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Return dynamics and volatility spillovers between FOREX and MENA stock markets: what to remember for portfolio choice?

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Abstract

This article investigates stock-forex markets interdependence in MENA countries for the period spanning from February 26, 1999 to June 30, 2014. The analysis has been performed through three competing models; the VAR-CCC-GARCH model, the VAR-BEKK-GARCH model and the VAR-DCC-GARCH model. Our findings confirm that both markets are interdependent and corroborate with stock and flow oriented approaches. We find also that, comparing to optimal weights, hedge ratios are typically low, which denote that hedging effectiveness is quite good. Estimation of hedging effectiveness allow concluding that the incorporation of foreign exchange in a full stock portfolio increase the risk-adjusted return while reducing its variance. We note here that the forex market is overweighed for both portfolio designs and hedging strategies. More importantly, this evidence holds for all countries as well as for all considered models. These findings open up new insights for managerial and governmental policy purpose.

Keys words: MENA markets, Foreign exchange, flow oriented model, portfolio balance approach, volatility spillovers, portfolio designs, hedging effectiveness.

JEL classification: F21, F31, G11, G15.

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1. Introduction

The current framework of liberalized capital flows, internationalized stock markets and sustained international diversification has led stocks and foreign exchange (forex) markets to be ever more interdependent. For instance, in order to pay for stocks from a particular country, one must first have the local currency of that country. So the increased demand for a given currency causes the value of that currency to appreciate. On the other hand, selling home currency increases its supply, which drives its value lower. When the outlook for a certain stock market is looking good, international money flows in. Then again, when the stock market is struggling, international investors take their money out and look for a better place to park their funds. Accordingly, the country with the stronger stock market could lead to a rise in value of its currency while the country with the weaker stock market will have a depreciating value of the national currency. Consequently, strong stock market leads to strong currency but weak stock market leads to weak currency.

The forex markets have truly become a global market, bigger than any other security markets. So when thinking about the association between stocks and forex markets, we actually have to think globally. This fact is akin to commodities market which has gradually acquired a global feature. Indeed, crude oil, metals, wheat, corn, sugar have become with global influence specially when denominated in US dollars and as well related to the forex markets. We state here that the existing empirical studies support a close association between forex and commodities market.

Equity markets can also influence forex markets in another way; a weak national currency favors domestic exporters to be cheaper and competitive abroad. This fact helps stimulate growth and profits of those exporters. When earnings are growing, equity markets are likely to do well. Of course, the situation tends to occur in equity markets backed by the major global currencies such as USD, EUR, JPY, GBP, etc. The investigation of volatility spillovers should also look for return dynamics and attempt to ensure cost-effectiveness of findings for managerial purposes and hedging effectiveness as well as regulatory policies.

The aim of this study is to shed light on interdependence mechanisms between stock and forex markets. We focus on linkages in return and volatility and try to establish a global analysis. The special awareness for forex markets, rather than for other financial, real or commodity markets, is motivated by their special features that investors may get. As stated above, when we think forex we think globally. That is to say, forex never sleeps, go long or short horizons, offer low trading costs, unmatched liquidity, availability of leverage, international exposure etc. We link the forex market to a set of MENA stock markets that are recognized as financially emergent and have growing economic sectors with sustainable trade activities, technology transfer as well as regional and international cooperation. Accordingly, we consider that the selected markets are representative of a wide range of economic sectors and financial raised area.

The used econometric methodology, for this analysis, is a VAR-GARCH approach of Ling and McAleer (2003). We try to perform the analysis using VAR-CCC-GARCH, VAR-DCC-GARCH and VAR-BEKK-GARCH competing specifications. One of the main advantages of those specifications is that they let to investigate the inter-markets return dynamics and the conditional volatility spillovers. Additionally, the model provides meaningful estimates of the unknown parameters which tell about innovations and shock transmissions effect. It allows us to detect the outcome of forex market events on the stock market returns, on foreign market exchange returns and on both forex-stock inter-market. On the whole, we beg the following questions: are foreign exchange and stock markets interdependent in MENA countries? and what lessons to get for managerial purposes?

We run three VAR-GARCH models to investigate correlations through inter-markets return dynamics and conditional volatility spillovers. We studied the conditional correlations between markets and tried to get optimal weights, hedging ratios and hedging effectiveness for portfolio management purposes. The three models confirm the interdependence between stock and forex markets for mean and variance equations and support both stock oriented approach of Branson et al., (1977) and flow oriented approach of Dornbusch and Fisher (1980). This evidence point out that both stock and forex markets are weakly efficient and tell about short-term predictability. The findings corroborate statement of recent studies and confirm rejection of weak-form informational efficiency of international stock-forex markets (we cite, Shambora and Rossiter, 2007; Elder and Serletis, 2008; Arouri et al., 2011b).

For portfolio management, we find that comparing to optimal weights, hedge ratios are typically low, which denote that hedging effectiveness is quite good. Estimation of hedging effectiveness allow concluding that the incorporation of foreign exchange in a full stock portfolio increase the risk-adjusted performance while reducing its variance. We note here that the forex market is overweighed either for portfolio designs or for hedging strategies. More importantly, this evidence holds for all countries as well as for all considered models.

