Mongi Arfaoui, Aymen Ben Rejeb

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Mongi Arfaoui[1]
Faculty of Economics and Management of Mahdia,University of Monastir, Tunisia

Aymen Ben Rejeb[2]
Faculty of Economics and Management of Mahdia,University of Monastir, Tunisia

Return Dynamics and Volatility Spillovers Between FOREX and Stock Markets in MENA Countries: What to Remember for Portfolio Choice?

Abstract

This article investigates the interdependence of stock-forex markets in MENA (Middle East and North Africa) countries for the February 26, 1999 to June 30, 2014 period. The analysis has been performed through three competing models: the VAR-CCC-GARCH model of Bollerslev [1990]; the VAR-BEKK-GARCH model of Engle and Kroner [1995]; and the VAR-DCC-GARCH model of Engle [2002]. Our findings confirm that both markets are interdependent and corroborate the stock and flow oriented approaches. We also find that, comparing to optimal weights, hedge ratios are typically low, denoting that hedging efficiency is quite good. Our estimation of hedging efficiency suggests that incorporating foreign exchange in a full stock, unhedged portfolio increases the risk-adjusted return while reducing its variance. (We note here that the forex market is overweighted for both portfolio allocations and hedging strategies.) Moreover, this conclusion holds for all countries in all three models.

Keywords: MENA markets, foreign exchange, flow-stock oriented model, volatility spillovers, portfolio allocations, hedging efficiency, VAR-GARCH model
JEL: F21, F31, G11, G15

Introduction

The current framework of liberalized capital flows, financial integration and sustained international diversification has led stocks and foreign exchange (forex) markets to become increasingly interdependent. For instance, stocks from a given country are bought in the local currency of that country, which fluctuates in value based on supply and demand. When the outlook for a particular stock market is highly positive, international funds flow in. When that stock market struggles, international investors seek alternative markets and withdraw their funds. Accordingly, a stronger stock market may cause local currency to rise in value, and a weak stock market may have the opposite effect. Consequently, strong stock markets strengthen and weak stock markets weaken local currency.

The forex market can also influence equity market. A weak national currency renders domestic exporters more competitive, which helps stimulate export growth. When the earnings (of listed companies) are growing, equity markets are likely to do well. Of course, this situation is most apparent in equity markets backed by major global currencies, such as the USD, EUR, JPY, GBP, etc. Forex markets have truly become a global market, larger than any security market. So, when thinking about the association between stock and forex markets, we actually have to think globally.

The aim of this article is to shed light on the interdependence mechanisms between stock and forex markets. We focus on linkages in return and volatility, to fashion a global analysis. We focus on global forex, as opposed to other financial, real or commodity markets because forex markets offer investors unique opportunities not found elsewhere. In particular, forex is always open, and offers long or short positions, low trading costs, unmatched liquidity, availability of leverage, international exposure, etc. We link forex to a set of emerging MENA stock markets (namely, Bahrain, Egypt, Kuwait, Morocco, the Kingdom of Saudi Arabia, Oman, Qatar and the United Arab Emirates) that have growing economic sectors with sustainable trade activities, technology transfer, and regional – as well as international – cooperation. Accordingly, the selected markets represent a wide range of economic sectors and emerging financial systems.

The econometric methodology used for the analysis is the VAR-GARCH approach of Ling and McAleer [2003]. We perform that analysis using three competing specifications: VAR-CCC-GARCH of Bollerslev [1990]; VAR-DCC-GARCH of Engle [2002]; and VAR-BEKK-GARCH of Engle and Kroner [1995]. A key advantage of these specifications is to permit the investigation of inter-markets return dynamics and conditional volatility spillovers. Additionally, the model meaningfully estimates the unknown parameters, which speak to innovations and shock transmission effects. It also allows us to detect forex market event outcomes on stock market returns, foreign market exchange returns, and forex-stock cross-market. On the whole, we pose, and answer, two questions: (1) are forex and stock markets interdependent in MENA countries? and (2) what lessons does this interdependency offer to international portfolio management?

Our three VAR-GARCH models investigate inter-markets correlations. We studied conditional correlations to obtain optimal weights, hedging ratios, and hedging efficiency for portfolio management purposes. The three models confirm the interdependence between stock and forex markets for mean and variance equations and support both, the stock-oriented approach of Branson et al. [1977] and the flow-oriented approach of Dornbusch and Fisher [1980].

For portfolio management, we find hedge ratios are relatively low, denoting that hedging efficiency is quite good. Our estimation of hedging effectiveness suggests that the incorporation of forex in a full stock portfolio increases risk-adjusted performance, while reducing variance. (We note here that the forex market is overweighed either for portfolio allocations or for hedging strategies.) Moreover, this conclusion holds for all countries in all three models.

This article differs from other studies in several aspects. First, a number of previous studies on interactions between these two markets' returns used co-integration and the Granger causality tests and, in some cases, incorporated the effect of exogenous economic and financial variables. Other recent studies on market interdependencies focus on both return and volatility spillover channels, using a simple VAR-GARCH specification model. We confirm that the cross-markets correlation of conditional shocks were absent insofar as the CCC for returns across markets was very weak and not statistically significant. At the same time, we find that the DCC model estimates are significant for examined periods, which does not empirically support the assumption of constant conditional correlations. This highlights the dynamic conditional correlations between the selected markets.

We run three competitive specifications to confirm our findings. We investigate MENA emerging markets that contribute to global economic growth. These economies are exporters (e.g., oil, manufactured products, minerals...) as well as importers (e.g., machinery, technology), meet international labor standards and have regular international money transfers. Oil exporting countries enjoy huge surpluses on trade balances, current accounts, and national incomes and have supportive fiscal policies. Furthermore, these countries are actively reforming and modernizing their economic and financial systems. We take an international investor perspective and run an implicit test of financial integration using Eurodollar parity as a proxy for the foreign exchange market, and do not account for local currency against a major global currency. Currency is often included as an asset in international diversified portfolios. So, the accurate variability of a given portfolio requires a successful estimate of the correlation between stock prices and exchange rates. Understanding the link between currency rates and other assets in a diversified portfolio is therefore fundamental. We therefore assess the managerial usefulness of our findings through an assessment of their effect on portfolio allocations and hedging efficiency.

Finally, the study allows stock and forex markets to be compared for managerial and governmental executive purposes.

The rest of the paper is organized as follows. Next section presents a brief literature review. The following sections outline the empirical methodology employed and describe the data and their statistical properties, and then discuss empirical results. Final sections present the implications of these results for portfolio management, and conclude the study.

Theory and Literature Review

According to empirical literature, international markets are interdependent through two channels, corporate cash-flows and the stock prices of listed companies. Classic economic theory likewise assumes that stock prices and foreign exchange rates can interact. This supports the following two approaches.

The first approach is the flow-oriented model [Dornbusch and Fisher, 1980], which suggests that movements in exchange rates cause movements in stock prices. In terms of causality terminology, it is uni-directional Granger causality. From a macroeconomic perspective, stock prices correspond to the present value of expected future cash flows. So, under the hypothesis of market efficiency, stock prices reflect any phenomenon affecting a firm's cash flow that is associated with changes in the value of the exchange rate. We note here that the growing use of hedging instruments, such as derivatives, is likely to shrink the shock of currency movements on firm earnings.

The second approach is the stock oriented or portfolio balance approach [Branson et al., 1977], which assumes that stock prices may affect exchange rates. In Granger terminology, stock price movements Granger-cause exchange rates behavior through capital account transactions. Consequently, stock and forex markets are bi-directionally interacting; but note that various factors- such as market liquidity, integration-segmentation level, market imperfection, and international trade are likely to boost or lessen this effect. Therefore, empirical analyses of the extent, depth and direction of interdependence between stock and forex markets suggest that the relationship should exist.

Studies by Aggarwal [1981], Soenen and Hennigar [1988] have adduced evidence in support of the flow model. Later studies show that market interdependence exists and is conducted through both return series and volatility innovations. For example, Eun and Shim [1989] showed that about26 percent of the error variance of stock returns could be explained by innovations in other stock markets. They reported that the US market was the most influential stock market. King and Wadhwani [1990] demonstrated the transmission of information across markets through volatility innovations, which resulted in a contagion effect. Chiang et al. [2000] suggested that national Asian stock market returns were positively associated with the value of the national currency. Likewise, Sabri [2004] focused on the increasing volatility and instability of emerging markets, and pointed out that stock trading volume and currency exchange rates were most positively correlated with emerging stock price changes. Kanas [2000] examined the interdependence of stock returns and exchange rate changes within the national economy in six developed countries (the USA, UK, Japan, Germany, France and Canada) and confirmed the existence of co-integration between stock and exchange markets. The author observed the evidence of spillover from stock returns to exchange rate changes for all countries except Germany, but not volatility spillovers from exchange rate changes to stock returns for all the countries. Conversely, Bodart and Reding [2001] examined the effect of exchange rates on expected industry returns and volatility, and showed that the effect of forex spillovers on stock markets existed but was quite small, and affirmed that exchange rate changes are influenced by the exchange rate regime, as well as the direction and magnitude of exchange market shocks. Nieh and Lee [2001],using both Engel-Granger and Johansen's co-integration tests, found no significant long-run relationship between stock prices and exchange rates in G7 countries. Bhattacharya and Mukherjee [2003] studied the causal relationship between exchange rates and the stock index in India, which indicated the absence of a causal relationship between that stock market index and exchange rates. More recently, Ramasamy and Yeung [2005], stipulated that the reason for the divergent empirical results is that the nature of the interaction between stock and currency markets is sensitive to business cycles and wider economic factors, as well as market and economic structures.

Pan et al. [2007], examined the relationship for seven East Asian countries for the 1988 to 1998 period, finding bidirectional causality for Hong Kong before the 1997 Asian crisis and a unidirectional causal relation from exchange markets to stock markets for Japan, Malaysia, and Thailand, but from stock markets to exchange markets for South Korea and Singapore. During the Asian crisis, only a causal relation from the exchange market to the stock market was observed for all countries, except Malaysia. At the same time Erbaykal and Okuyan [2007] focused on 13 developing economies using different time periods, and found a causality relationship for eight economies; that is, being unidirectional from stock markets to exchange markets in five cases, and bidirectional for the remaining three cases. Dilrukshan et al. [2009], demonstrated evidence of a positive co-integrating relationship in the Australian context, which corroborates the stock oriented approach; that is, stock market movements' caused forex market changes. At the same, Agrawal et al. [2010], found a negative correlation between fifty stock market returns and exchange rates, and highlighted a unidirectional Granger Causality relationship running from the former towards the latter, supporting the stock oriented approach. Other studies, finding more recently an absence of co-integration between stock prices and exchange rates include; Zubair [2013], Okpara and Odionye [2012], Zia and Rahman [2011] etc.

