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**EMERGING EQUITY MARKET VOLATILITY AB EMPIRICAL
INVESTIGATION OF MARKETS IN KENYA NIGERIA**

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ABSTRACT

This paper offers a comprehensive view of four time properties that emerge from the empirical time series literature on asset returns. It examines: (1) the predictability of returns from past observations; (2) the auto-regressive behavior of conditional volatility; (3) the asymmetric response of conditional volatility to innovations; (4) and the conditional variance risk premium. Three emerging markets previously under-researched in this respect are considered: South Africa (ALSI, IND, GOLD indexes), Kenya (NSE index) and Nigeria (LSE index). The paper employs exponential GARCH (EGARCH) framework for analysis. The results indicate that asymmetric volatility found in the U.S. and other developed markets does not appear to be a universal phenomenon. Significant asymmetric volatility is found in both South Africa and Nigerian stock markets. However, in one market, NSE (Kenya), the asymmetric volatility coefficient is significant but positive, suggesting that positive shocks increase volatility more than negative shocks of an equal magnitude. LSE (Nigeria), GOLD (the post-announcement sample) and IND (the pre-announcement sample) return series exhibit a significant and positive time-varying risk premium. NSE (Kenya) and ALSI (South Africa) return series report negative but insignificant risk-premium parameters. The results also indicate that expected returns in these emerging markets are predictable. The auto-regressive return parameter (ϕ_1) is significant in all the markets. The auto-regressive structure, however, is more severe in Nigeria and Kenya than in South Africa. This implies that the percentage of stocks that do not trade in a time interval in the Lagos and Nairobi Stock Exchanges are less than that of the Johannesburg Stock Exchange. Finally, volatility persistence is significant in all the return series of the markets. The GARCH parameter (β) is statistically significant in all cases indicating that volatility persistence found in the developed markets is present in these three emerging markets. The behavior of (β) in the ALSI, IND and GOLD return series, however, provides insight into how time series properties of an emerging market may be expected to change over time as it gradually integrates into the global markets.

1. INTRODUCTION

The purpose of this paper is to examine the nature of volatility and the persistence of stock returns. It also investigates the extent to which shocks exert an asymmetric impact on conditional variance of stock returns, and further evaluates whether there exists a trade-off between an increased volatility and expected return (risk premium) in an emerging economy. We consider three Sub-Saharan Africa (SSA) countries, namely South Africa, Kenya and Nigeria.

Volatility is fundamental, in the context of financial markets, to the paradigm of the trade-off between risk and expected return. This paradigm is the foundation upon which much of the modern finance theory, such as portfolio theory, asset pricing, capital structure theory and valuation theory is based. Stock market volatility is also fundamental to the pricing of equities and associated derivatives. While individual stock variance is not a direct input into the CAPM, the aggregate market's variance is relevant through individual stock betas. In the Black-Scholes option-pricing model, a key parameter is the standard deviation of the underlying stock's returns. Stock market

volatility is also used as an economic indicator by economists, hence, given the importance of volatility in finance theory, it is important to understand the behavior and nature of stock market volatility.

From a practical perspective, market participants seem increasingly concerned with both the level and the pattern of stock market volatility. Practitioners place heavy reliance upon volatility estimates in risk management, option pricing, program trading and dynamic hedging strategies. Additionally, fund managers rely upon volatility estimates in determining their asset allocation through estimates of efficient portfolios. Given that these investors have a substantial influence in the market and affect market prices, volatility estimates are vital in the determination of security prices.

Volatility clustering over time is a stylized fact that has been repeatedly observed over long periods and in many financial markets across the globe. Accurate modeling of this behavior is of great interest and importance because of the potential financial benefits that it may ultimately deliver¹. Thus, there is a clear motivation for the study of volatility models. Merton (1980) mentioned that we could not ignore the effect of heteroscedasticity when estimating expected return on the market. Likewise, the issue of asymmetric volatility is very important given the degree of interdependence of the various national stock markets. Evidence on first and second moment interdependence across national stock markets is provided by Hamao, Masulis and Ngo (1990), for the U. S. the Japanese and the U. K. markets. Thus, if all major stock markets exhibit characteristics of asymmetric volatility, similar to the U. S. market, one should expect market declines worldwide to be associated with high levels of volatility.