This present paper differs from previous studies in few aspects. First, several prior studies focused on the interaction between the two market returns using cointegration and granger causality tests and in some cases incorporates the effect of exogenous economic and financial variables. Although recent studies on markets interdependency focus on both return and volatility spillover channels and make use of simple VAR-GARCH specification model we confirm that the cross-markets correlation of conditional shocks were absent in so far as the CCC for returns across markets was very weak and not statistically significant. At the same line, we find that the estimates of DCC model are for all time significant, which is far from supporting empirically the assumption of constant conditional correlations. This highlights the evidence of dynamic conditional correlations between the selected markets. Consequently, we try here to run four competitive specifications to perform our findings. Second, we implement our investigation on MENA emerging markets which have a contribution in global economic growth. Indeed, those economies are exporters (oil, manufactures, minerals…) as well as importers (engine, technology transfer…), accommodate international labors and have regular international money transfer. Especially oil exporter countries enjoy huge surpluses on trade balance, current accounts, and national incomes and have helpful fiscal policies. Furthermore, these countries expressed an effort of reform and modernization of their economic and financial systems. Third, we develop the investigation in view of an international investor and run an implicit test of financial integration using the Eurodollar parity as proxy for foreign exchange market and do not account for the local currency against a major global currency. Fourth, currency is more often being included as an asset in international investment portfolios. The Mean-Variance approach recommends that the expected return is implied by the variance of the portfolio. 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 portfolio is then fundamental for the performance of the fund. Hence, we go away to demonstrate the managerial usefulness of our findings through an assessment of their effect on portfolio designs and hedging effectiveness. Finally, the study provides an implicit service which allows comparing between stock and forex markets for managerial and governmental executive purpose.

The remainder of the paper is organized as follows. Section 2, presents a brief literature review. Section 3, outlines the empirical methodology. Section 4, describes the data's statistical properties and discusses empirical results. Section 5, presents the implications for portfolio management and section 6, concludes the study.

2. Theory and literature review

Empirical literature focusing on markets interdependencies states that international markets are interdependent through two channels: corporate cash-flows and stock prices. In the same line, Classical economic theory assumes that stock prices and exchange rates can interact and then supports the two approaches.

The first approach is flow oriented models (Dornbusch and Fisher, 1980), which suggest that movements in exchange rates cause movements in stock prices. In terms of causality terminology, it is uni-directional Granger causality. In macroeconomic perspective, stock prices correspond to the present value of firm's expected future cash flows. So, under the hypothesis of market efficiency, stock prices would reflect any phenomenon that affects a firm's cash flow that has been associated with changes in the value of the exchange rate. We notice here that the growing use of hedging instruments, such as derivatives is likely to shrink currency movements' shocks on firm's earnings. The second approach is stock oriented or portfolio balance approach (Branson et al., 1977) which supports the reverse direction and assumes that stock prices may affect exchange rates. In Granger terminology, stock prices movements Granger-cause exchange rates behavior through capital account transactions. Consequently, stock and forex markets are interacting in different ways but note that various aspects such as market liquidity and integration-segmentation level, market imperfection, international trade are likely to boost or lessen this fact. Therefore, empirical analysis of the extent, depth and direction of interdependence between stock and forex markets states that the relationship should exist.

Early studies by Aggarwal (1981) and Soenen and Hennigar (1988) provide evidence in support of the flow model. Later studies shows that market interdependence exist and are conducted by both return series and volatility innovations. For instance, Eun and Shim (1989) show that around 26 percent of the error variance of stock market returns can be explained by innovations in other stock markets, and, not surprisingly, report that the US market is the most influential stock market. King and Wadhwani (1990) support the transmission of information across markets through volatility innovations which results in a contagion effect. Chiang et al. (2000), show that national Asian stock market returns are positively associated with the value of the national currency. Likewise, Sabri (2004) focused on the increasing volatility and instability of emerging markets and points out that stock trading volume and currency exchange rate are the most positively correlated with the emerging stock price changes. Kanas (2000), examines the interdependence of stock returns and exchange rate changes within the national economy in six developed countries (namely, USA, UK, Japan, Germany, France and Canada) and confirm the existence of cointegration between stock and exchange markets. The author observed the evidence of spillover from stock returns to exchange rate changes for all countries except for Germany but no volatility spillovers from exchange rate changes to stock returns for all the countries. Conversely, Bodart and Reding (2001) examined the effect of exchange rate on expected industry return and volatility and show that the effect of forex spillovers on stock markets exist but is it quite small and affirm that exchange rate changes is influenced by the exchange rate regime, the direction and the magnitude of exchange market shocks. Nieh and lee (2001) found no significant long-run relationship between stock prices and exchange rates in G7 countries, using both Engel-Granger and Johansen's cointegration tests. Bhattacharya and Mukherjee (2003) study causal relationship between exchange rate and stock index in India and support the absence of causal relationship between stock market index and exchange rate. Mote later, Ramasamy and Yeung (2005) stipulate 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 this relationship for seven East Asian countries over the period 1988 to 1998, and found a bidirectional causal relation for Hong Kong before the 1997 Asian crises and unidirectional causal relation from exchange markets to stock markets for Japan, Malaysia, and Thailand but from stock markets to exchange markets for Korea and Singapore. During the Asian crises, only a causal relation from exchange market to stock market is seen for all countries except for Malaysia. At the same time, Erbaykal and Okuyan focused on that question in 13 developing economies using different time periods and found causality relationship for eight economies, unidirectional from stock market to exchange market in the five cases and bidirectional for the remaining three. Dilrukshan et al. (2009), support the evidence of a positive co-integrating relationship in the Australian context which corroborate with the stock oriented (or portfolio balance model), that is, stock market movements cause forex market changes. At the same, Agrawal et al. (2010), finds negative correlation between Nifty stock market returns and exchange rates and highlights unidirectional Granger Causality relationship running from the former towards the latter supporting the stock oriented approach. More recently, Other studies found the absence of cointegration between stock prices and exchange rates include Zubair (2013), Okpara and Odionye (2012), Zia and Rahman (2011) etc. In overall, even though the theoretical explanation may seem obvious at times, empirical results have always been mixed and existing literature is inconclusive on the right features of this interdependence. However, we state here that while empirical tests are plausible and apparent they either test interdependence between return dynamics using return series or interdependence between volatility effects using conditional variances. We attempt to run various VAR-GARCH specification models to join the first and the second conditional moments and provide meaningful estimates of the unknown parameters.

