Volatility Co-movement in Saudi Arabian and Kuwaiti Stock Markets

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Abstract

We use data on realized volatility to establish co-movement in volatility on the Saudi Arabian and Kuwaiti stock exchanges. We show, in addition, that the probability of positive and negative co-movement are related to the volatility of international equity prices and volatility of oil prices.

Keywords: realized volatility; co-movement; return volatility

JEL classification: F36, G15

1. INTRODUCTION

This paper uses monthly ex post realized volatility to analyze the co-movement in standardized volatility on the Saudi Arabian (SASE) and Kuwaiti (KWSE) stock exchanges. During the last three years, stock returns on these exchanges have been among the highest in the world: in 2005, the return was 104 percent on the SASE and 78 percent on the KWSE. The recent sizeable corrections highlight the potential for volatility spillovers and policies to limit the effects of volatile asset prices. We follow Schwert (1989), who analyses relations among volatility measures, and Bracker et al (1999), who examine the economic determinants of co-movement in international stock markets, but we use the concept of realized volatility and a different definition of co-movement. Realized volatility provides a model-free measure of volatility, which can be treated as observed instead of latent. This contrasts with the volatility estimates obtained in ARCH, stochastic, and implied volatility models (Engle 2004), which are conditional on the specific assumptions of the model used. For co-movement, we use a measure that captures the time-varying nature of cross-market dependence.

Our results make three contributions to the literature. First, the distribution of the logarithm of realized volatility is approximately normal, similar to that obtained for the mature markets like the United States. Second, the distribution of the co-movement of standardized volatility is positively skewed, indicating that co-movements are less frequent for large values of volatility. Third, co-movement of standardized volatility in the two markets is explained in part by volatility in the Dow Jones Industrial Average (DJIA) and in the price of crude oil, suggesting a significant role for external factors common to both markets. Consequently, risk management practices are likely to be the most effective measures to limit the macroeconomic effects of asset price volatility.

2. METHODOLOGY

We use contemporaneous and simple nonparametric measures, based on the concepts of realized volatility and co-movement, to investigate interdependence. Realized volatility is based on the theoretical framework in Andersen et al (2003). Let the $N$-dimensional logarithmic price process, $p_t$, follow a multivariate continuous-time stochastic volatility diffusion,

* Corresponding author. Email: hleon@imf.org The views expressed do not represent the views of the International Monetary Fund. I would like to thank Malina Savova for research assistance, and Aasim Husain, Mohsin Khan, Abdel Senhadji, Lucio Sarno, Oral Williams, and participants at the Central Bank of Barbados 2006 Review Seminar for helpful comments.
\[ dp_t = \mu_t dt + \Omega_t dW_t \]

where \( W_t \) is a standard \( N \)-dimensional Brownian motion, \( \Omega_t \) is the \( N \times N \) positive definite diffusion matrix, and \( \mu_t \) is the \( N \)-dimensional instantaneous drift. \( \Omega_t \) and \( \mu_t \) are strictly stationary and jointly independent of \( W_t \). By the theory of quadratic variation and under weak regularity conditions, the compounded \( q \)-period return, \( r_{t,t+q,q} \equiv p_{t,t+q} - p_{t,t} \), has the property

\[
\sum_{j=1,\ldots,[q/d]} r_{t+j,d,d} \cdot r'_{t+j,d,d} - \int_0^q \Omega_{t+\tau} d\tau \to 0
\]

almost surely for all \( t \) as the sampling frequency increases \((d \to 0)\). Thus, the integrated diffusion matrix \((\int_0^q \Omega_{t+\tau} d\tau)\), a natural measure of the true \( q \)-period latent volatility, can be approximated by a realized diffusion matrix, by using sufficiently high-frequency returns. The ex post realized variance is the sum of \( q/d \) squared returns over the period \( t, t+q \) and the standardized return is the \( q \)-period return divided by the \( q \)-period return realized variance. Although finite sampling and microstructure noise (e.g., infrequent trading) impart some bias to the estimates, the realized variance is typically sufficiently accurate to approximate the true variance.

