RESEARCH ARTICLE

Relationship between Volatility and Expected Returns in Two Emerging Markets

Business and Economics Journal, Vol. 2013: BEJ-84

Relationship between Volatility and Expected Returns in Two Emerging Markets

Kenneth A Tah
Department of Economics and Finance, Louisiana Tech University, Ruston, LA 71272, USA.
College of Business, Grambling State University, Grambling, LA 71245, USA.

Correspondence: kat023@latech.edu

Accepted: Jun 21, 2013; Published: Jul 4, 2013

Abstract
This paper provides an insight into the stochastic behavior of monthly stock market returns for two emerging markets – the Nairobi Stock Exchange (of Kenya) and Lusaka Stock Exchange (of Zambia) for the period February 1997 to October 2012. I investigated the relationship between market expected returns and conditional volatility for Kenya and Zambia stock indices. I am curious to know if Kenya and Zambia stock exchanges are vulnerable to external shock from the South Africa stock exchange, a major African security market. The GARCH-in-mean (GARCH-M) model was used for this study and the estimates show that the dynamic relationship between risk and return is quite different between Kenya and Zambia stock markets. There is a negative and significant relationship between conditional mean and variance for Lusaka Stock Exchange whereas, there is no significant relationship between expected returns and conditional variance for Nairobi Stock Exchange. These results suggest that Nairobi Stock Exchange investors consider some other risk measure to be more important. This paper finds that Nairobi Stock Exchange is vulnerable to external shock.

Keywords: Expected returns; conditional volatility; volatility spillover; GARCH-in-mean model.

1. Introduction

In his intertemporal capital asset pricing model, Merton [1] postulated a positive relationship between risk and expected return. Several papers have studied the intertemporal relationship between stock market conditional volatility and expected return on the industrialized markets. Results, however, have been inconclusive. Campbell and Hentschel [2], Bansal and Lundblad [3], Girard *et al.* [4], Xing and Howe [5], León *et al.* [6] and Nyberg [7] have reported a positive relationship between risk and return. On the other hand, Baillie and DeGennaro [8], Glosten *et al.* [9], Wang [10] and Hibbert *et al.* [11] have reported the opposite. León *et al.* [6] used the mixed data sampling on several European stock indices including stock markets of France, Germany, Spain and the United Kingdom for the period, January 1988 to December 2003. They illustrated a significant positive relationship between expected market excess return and conditional variance. Nyberg [7] used U.S. monthly data to study the risk–return tradeoff, but allowed for the state of the economy effect by taking the state of the business cycle into account. He documented a positive relationship between the conditional mean and variance of returns regardless of the state of the business cycle. On the other hand, Baillie and DeGennaro [8] used both monthly and daily center research security prices (CRSP) data on GARCH-in-mean (GARCH-M) model with conditional student *t* distribution and found no statistical significant relationship between stock expected return and its own volatility. Hibbert *et al.* [11] used daily and intraday data of SP 500 stocks to examine the short-term dynamics relation between return and changes in implied volatility. They documented a negative and significant relation and linked their results to the behavioral explanation of representativeness, affect and extrapolation bias as documented by Shefrin [12, 13]. With representativeness, investors view high risk, low return to be representative of bad investment; hence judgment on the risk–return relation for stocks as poor will be negative. Affect, which is closely related to representativeness, holds that people form emotional connections to activities and labels negative affect to be associated with bad and positive affect to be associated with good. Decision making on market return with affect and representativeness for negative returns and high risk, causes the negative return–volatility relation[1]. Lastly, extrapolation bias, holds that, if investors extrapolate past events to form forecast base on their belief that recent events are representative of the future, negative (positive) return would cause investors to increase (decrease) put option premiums.

An extension to the study of risk has been the desire to explore the transmission of volatility across stock markets. Lee and Stewart [15] explored the interactions among six Baltic and Nordic exchanges (Estonia, Latvia, Lithuania, Denmark, Finland and Sweden) together with the possibility of spillovers from three major external markets – the German DAX, the UK FTSE 100 and the US SP 500. They found volatility spillover from all three external sources. The Baltic exchanges received external shock from FTSE 100 and SP 500 while all six markets received external shock from the DAX.