3. The empirical methodology

The interdependence is the evidence of movements of information flows between markets which get their delivery from correlation in the second moment (volatility effect) more better that through correlation in the first moment (return dynamics). The better proxy for information is the conditional volatility (we cite for instance, Clark (1973), Tauchen and Pitts (1983) and Ross (1983)). However, in the framework of out aiming, we try to study the interdependence between stocks and forex markets and focus on possible feedback. Accordingly, we consider that a heteroscedastic autoregressive specification is appropriate for the aims of 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 return dynamics and volatility transmission. We present separately the conditional mean equation specification and the conditional variance equation specification in the multivariate framework. The former describe the return channel spillover and the later is considered for the variance spillover with three competitive models: the CCC-, the DCC- and the BEKK-GARCH(1,1).

3.1. The conditional mean equation specification

The return channel spillover 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 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 measures 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 $(E(\varepsilon_t^S \varepsilon_t^{FX}) \neq 0)$.

3.2. The conditional variance equation specification

The dynamics of conditional volatility is modeled by three MVGARCH class models. The first model includes the multivariate CCC-GARCH developed by Bollerslev (1990) with constant correlations between markets which allow to easy estimation and inference of the conditional volatility and the conditional correlation. The second specification is the DCC-GARCH model introduced by Engle (2002), as generalization of CCC model, which allow obtaining different perspective of correlation through modeling wide variance-covariance matrices and to time varying cross-market comovements.

The third specification is the full BEKK-GARCH model of Engle and Kroner (1995), which consider volatility persistence within each market and cross-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;
- $\sqrt{h_t} = \text{diag}\left(\sqrt{h_t^S}, \sqrt{h_t^{FX}}\right)$, 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 representation, it 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 the stock and forex market indices. The cross value of the error terms $(\varepsilon_{t-1}^S)^2$ and $(\varepsilon_{t-1}^{FX})^2$ represents the return innovations in the stock indices across the corresponding forex markets at time (t−1) and represents short run persistence (or the ARCH effect of past shocks), which captures the impact of the direct effects of shock transmission. The presence of (h^{S}_{t-1}) and (h^{FX}_{t-1}) captures the volatility spillovers or interdependencies between stock markets and forex markets. It accounts for the long-run persistence (or the GARCH effects of past volatilities). We remember that the reciprocal effect allows to volatility of one market to be affected by its own past shock and volatility but also by past shock and volatility of other markets.

The conditional covariance between the stock returns 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 in so far as the conditional correlation is assumed to be constant while the conditional variances are varying. Apparently, this assumption is unfeasible 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 ($\overline{Q}$) and its own lagged value as represented as follows:

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

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 Ht rather than the conditional correlations. The BEKK-GARCH class model defines the conditional variance-covariance matrix (H_t) as follows:

$$H_t = CC' + A\varepsilon_{t-1}\varepsilon'_{t-1} A' + BH_{t-1}B'$$

The element C is a (2 × 2) upper triangular matrix of constants for the pair of mark (Eq. 12) (2 × 2) matrix of coefficients that capture the effects of own and cross-market shocks; and B is a (2 × 2) matrix of coefficients that capture the own 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 returns forex market returns 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 computing the optimal weights of a stock-forex portfolio as well as the optimal hedge ratios. We note that in order to be aware from the fact that 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 parameters of the model.

4. Descriptive statistics and empirical results

4.1. Sources of data and descriptive statistics

Our sample data are monthly return indices of eight national MENA stock markets (namely, Bahrain, Egypt, Kuwait, Morocco, Kingdom of Saudi Arabia, Oman, Qatar and United Arab

Emirates,) and the Eurodollar exchange rate series. The sample period is spanning from February 26, 1999 to June 30, 2014. The data of stock markets are sourced from MSCI while the Eurodollar is from the European central bank, ECB, website.

We use monthly data for a number of motivations; first, monthly data allows focusing on *strategic* long term dealing while weekly and daily data fit well on short-term/medium *tactical* dealing. Second, some potential biases arising from the bid-ask bounce, non-synchronous trading days, days of the week, weekend effects, 5 or 7 days a week are far from being discussed with monthly data. We prove the chosen sample period by the intention to cover the global recessions and special events, to account for several sub-periods of economic growth and, of course, the recent global financial crisis which mark an observable separate dynamic pattern since 2007. Moreover, 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 globally similar to the findings of previous studies. First, market returns are significantly departed from the normality hypothesis according to the Jarque – Bera test. Second, the analysis of stationarity using the Augmented Dickey – Fuller (ADF) unit root test clearly shows 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 monthly return series is examined using the Ljung–Box autocorrelation test of lags orders between 6 and 12. The results suggest that stock returns are relatively not autocorrelated. Finally, the Engle's (1982) test for conditional heteroscedasticity rejects the null hypothesis of no ARCH effect in monthly returns which lends support to the use of GARCH specification.

4.2. Stock markets and Forex in MENA countries

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

4.3. 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 in the stock versus forex market return indices. We then present and discuss the results of return dynamics and volatility transmission.

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 constant conditional correlations (CCC) between the stock and forex market return indices are all significantly positive except for Kuwait and Saudi Arabia. It ranges between 30.23% for Morocco and 15.74% for Egypt. This evidence suggests factual and mutual interdependence between markets which allows for diversification opportunities as well as hedging strategies.