Overall, even though the theoretical explanation may seem understandable at times, empirical results have been mixed and the existing literature is inconclusive on the precise features of this interdependence. While empirical tests are plausible, they examine either the interdependence between return dynamics using return series, or the interdependence between volatility effects using conditional variances. We simultaneously run a VAR-GARCH model in three specifications to join the first and the second conditional moments and provide meaningful estimates of the unknown parameters.

The Methodology

We define interdependence as the evidence of movements of information flows between markets which get their delivery from correlation in second moments (volatility spillovers) rather than through correlation in the first moment (return dynamics). The better proxy for information is conditional volatility [Clark, 1973; Tauchen and Pitts, 1983; Ross 1983]. However, in our analytical framework, we test the interdependence between stocks and forex markets, and focus on the possible feedback. Accordingly, we consider a heteroscedastic, autoregressive specification appropriate for this research.

We make use of the VAR-GARCH model, of Ling and McAleer [2003] which has been applied by Chan et al. [2005, 2011] and Hammoudeh et al. [2009], Arouri et al. [2012], Mensi et al. [2014] for miscellaneous economic topics, to explore the interdependence between various markets. The conditional mean equation and the conditional variance equation in the multivariate framework are presented separately. The former describes the return channel spillover, while the latter is considered for the variance spillover with three competitive models: the CCC-, the DCC- and the BEKK-GARCH(1,1).

The Conditional Mean Equation

The return dynamics is represented by a var (1) model as follows:

$$Y_t = c + \Phi Y_{t-1} + \varepsilon_t \qquad \text{(Eq. 1)}$$

Where,

- $Y_t = \left(r_t^S, r_t^{FX}\right)'$. r_t^S and r_t^{FX} are the logarithmic returns on stock market return indices and returns on foreign exchange indices at time t, respectively. Foreign exchange indices are the Eurodollar parity;
- Φ is (2 x 2) matrix of coefficients to be estimated of the form $\Phi = \begin{pmatrix} \Phi_{11} & \Phi_{21} \\ \Phi_{12} & \Phi_{22} \end{pmatrix}$;
- the coefficients ϕ_{11} and ϕ_{22} provide the measure of own-mean spillovers, while the coefficients ϕ_{21} and ϕ_{12} measure the cross-mean spillovers.
- $\varepsilon_t = \left(\varepsilon_t^S, \varepsilon_t^{FX}\right)'$, ε_t^S and ε_t^{FX} are, respectively, the residuals of the mean equations for stock and forex returns. They are assumed to be serially uncorrelated but with non-nul covariances $(E(\varepsilon_t^S \varepsilon_t^{FX}) \neq 0)$.

The Conditional Variance Equation

The dynamics of conditional volatility is modeled by three MV-GARCH class models. The first model includes the multivariate CCC-GARCH developed by Bollerslev [1990] which allows estimations and conclusions about conditional volatility and conditional correlation. The second specification is the DCC-GARCH model introduced by Engle [2002], as a generalization of the CCC model, which permits different perspectives of correlation to be obtained through modeling wide variance-covariance matrices and time-varying cross-market co-movements.

The third specification is the full BEKK-GARCH model of Engle and Kroner [1995], which considers volatility persistence within each market and volatility spillover between markets. The residuals of the mean equation are defined as follows:

$$\varepsilon_t = \sqrt{h_t}\,\eta_t \sim N(0, h_t) \qquad \text{(Eq. 2)}$$

$$h_t = c + \alpha\varepsilon_{t-1}^2 + \beta h_{t-1} \qquad \text{(Eq. 3)}$$

- $\eta_t = \left(\eta_t^S, \eta_t^{FX}\right)'$ refers to (2 x 1) vector iid random vectors;
- $\sqrt{h_t} = \operatorname{diag}\left(\sqrt{h_t^S}, \sqrt{h_t^{FX}}\right)$, with h_t^S and h_t^{FX} are the conditional variances of r_t^S and r_t^{FX} respectively, which are given by Eq. (4) and Eq. (5):

$$h_t^S = c_S + \alpha_S(\varepsilon_{t-1}^S)^2 + \beta_S h_{t-1}^S + \alpha_{FX}(\varepsilon_{t-1}^{FX})^2 + \beta_{FX} h_{t-1}^{FX} \qquad \text{(Eq. 4)}$$

$$h_t^{FX} = c_{FX} + \alpha_{FX}(\varepsilon_{t-1}^{FX})^2 + \beta_{FX} h_{t-1}^{FX} + \alpha_S(\varepsilon_{t-1}^S)^2 + \beta_S h_{t-1}^S \qquad \text{(Eq. 5)}$$

In matrix, the representation will be:

$$\begin{pmatrix} h_t^S \\ h_t^{FX} \end{pmatrix} = \begin{pmatrix} c_S \\ c_{FX} \end{pmatrix} + \begin{pmatrix} \alpha_{S1} & \alpha_{S2} \\ \alpha_{FX2} & \alpha_{FX1} \end{pmatrix} \times \begin{pmatrix} (\varepsilon_{t-1}^S)^2 \\ (\varepsilon_{t-1}^{FX})^2 \end{pmatrix} + \begin{pmatrix} \beta_{S1} & \beta_{S2} \\ \beta_{FX2} & \beta_{FX1} \end{pmatrix} \times \begin{pmatrix} h_{t-1}^S \\ h_{t-1}^{FX} \end{pmatrix} \qquad \text{(Eq. 6)}$$

Eqs. (4) and (5) show how volatility is transmitted through time and across stock-forex market return indices. The cross value of the error terms (ε_{t-1}^S)^2 and (ε_{t-1}^{FX})^2 represents return innovations on the corresponding market at time (t−1) and represents short run persistence (the ARCH effect of past shocks), which captures the impact of the direct effects of shock transmission. The presence of (h_{t-1}^S) and (h_{t-1}^{FX}) captures volatility spillovers between stock markets and forex markets. It accounts for long-run persistence (the GARCH effects of past volatilities). We note here that the reciprocal effect allows the volatility of one market to be affected by its own past shock and volatility, and also by past shocks and the volatility of other markets.

The conditional covariance between stock and forex returns may be derived as follows:

$$H_t = D_t R_t D_t \,;\; D_t = \mathrm{diag}\left(\sqrt{h_t^{SS}}, \sqrt{h_t^{FXFX}}\right) \qquad \text{(Eq. 7)}$$

Where, $R_t = \rho_t^{S,FX}$ is the (2 x 2) matrix containing the conditional constant correlations (CCC). We note that the CCC is a restrictive assumption insofar as the conditional correlation is assumed to be constant while the conditional variances are time-varying. Apparently, this assumption is not feasible for real financial time series.

The conditional variances and covariances are given by:

$$\begin{cases} h_t^S = C_S + \alpha_S(\varepsilon_{t-1}^S)^2 + \beta_S h_{t-1}^S \\ h_t^{FX} = C_{FX} + \alpha_{FX}(\varepsilon_{t-1}^{FX})^2 + \beta_{FX} h_{t-1}^{FX} \\ h_t^{S,FX} = \rho\sqrt{h_t^S h_t^{FX}} \end{cases} \qquad \text{(Eq. 8)}$$

The positiveness of the arch and garch coefficients is not required to get a positive definite matrix [Bollerslev, 1990]. This process is covariance stationary when the roots of $\det(I_2 - \lambda A - \lambda B) = 0$ are outside the unit circle of the complex plan, where I_2 is (2 x 2) identity matrix and $A = \begin{pmatrix} \alpha_S & 0 \\ 0 & \alpha_{FX} \end{pmatrix}$ and $B = \begin{pmatrix} \beta_S & 0 \\ 0 & \beta_{FX} \end{pmatrix}$.

The DCC-GARCH(1,1) of Engle [2002] overcomes the restrictive assumption of the CCC by allowing the conditional correlation matrix to be time varying. Consequently, R_t is the matrix of time-varying conditional correlations given by:

$$R_t = (\rho_t^{S,FX}) = \left[\mathrm{diag}(Q_t)\right]^{-\frac{1}{2}} \times Q_t \times \left[\mathrm{diag}(Q_t)\right]^{-\frac{1}{2}} \qquad \text{(Eq. 9)}$$

R_t is the (2 × 2) symmetric positive-definite matrix, which depends on squared standardized residuals ($\eta_t / \varepsilon_t = \sqrt{h_t} \times \eta_t$), their unconditional variance-covariance matrix ($\bar{Q}$) and its own lagged value as represented in the following manner:

$$Q_t = (1-\alpha-\beta)\bar{Q} + \alpha\eta_{t-1}\eta'_{t-1} + \beta Q_{t-1} \qquad \text{(Eq. 10)}$$

Where, α and β are non-negative scalars as it is $\alpha + \beta \langle 1$.

Subsequently, the conditional variance-covariance matrix of the DCC-GARCH(1,1) specification (Eq. 7) will be:

$$H_t = D_t R_t D_t = \begin{pmatrix} h_t^{SS} & h_t^{SFX} \\ h_t^{FXS} & h_t^{FXFX} \end{pmatrix} = \begin{pmatrix} h_t^{SS} & \rho_t^{S,FX}\sqrt{h_t^{SFX} \times h_t^{FXS}} \\ \rho_t^{S,FX}\sqrt{h_t^{FXS} \times h_t^{SFX}} & h_t^{FXFX} \end{pmatrix} \quad \text{(Eq. 11)}$$

We then make use of another class of GARCH processes that model the conditional covariance matrix H_t rather than conditional correlations. The BEKK-GARCH class model defines the conditional variance-covariance matrix (H_t) as follows:

$$H_t = CC' + A\varepsilon_{t-1}\varepsilon'_{t-1}A' + BH_{t-1}B' \quad \text{(Eq. 12)}$$

The element C is a (2 × 2) upper triangular matrix of constants for the pair of markets; A is a (2×2) matrix of coefficients that capture the effects of own market and cross-market shocks; and B is a (2 × 2) matrix of coefficients that capture the own market volatility persistence and the volatility transmissions between stock and forex markets.

In view of that, the conditional variance and covariance processes take the following forms:

$$\begin{cases} h_t^S = C_S + \alpha_S^2(\varepsilon_{t-1}^S)^2 + \beta_S^2 h_{t-1}^S \\ h_t^{FX} = C_{FX} + \alpha_{FX}^2(\varepsilon_{t-1}^{FX})^2 + \beta_{FX}^2 h_{t-1}^{FX} \\ h_t^{SFX} = C_{SFX} + \alpha_S\alpha_{FX}\varepsilon_{t-1}^S\varepsilon_{t-1}^{FX} + \beta_S\beta_{FX}h_{t-1}^{SFX} \end{cases} \quad \text{(Eq. 13)}$$

Where, h_t^S and h_t^{FX} are the conditional variances of r_t^S and r_t^{FX}. Eq. (13) thus shows that direct volatility transmission between stock and forex markets is not possible since the conditional volatility of each market depends only on its own shocks and its long-run persistence. This volatility model is covariance stationary when $\alpha_S^2 + \beta_S^2 \langle 1$, $\alpha_{FX}^2 + \beta_{FX}^2 \langle 1$ and $|\alpha_S\alpha_{FX} + \beta_S\beta_{FX} \langle 1|$.