Even though there have been a number of studies devoted to understanding the relationship between condition variance and expected return, most of these studies have been on industrialized market. Compared to developed economies, emerging markets are subject to global risk due to their increasing degree of financial integration. For example, Grabel [16] showed that the severity of the contagion risk depends on the degree of financial openness and the hedge in place against currency and contagion risks for emerging economies.

The objective of this paper is to provide an insight into the stochastic behavior of monthly stock market returns for two emerging markets – the Kenya and Zambia stock indices. I investigated the relationship between market returns and conditional volatility for Kenya and Zambia stock indices. Lastly, I would like to know if Kenya and Zambia stock exchanges are vulnerable to shocks from the South Africa stock exchange, a major African security market. This paper uses the GARCH-M model with slight modification to account for the possibility of external shock from the South African stock market.

This paper adds to the literature by providing evidence of the return–volatility relation for two emerging markets. I documented a negative and significant relation between conditional variance and expected return for Zambia stock market. On the other hand, no significant relation is found between conditional variance and expected return for Kenya stock market. The stochastic behavior of return series is different between Kenya and Zambia stock markets. We find serial correlation in the return series for Kenya exchange in violation to the martingale model of stock prices. That is, there is a significant first moment dependency of stock returns. Zambia return series has second moment dependency which violates the random walk model for stock prices but in line with the martingale model, since the return series has no serial correlation. This paper provides additional insight into the nature and degree of interdependence of stock markets in emerging countries. Kenya stock market is found to be vulnerable to external shock from the South Africa stock market.

[1]This is consistent with the perception that dealers and investors of options bid up put prices during market downturn to protect against additional future losses [14].

The remainder of the paper proceeds as follows: Section 2 presents the data, Section 3 gives a review of the GARCH-M model used in this study, Section 4 provides the empirical results and Section 5 provides the conclusion.

2. Data

The data used in this study are monthly returns from for Kenya, Zambia and South Africa stock exchanges, covering the period February 1997 to October 2012 (189 observations). Respective security prices were obtained from the International Financial Statistics (IFS) of IMF. Percentage returns for each of the indices are obtained by multiplying the first difference of the natural logarithm of each market indices by 100. That is,

$$R_t = 100 \times \left[\log(P_t) - \log(P_{t-1})\right] \quad (1)$$

where, P_t is the level of the price index at time t. Table 1 reports a number of descriptive statistics for the return series. These include mean, standard deviation, maximum, minimum, skewness, kurtosis, Jarque-Bera statistic and Augmented Dickey-Fuller (ADF) and Phillip–Perron (PP) unit root test statistics. Based on the standard deviation, Zambia stock market returns appear to be more volatile than Kenya's. However, Zambia stock market returns are positively skewed, whereas Kenya stock market returns are negatively skewed. Both the ADF and PP unit root test suggests that both Kenya and Zambia return series are stationary at their levels.

Table 1: Descriptive summary statistics for monthly stock market returns data: February 1997 to October 2012.

Parameter estimates	Kenya (Nairobi Stock Exchange)	Zambia (Lusaka Stock Exchange)
Mean	0.095	1.929
Standard deviation	6.053	7.112
Maximum	15.989	32.398
Minimum	−25.663	−17.879
Skewness	−0.291	0.700
Kurtosis	5.104	5.598
Jarque-Bera	37.533**	68.584**
ADF (k)	−4.773(3)**	−7.852**
PP (h)	−12.198(7)**	−12.884**

Mean, standard deviation, maximum and minimum are all in percentages.
ADF (k) is the ADF unit root test with lag k based on the Akaiki Information Criteria.
PP (h) is the PP unit root test with lag h based on Newey-West using Bartlett Kernel.
**Statistical significant at the 5% level.

3. Measuring Volatility Using the GARCH-M Approach

The GARCH-M model introduced by Engle *et al.* [17], is often considered to explore the stochastic behavior in many financial time series particularly the relation between conditional volatility and expected return. Past information is considered in this model, such as past volatility and past return. Let μ_t and σ_t^2 represent the conditional mean and variance of stock returns for each market. A mean equation is developed in which the dependent variable is the conditional mean and the independent variables are the past returns and conditional variance. That is,

$$\mu_t = \beta_0 + \beta_1 R_{t-1} + \ldots + \beta_k R_{t-k} + \delta \log(\sigma_t^2) \quad (2)$$

where, R_{t-n} and β_n, for $n = 1,\ldots,k$, denotes past returns and their corresponding autoregressive coefficient, and $\log(\sigma_t^2)$ is its conditional variance in natural logarithm. Logarithmic specification usually provides a better fit for financial data and is based on empirical grounds, e.g., Engle *et al.* [17]. Random walk and martingale model for stock prices holds that β_n for $n = 1,\ldots,k$, should not be statistically significant[2].