Taking a close look at the mean equations we observe that stock returns depend on their own one period lagged return with the exception for Bahrain, Saudi Arabia, Qatar and UAE. On the contrary, forex market return indices are independent from their own past except for KSA. What deserves to be mentioned is that one lagged stock market return significantly affects all the current forex markets return except for Morocco, Qatar and UAE. This fact supports the stock oriented or portfolio balance approach of Branson et al. (1977). In the opposite direction, only Kuwait lagged forex market do not affect the current stock market returns and opposes the flow oriented model of Dornbusch and Fisher (1980). This evidence point out that both stock and forex markets are weakly efficient and tell about the possible success of short-term predictability. The findings corroborate statement of recent studies and confirm rejection of weak-form informational efficiency of international stock-forex markets (we cite, 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 number of cases. The current conditional volatility of stock market is significantly affected by both own past volatility and the one lagged volatility of forex markets except for Morocco and Oman for only stock market conditional variance. So past stock market's conditional volatility helps significantly predict current forex markets GARCH terms solely in Morocco and Oman. Consequently, there are no effective mutual effects between stock and forex GARCH terms.

ARCH terms exhibit relatively more better patterns and prove that current conditional volatility depends with own past shocks except for Bahrain and Kuwait. We state that past own and bidirectional shocks are leading volatility spillovers between stock and forex markets and then help predicting future pricing behaviors. Comparing to GARCH terms, ARCH coefficients have relatively small size which allow inferring that conditional volatility does not react simultaneously to impulses on own and bidirectional shocks. They are likely to progress steadily over time regarding substantial effects of past volatility, as indicated by the large values of GARCH terms. We state that the current findings seem to be plausible and corroborate recent empirical investigations focusing on oil and stock sectors, and stock and 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 departure from normality and autocorrelation are reduced to a great extent than those presented in Table 1 of statistical properties of return series. More prominently, standardized residuals do not exhibit remaining ARCH effects. Therefore, the bivariate VAR(1)-GARCH (1,1) model fits better to capture the bidirectional dynamics between stock and forex markets.

Interpretation of the conditional mean equation makes it possible to confirm the obtained results from the CCC specification model with slightly superior effect regarding values of the significant coefficients. Indeed, return dynamics of forex significantly affect stock market returns except for Kuwait and corroborate with the flow oriented approach. We may explain this fact by the exchange rate regime of Kuwaiti Dinar (KWD) comparing to the other cases in our sample. Reciprocally, the stock market return indices have an effect on forex markets except for Morocco, Qatar and UAE.

On the subject of the conditional variance equation, the DCC specification confirms the effect of forex past volatility on the current stock market's 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 is solely persistent on GCC countries. The results seem to be plausible in so far as GCC countries are providers of oil denominated in US dollars, have a regular large part in international trade and stacking up official foreign exchange reserves in major global currencies such as dollars, Euros, Pound, and Yen). For illustration, look upon the total volume of public financial assets, including official reserves in addition to assets held by public investment vehicles, the GCC states presently dispose of an estimated USD 1.8 tr of which Saudi Arabia and the United Arab Emirates together hold almost 75%. These assets amount to USD 45,000 per inhabitant, which exceeds the per capita public wealth of China, for example, by a factor of 15. (Sources: OPEC, IMF, OECD Researches).

Taking a close look at the mean equations on the estimates of the VAR-BEKK-GARCH class models (Table 5), we observe that the current stock return significantly depends on the own one month lagged return and those of forex markets. This result illustrates the evidence of short-term predictability in some stock price changes through time. As for the cross-markets mean interdependencies, we state that results were mixed and confirm the weak-form of informational efficiency but help predict the trend of stock market pricing behavior. This statement corroborate those observed by Mensi et al.(2014) using DCC-GARCH and BEKK-GARCH class model for dynamic spillovers between international prices commodities markets.

Regarding the conditional variance equations, the current conditional volatility of the stock and forex markets is closely associated with owns past shocks (a_{11} and a_{22}) and past conditional volatility (b_{11} and b_{22}). For spillover mechanisms, the cross-markets shock effects (a_{12}, a_{21}) are found for stock market which significantly affect forex in Egypt and Morocco and Oman (a_{12}) and for foreign exchange market shocks that affect stock market current pricing on Morocco, Oman and Qatar (a_{21}). So stock-forex shocks are perfectly interdependent in Egypt, Morocco and Oman. We state here that Morocco has a special pattern regarding the own and bilateral effects between stock and forex shocks. The conditional volatility of Kuwaiti, Moroccan and Qatari Forex markets are the solely that 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 conditional variances are still influencing on both stock and forex markets. Stock market conditional volatility remains influencing for Bahrain, Egypt, Saudi Arabia, Qatar and UAE (b_{11}) and for Morocco, Saudi Arabia, Oman, Qatar and UAE (b_{22}).

Figures 1, display 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. The significant fluctuations reach their high level during the recent global financial crisis with a peak in, 2010 Q2 and 2011 Q3. Conversely, they mark a number of dips such as in, 2003 Q2 (Irak war) and Q3, 2008 Q4 (Subprime crisis), 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 relationship can be explained by special features of a number of markets, their microstructure, efficiency and especially their exchange rate regimes as well as baskets of currencies which are pegged to.

For comparison, although both the DCC and BEKK estimates evolve similarly over time and increase in recent years, the magnitude of the DCC dynamics is slighter than those observed from the BEKK specification. The current findings confirm those obtained by recent empirical studies such as Schmidbauer and Rösch (2012) and Mensi et al.(2014), who study the effect of OPEC news announcement on energy-markets volatility and dynamic spillovers.