The estimation of the conditional variances and covariances allows computation of optimal weights of a stock-forex diversified portfolio, as well as optimal hedge ratios. We note that because normality condition is often rejected for economic and financial series, we follow Ling and McAleer [2003], and use the quasi-maximum likelihood estimation (QMLE) method to estimate the parameters of the model.

Descriptive Statistics and Empirical Results

Sources of Data and Descriptive Statistics

Our sample data are monthly return indices for eight national MENA stock markets (namely, Bahrain, Egypt, Kuwait, Morocco, the Kingdom of Saudi Arabia, Oman, Qatar and the United Arab Emirates) and the Eurodollar exchange rate series. The sample period is February 26, 1999 to June 30, 2014. Stock market data were sourced from MSCI, and Eurodollar data from the European Central Bank, ECB, website.

We use monthly data for several reasons. First, monthly data allows a focus on *strategic* long term dealing, while weekly and daily data are best suited for short-term/medium *tactical* dealing. Second, potential biases arising from the bid-ask bounce, non-synchronous trading days, days of the week, weekend effects, and 5 or 7 days a week are avoided with monthly data. Third, the chosen sample period encompasses global recessions and special events, several sub-periods of economic growth and, of course, the recent global financial crisis, which marks an observable separate dynamic pattern since 2007. Stock and forex returns are computed by taking the natural logarithm of the ratio of two consecutive prices.

Table 1 reports the descriptive statistics of monthly returns. We note that they are similar to the findings of previous studies. First, market returns show a significant departure from the normality hypothesis according to the Jarque – Bera test. Second, the analysis of stationarity, using the adf unit root test, shows clearly that the distribution of market returns is stationary at the 1% level, since the calculated ADF values are strictly below the critical threshold. The correlation structure of our monthly return series is examined using the Ljung – Box autocorrelation test of lags orders between 6 and 12. Results suggest that stock returns are relatively not auto correlated. Finally, the Engle's [1982] test for conditional heteroscedasticity rejects the null hypothesis of no ARCH effects for monthly returns, which lends support to use of the GARCH specification.

Stock Markets and Forex in MENA Countries

MENA markets share some common characteristics that are useful to explore. They have made progress in liberalizing trade, opening financial systems, and adopting market-based financial systems. Indeed, capital markets of this region are focused on establishing financial centers and diversifying financial instruments in their respective markets. However, some heterogeneity deserves to be noted – such as age and size of some markets relative to others, the level of retail investment and the domination of a few sectors. Table 2, displays some of these keys features.

Return Dynamics and Volatility Transmissions: Results and Discussion

The empirical analysis is conducted on eight return indices and seven bivariate VAR-GARCH models (systems). Each system consists of stock versus forex market return indices. We then present and discuss the results.

The interdependencies and volatility spillovers between pairs of markets are summarized in tables 3 to 5 for the three VAR-GARCH class models. The computed CCC between stock and forex markets are low and significantly positive, except for Kuwait and Saudi Arabia. It ranges between 30.23% for Morocco and 15.74% for Egypt. The low correlations suggest factual and mutual interdependence between markets but allow for diversification benefits as well as hedging strategies. We remember here that since Grubel [1968], Levy and Sarnat [1970] diversification benefits and Solnik [1974] international diversification benefits are sourced from low correlations between assets composing a given portfolio.

From the mean equation, we observe that stock returns depend on their own one period lagged return, with the exception for Bahrain, Saudi Arabia, Qatar and UAE. By contrast, forex market return indices are independent from their own past except for KSA. Notably, one lagged stock market return significantly affects all current forex market returns, except for Morocco, Qatar and UAE. This result supports the stock oriented approach of Branson et al. [1977]. In the opposite direction, only Kuwait's lagged forex market did not affect current stock market returns, contrary to the flow oriented model of Dornbusch and Fisher [1980]. This suggests about the evidence of short-term predictability. These findings corroborate recent studies [Shambora and Rossiter, 2007; Elder and Serletis, 2008; Arouri et al., 2011b].

On the subject of the conditional variance equation, common patterns are observed for both stock and forex markets. In fact, arch and garch coefficients are significant for a number of cases. The current conditional volatility of stock markets is significantly affected by both the own market past volatility and the one lagged volatility of forex markets of Morocco and only stock market conditional variance of Oman. However, the forex market does significantly help predict current conditional volatility, especially in the case of KSA, Kuwait, Oman, Qatar and the UAE.

ARCH terms exhibit relatively more suitable patterns and prove that current conditional volatility depends on own past market shocks, except for Bahrain and Kuwait. We state that past own market impulses and bidirectional shocks are leading volatility spillovers between stock and forex markets, and help predict future pricing behaviors. Compared to GARCH terms, arch coefficients are relatively small, which allows the inference that conditional volatility does not react simultaneously to impulses on own market and bidirectional shocks. They are instead more likely to progress steadily over time regarding the substantial effects of past volatility, as indicated by the large values of GARCH terms. We state that the current findings seem plausible, and corroborate recent empirical investigations focusing on various interdependences such as oil versus stock sectors, and stock versus commodities markets. We cite, *inter alia*, Arouri et al. [2011ab, 2012], Chang et al. [2011], Mensi et al. [2013, 2014].

Results of diagnostic tests based on standardized residuals are shown in each estimation table. We find that departures from normality and autocorrelation are reduced to a greater extent than those presented in Table 1 (statistical properties of return series). More prominently, standardized residuals do not exhibit remaining arch effects. Therefore, the bivariate VAR(1)–GARCH(1,1) model better captures the bidirectional dynamics between stock and forex markets.

For the DCC model, interpretation of the conditional mean equation makes it possible to confirm the results obtained from the CCC specification model with slightly superior effect regarding significant coefficient values. Indeed, return dynamics of forex significantly affect stock market returns, except for Kuwait, and corroborate the flow oriented approach. This may be explained by the exchange rate regime of the Kuwaiti Dinar (kwd), compared to the other cases. Reciprocally, stock market return indices have an effect on forex markets, except for Morocco, Qatar and the UAE.

On the subject of the conditional variance equation, we observe that in contrast to the CCC, the DCC specification shows a significant effect of past forex volatility on current stock market volatility, especially for Oman. The effect of stock market conditional volatility is persistent on the Bahraini, Saudi and Qatari stock markets, while for the forex market is persistent only in GCC countries. The results seem to be plausible insofar as GCC countries are providers of oil denominated in US dollars, constitute a large portion of overall international trade, and accumulate official foreign exchange reserves in such major global currencies as dollars, Euros, Pounds, and Yen. Looking at the total volume of public financial assets (including official reserves in addition to assets held by public investment vehicles), the GCC states presently hold an estimated USD 1.8 tr, of which Saudi Arabia and the United Arab Emirates hold together almost 75 percent. These assets amount to USD 45,000 per inhabitant, which, according to OPEC, IMF, OECD, exceeds for example, the per capita public wealth of China by a factor of 15.

Looking at the mean equations on the estimates of the VAR-BEKK-GARCH class models (Table 5), we observe that current stock returns depend significantly on own market one month lagged return in Kuwait, KSA, Morocco and Qatar, and on one period lagged forex returns for all countries. This result evidences the short-term predictability in some stock price changes over time. Regarding cross-markets mean interdependencies, the results were mixed, confirm the weak-form of informational efficiency, but help predict the trend of stock market pricing behavior. This observation corroborates the observations Mensi et al. [2014] using the DCC-GARCH and BEKK-GARCH class model for dynamic spillovers between international commodities markets.

Regarding the conditional variance equation, the current conditional volatility of the stock and forex markets is closely associated with own market past shocks (a_{11} and a_{22}) for all countries and past conditional volatility (b_{11} and b_{22}) for all countries except Kuwait. For spillover mechanisms, cross-markets shock effects (a_{12}, a_{21}) are found for stock markets that significantly affect forex in Egypt, Morocco, and Oman (a_{12}) and for foreign exchange market shocks that affect stock market current pricing on Morocco, Oman and Qatar (a_{21}). Stock-forex shocks are therefore perfectly interdependent in Egypt, Morocco and Oman. Morocco has a unique pattern regarding the own market and bilateral effects between stock and forex shocks. The conditional volatility of Kuwaiti, Moroccan, and the Qatari forex markets affect current stock market pricing volatility (b_{21}). Reciprocally, stock market conditional volatility does not affect forex markets except for Saudi and Omani forex markets (b_{12}).

At the same, own market conditional variances are still influencing both stock and forex markets in Bahrain, Egypt, Saudi Arabia, Qatar, and the UAE (b_{11}) and for Morocco, Saudi Arabia, Oman, Qatar and the UAE (b_{22}).

Figure 1 displays the dynamics of conditional correlations obtained from the DCC-GARCH and BEKK-GARCH class models. The conditional correlations are time-varying and marked by common blips. Significant fluctuations reached their highest level during the recent global financial crisis, peaking in, 2010 Q2 and 2011 Q3. Dips were also observed in 2003 Q2 (Iraq war) Q3, 2008 Q4 (Subprime crisis), and 2012 Q2 (the recent global recession). At the same, the BEKK-GARCH specification exhibit a continuous evolving over time with rising and falling periods.

The observed irregularity in some relationships can be explained by the special features of a number of markets, their microstructure, efficiency, and – especially – their exchange rate regimes, as well as the baskets of currencies that they are pegged to. For comparison, although both the DCC and BEKK estimates evolve similarly, the magnitude of the DCC dynamics is slightly different than observed from the BEKK specification. This finding confirms those obtained by recent empirical studies, such as Schmidbauer and Rösch [2012] and Mensi et al. [2014], which analyzed the effect of opec news announcements on energy-market volatility and dynamic spillovers.

Implications for Portfolio Management: Asset Allocation and Hedging

The estimation results have managerial implications for international investors. We compute optimal portfolio weights and hedge ratios and seek to appraise a diversification strategy using hedging efficiency statistics.