The conditional variance equation is model as a linear function of past volatility shocks[3] (ε_{t-s}^2, for $s = 1,\ldots,p$) and past conditional variances[4] (σ_{t-s}^2, for $s = 1,\ldots,q$). That is:

$$\sigma_t^2 = \alpha_0 + \alpha_1\varepsilon_{t-1}^2 + \ldots + \alpha_p\varepsilon_{t-p}^2 + \gamma_1\sigma_{t-1}^2 + \ldots + \gamma_p\sigma_{t-q}^2 \tag{3}$$

where, ε_{t-s} is the difference between return for period $t-s$ and its conditional mean. It represents unexpected shock or market innovation. The above variance equation can be slightly modified to capture the possibility of external shock. For example, if SA represents stock returns from another market and we wish to investigate its volatility spillover to the market we are studying, the modified variance equation becomes,

$$\sigma_{i,t}^2 = \alpha_0 + \alpha_1\varepsilon_{t-1}^2 + \ldots + \alpha_p\varepsilon_{t-p}^2 + \gamma_1\sigma_{t-1}^2 + \ldots + \gamma_p\sigma_{t-q}^2 + \lambda_1 \mathrm{SA}_{j,t} \tag{4}$$

A statistically significant λ_1 value implies market *i* receives external shock from market *j*. For $p = q = 0$, the GARCH (p, q) mean model trims to GARCH (1, 1)-M model. The constraints that $\alpha_t \geq 0$ and $\gamma_t \geq 0$ are needed to ensure that the conditional variance is non-negative [18].

4. Empirical Results

Table 2 reports the autocorrelation coefficient for the Kenya and Zambia return series together with their Ljung–Box portmanteau test statistics for both return and squared return series for 12 lags.

Table 2: Autocorrelation coefficients for monthly stock market returns.

Autocorrelation coefficients	Kenya (Nairobi Stock Exchange)	Zambia (Lusaka Stock Exchange)
ρ (1)	0.152	0.083
ρ (2)	0.086	0.174
ρ (3)	0.181	0.059
ρ (4)	0.155	0.204
ρ (5)	0.031	−0.086
ρ (6)	0.114	0.035
ρ (7)	0.050	−0.060
ρ (8)	0.011	0.041
ρ (9)	0.059	−0.014
ρ (10)	0.045	−0.002
ρ (11)	0.011	−0.067
ρ (12)	0.014	0.060
$Q(12)$	21.378**	20.375
$Q^2(12)$	46.898**	59.273**

$Q(12)$ and $Q^2(12)$ are the 12th lag Ljung–Box test statistics applied to the return and squared return series.
**Statistical significant at the 5% level.

[2] Random walk and martingale models simply state that stock prices cannot be predicted using past prices. In order words, prices are serially uncorrelated. Random walk deviates from martingale in that random walk assumes the variance of price changes are homoskedastic, whereas conditional heteroskedasticity is attuned with the martingale model.

[3] This captures news from past periods and is measured as the lag of the squared residuals from the mean equation. It is also called the ARCH term.

[4] Past conditional variances are also called the GARCH term.

$Q(k)$ and $Q^2(k)$ are the test statistics for K^{th}-order serial correlation for the returns and squared returns, respectively. Both statistics follow the chi-square distribution with 12 degree of freedom under the null hypothesis of no serial correlation. Both the Kenya and the Zambia autocorrelation coefficient appears to decay with increased lag returns suggesting both return series are stationary over time. A statistically significant $Q(12)$ for Kenya suggests the presence of serial correlation in their return series. $Q^2(12)$ is significant for both Kenya and Zambia stock returns indicating the presence of serial correlation in the squared return series. That is, the presence of conditional heteroskedasticity[5].