5. Implications for portfolio management /structure and hedging

We capitalize on estimation results to draw attention to the managerial implication in view of an international investor. We compute optimal portfolio weights and hedge ratios and seek to appraise the diversification strategy using the hedging effectiveness statistics.

5.1. Optimal portfolio weights

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

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

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

Where, $w_t^{forex,stock}$ denotes the weight of 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 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 index in the considered portfolio is obtained by computing the $(1 - w_t^{forex,stock})$. Statistics for the portfolio weights are computed from fitting the cited three VAR(1)-GARCH(1,1) class models.

5.2. Hedging strategy

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

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

Table 6, summarize the statistics of portfolio designs for three competing specifications of VAR-GARCH class model.

As shown in table 6, the hedge ratios are typically low, signifying that hedging effectiveness involving stock and forex markets is quite good, allow inferring that the incorporation of foreign exchange in a diversified portfolio of stocks increase the risk-adjusted performance. Optimal weights in the hedged portfolios vary substantially across stock and forex but slightly differ across the used class models. This results corroborate with those obtained by recent empirical studies such as Arouri et al.(2011b). Values of w_t range between 0,84 for UAE in VAR-BEKK-GARCH model and 0,97 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 investor should hold, on average, fewer financial assets (i.e., stock) with mean value of w_t = 91%. When hedging with forex market, he is supposed to overweight financial assets on Moroccan market (w_t = 94%) but to underweight on Saudi or Omani markets (w_t = 86%). This finding suggests that the forex market provide a substantial alternative way for higher benefits as well as hedging of such position. We state that the three class models point out equivalent findings with and relatively smaller values for BEKK specification. The found results confirm those obtained by major recent investigations such as Arouri et al.(2011b).

As for hedge ratios, we find that they are varying between markets but slightly between the three competing class models. Average values are ranging between 0.01 for Kuwait using VAR-CCC-GARCH and 0.13 for Morocco using VAR-BEKK-GARCH model. Greatest values of β_t are found for Morocco (ranging between 12.46% and 13.63%) but smallest values are observed for Kuwait (ranging between 1% and 8.62%).

Interpretation of the present results makes it possible to deduce that the forex market is overweighed either for portfolio designs or for hedging strategies. The VAR-DCC-GARCH class models overweighed forex assets than stocks to build or hedge positions on the international portfolio. We assume that the current findings offer several insights for short hedgers. First, the low ratios suggest that portfolio investment risk can be hedged by taking a short position in 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.

5.3. Diversification and hedging effectiveness

As cited here before, we actually draw on the estimated optimal parameters (weights and hedging ratios), to manage and simulate global portfolio diversification and to learn about the hedging effectiveness. We use the estimates of three VAR-GARCH class models to conceive two portfolios: a first full-stocks portfolio (PFI) and a second stock-forex weighted portfolio (PFII). We try to test the contribution of a weighted stock-forex portfolio to the unhedged stock portfolio (PFI).

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

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

Where, var^{unhedg} and var^{hedg} denote the variances of the unhedged and hedged portfolios respectively. A higher value of HE ratio represent a better hedging effectiveness in terms of the portfolio's variance reduction, and consider the associated investment method as successful hedging strategy.

Table 7 present summary statistics of the diversification strategy of weighted portfolios as well as values of the hedging effectiveness ratio. We consider the non diversified portfolios and incorporate forex assets to implement diversification strategy and assess the reward-to-risk and the hedging effectiveness for each portfolio.

The results, in Table 7, provide evidence that adding forex assets to the diversified portfolios lessens its variance and gets better the risk-adjusted return ratios. More importantly, this evidence holds for all countries as well as for 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 allow reducing the variance of the portfolio. The reduction of variance ranges from 67.1% (Kuwait in the bekk specification) to 93.8% (Qatar in the bekk specification). The variance reduction is then significantly different between countries, but remains relatively stable across the three var-garch class models. The portfolio variance is reduced, or the hedging effectiveness is greater, when the BEKK-GARCH and DCC-GARCH models are used. However, we state here that the BEKK-GARCH is the best one. Chang et al. (2011), Arouri et al.(2011) get to the same finding as regards the superior ability of bivariate diagonal BEKK-GARCH over the

DCC-GARCH and CCC-GARCH when examining the optimal hedging effectiveness between crude oil spot and futures markets and between oil prices and stock sector returns respectively. We state here that the current findings are plausible and economically interpretable and provide practical usefulness for portfolio management as well as for governmental policy making.

6. Conclusion

Learning about the relationship between stocks and forex markets is fundamental for several reasons. First, decisions about monetary and fiscal policy might be affected by such relationship. When policy-makers depreciate national currency so as to boost domestic exporters, they may depress the stock market. Accordingly, expansionary monetary or contractionary fiscal policies that target the interest rate and the real exchange rate should consider the positive effect of a booming stock market on aggregate demand (Gavin, 1989). Second, the nature of tie between the two markets help predict trend of the exchange rate and then advocate multinational corporations to deal with their exposure to foreign exchange rate risk. Third, currency is most of the time built-in as an asset in investment portfolios and the performance of the portfolio is closely associated with the understanding of the link between the incorporated assets. In the framework of portfolio analysis, the Mean-Variance approach suggests that the expected return is implied by the variance of the portfolio which requires accurate estimates of the correlation between stock prices and exchange rates. We note that the magnitude of this correlation may change when the stock prices are the trigger variable or when the forex are the trigger variable. Finally, the understanding of the stock-forex relationship may prove helpful to foresee a crisis. So awareness about such interdependence between the two markets would set off precautionary action before the spread of a crisis (we cite for instance, Khalid and Kawai, 2003; Ito and Yuko, 2004).