Optimal Portfolio Weights

According to Kroner and Ng [1998], the optimal weights of holding stock market indices and the forex are given by:

$$w_t^{forex,stock} = \frac{h_t^{stock} - h_t^{forex,stock}}{h_t^{forex} - 2h_t^{forex,stock} + h_t^{stock}} \qquad \text{(Eq. 14)}$$

$$w_t^{forex,stock} = \begin{cases} 0 & \text{if} \quad w_t^{forex,stock} \langle 0 \\ w_t^{forex,stock} & \text{if} \quad 0 \le w_t^{forex,stock} \le 1 \\ 1 & \text{if} \quad w_t^{forex,stock} \rangle 1 \end{cases} \qquad \text{(Eq. 15)}$$

Where, $w_t^{forex,stock}$ denotes the weight of the forex market index in the one-dollar portfolio of two assets at time t. h_t^{stock} and h_t^{forex} refer to conditional variances of stock market return indices and the forex return index respectively. The term $h_t^{forex,stock}$ is the conditional covariance between the stock and forex markets at time t. The weight of the stock market in the considered portfolio is obtained by computing the $(1 - w_t^{forex,stock})$. Statistics for portfolio weights are computed from fitting the cited three VAR(1)–GARCH(1,1) class models.

Hedging Strategy

Portfolio design might be likened to an early hedging strategy against adverse progress of asset prices. A timely strategy is also available for investors to the extent that they can decide on optimal portfolio hedge ratios. In that framework, the hedging question consists of identifying how much a one dollar long position (buy) in a stock market should be hedged by a short position (sell) in β_t dollar in a forex market. We follow Kroner and Sultan [1993] and use the hedge ratio that takes the following form:

$$\beta_t = \frac{h_t^{forex,stock}}{h_t^{stock}} \qquad \text{(Eq. 16)}$$

Table 6 summarizes the statistics of portfolio designs for three competing specifications of the VAR-GARCH class model. As shown in table 6, hedge ratios are typically low, which suggests that hedging efficiency involving stock and forex markets is quite good, and that incorporating foreign exchange in a diversified portfolio of stocks increases risk-adjusted performance.

Optimal weights in hedged portfolios vary substantially across stock and forex, but differ slightly across the used class models. These results corroborate those obtained by recent empirical studies, such as Arouri et al. [2011b]. The values of w_t range between 0,85 for the UAE in VAR-BEKK-GARCH model, and 0,98 for Egypt in the VAR-DCC-GARCH class model.

On the whole, we observe that to maximize the risk-adjusted return of the same one-dollar stock-forex portfolio, international investors should hold, on average, fewer financial assets (i.e., stock) with a mean value of $w_t = 91\%$. When hedging with a forex market, he should overweight financial assets on the Moroccan market ($w_t = 94\%$) but underweight on the Omani market ($w_t = 88\%$). This finding suggests that forex provides a substantial alternative way to attain higher benefits, as well as hedging one's position. For the the three class models we obtained equivalent findings, with relatively smaller values for BEKK specification. These results confirm those obtained by major recent investigations, such as that of Arouri et al. [2011b].

As for hedge ratios, we find that they vary between markets, but only slightly between the three competing class models. Average values ranged between 0.01 for Kuwait using VAR-CCC-GARCH, and 0.14 for Morocco using VAR-DCC-GARCH model. The greatest values of β_t were found for Morocco (ranging between 12.46% and 13.63%), and the smallest values were observed for Kuwait (ranging between 1% and 8.62%).

These results make it possible to deduce that the forex market is overweighted for either portfolio design or hedging strategies. The VAR-DCC-GARCH class models overweighted forex assets to build or hedge positions on the international portfolio. We assume that the current findings offer several insights for short hedgers. Low ratios suggest that portfolio investment risk can be hedged by taking a short position on stock markets. For instance, the largest ratio, 0.1363, is for Morocco from the DCC-GARCH model, meaning that one-dollar long (buy) in the forex market index should be shorted (sell) by 13.63 cents of stock index.

Diversification and Hedging Efficiency

As previously stated, we draw on estimated optimal parameters (weights and hedging ratios) to manage and to simulate global portfolio diversification and to learn about hedging efficiency. We use the estimates of three VAR-GARCH class models to conceive three portfolios: a t full-stocks portfolio (PF1); a stock-forex weighted portfolio (PF2); and a full-forex portfolio (PF3). We then test the contribution of a weighted stock-forex portfolio to the unhedged stock portfolios (PF1 and PF3).

As a decision rule, we controlled for the efficiency of the diversification strategy by comparing the realized risk and return characteristics of the considered portfolios. We made use of the realized hedging errors of (Ku et al., 2007) which is presented as follows:

$$HE = \frac{var^{unhedg} - var^{hedg}}{var^{unhedg}} \qquad \text{(Eq. 17)}$$

Where, var^{unhedg} and var^{hedg} denotes the variances of the unhedged and hedged portfolios, respectively. A higher value of HE ratio represents a better hedging efficiency in terms of the portfolio's variance reduction, and the associated investment method is then considered a successful hedging strategy.

Table 7 presents summary statistics of the diversification strategy of weighted portfolios, as well as values of the hedging efficiency ratio. We consider the non-diversified portfolios and incorporate forex assets to implement the diversification strategy and assess the reward-to-risk and the hedging efficiency for each portfolio. The results show that adding forex assets to the diversified portfolios lessens its variance and improves the risk-adjusted return ratio. More importantly, this holds for all countries under all considered models.

From the perspective of return, the full stocks unhedged portfolio provides the best risk-adjusted return ratios in five out of eight pairs of stock-forex portfolios. From the perspective of variance, our findings show that hedging strategies involving stock and forex markets reduce portfolio variance. Variance reduction ranges from 67.1 percent (Kuwait in the BEKK specification) to 93.8 percent (Qatar in the BEKK specification). The variance reduction is significantly different between countries, but remains relatively stable across the three VAR-GARCH class models. Portfolio variance is reduced, or hedging efficiency is greater, when the BEKK-GARCH and DCC-GARCH models are used. However, we state that the BEKK-GARCH is the best one. Chang et al. [2011], Arouri et al. [2011] reach the same finding regarding the superior ability of bivariate diagonal BEKK-GARCH over the DCC-GARCH and CCC-GARCH when examining optimal hedging efficiency between crude oil spot and futures markets and between oil prices and stock sector returns, respectively. We observe here that the current findings are plausible, economically interpretable, and useful for portfolio management, as well as for governmental policy making.

Conclusion

The relationship between stock and forex markets is of fundamental importance for various investment or managerial decisions. Currency is often built-in as an asset in an internationally diversified portfolio. In the framework of the Mean-Variance approach, the variance of a diversified portfolio is determined by the correlation between the incorporated assets.

The aim of this article was to study the interdependence between stock and forex using the recent VAR-GARCH approach of McAleer [2003] and reveal interesting in portfolio management implications. We studied the conditional correlations between markets and were able to reach conclusions about portfolio designs and hedging efficiency. Our estimates from three specifications; namely the VAR-CCC-GARCH model of Bollerslev [1990], the VAR-BEKK-GARCH model of Engle and Kroner [1995], and the VAR-DCC-GARCH model of Engle [2002] confirm the bidirectional interdependence between stock and forex markets and support both the stock oriented approach of Branson et al. [1977] and flow oriented approach of Dornbusch and Fisher [1980] in observing that the effect of stock market's volatility is persistent on all markets, while forex market volatility is solely persistent in gcc countries. We note that the forex market is overweighted for either portfolio designs or for hedging strategies. This positions forex markets as a mean to improve risk-adjusted performance and hedging efficiency. More importantly, this observation holds for all countries under our analysis and considered models.

An optimally hedged stock-forex portfolio outperforms full stock and full forex non-diversified portfolios and, additionally, the VAR-BEKK-GARCH specification is superior, followed by the VAR-DCC-GARCH specification. These findings align with recent, similar studies and has practical utility for portfolio managers and governmental policy makers.

TABLE 1. Statistical properties for monthly return series

	Mean	Std. Dev.	Skewness	Kurtosis	Jarque-Bera	ADF Statistics	Q(6)	Q(12)	ARCH(6)	ARCH(12)
FOREX	0.111	2.604	0.001	2.938	0.022	-10.101^{+++}	15.600^{++}	19.407^{+}	2.932^{+++}	1.748^{+}
Bahrain	–0.096	6.439	–0.963	6.494	96.224^{+++}	-5.163^{+++}	48.639^{+++}	51.852^{+++}	3.819^{+++}	2.141^{++}
Egypt	0.560	9.298	–0.411	5.498	41.812^{+++}	-10.326^{+++}	26.625^{+++}	27.645^{+++}	0.313	0.581
Kingdom of Saudi Arabia	0.827	8.486	–1.015	5.287	56.523^{+++}	-9.678^{+++}	10.778^{+}	16.336	9.936^{+++}	4.693^{+++}
Kuwait	0.362	6.289	–0.727	4.675	29.764^{+++}	-8.069^{+++}	29.332^{+++}	34.069^{+++}	2.716^{++}	2.059^{++}
Morocco	0.397	5.843	–0.053	4.061	6.869^{++}	-13.175^{+++}	7.536	11.235	2.792^{++}	1.635^{+}
Oman	0.584	5.992	–1.658	11.797	534.11^{+++}	-5.382^{+++}	43.365^{+++}	71.164^{+++}	2.323^{++}	1.110
Qatar	1.060	9.806	0.023	6.616	79.012^{+++}	-9.674^{+++}	5.567	10.761	6.070^{+++}	3.149^{+++}
United Arab Emirates	0.381	6.118	–0.392	5.218	33.471^{+++}	-10.375^{+++}	35.992^{+++}	42.170^{+++}	4.319^{+++}	2.477^{+++}

Notes: The table presents basic statistics of monthly returns. Columns 1 to 5 are reserved to the mean (%), the standard deviation (%), the skewness, the kurtosis and the Jarque and Bera normality test statistics. Q (6) and Q (12) are statistics of the Ljung-Box autocorrelation test applied to returns with lags between 6 and 12. ARCH (6) and ARCH (12) are the statistics of the conditional heteroskedasticity test proposed by Engle (1982), using the residuals of the AR (1) model. ADF is the statistics of the ADF unit root test proposed by Dickey and Fuller (1981). The ADF test is conducted without time trend or constant. $^{+}$, $^{++}$ and $^{+++}$ denote that the null hypothesis of tests (no-autocorrelation, normality, no-stationarity and homogeneity) are rejected at, respectively, 5% and 1% levels.

Source: own elaboration.