A significant amount of research on the volatility of the U. S. stock market, Japan and the U. K. has been published. These studies include French *et al.*, (1987) Chou (1988) and Baillie and DeGennaro

(1990) who analyzed the relationship between stock return and volatility in the U. S. market. Poon and Taylor (1992) studied the same issue on the U. K. market. Most of these studies have been conducted on the developed markets. This type of research has rapidly expanded to include the emerging markets of the Pacific Rim and Latin America. The financial markets of Eastern Europe have also recently become the focus of new academic research on emerging economies. A legitimate research extension is to determine the applicability of the ARCH class of models to other markets. Indeed Bollerslev *et al.*, (1992, p.31) make a call for further investigations in markets beyond the U.S. Our paper extends this strand of research to the Sub-Saharan Africa (SSA) emerging markets. We examine four time series properties identified in asset returns literature: auto-regressive behavior of conditional mean and volatility; the predictability of returns from past observations; the asymmetric response of conditional volatility to innovations; and the conditional variance risk premium in the stock markets of South Africa, Kenya and Nigeria.

The SSA stock markets are of particular interest because they provide a stark contrast with other stock markets such as the NYSE. First, the SSA markets are small and relative to the global economy and are typified by far few listed companies. SSA companies are invariably price takers and react to global trading conditions rather than having an influence on these conditions. This is very different from the US stock market, for example, which represents a significant proportion of the world's economy. As a result, there could well be volatility trends and observations that are unique to the SSA stock markets. Second, South Africa's Stock Market, the Johannesburg Stock Exchange (JSE), is the largest stock market in Africa [by market capitalization (\$232 billion) in 1997]. It is more than ten times the size of all the other African stock markets combined and the nineteenth largest in the world. In spite of the growing importance of the African emerging markets, much of the extant academic research on asymmetric volatility and risk premia has neglected this region. Therefore, this paper extends similar research to these neglected emerging markets of the Sub-

Saharan Africa (SSA). Third, an understanding of the dynamics of volatility has important implications for regulators, investors and governments. Stock market regulators need to understand precisely the volatility of their markets in order to formulate appropriate regulatory and policy decisions. For fund managers, investment decisions must take into account the volatility of the relevant financial market. All in all, the paper examines the nature of volatility by seeking empirical evidence to support or dispel the existence of volatility asymmetries in the SSA stock markets.

The remainder of the paper is organized as follows: Section 2 reviews the literature on the time series properties of the U. S. and Emerging Stock Markets (henceforth ESMs). Section 3 describes the data and summary statistics. Section 4 outlines the test strategy and presents the EGARCH-M model used in this paper. Section 5 reports the empirical results while Section 6 offers a summary and conclusion.

2. LITERATURE REVIEW

The observation that financial asset returns series are characterized by clustering of volatility dates to Fama (1965). Modeling the mean and volatility (i.e. the conditional variance) of the return generating process can provide insight into market behavior and efficiency. Perhaps more importantly, modeling the JSE, NSE and LSE indexes may provide some insight into the process of stock market maturation as the period analyzed captures significant changes in the Sub-Saharan African markets. Recently, South Africa has undertaken capital market liberalization measures and political changes that have increased the investors' confidence in the JSE. For instance, Nelson Mandela and all political detainees were released from prison in early 1990. The United Nations lifted the trade sanctions against South Africa toward the end of 1993. The first democratically elected government was

installed in 1994. Accordingly, the study of the JSE may provide some insight into the process of integration of an emerging market into the global capital markets.

Models of conditional heteroskedasticity have been extensively employed to explain the behavior of the world's developed stock markets. The volatility of the International Stock Exchange of London has been modeled using GARCH (e.g. Masulis and Ng, 1995; and Poon and Taylor, 1992). The conditional volatility of stock returns in the U. S. has also been extensively examined, most notably by French *et al.* (1987), Nelson (1991) and Baillie and DeGennaro (1990). Couhray and Rad (1994) investigate the time series properties of five developed markets (U. K., France, Italy, Germany and Netherlands). More recently, Koutmous (1998) models the major stock indices of nine industrialized nations using a threshold GARCH methodology.

The GARCH type models have also been employed to explain the behavior of smaller European as well as Emerging Stock Markets. Cloquette *et al.* (1995), model daily returns in the Belgian Stock Market for the period 1980 – 1990. Leon and Mora (1996) consider the daily returns series of the Spanish equity index, IBEX-35, for the period 1990 – 1995. Choudhry (1996) models the conditional variance of monthly returns in six emerging markets, including Nigeria, and compares the pre- and post- October 19, 1987 periods. De Santis and Imrohorglou (1997) model the conditional variance in nineteen emerging markets, including the Greek market.