To identify the optimal lag structure for the mean equation of the GARCH-M model, I used the Akaike Information Criterion (AIC). The AIC suggests an optimal lag of four for Kenya stock returns and two for Zambia stock returns. Robustness checks of each model are done using the Ljung–Box statistics of the standardized residual and squared standardized residuals of each model. In addition, an *F*-test is performed to test for the correct specification of the conditional variance equations. Table 3 presents the results of the GARCH (1, 1)-M model with the logarithmic specification for the mean equation. The mean equation results show serial correlation in the return series for Kenya exchange in violation to the martingale model of stock prices. That is, there is a significant first moment dependency of stock returns. Zambia return series have second moment dependency which violates the random walk model for stock prices but in line with the martingale model, since the return series has no serial correlation (See Lo and MacKinlay [20] for test on random walk). No significant relation is found between conditional variance and expected return for Kenya exchange (δ coefficient is insignificant). However, there is a negative and significant relation between conditional variance and expected for Zambia (δ coefficient is negative and significant). The GARCH (1, 1)

Table 3: GARCH-M model for monthly stock market returns: logarithmic specification.

$$\mu_t = \beta_0 + \beta_1 R_{t-1} + \beta_2 R_{t-2} + \beta_3 R_{t-3} + \beta_4 R_{t-4} + \delta \log(\sigma_t^2),$$
$$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \gamma_1 \sigma_{t-1}^2 + \lambda_1 \mathrm{SA}_t$$

Parameter estimate	Kenya (Nairobi Stock Exchange)	Zambia (Lusaka Stock Exchange)
β_0	−0.604 (−1.16)	10.626** (3.28)
β_1	0.179** (2.03)	0.044 (0.56)
β_2	0.076 (0.89)	0.161** (2.37)
β_3	0.113 (1.51)	–
β_4	0.083 (1.29)	–
δ	0.197 (1.21)	−2.537** (−2.75)
α_0	13.80** (2.59)	5.508 (1.71)
α_1	0.135 (1.31)	0.158** (2.15)
γ_1	0.518** (2.80)	0.715** (5.96)
λ_1	−1.89** (−3.36)	−0.669 (−1.59)
$Q(12)$	1.95	3.54
$Q^2(12)$	19.83	6.81
F-value	0.662	1.343

μ_t and σ_t^2 represent the conditional mean and variance.

Parentheses includes *t*-values for the estimates.

R_t is the market return. ε_t^2 is the market innovation.

$Q(12)$ and $Q^2(12)$ are the 12^{th} lag Ljung–Box test statistics applied to the return and squared return series.

F-values test for correct specification of the conditional variance equations.

**Statistical significant at the 5% level.

[5] Statistically significant illustrate that return series exhibits strong second moment dependencies, as such, cannot be modeled as white linear processes like AR or ARMA [19].

process captures past volatility shock (represented by $\propto_1$ coefficient) and past conditional variances from the previous month (represented by γ_1 coefficient). Conditional volatility from the previous month is present in both markets, and it only persists for more than a month in the Zambia stock market. Modifying the GARCH-M variance equation by including South African stock returns (SA_t) will imply a significant λ_1 coefficient suggest volatility spillover from South African stock exchange. Table 3 show a negative and significant λ_1 coefficient for the Kenya regression, suggesting that Kenya stock exchange is vulnerable to external shock from South Africa.

Series of misspecification tests are used to evaluate the robustness of results. This paper used the Ljung–Box *Q*-test to assess autocorrelation. Also, the Ljung-Box *Q*-test on a squared residual series is conducted to test for conditional heteroskedasticity. Both the $Q(12)$ and $Q^2(12)$ tests are lower than their critical values at five percent level for the two markets. I also tested correct specification of the conditional variance by using the Engle's ARCH test which is the *F*-statistic for the regression on the squared residuals. Under the null hypothesis that the coefficient of all the independent variables are equal to zero against the alternative hypothesis that at least one coefficient is different from zero, the *F*-statistic follows a Chi-square distribution. The *F*-statistics for both regressions are not significant at 5% level – a support for correct specification for the conditional variance equation.