TABLE 2. MENA stock exchanges and forex markets

	Bahrain	Egypt	Kuwait	Morocco	Oman	Qatar	KSA	UAE
Panel A. Stock markets								
Market cap. (USD bn)	21,522	73,167	109,500	55,714	38,746	197,100	602,500	220,200
# listed companies	47	236	216	75	131	43	168	122
Market cap. over GDP	66%	21%	57%	61%	27%	72%	59%	26%
Share turnover velocity	1,5%	19%	4,8%	1.7%	4,1%	11%	33,7%	15,9%
Weight in AMF index	1.01	4.64	8.71	4.11	2.27	15.05	42.77	17.56
Ownership structure	State-owned	Public institution	State owned	Mutuali-sed	State owned	State owned	State owned	State owned
Exchange rate per USD	0.377	7.152	0.282	8.193	0.385	3.641	3.750	3.673
Panel B. Forex Arrangements								
Bahrain	Peg to the US dollar since October 1965.							
Egypt	De facto crawling band (±5%) around US dollar/Multiple rates until October 8, 1991, and De facto moving peg to US dollar/Multiple rates.							
Kuwait	Official peg to the US dollar with official band ±3.5% -de facto ±–1% until May 19, 2007. De facto peg to US dollar, Officially pegged to an undisclosed basket of currencies.							
Morocco	Moving band around euro (±2% band. officially pegged to a basket of currencies) until October 2000 and then De facto crawling peg to euro.							
Oman	Official peg to the US dollar since January 2002.							
Qatar	Until march 1975, Quatar Riyal replaces Quatar/Dubai Riyal. And then officially pegged to the IMF's SDR.							
S. Arabia	De facto peg to the US dollar.							
U.A. Emirates	Since January 1990, officially Peg to US dollar.							

Source: Information sourced from the Arab Monetary Fund (AMF) and World Federation of Exchanges (WFE). December 2014.

TABLE 3. Estimation of VAR-CCC-GARCH model

	Bahrain		Egypt		Kuwait		KSA		Morocco		Oman		Qatar		UAE	
	Stock	Forex	Stock	Forex	Stock	Forex	Stock	Forex	Stock	Forex	Stock	Forex	Stock	Forex	Stock	Forex
Panel A: Conditional mean Equation																
Constant	0.0163	−0.0351	0.1194	0.7116	−0.0055	0.0237	0.0466	0.0356	0.1089	−0.2311	0.0665	0.7922	0.0004	0.0364	0.0389	0.0389
	(0.9505)	(0.9626)	(0.5258)	(0.3095)	(0.9839)	(0.9699)	(0.7953)	(0.9415)	(0.5103)	(0.5727)	(0.7364)	(0.1620)	(0.9984)	(0.9250)	(0.8294)	(0.9192)
Stock {1}	0.0146	0.2596*	0.0358*	0.2801***	0.1104***	0.2398*	−0.0061	0.2706***	0.1028***	−0.0464	0.0908***	0.2983***	0.0114	−0.0137	0.0050	0.1523
	(0.7133)	(0.0897)	(0.0757)	(0.0000)	(0.0007)	(0.0840)	(0.7417)	(0.0028)	(0.0005)	(0.6142)	(0.0053)	(0.0069)	(0.5406)	(0.9143)	(0.8679)	(0.2091)
Forex {1}	0.2865**	0.1026	0.2463***	−0.1213	0.1209	0.0031	0.2562***	0.5995**	0.1968***	0.1325	0.1878*	−0.1836	0.1065*	0.0301	0.2712***	0.0372
	(0.0455)	(0.7055)	(0.0027)	(0.6301)	(0.3098)	(0.9909)	(0.0018)	(0.0197)	(0.0080)	(0.4756)	(0.0962)	(0.4838)	(0.0850)	(0.8817)	(0.0004)	(0.8265)
Panel B: Conditional variance equation																
constant	2.3216	17.0634	1.8039	26.5637***	2.8381	8.4002	2.1156	0.6528	2.2906	31.0981***	1.2204	5.8088***	5.0388	1.2719	2.5063	3.1496
	(0.4601)	(0.2691)	(0.6432)	(0.0000)	(0.2712)	(0.3646)	(0.2175)	(0.9236)	(0.3056)	(0.0000)	(0.5556)	(0.0000)	(0.3762)	(0.8540)	(0.1955)	(0.6216)
$(\varepsilon_{t-1}^{stock})^2$	−0.0223	0.1057	0.0257	0.0191	0.0281	0.0570	−0.0307*	0.0540*	−0.0064	0.0657**	0.0048	0.0425	−0.129***	0.0406*	−0.0132	0.0928
	(0.3756)	(0.2374)	(0.8047)	(0.5888)	(0.1348)	(0.2371)	(0.0542)	(0.0801)	(0.8967)	(0.0388)	(0.9531)	(0.3149)	(0.0000)	(0.0895)	(0.7277)	(0.1646)
$(\varepsilon_{t-1}^{forex})^2$	−0.1769	0.2980	0.6523***	−0.0182	−0.0410	0.2521	0.0637	0.3389*	0.3868	0.1959*	−0.817***	0.3525***	0.3334	0.8301***	−0.0665*	0.2325**
	(0.7449)	(0.3074)	(0.0001)	(0.7759)	(0.9287)	(0.1019)	(0.8811)	(0.0564)	(0.1578)	(0.0709)	(0.0000)	(0.0014)	(0.4788)	(0.0059)	(0.8342)	(0.0446)
h_{t-1}^{stock}	0.5953	−0.1090	0.6344	−0.0493	0.3753	−0.0065	0.5829	0.0451	1.0867***	−0.8123	0.7849*	−0.1172	0.9057	0.0505	0.5005	0.0214
	(0.3194)	(0.9327)	(0.7099)	(0.9771)	(0.5698)	(0.9988)	(0.1401)	(0.9614)	(0.0001)	(0.3509)	(0.0646)	(0.7420)	(0.2033)	(0.8238)	(0.1919)	(0.9782)
h_{t-1}^{forex}	−0.0034	0.2401	−0.0059	0.6465	0.0011	0.5272*	0.0324	0.06956***	−4.311***	0.2457	−0.0444	0.5664**	−0.0337	0.4811***	−0.0208	0.6776***
	(0.9997)	(0.7234)	(0.9998)	(0.5935)	(0.9999)	(0.0869)	(0.9986)	(0.0006)	(0.0060)	(0.2513)	(0.9885)	(0.0153)	(0.9960)	(0.0097)	(0.9972)	(0.0058)
CCC	0.2218*** (0.0000)		0.1574** (0.0328)		0.0242 (0.7852)		0.0495 (0.5099)		0.3023*** (0.0000)		0.1707* (0.0515)		0.1600* (0.0629)		0.1751** (0.0213)	
Log-likelihood	−762.7686		−1061.6715		−762.8359		−798.2069)		(−965.6961)		−755.9713		−814.6019		−963.0643	
AIC	10.8301		11.7247		10.8588		11.3223		10.6815		10.7357		11.5500		10.6528	
LB_1 Q (12)	9.2075 (0.6851)		7.2922 (0.8377)		12.5798 (0.4003)		10.5476 (0.5680)		11.6434 (0.4747)		10.7716 (0.5486)		10.9007 (0.5374)		5.4690 (0.8405)	
LB_2 Q (12)	16.5629 (0.1668)		12.9911 (0.3697)		9.2254 (0.6836)		2.9089 (0.9962)		14.5194 (0.2688)		21.2940 (0.0462)		7.8954 (0.7933)		18.1451 (0.1114)	
McLeod-Li_1(12)	30.3486 (0.0025)		14.9063 (0.2466)		22.0954 (0.0365)		23.7317 (0.0221)		11.5594 (0.4817)		28.1153 (0.0053)		24.8762 (0.0154)		18.1827 (0.1103)	
McLeod-Li_2(12)	11.8226 (0.4600)		10.1516 (0.6027)		2.7162 (0.9972)		4.8668 (0.9623)		5.6500 (0.9327)		4.5435 (0.9715)		11.6743 (0.4722)		8.9137 (0.7103)	
McLeod-Li_1^2(12)	18.4657 (0.1023)		13.4214 (0.3392)		16.3466 (0.1759)		21.0456 (0.0497)		5.3721 (0.9444)		11.9347 (0.4509)		18.9362 (0.0901)		15.0066 (0.2411)	
McLeod-Li_2^2(12)	4.9262 (0.9604)		5.4457 (0.9414)		1.5299 (0.9999)		4.5108 (0.9724)		1.1297 (0.9999)		1.7555 (0.9997)		5.4030 (0.9431)		11.9881 (0.4466)	
Usable Obs.	144		184		144		144		184		144		144		144	

Source: own elaboration.