We define co-movement as in Baur (2004) and Baur and Schulze (2005). That definition differs from measures based on the Pearson correlation coefficient, which can be biased from heteroscedasticity, asymmetric response, and nonlinearity (Embrechts et al., 2002), and is based on a notion of common movement in the same direction. For two variables, with observations \( x_{1t}, x_{2t} \), then

\[
\text{Comov}_t = \begin{cases} 
\min(x_{1t}, x_{2t}), & \text{if } x_{it} > 0 \quad i = 1, 2 \\
\max(x_{1t}, x_{2t}), & \text{if } x_{it} < 0 \quad i = 1, 2 \\
0, & \text{otherwise}
\end{cases}
\]

For every time \( t \), the definition measures the direction of the instantaneous movement shared by the variables (both positive or both negative), and can be interpreted as the common response of the variables to a shock. Thus, we examine dependence from the joint information across the series of interest. By standardizing the variables, the magnitude of co-movement can be interpreted as the common relative movement among the variables. The counts of common positive and negative responses provide constant probabilities of co-movement, as percentages of the sample of observations. While easily extended to more than two variables, many variables would yield few counts of common responses and less efficient estimates.

To explore the potential time-varying nature of the probabilities of negative, positive, and no co-movements, we estimate a multinomial logit model with three categories. Thus, the probability of co-movement at time \( t \) being in category \( j = 1, 2, 3 \) is:

\[
\Pr(y_t = j) = \frac{\exp(\beta_j' z_t)}{\sum_{j=1}^3 \exp(\beta_j' z_t)}
\]

where \( y_t \) is the index of the event, \( j \) is the category at \( t \), \( z_t \) a vector of exogenous variables, and \( \beta_j \) the parameter vector to be estimated. \( z_t \) consists of a constant, a dummy for structural change since 9/11, volatility measures for the price of oil (a fundamental) and the Dow Jones Industrial Index (an international spillover), and the lag of co-movement. That framework allows us to examine whether the probabilities of co-movement have changed since 9/11, are different for positive and negative co-movements, and are explained by factors common to both markets. In particular, we examine whether volatility co-movement is responsive to changes in
3. EMPIRICAL RESULTS

We use the daily continuously-compounded stock index returns from Bloomberg, for the period January 1996 to April 2006, to compute the monthly realized variance and standard deviations (volatility) for the SASE and KWSE. Daily frequency reduces the microstructure noise in intra-day returns but is farther from the continuous-time concept provided by intra-day returns. The daily returns used are de-meaned and MA(1)-filtered to remove any serial correlation. The realized variances are standardized (for interpretation and comparisons) before analyzing the co-movement between the KWSE and SASE.

3.1. Distributions of Realized Volatility

As in Andersen et al (2001), the realized variances are highly skewed and leptokurtic, but the logarithm of realized volatility in both markets is approximately normal. As in developed financial markets (e.g., US, UK), the distribution of returns standardized by realized volatility is also approximately normal (Table 1), suggesting that if the objective was the parametric modeling of the return-volatility relationship, a normal/log-normal mixture would be appropriate (see Andersen et al, 2001). While volatility in the two markets were similar in magnitude up through 2002 (Figure 1), realized volatility on the SASE was higher especially since 2003. The time-varying volatilities generate time-varying correlations, which also have an approximately normal distribution.