We focused on the third reason and run three VAR-GARCH models to a best estimate of correlations through inter-markets return dynamics and conditional volatility spillovers. We studied the conditional correlations between markets and tried to get optimal weights, hedging ratios and hedging effectiveness for portfolio management purposes. The three models confirm the interdependence between stock and forex markets for mean and variance equations and support both stock oriented approach of Branson et al., (1977) and flow oriented approach of Dornbusch and Fisher (1980). This evidence point out that both stock and forex markets are weakly efficient and tell about short-term predictability. The findings corroborate statement of recent studies and confirm rejection of weak-form informational efficiency of international stock-forex markets (we cite, Shambora and Rossiter, 2007; Elder and Serletis, 2008; Arouri et al., 2011b).

For portfolio management, we find that comparing to optimal weights, hedge ratios are typically low, which denote that hedging effectiveness is quite good. Estimation of hedging effectiveness allow concluding that the incorporation of foreign exchange in a full stock portfolio increase the risk-adjusted performance while reducing its variance. We note here that the forex market is overweighed either for portfolio designs or for hedging strategies. More importantly, this evidence holds for all countries as well as for all considered models. We state that the current findings corroborate with previous studies and provide practical usefulness for portfolio management as well as for governmental policy making.

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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^{+}
Bahreïn	-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 on 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.

Table 2. MENA **stock exchanges and forex markets**

	Bahrain	**Egypt**	**Kuwait**	**Morocco**	**Oman**	**Qatar**	**S. Arabia**	**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	Mutualised	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.

Notes: Informations are 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)
$(\varepsilon^{stock}_{t-1})^2$	-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)
$(\varepsilon^{forex.}_{t-1})^2$	-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^{stock}_{t-1}	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^{forex}_{t-1}	-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	

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																
$\boldsymbol{k_1}$	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)	
$\boldsymbol{k_2}$	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	
LB1 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)	
LB2 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	

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-Li$_1$(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-Li$_2$(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-Li$_1^2$(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-Li$_2^2$(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

Table 6. Summary statistics for optimal weights and hedge ratios

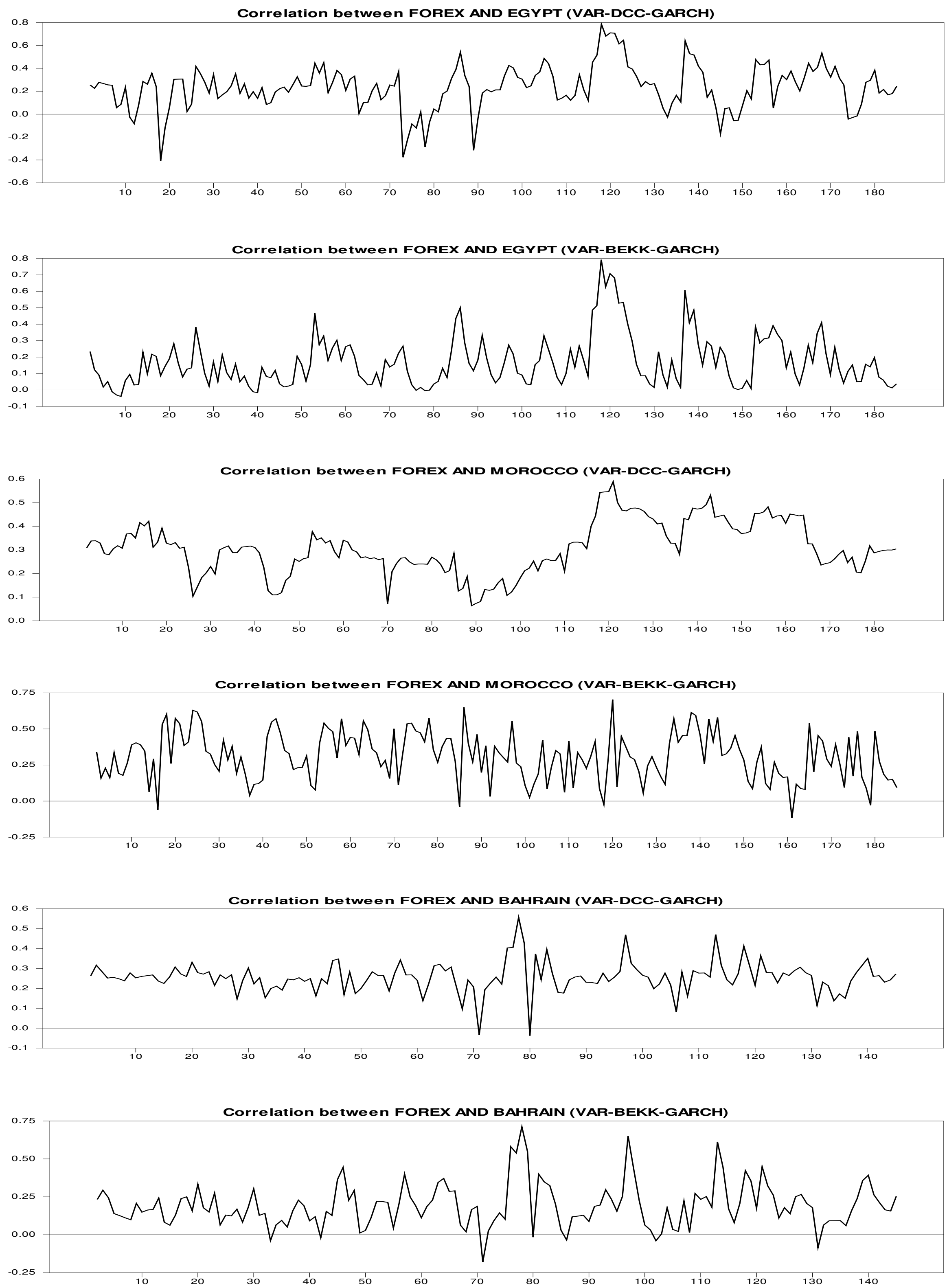
Portfolio	Weights & hedge ratios	VAR-CCC-GARCH	VAR-DCC-GARCH	VAR-BEKK-GARCH
Bahrain/forex	ω_t	0.9167	0.9332	0.8977
	β_t	0.0906	0.1074	0.0778
Egypt/forex	ω_t	0.9662	0.9753	0.9651
	β_t	0.0797	0.0582	0.0420
Kuwait/forex	ω_t	0.8706	0.9238	0.8619
	β_t	0.0095	0.0862	0.0370
Morocco/forex	ω_t	0.9444	0.9308	0.9409
	β_t	0.1246	0.1363	0.1291
Kingdom of Saudi Arabia/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