TABLE 4. Estimation of VAR-DCC-GARCH model

	Bahrain		Egypt		Kuwait		KSA		Morocco		Oman		Qatar		UAE	
	Stock	Forex	Stock	Forex	Stock	Forex	Stock	Forex	Stock	Forex	Stock	Forex	Stock	Forex	Stock	Forex
Panel A: Conditional mean equation																
Constant	0.0658	0.1584	0.0446	0.3148	−0.0427	−0.0085	0.0025	0.0404	0.1400	0.0371	0.1118	0.2561	0.0489	0.0629	0.0281	−0.0285
	(0.7604)	(0.7720)	(0.8043)	(0.6546)	(0.8401)	(0.9857)	(0.9895)	(0.9384)	(0.3798)	(0.9281)	(0.5457)	(0.5685)	(0.876)	(0.9689)	(0.896)	(0.9598)
Stock {1}	0.0200	0.326***	0.0404**	0.198***	0.118***	0.2297**	−0.0177	0.2354**	0.083***	−0.0716	0.075***	0.2166**	0.0092	0.0554	−0.017	0.0792
	(0.6142)	(0.0099)	(0.0489)	(0.0069)	(0.0013)	(0.0448)	(0.2643)	(0.0235)	(0.0006)	(0.3488)	(0.0097)	(0.0442)	(0.668)	(0.6799)	(0.676	(0.6412)
Forex {1}	0.275***	0.0210	0.266***	0.1011	0.1541	−0.0116	0.240***	0.4157**	0.287***	0.2215	0.257***	0.2490	0.31**	0.0960	0.21**	0.0539
	(0.0077)	(0.9259)	(0.0005)	(0.6852)	(0.1658)	(0.9612)	(0.0028)	(0.0511)	(0.0001)	(0.1953)	(0.0000)	(0.2239)	(0.031)	(0.7689)	(0.021)	(0.8078)
Panel B: Conditional variance equation																
Constant	2.4613*	12.9424	5.7208*	63.2913*	1.9514	2.3747	2.219***	1.7239	4.0287	29.08***	7.773***	17.67***	2.2194	1.3048	3.6548	3.7865
	(0.0751)	(0.2698)	(0.0515)	(0.0516)	(0.3913)	(0.6546)	(0.0008)	(0.5596)	(0.1167)	(0.0002)	(0.0000)	(0.0001)	(0.106)	(0.569)	(0.307)	(0.2274)
$(\varepsilon^{stock}_{t-1})^2$	−0.0451	0.0908	−0.0717	−0.0075	−0.0476	0.0366	0.0145	0.069***	−0.0368	−0.0166	−0.0872	−0.0185	−0.013	0.06***	−0.016	0.0939
	(0.5869)	(0.3165)	(0.3214)	(0.7567)	(0.5763)	(0.6377)	(0.8251)	(0.0020)	(0.6135)	(0.6754)	(0.3296)	(0.2782)	(0.905)	(0.0000)	(0.697)	(0.1541)
$(\varepsilon^{forex}_{t-1})^2$	−0.0266	0.2028	0.7656*	0.1351	0.0783	0.1732	0.0436	0.4018*	0.5636*	0.1460	0.5396*	0.1169	−0.015	0.663**	0.0191	0.278**
	(0.9445)	(0.2454)	(0.0745)	(0.1962)	(0.8495)	(0.1289)	(0.9489)	(0.0651)	(0.0765)	(0.2877)	(0.0659	(0.2787)	(0.979)	(0.0349)	(0.962)	(0.0499)
h^{stock}_{t-1}	0.389***	0.2023	−0.2726	0.2692	0.5656	0.0894	0.565***	−0.0279	−0.5845	1.1244*	−0.6018	0.2639	0.60**	−0.0343	0.2671	0.0186
	(0.0006)	(0.7483)	(0.6701)	(0.2152)	(0.4367)	(0.8695)	(0.0010)	(0.7130)	(0.1225)	(0.0729)	(0.1956)	(0.6031)	(0.037)	(0.6681)	(0.762)	(0.9718)
h^{forex}_{t-1}	−0.0169	0.4025	3.0053	−0.1616	0.3706	0.732***	0.0257	0.649***	−2.0514	0.0767	−7.46***	0.593***	−0.013	0.58***	0.0306	0.62***
	(0.9944)	(0.4548)	(0.1734)	(0.7357)	(0.9030)	(0.0003)	(0.9878)	(0.0000)	(0.2389)	(0.8017)	(0.0000)	(0.0000)	(0.994)	(0.0002)	(0.989)	(0.0046)
DCC																
k_1	0.0991 (0.5393)		0.1997** (0.0362)		0.1445 (0.2883)		0.4277*** (0.0011)		0.0567 (0.1459)		0.1493*** (0.0032)		0.2031 (0.2121)		0.1302 (0.3742)	
k_2	0.1803 (0.8356)		0.4667 (0.0665)		0.0052 (0.9813)		(0.0050 (0.9745)		0.8889 (0.0000)		0.0615 (0.7997)		0.2693 (0.7339)		0.1165 (0.8141)	
Log-likelihood	−765.1253		−1060.4683		−762.2775		−793.3358		−962.2343		−749.8800		−809.8965		−961.8312	
AIC	10.8767		11.7225		10.8372		11.2685		10.6547		10.6650		11.4985		10.6503	
LB_1 Q (12)	8.7687 (0.7226)		7.3749 (0.8319)		12.1142 (0.4366)		11.6208 (0.4766)		9.0980 (0.6945		12.6056 (0.3983)		7.5944 (0.8160)		6.7628 (0.8729)	
LB_2 Q (12)	15.8286 (0.1992)		11.7284 (0.4677)		9.6258 (0.6487)		3.2559 (0.9935)		14.0358 (0.2984)		18.6268 (0.0979)		6.7756 (0.8721)		20.4911 (0.0583)	
McLeod-Li_1(12)	27.5908 (0.0063)		16.2684 (0.1793)		24.0838 (0.0198)		22.6661 (0.0307)		11.2826 (0.5049)		26.2042 (0.0100)		32.1193 (0.0013)		18.4061 (0.1039)	
McLeod-Li_2(12)	9.3495 (0.6728)		11.7218 (0.4683)		3.2829 (0.9932)		4.6339 (0.9691)		6.8378 (0.8681)		7.9747 (0.7871)		8.1291 (0.7750)		8.3975 (0.7533)	
McLeod-Li_1^2(12)	16.2825 (0.1786)		14.5811 (0.2651)		17.2963 (0.1388)		19.1929 (0.0840)		8.8613 (0.7147		20.5176 (0.0579)		22.2641 (0.0347)		16.3647 (0.1751)	
McLeod-Li_2^2(12)	4.2024 (0.9795)		6.3560 (0.8971)		6.5065 (0.8884)		4.0312 (0.9829)		1.8458 (0.9996)		3.0638 (0.9951)		2.2462 (0.9989)		13.3086 (0.3470)	
Usable Obs.	144		184		144		144		184		144		144		144	

Source: own elaboration.

TABLE 5. Estimation of VAR-BEKK-GARCH model

	Bahrain	Egypt	Kuwait	KSA	Morocco	Oman	Qatar	UAE
Panel A: Conditional mean equation								
Constant	0.3486 (0.1175)	0.0975 (0.5878)	0.1344 (0.4954)	0.2222 (0.2784)	0.1812 (0.2631)	0.2353 (0.2317)	0.2327 (0.2271)	0.1451 (0.4354)
Stock {1}	0.0141 (0.7021)	0.0326 (0.1254)	0.0970*** (0.0030)	0.4146* (0.0880)	0.1421*** (0.0005)	0.0303 (0.4629)	0.0072* (0.0787)	0.0338 (0.2902)
Forex {1}	0.1874* (0.0985)	0.2599*** (0.0016)	0.2281** (0.0185)	0.2295** (0.0177)	0.2522*** (0.0025)	0.2167** (0.0145)	0.2897*** (0.0042)	0.2410*** (0.0062)
Constant	0.9524* (0.0587)	0.5795 (0.4090)	0.7568* (0.0946)	1.5624** (0.0037)	0.1885** (0.0125)	0.4199 (0.4146)	1.0297** (0.0491)	0.0832 (0.9834)
Stock {1}	0.2657* (0.0510)	0.2093** (0.0117)	0.1589* (0.0795)	0.1447 (0.1091)	0.0227 (0.7458)	0.1665* (0.0951)	0.0093* (0.0930)	0.2053** (0.0484)
Forex {1}	−0.0507 (0.7982)	0.1291 (0.6642)	−0.1351 (0.5814)	0.2897 (0.2585)	0.1270 (0.5284)	0.1874 (0.4787)	0.3105 (0.1525)	0.2652 (0.1031)
Panel B: Conditional variance equation								
C (1,1)	1.0833 (0.1445)	0.6327 (0.7633)	1.2479 (0.1328)	1.7936*** (0.0001)	0.9041 (0.3694)	1.9334*** (0.0000)	0.5474 (0.2447)	1.2382 (0.1894)
C (2,1)	2.0271 (0.6568)	5.1875 (0.1974)	−1.9585 (0.6569)	0.6882 (0.5775)	−3.1140 (0.6290)	0.4427 (0.6796)	0.5563 (0.4439)	1.1802 (0.1477)
C (2,2)	3.3758 (0.3321)	0.1642** (0.0215)	−0.0161** (0.0396)	0.2711** (0.0231)	0.4028** (0.0194)	0.0863 (0.1684)	−0.3930* (0.0742)	0.0494* (0.0840)
A (1,1)	0.2565* (0.0992)	0.1968 (0.1617)	0.0924 (0.6603)	0.2723* (0.0624)	0.4690*** (0.0001)	−0.1327 (0.5062)	0.1813* (0.0569)	0.2035* (0.0557)
A (1,2)	−0.0400 (0.9013)	1.0921* (0.0460)	0.3211 (0.3544)	0.6505 (0.1298)	0.9741*** (0.0002)	1.1305*** (0.0001)	−0.2685 (0.2014)	0.1854 (0.3803)
A (2,1)	0.0309 (0.5943)	0.0480 (0.1349)	0.0673 (0.1903)	0.0311 (0.3176)	−0.2610 (0.0000)	0.1909** (0.0116)	0.0377** (0.0199)	0.0431 (0.3018)
A (2,2)	0.6841*** (0.0000)	0.3324** (0.0106)	0.5371*** (0.0002)	0.5557*** (0.0000)	−0.0500 (0.5995)	0.2862*** (0.0029)	0.5685*** (0.0000)	0.4003*** (0.0008)
B (1,1)	0.8230*** (0.0004)	0.9331*** (0.0021)	0.4198 (0.2247)	−0.4159 (0.3200)	−0.1649 (0.6045)	−0.2031 (0.4765)	0.9434*** (0.0000)	0.8162*** (0.0038)
B (1,2)	−0.3631 (0.7743)	−0.5027 (0.8362)	2.0424 (0.2127)	−1.2894*** (0.0017)	0.5178 (0.4901)	−1.3841*** (0.0034)	−0.1077 (0.2421)	−0.3326 (0.2685)
B (2,1)	0.0158 (0.8657)	−0.0421 (0.5098)	−0.2667* (0.0544)	−0.0866 (0.1399)	0.2931** (0.0114)	−0.0585 (0.5362)	−0.0710* (0.0575)	−0.0131 (0.7203)
B (2,2)	0.3820 (0.2101)	0.6683 (0.1519)	0.0492 (0.8323)	0.7604*** (0.0000)	0.6291* (0.0546)	0.6924*** (0.0005)	0.8722*** (0.0000)	0.8916*** (0.0000)
Log-likelihood	−767.9282	−1061.7300	−763.3982	−797.6446	−963.3516	−756.8657	−809.0373	−965.6217
AIC	10.9018	11.7253	10.8388	11.3145	10.6560	10.7481	11.4727	10.6806
LB1 Q (12)	12.1756 (0.4317)	7.2659 (0.8395)	9.4568 (0.6635)	11.8644 (0.4566)	8.1319 (0.7747)	12..0358 (0.4428)	9.2216 (0.6839)	7.1182 (0.8497)
LB2 Q (12)	16.5943 (0.1655)	10.2249 (0.5962)	10.2097 (0.5976)	5.1607 (0.9524)	11.0309 (0.5263)	27.7195 (0.0061)	8.5481 (0.7410)	17.0558 (0.1475)
McLeod-Li1(12)	20.0621 (0.0659)	15.8440 (0.1985)	22.6780 (0.0306)	24.6051 (0.0168)	5.1907 (0.9513)	27.0981 (0.0075)	26.5418 (0.0090)	18.6812 (0.0965)
McLeod-Li2(12)	11.5907 (0.4791)	13.1086 (0.3612)	5.2598 (0.9487)	4.8905 (0.9615)	11.7388 (0.4669)	21.3676 (0.0452)	9.6769 (0.6443)	7.0676 (0.8531)
McLeod-Li12(12)	10.1747 (0.6006)	15.3474 (0.2230)	17.1087 (0.1456)	13.4152 (0.3396)	6.3985 (0.8947)	23.6482 (0.0227)	15.5248 (0.2131)	17.2415 (0.1407)
McLeod-Li22(12)	5.8007 (0.9258)	8.5989 (0.7367)	3.3331 (0.9927)	2.4799 (0.9982)	4.1367 (0.9808)	9.5855 (0.6523)	4.9006 (0.9612)	5.1044 (0.9544)
Usable Obs.	144	184	144	144	184	144	144	144

Source: own elaboration.

