals for the system (S&P GSCI – EUR/MAD)

	Q-Stat for each Sample			
Lags	Before Subprime	After Subprime	Before Debt Crisis	After Debt Crisis
1	8.879*	4.876	5.732	7.841*
2	14.65*	10.41	9.556	8.914
3	18.45	10.60	16.91	11.37
4	21.51	11.68	22.59	13.90
5	27.72	18.38	30.19*	16.63
6	31.21	19.57	33.36*	18.57
7	32.57	21.71	37.18	21.65
8	33.72	25.52	42.06	24.37
9	41.22	30.87	44.79	28.48
10	43.55	34.82	45.74	32.18
11	45.63	37.16	48.37	34.67
12	48.74	40.73	50.81	38.20

[a] *significant at the level of 10%, **significant at the level of 5%, ***significant at the level of 1%

[b] The test is valid only for lags larger than the System lag order.

Table 8. Portmanteau Test using Standard Residuals for the system (S&P GSCI-USD/MAD)

| | Q-Stat for each Sample | | | |
Lags	Before Subprime	After Subprime	Before Debt Crisis	After Debt Crisis
1	0.957	0.977	1.898	3.491
2	2.407	2.923	3.337	8.169
3	6.244	4.326	6.179	12.97
4	12.05	7.373	7.527	14.96
5	14.71	14.96	9.057	19.90
6	16.48	18.06	11.37	22.67
7	18.02	20.87	15.52	27.32
8	19.14	26.79	19.49	29.13
9	24.30	29.37	20.78	32.00
10	27.95	30.66	22.17	33.00
11	31.31	31.67	24.14	36.82
12	35.38	34.13	28.28	39.50

[a] *significant at the level of 10%, **significant at the level of 5%, ***significant at the level of 1%

[b] The test is valid only for lags larger than the System lag order.

Table 9. Spillovers effects Testing by Wald test

Samples	Wald Tests			
	H_1^0	H_2^0	H_3^0	H_4^0
S&P GSCI-EUR/MAD B.S	14.103***	21.443***	-	46.52992***
S&P GSCI-EUR/MAD A.S	140.53***	1405.0***	4.43E+12***	4.53E+12***
S&P GSCI-EUR/MAD B.D	-	17.474***	8.419776**	34.11311***
S&P GSCI-EUR/MAD A.D	0.185351	58.297***	100.0154***	115.3517***
S&P GSCI-USD/MAD B.S	83.965***	13.429***	42.84801***	138.3896***
S&P GSCI-USD/MAD A.S	9.5045***	-	29.81686***	38.78979***
S&P GSCI-USD/MAD B.D	-	-	1.203926	1.203926
S&P GSCI-USD/MAD A.D	13833***	12.216***	6187.962***	32907.71***

[a]*significant at the level of 10%, **significant at the level of 5%, ***significant at the level of 1%
[h] B.S(Before the Subprime), A.S(After the Subprime), B.D(Before Debt Crisis), A.D(After Debt Crisis)

CONCLUSION

This study examines the impact of the Subprime crisis and the Debt crisis on the mean and volatility spillovers between S&P GSCI and both Exchange rates EUR/MAD and USD/MAD. Our empirical research is among the first to investigate the impact of those two crises on the relationship between an international commodity index and the Moroccan exchange rate. It provides a comprehensive analysis on the return and volatility behaviors among S&P GSCI, EUR/MAD, and USD/MAD Exchange rates, during the periods (before & after) Subprime crisis and (before & after) the European Debt crisis periods, using various newly developed multivariate econometric methods.

Mean Equation shows that before the Subprime crisis, S&P GSCI and the two Exchange rates are firmly linked, but, after the Subprime crisis, the influence of the USD/MAD exchange rate on the S&P GSCI is lost. It also shows that before the Debt crisis, the cross-market mean spillover became very weak, leaving only the influence of EUR/MAD on the S&P GSCI.

However, after the Debt crisis, the linkages among those markets grew more robust, leaving only S&P GSCI without influence on EUR/MAD exchange rate (see Table 9).

In conditional variance-covariance equations, before the Subprime crisis, there was no volatility spillover between S&P GSCI and EUR/MAD, but the volatility spillover between S&P GSCI and USD/MAD was significant. However, after the Subprime Crisis, the linkage between S&P GSCI and EUR/MAD grew more robust. However, the relationship between S&P GSCI and USD/MAD stayed relatively the same as before the Subprime crisis. this study also shows that Before the Debt crisis, there was no volatility spillover between USD/MAD and S&P GSCI, leaving only the relationship between EUR/MAD and S&P GSCI in terms of cross-market volatility spillover. However, after the Debt crisis, the volatility spillover between USD/MAD and S&P GSCI became significant (see Table 9).

The findings of these paper present interesting policy implications for both investors and policy makers in their optimization of monetary policies to control risks that originate from commodities or exchange rate fluctuations.

1- Importantly, policymakers should consider exchange rate regimes while formulating monetary policy.

2- The increased dependence, particularly following the global financial crisis, is an indication of Morocco's quicker recovery rate. As a result, investors should be encouraged to increase their investments in these nations since growth is projected to be stronger.

3- Commodities play a critical role in risk transmission between the two markets in terms of volatility, and there is evidence of bi-directional risk transfer.

To complement the current study, research on the influence of news events and small crises on the return and volatility transmissions between the commodities and currency markets,

in order to get a better understanding of the causes and effects of various news/crises. Then, based on the occurrences we could be able to forecast the influence on spillovers.

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