We characterize four time series properties that emerge from the empirical time series literature on asset returns: auto-regressive behavior of conditional mean and volatility; the predictability of returns from past observations; the asymmetric response of conditional volatility to innovations; and the conditional variance risk premium. We now briefly address the extant literature on these issues. If returns are predictable from historical information, then the market is not 'weak-form' efficient as

defined by Fama (1970). Examining the time series properties of returns has implications for market efficiency and the random walk hypothesis. In a strict test of the random walk that assumes independent and identically distributed (i.i.d.) increments, the presence of conditional heteroscedasticity will lead to rejection of the null. Lo and Mackinlay (1988) find evidence of positive serial correlation in index and portfolio returns due to the effects of asynchronous trading. They contend that the magnitude of the first order auto-correlations in index returns (after accounting for asynchronous trading effects) is an indicator of market efficiency. Amihud and Mendelson (1987) use one minus the first-order serial correlation in portfolio returns as a metric of market efficiency with respect to systematic (i.e. market-wide) information.

Under certain restrictions, expected returns are a positive linear function of the conditional variance (Merton, 1980). Intuitively, we would expect a risk-return tradeoff for risk-averse investor. Whether risk in emerging stock markets (henceforth, ESMs) as measured by conditional variance, has qualitatively similar properties with developed markets is an empirical question. DeSantis and Imrohorglou (1997) suggest that segmented markets are more likely to price own conditional variance than integrated capital markets. However, the evidence on the presence of a risk premium associated with own conditional variance in the U. S. is mixed. French *et al.*, (1987), modeling innovations as conditionally normal find a significant risk premium associated with the conditional volatility of excess returns. This contrasts with Baillie and DeGennaro's (1990) findings when return innovations are modeled as drawn from a conditional t -distribution. Nelson's (1991) results indicate that the risk premium for conditional variance is insignificant for daily returns (1962-1987). Koutmos *et al.*, (1993), consider weekly returns and conditional normal innovations and find no evidence of a risk premium for own conditional variance when returns are measured in local currency. They examine the stochastic behavior of the Athens Stock Exchange composite index for the years 1981 to 1990. Using models of conditional heteroskedasticity (EGARCH-M), they find that the volatility of

weekly returns is an asymmetric function of past shocks. They also find that market risk, as measured by conditional variance is priced by international investors, while there is no evidence that domestic investors require higher returns for this increased risk. They conclude that significant risk premium reflects the exchange rate risk faced by international investors. Additionally, they find that in contrast to the existing evidence for the U. S. market, positive return innovations in the Athens Stock Exchange have a greater effect on conditional return volatility than do negative innovations – a reverse ‘leverage effect’. Koutmos (1998) using daily returns from nine industrialized nations (including the U.S.) also documents results consistent with the ‘leverage effect’. In sum, the ‘leverage effect’ appears to be a time series property of mature markets.

Ross (1989) shows that in a market without arbitrage the variance of returns will equal the variance of the information flow. Intuitively, under the assumption that the innovation in the return series reflects the arrival of new information, then it follows that in an efficient market the variance of the innovation should define the conditional variance of the returns series. This leads us to conjecture that a lower first order auto-regressive term for the conditional variance would be indicative of a market becoming more efficient in impounding information flow. Although there is ample evidence on the asymmetric effect of shocks on the conditional volatility of U. S. stock returns, there is substantially less work on emerging markets of Sub-Saharan Africa. It is generally accepted for the U. S. that positive innovations in stock returns in a given period lead to lower volatility in the following periods than negative innovations and vice versa (see for example: Black, 1976; Nelson, 1991; Schwert, 1990; Pagan and Schwert, 1990; and Koutmos, 1998). According to Black’s (1976) ‘leverage effect’, as the market value of equity falls (rises) following a negative (positive) innovation in returns, financial leverage increases (decreases), and thus conditional volatility increases (decreases). If the ‘leverage effect’ hypothesis is accepted for this empirical finding, there is no *a priori* reason to expect that ESMs should behave differently. Shields (1997), discusses asymmetry in

stock market return volatility of ESMs. She does not find evidence of asymmetry in two Eastern European emerging markets (i.e. Poland and Hungary), and suggests the possibility of ‘non-rational investor behavior’ and ‘a comparatively lower level of understanding’ of the market in ESMs. Another plausible explanation maybe that information dissemination is slower in these markets as compared to those in developed markets, and/or that investors in general may be less responsive to negative news because dramatic fluctuations during the recent transition process have posited them to view current fluctuation as insignificant.