TABLE 6. Summary statistics for optimal weights and hedge ratios

Portfolio	Weights & hedge ratios	VAR-CCC-GARCH	VAR-DCC-GARCH	VAR-BEKK-GARCH
Bahrain/forex	ω_t	0.9167	0.9332	0.8977
	β_t	0.0906	0.1074	0.0778
Egypt/forex	ω_t	0.9662	0.9753	0.9651
	β_t	0.0797	0.0582	0.0420
Kuwait/forex	ω_t	0.8706	0.9238	0.8619
	β_t	0.0095	0.0862	0.0370
Morocco/forex	ω_t	0.9444	0.9308	0.9409
	β_t	0.1246	0.1363	0.1291
KSA/forex	ω_t	0.8873	0.9099	0.9093
	β_t	0.0176	0.0548	0.0621
Oman/forex	ω_t	0.8672	0.8881	0.8749
	β_t	0.0627	0.1051	0.0607
Qatar/forex	ω_t	0.8959	0.9118	0.8865
	β_t	0.0583	0.0823	0.0737
UAE/forex	ω_t	0.8627	0.8912	0.8473
	β_t	0.0818	0.1098	0.0618

Notes: The data are summary statistics for the average values of optimal weights (w_t) and hedge ratios (β_t) for a stock-forex portfolio using conditional variance and covariance estimated from three competitive volatility spillover models for a bivariate specification.

Source: own elaboration.

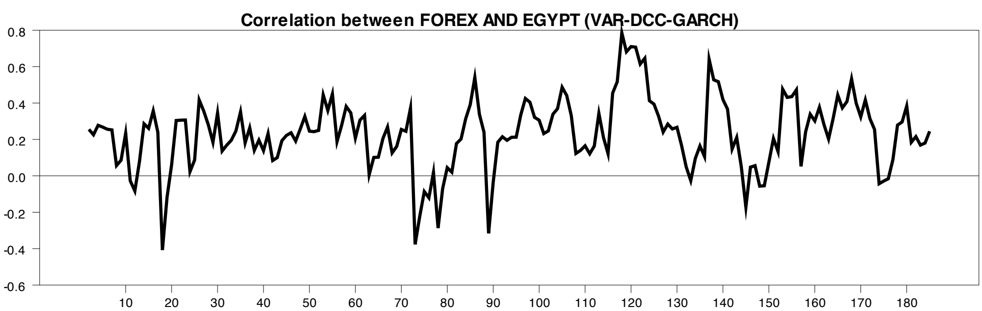
TABLE 7. Diversification and hedging efficiency

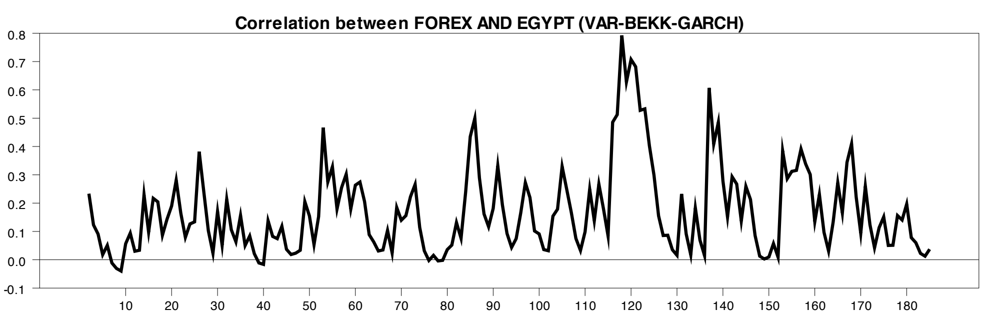
	Mean	Std. Dev.	Risk-adjusted return (x100)	HE	Mean	Std. Dev.	Risk-adjusted return (x100)	HE
	Bahrain/Forex				*Morocco/Forex*			
PF1.	–0.0968	6.4392	–1.5033	–	**0.3970**	5.8430	**6.7945**	–
PF2. VAR-CCC-GARCH	0.0937	2.5600	3.6591	0.8419	0.1269	2.5761	4.9261	0.806
PF2. VAR-DCC-GARCH	0.0971	2.5094	3.8701	0.8481	0.1308	**2.4798**	5.2742	**0.820**
PF2. VAR-BEKK-GARCH	0.0114	**1.9758**	0.5747	**0.9058**	0.1279	2.9742	4.3003	0.741
PF3.	**0.1110**	2.6040	**4.2627**	–	0.1110	2.6040	4.2627	–
	Egypt/Forex				*Oman/Forex*			
PF1.	**0.5600**	9.2980	**6.0228**	–	**0.5850**	5.9930	**9.7614**	–
PF2. VAR-CCC-GARCH	0.1262	2.5842	4.8827	0.9228	0.1739	2.5192	6.9048	0.823

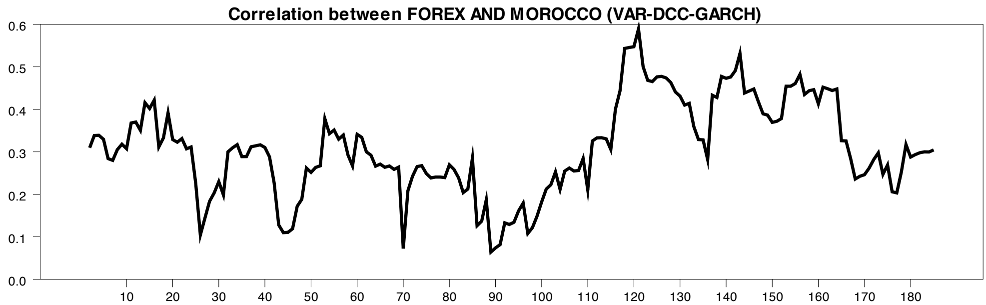
PF2. VAR-DCC-GARCH	0.1221	2.5953	4.7043	0.9221	0.1640	**2.5022**	6.5559	**0.826**
PF2. VAR-BEKK-GARCH	0.1267	**2.5168**	5.0330	**0.9267**	0.1743	4.2850	3.9743	0.489
PF3.	0.1110	2.6040	4.2627	–	0.1110	2.6040	4.2627	–
	Kuwait/Forex				*Qatar/Forex*			
PF1.	**0.3630**	6.2890	5.7720	–	**1.0603**	9.8066	**10.8121**	–
PF2. VAR-CCC-GARCH	0.1436	**2.4271**	**5.9168**	**0.851**	0.2098	2.6920	7.7942	0.925
PF2. VAR-DCC-GARCH	0.1302	2.5198	5.1671	0.839	0.1947	2.6870	7.2471	0.925
PF2. VAR-BEKK-GARCH	0.1458	3.6092	4.0397	0.671	0.2187	**2.4409**	8.9617	**0.938**
PF3.	0.1110	2.6040	4.2627	–	0.1110	2.6040	4.2627	–
	KSA/Forex				*UAE/Forex*			
PF1.	**0.8280**	8.4864	**9.7568**	–	**0.3810**	6.1180	6.2275	–
PF2. VAR-CCC-GARCH	0.1918	4.3047	4.4557	0.743	0.1481	2.5324	5.8471	0.829
PF2. VAR-DCC-GARCH	0.1756	4.5199	3.8851	0.716	0.1404	2.4962	5.6236	0.834
PF2. VAR-BEKK-GARCH	0.1760	3.2413	5.4309	**0.854**	0.1502	**2.0331**	**7.4875**	**0.890**
PF3.	0.1110	**2.6040**	4.2627	–	0.1110	2.6040	4.2627	–

Source: own elaboration.

FIGURE 1. Correlation between FOREX and MENA stock markets with different estimated models






Correlation between FOREX AND MOROCCO (VAR-DCC-GARCH)
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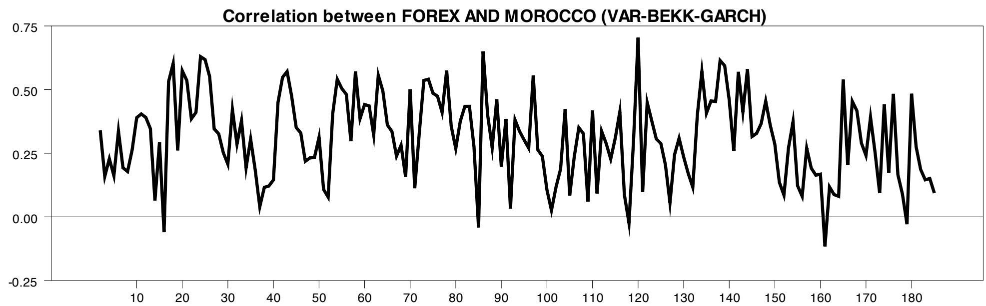
0.5
0.4
0.3
0.2
0.1
0.0
10 20 30 40 50 60 70 80 90 100 110 120 130 140 150 160 170 180


Correlation between FOREX AND MOROCCO (VAR-BEKK-GARCH)
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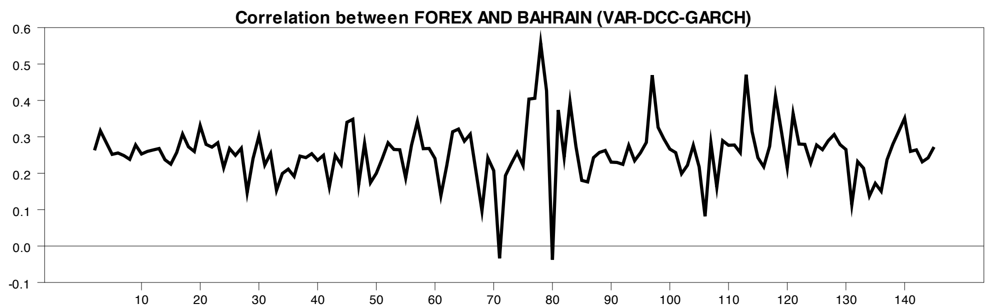
0.50
0.25
0.00
-0.25
10 20 30 40 50 60 70 80 90 100 110 120 130 140 150 160 170 180


Correlation between FOREX AND BAHRAIN (VAR-DCC-GARCH)
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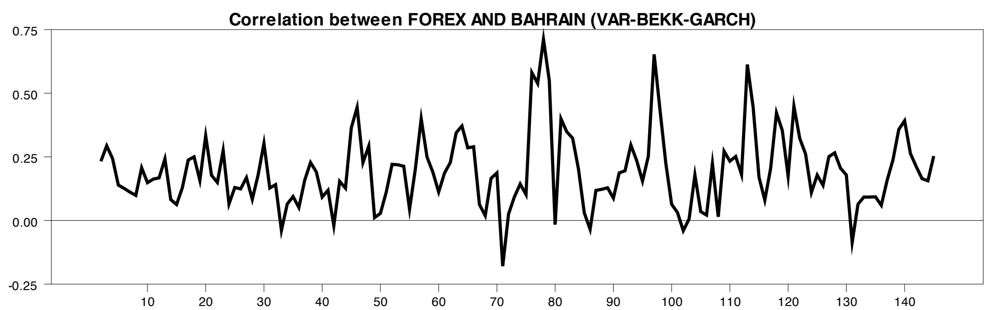
0.5
0.4
0.3
0.2
0.1
0.0
-0.1
10 20 30 40 50 60 70 80 90 100 110 120 130 140