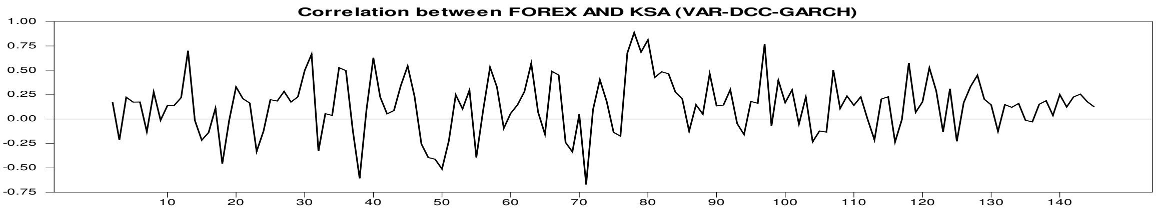
Notes: The data are summary statistics for average values of optimal weights (w_t) and hedge ratios (β_t) for stock-forex portfolio using conditional variance and covariance estimated from three competitive volatility spillover models for a bivariate specification.

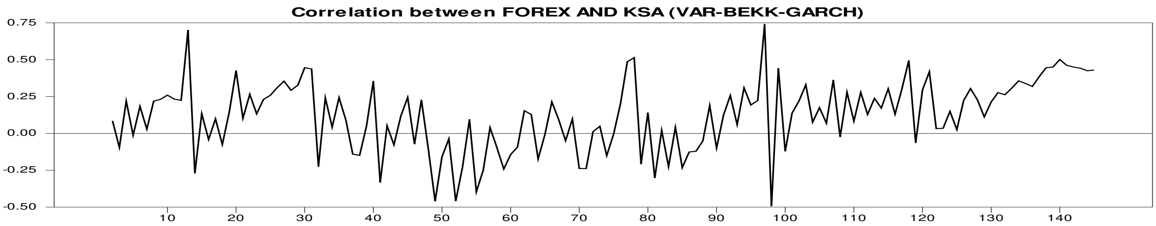
Table7. Diversification and hedging effectiveness

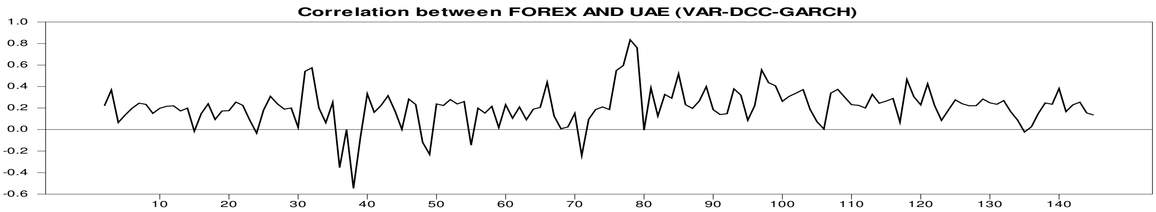
	Mean	Std. Dev.	Risk-adjusted return (x100)	HE	Mean	Std. Dev.	Risk-adjusted return (x100)	HE
	Bahrain/Forex				**Morocco/Forex**			
PF1.	-0.0968	6.4392	-1.5033	–	**0.3970**	5.8430	**6.7945**	–
PF2. VAR-CCC-GARCH	0.0937	2.5600	3.6591	0.8419	0.1269	2.5761	4.9261	0.806
PF2. VAR-DCC-GARCH	0.0971	2.5094	3.8701	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	–

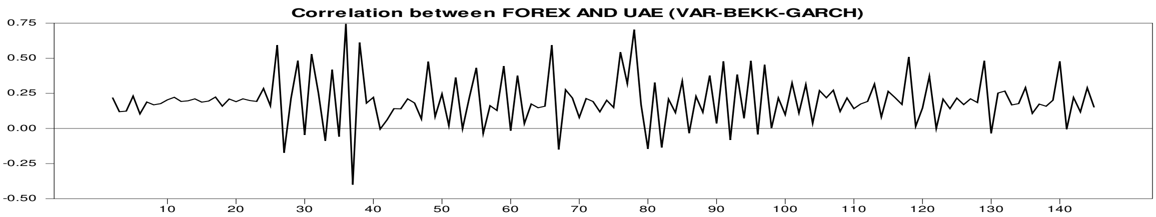
Figure 1. Correlation between FOREX and MENA stock markets with different estimated models.