Roll (1992), compares stock indices across countries (using of the 24 FT Actuaries/Goldman Sachs National Equity Market indexes), in an attempt to explain why they exhibit disparate behavior. His findings suggest that large differences in volatilities of country index returns exist during the sample period April 1988 – March 1991. South Africa had the highest (unconditional) volatility (30.20% standard deviation of dollar-denominated annualized rate of return). Mexico and Hong Kong, well known high volatility countries, had volatilities above 24%. Netherlands and the U. S. had lower volatilities below 15% (annualized standard deviation). He also documents three explanatory influences. First, stock market indexes vary widely in the number of constituent individual common stocks. Second, national stock markets reflect the idiosyncrasies of the country’s industrial structure. Third, the stock markets of most, but not all, countries are influenced by exchange rates. He concludes that regardless of region, countries with similar industries tend to be more correlated than countries with dissimilar industries. Brooks, *et al.*, (1997) examine the effects of political change on stock market volatility of South Africa. They also examine whether ARCH class models can be fitted to daily returns data on the Johannesburg Stock Exchange (JSE) over the period March 20, 1986 – February 23, 1996. Their results support the applicability of these models. Furthermore, they find that more complex volatility models can be supported by the data in the post-1990 period, suggesting greater international integration of the JSE in the post-1990s period.

Appiah-Kusi and Pescetto (1998) investigate the volatility and volatility spillovers in the emerging African Stock markets (over the period 1990 – 1995). Using EGARCH model, they find that most of the African Stock markets are characterized by changes in volatility levels, with some periods having extremely high volatility. Their study also confirms that investors are compensated for bearing higher risk, since risk premium tends to follow changes in volatility. The evidence they present suggests there are considerable asymmetries in the response of volatility to news. These asymmetries, however, are not always consistent with traditional leverage effect explanation, since they find that sometimes good news cause a more accentuated reaction than comparable bad news. These findings could indicate the presence of noise trading and speculative bubbles. In sum, the study presents evidence of volatility spillovers between the African Stock Markets. Choudhry (1996), uses GARCH-M model to study volatility, risk premia and persistence of volatility in six emerging stock markets (including Nigeria) before and after the 1987 stock market crash. He documents changes in the ARCH parameters before and after the 1987 crash, but finds no evidence of risk premium and volatility persistence. In passing, we note that SSA Stock Markets have received little attention in the (international) time-varying literature. Indeed, to the best of our knowledge [apart from Brooks, *et al.*, (1997) and Appiah-Kusi and Pescetto (1998)] the time varying volatility aspects of these markets have not been previously examined. Accordingly, this paper extends this line of research to the SSA markets.

Bekaert and Harvey (1997) examine volatility of 20 emerging markets. The period of study covers 1976 – 1992. They use semi-parametric ARCH (SPARCH) specification for six of the twenty countries in their sample, while the normal specification is used for 13 other countries. The normal model is a variant of the GJR GARCH. Their results indicate that more open economies (in terms of world trade) have significantly lower volatilities. The evidence also suggests that volatility decreases

significantly in most countries that experience capital market liberalization. They also find that, on average, the proportion of variances attributable to world factors for emerging markets is quite small.

Finally, Aggarwal, *et al.*, (1999) examine shifts in volatility of emerging stock market returns and the events that are associated with the increased volatility. They examine 10 of the largest emerging markets in Asia and Latin America in addition to Hong Kong, Singapore, Germany, Japan, the U.K. and the U.S. Returns in local currency and dollar-adjusted returns are examined during the period 1985 – 1995. They use a model that combines iterated cumulative sums of squares (ICSS) algorithm with a GARCH model (with dummy variables in the variance equation) to capture sudden changes in variance of returns in each emerging market. Their results show that large changes in volatility are related to important country-specific, political, social and economic events (for example, the Mexican peso crisis and hyperinflation in India). The results are consistent with Bekaert and Harvey (1997) and Susmel (1997) who find that, on average, the proportion of variance attributable to world factors is quite small for emerging markets. Their results strongly support the findings of Bailey and Chung (1995) that important political events tend to be associated with sudden changes in volatility.

Most of the cited studies exclude the countries of Sub-Saharan Africa, particularly South Africa (the largest stock market in Africa) and Nigeria - the largest country (in terms of population) in Africa. To the best of this author's knowledge [apart from Brooks, *et al.*, (1997) and Appiah-Kusi and Pescetto (1998)] the time-varying volatility aspects of South Africa, and other Sub-Saharan Africa markets have not been previously examined. Indeed Bollerslev, *et al.*, (1992) call for further investigations of markets beyond the U. S. Accordingly, this author is convinced that Sub-Saharan Africa presents an opportunity to extend this line of research. In particular, South Africa presents the opportunity of examining the “emergence” of a sophisticated but developing market that was once isolated from the international community by the UN trade sanctions.