Correlation between FOREX AND BAHRAIN (VAR-BEKK-GARCH)
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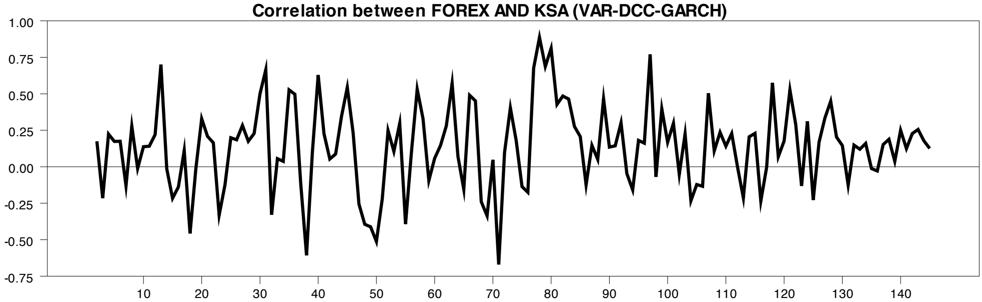
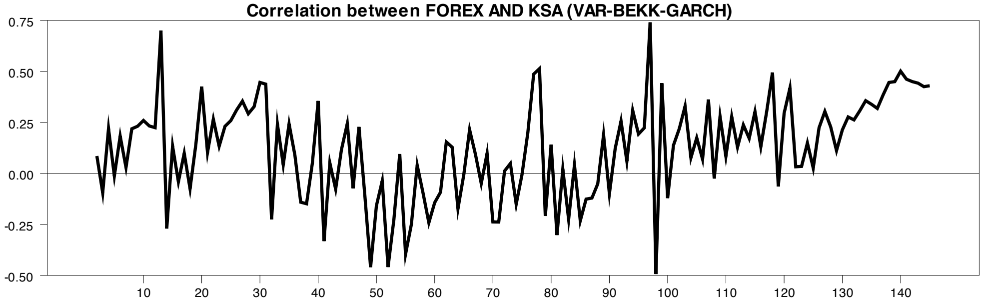
0.50
0.25
0.00
-0.25
10 20 30 40 50 60 70 80 90 100 110 120 130 140

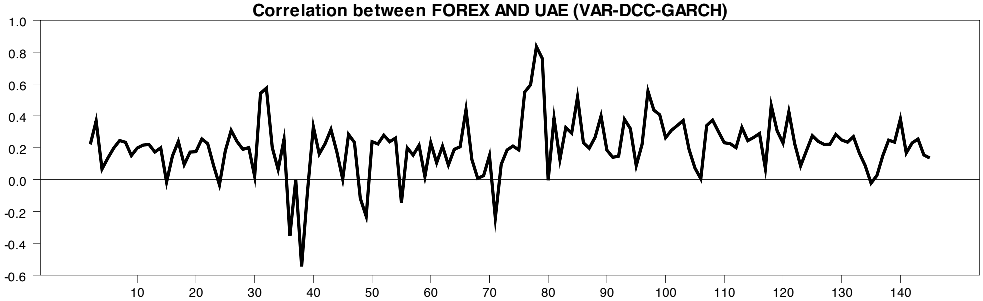
Correlation between FOREX AND KSA (VAR-DCC-GARCH)



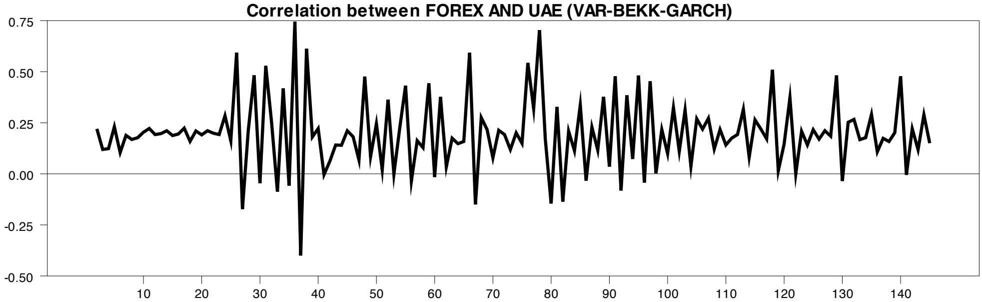
Correlation between FOREX AND KSA (VAR-BEKK-GARCH)

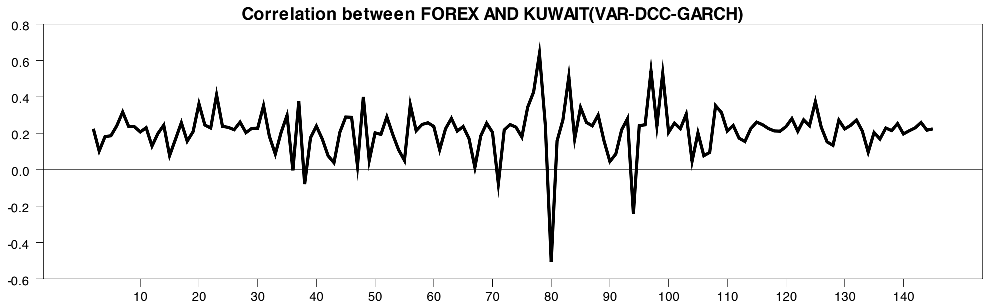


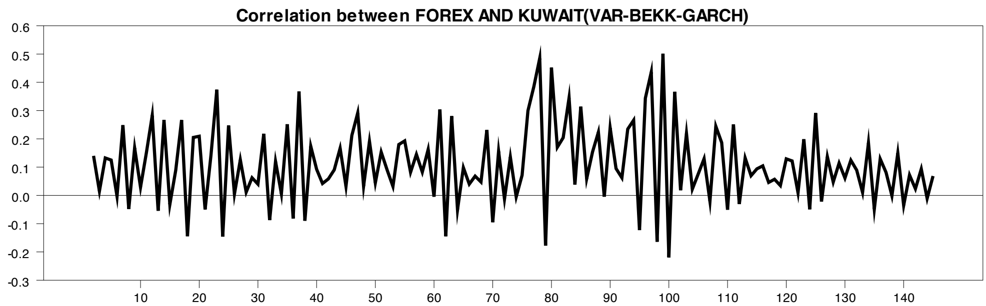
Correlation between FOREX AND UAE (VAR-DCC-GARCH)

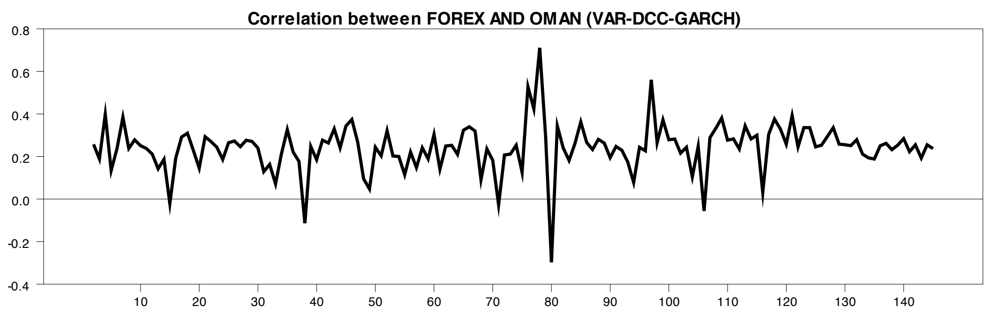


Correlation between FOREX AND UAE (VAR-BEKK-GARCH)




Correlation between FOREX AND KUWAIT(VAR-DCC-GARCH)
0.8
0.6
0.4
0.2
0.0
-0.2
-0.4
-0.6
10 20 30 40 50 60 70 80 90 100 110 120 130 140


Correlation between FOREX AND KUWAIT(VAR-BEKK-GARCH)
0.6
0.5
0.4
0.3
0.2
0.1
0.0
-0.1
-0.2
-0.3
10 20 30 40 50 60 70 80 90 100 110 120 130 140


Correlation between FOREX AND OMAN (VAR-DCC-GARCH)
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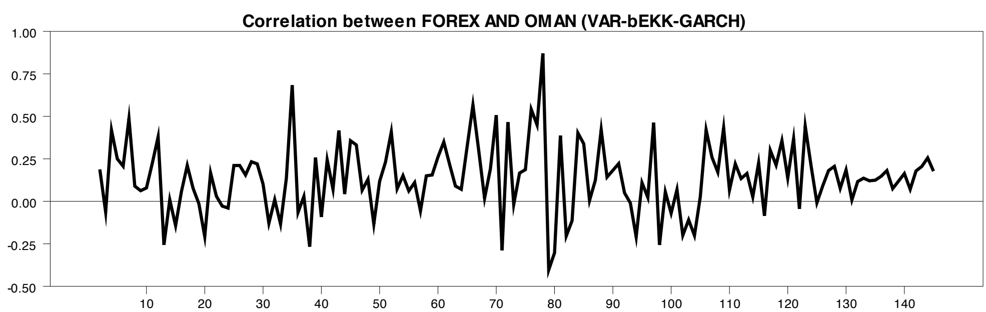
0.6
0.4
0.2
0.0
-0.2
-0.4
10 20 30 40 50 60 70 80 90 100 110 120 130 140


Correlation between FOREX AND OMAN (VAR-bEKK-GARCH)
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0.75
0.50
0.25
0.00
-0.25
-0.50
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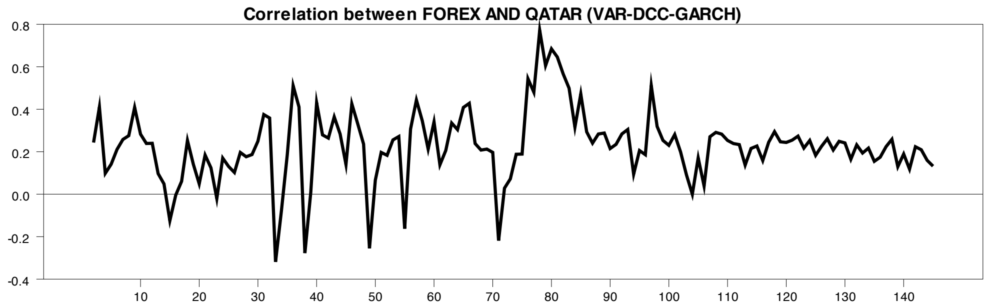

Source: own elaboration.

Notes

[1] Mongi Arfaoui – corresponding author: arfaoui.mongi@gmail.com
[2] Aymen Ben Rejeb: benredjeb_aymen@yahoo.fr

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