5. Conclusion

This paper empirically investigates the stochastic behavior of monthly stock market returns and the relationship between market returns and volatility for Kenya and Zambia stock indices. This paper applied the GARCH-M model with slight modifications to account for the possibility of external shock from the South African stock market. Both Kenya and Zambia stock returns have serial correlation in their squared return series. That is, the presence of conditional heteroskedasticity or volatility clustering. The mean equation results show serial correlation in the return series for Kenya exchange in violation to the martingale model of stock prices. That is, there is a significant first moment dependency of stock returns. Zambia return series has second moment dependency which violates the random walk model for stock prices but in line with the martingale model, since the return series has no serial correlation. There is a negative and significant relation between conditional variance and expected return for Zambia stock market. On the other hand, no significant relation is found between conditional variance and expected return for Kenya stock market, but Kenya stock market is found to be vulnerable to external shock from the South Africa stock market.

The stochastic behaviors of stock returns for emerging markets have important implication for market equilibrium models. Equilibrium models like Capital asset pricing model (CAPM) assumes that security prices follow a random walk. This fundamental assumption is clearly violated in emerging markets. Heed needs to be given in building new models or modifying existing models that better approximate reality.

Competing Interests

The author declares that he has no competing interest.

References

[1] Merton RC, 1973. An intertemporal capital asset pricing model. Econometrica, 41(5): 867–887.

[2] Campbell JY, Hentschel L, 1992. No news is good news: an asymmetric model of changing volatility in stock. Journal of Financial Economics, 31(3): 281–318.

[3] Bansal R, Lundblad C, 2002. Market efficiency, asset returns, and the size of the risk premium in global equity markets. Journal of Econometric, 109: 195–237.

[4] Girard E, Rahman H, Zaher T, 2001. Intertemporal risk–return relationship in the Asian markets around the Asian crisis. Financial Services Review, 10: 249–272.

[5] Xing X, Howe J, 2003. The empirical relationship between risk and return: evidence from the UK stock market. International Review of Financial Analysis, 12(3): 329–346.

[6] León A, Nave J, Rubio G, 2007. The relationship between risk and expected return in Europe. Journal of Banking and Finance, 31: 495–512.

[7] Nyberg H, 2012. Risk–return tradeoff in U.S. stock returns over the business cycle. Journal of Financial and Quantitative Analysis, 47: 137–158.

[8] Baillie RT, DeGennaro RP, 1990. Stock returns and volatility. Journal of Financial and Quantitative Analysis, 25(2): 203–214.

[9] Glosten LR, Jagannathan R, Runkle DE, 1993. On the relation between the expected value of the volatility of the nominal excess return on stocks. The Journal of Finance, 48(5): 1779–1801.

[10] Wang P, 2003. Financial Econometrics: Methods and Models. Routledge.

[11] Hibbert A, Daigler R, Dupoyet B, 2008. A behavioural explanation for the negative asymmetric return–volatility relation. Journal of Banking and Finance, 32: 2254–2266.

[12] Shefrin H, 2005. A Behavioral Approach to Asset Pricing Theory, 2nd Edition, Elsevier.

[13] Shefrin H, 2007. Behavioral Corporate Finance, McGraw Hill.

[14] Bollen NPB, Whaley RE, 2004. Does net buying pressure affect the shape of the implied volatility functions? The Journal of Finance, 59(2): 711–753.

[15] Lee J, Stewart G, 2010. Asymmetric volatility and volatility spillovers in Baltic and Nordic stock markets. European Journal of Economics, Finance and Administrative Sciences, 25: 136–143.

[16] Grabel I, 2003. Averting crisis? Assessing measures to manage financial integration in emerging economies, Cambridge. Journal of Economics, 27(3): 317–336.

[17] Engle RF, Lilien DM, Robins RP, 1987. Estimating time varying risk premia in the term structure: the ARCH-M model. Econometrica, 55(2): 391–407.

[18] Poon S-H, 2005. A Practical Guide to Forecasting Financial Market Volatility, Wiley Finance.

[19] Theodossiou P, Lee U, 1995. Relationship between volatility and expected returns across international stock markets. Journal of Business Finance and Accounting, 22(2): 289–300.

[20] Lo AW, MacKinlay AC, 1988. Stock market prices do not follow the random walks: evidence from a simple specification test. Review of Financial Studies, 1(1): 41–66.

How to cite this article

Tah KA, 2013. Relationship between volatility and expected returns in two emerging markets. Business and Economics Journal, Vol. 2013: 7 pages, Article ID: BEJ-84.