3.2. Co-movement of Volatility

Co-movement between realized volatility on the SASE and KWSE occurs 64 percent of the time, with 47 percent as negative co-movements and 17 percent as positive co-movements (Figure 2). This total percentage is much higher than the 50 percent expected. The average positive co-movement is 0.8 standard deviations, with the maximum recorded at 2.98 standard deviations. On the other hand, the average negative co-movement is 0.4 standard deviations, with a maximum of 0.9 standard deviations. Extending the analysis to include a third variable, we find co-movement among volatility measures of the SASE, KWSE, and the price of Dubai Fateh crude occurs 36 percent of the time, again much higher than the 25 percent expected. If instead the average spot price for West Texas Intermediate, Brent, and Dubai is used, co-movement occurs 33 percent of the time. Co-movement among the SASE, KWSE, and the DJIA occurs 38 percent of the time. Further, the co-movement among SASE, KWSE, DJIA, and the price of Dubai occurs 25 percent of the time, two times the expected percentage. The distribution of the co-movement is distinctly skewed with a greater mass at values below rather than above the mean, indicating that the markets co-move less for larger than "expected" changes, that is, the idiosyncratic noise increases for larger than expected changes. Further, Figure 2 indicates some clustering (temporal correlation) of positive and negative co-movements over the sample, with more negative co-movements in the pre-2001 period and more positive co-movements in the post-2001 period.

3.3. A Simple Probability Relationship

While informative, the average probabilities reported above do not indicate changes in the pattern of co-movement. Using the constant probability model (identical to the multinomial logit with only a constant) as a benchmark, we estimate a three-category (negative, positive, and no co-movement) multinomial logit model, with only the constant and the 9/11 dummy. The likelihood ratio test \( \chi^2(2) = 12.7 \) does not reject and the model estimates a shift in the probability (pre- and post-911) of negative co-movement from 59 to 31 percent and positive co-movement from 9 to 27 percent, showing the base probability model is an average of these two probabilities. To further explore the time-varying probabilities, we introduce the volatilities of the price of oil and the DJIA index. A likelihood-ratio test \( \chi^2(8) = 36.1 \) does not reject the joint significance of all the variables versus the base model. For this model, the probability of negative (positive) co-movements, averaged over all observations, has an elasticity of -0.2 (0.3) with respect to the 9/11 dummy; 0.2 (0.4) for volatility of the price of crude oil; -0.4 (-0.2) for the volatility of the DJIA; and 0.2 (0.1) with respect to the co-movement in the previous period. Since 2002, the probability of negative (positive) co-movement has decreased (increased), mirroring the higher and more frequent changes in volatility (Figure 3). Further the results show that while the
probability of negative co-movements was greater than the probability of positive co-movements before 2002, they have since equalized. These results suggest a promising line for further enquiry.

4. CONCLUSIONS

We find results for the distribution of realized volatility in two emerging stock markets that are similar to those in developed stock markets. Further, the realized standardized volatility co-moves and that co-movement is related to volatility of international equity prices and volatility of oil prices. These results suggest that part of the observed volatility and co-movement can be explained by external factors common to both markets. As such, policies to mitigate the observed volatility may be outside the control of the authorities. Consequently, defensive measures, such as improved regulation and risk management practices in financial institutions, may be the best policies to contain the impact of stock market volatility.

REFERENCES


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Max. (Min.) is the maximum (minimum) of the series; Std. is the standard deviation; Skew is the skewness; Kurt. is kurtosis; J-B is the Jarque-Bera test statistic for normality; ADF is the value of the t-statistic for the Augmented Dickey Fuller test for a unit root; SA (KW) is Saudi Arabia (Kuwait); Vol is volatility; Rtn is return; Comov is co-movement; and Prob is probability; Neg/Pos/Non is negative/positive/no co-movement.
Figure 1. Realized Volatility on Saudi Arabian (SASTD) and Kuwaiti (KWSTD) markets
Figure 2. Co-movement of Realized Volatility
Figure 3. Probability of Negative (NEG), Positive (POS) and no (NON) Co-movement
Figure 3 (continued). Probability of Negative (NEG), Positive (POS) and no (NON) Co-movement
Figure 3 (concluded). Probability of Negative (NEG), Positive (POS) and no (NON) Co-movement