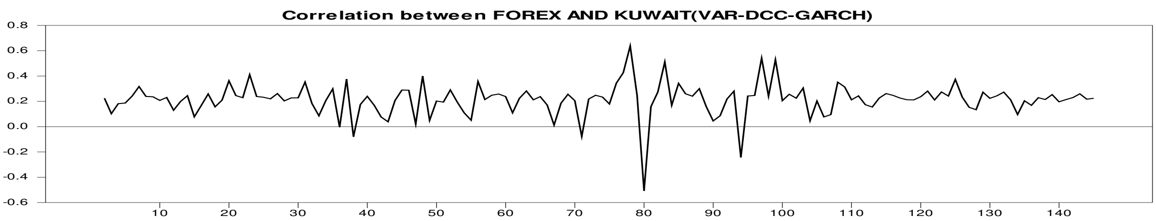


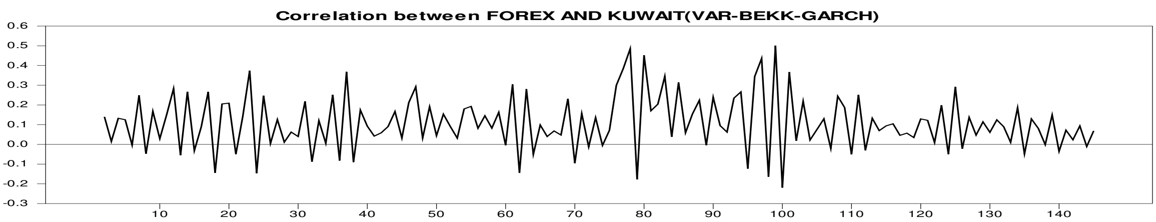

Correlation between FOREX AND KSA (VAR-DCC-GARCH)
1.00 0.75 0.50 0.25 0.00 -0.25 -0.50 -0.75
10 20 30 40 50 60 70 80 90 100 110 120 130 140

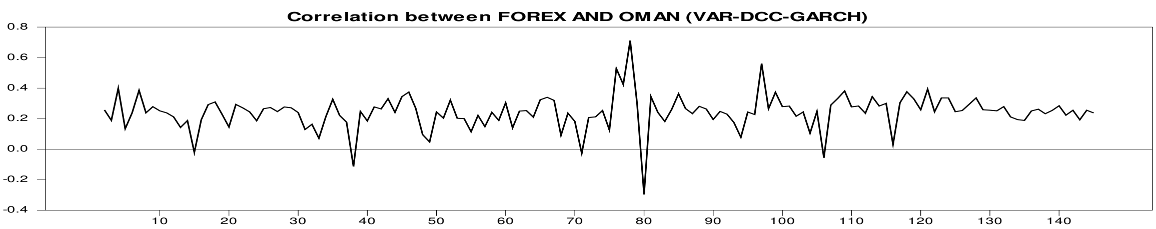

Correlation between FOREX AND KSA (VAR-BEKK-GARCH)
0.75 0.50 0.25 0.00 -0.25 -0.50
10 20 30 40 50 60 70 80 90 100 110 120 130 140

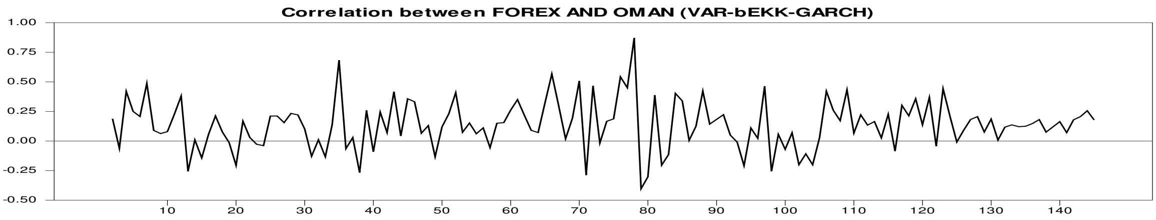

Correlation between FOREX AND UAE (VAR-DCC-GARCH)
1.0 0.8 0.6 0.4 0.2 0.0 -0.2 -0.4 -0.6
10 20 30 40 50 60 70 80 90 100 110 120 130 140

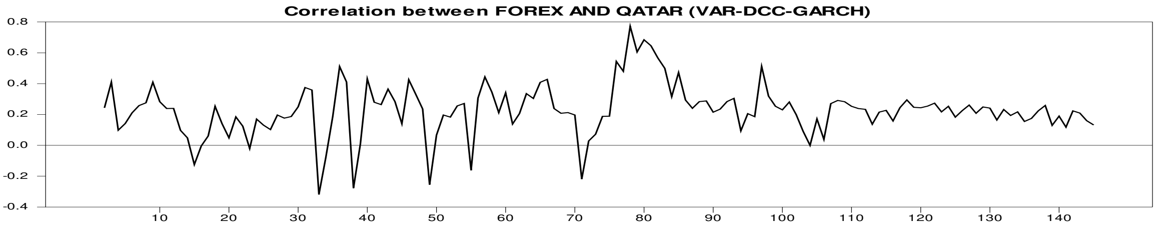

Correlation between FOREX AND UAE (VAR-BEKK-GARCH)
0.75 0.50 0.25 0.00 -0.25 -0.50
10 20 30 40 50 60 70 80 90 100 110 120 130 140


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)
0.8 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)
1.00
0.75
0.50
0.25
0.00
-0.25
-0.50
10
20
30
40
50
60
70
80
90
100
110
120
130
140


Correlation between FOREX AND QATAR (VAR-DCC-GARCH)
0.8
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