3. DATA AND SUMMARY STATISTICS

3.1 Descriptive Statistics and Test of Normality

The raw data used comprise the daily closing prices for Gold, Industrial and All Share Indexes of the Johannesburg Stock Exchange, the Nairobi Stock Exchange (NSE) and the Lagos Stock Exchange (LSE) obtained from Datastream. The sample periods include January 1, 1988 through December 31, 1998 for South Africa (2346 observations for each index); January 12, 1990 through December 31, 1998 for Kenya (2340 observations); and November 23, 1988 through March 23, 1996 for Nigeria (1914 observations). The daily stock returns of each index are defined as the first difference of the log of daily closing price levels on each index. In other words, continuously compounded daily returns (without dividend adjustment) have been calculated as the change in the logarithm of closing prices of successive days². The daily return series of each index is generated as follows:

$$R_t = (100) * (\ln(P_t) - \ln(P_{t-1})) \quad (1)$$

where \ln is the natural logarithm operator ; R_t is the return for period t ; P_t is the index closing price for period t and t is the time measured in days. Each return series is therefore expressed as a percentage. The daily return series does not represent excess return, that is, a risk-free bond rate is not subtracted from the return series. Modeling an index series in this manner is typical in the literature (see, for example, Nelson (1991)). The Jarque-Bera test was used to test for normality in the return series. The test rejects the null hypothesis of normality in the daily return series. The results of the normality test and the descriptive statistics for the daily returns of the three markets are presented in Tables 1 and 2. Excess (positive) kurtosis is found in all series for the period under study. The sample skewness coefficients indicate that the stock return distribution for South Africa (except GLD) are negatively skewed, while the return series for Nigeria and Kenya are positively skewed. Significant skewness is found in all the series. Skewness and Jarque-Bera normality statistics also

indicate that the stock return distributions are non-normal. GLD has the highest standard deviation, while LSE has the highest mean in the series. The sample means for all three markets are statistically different from zero (based on the t-distribution test). The Ljung-Box statistics for 12 lags applied to returns [denoted $Q(12)$] and squared returns [denoted $Q^2(12)$] indicate that significant linear and nonlinear dependencies exist. Linear dependencies may be due to some form of market inefficiency (Koutmos and Booth, 1995). Nonlinear dependencies can satisfactorily be captured by autoregressive conditional heteroscedasticity (ARCH) models³. Augmented Dicky-Fuller (ADF) statistics indicate that all stock return series are stationary. Additionally, the value of the Ljung-Box statistics are on average, greater for squared series, indicating that non-linear time dependencies are much stronger than linear time dependencies.

3.2 Test for Serial Dependence in First and Second Moments

The first five auto-correlations for the return series and return series squared are reported in Table 1B. The Ljung-Box Q-statistic rejects the null hypothesis of no serial dependence in both the first and second moments. The auto-correlations indicate significant time dependence in the return series and return series squared.

3.3 Two Sub-periods for South Africa

South Africa has undergone substantial political and economic transformation since September 23, 1993 when the (then) President to be, Nelson Mandela, urged the United Nations to lift the trade sanctions imposed against South Africa in the 1980s. Following a multi-racial election, a democratic government was installed in 1994. As South Africa has moved away from apartheid toward a more democratic society, it is reasonable to assume that its markets have become more integrated into the global capital markets. Accordingly, we divide the South African samples into two sub-periods to

investigate whether the lifting of the sanctions is associated with any structural break in the process driving returns and volatility. Hence, we analyze three samples for each index on the JSE in our study:

- (1) January 1, 1988 to December 31, 1998, which we refer to as the full sample period
- (2) January 1, 1988 to September 20, 1993 which we refer to as the “pre-announcement” period, and
- (3) September 27, 1993 to December 31, 1998, which we call the “post-announcement” period

We include a separate analysis of IND and GOLD because it is a widely held view in South Africa that gold (and mining shares in general) and industrial share returns are driven by different risk factors (see for example, Gilbertson and Goldberg, 1981). Mining firms sell their output into the integrated global commodity market and are exposed to international “shocks”. The gold sectors will most likely be largely immune from the political and economic factors experienced by the South African economy. We expect the ALSI and IND to reveal the greatest evidence of a ‘volatility effect’ reflecting economic change in South Africa. A priori we expect that the time-varying nature of the JSE market volatility will have changed from pre- to post-announcement period. We expect the behavior of conditional volatility over the latter period to conform more closely to the specifications well documented for the developed markets in recent years.

4. METHODOLOGY

4.1 *The AR-EGARCH-M Model*

In order to model the dynamics of volatility and time-varying risk premia in the Sub-Saharan Africa equity markets, a natural choice would be the GARCH approach introduced by Bollerslev (1986)³ and Taylor (1986) as a model with an alternative and more flexible lag structure than the initial ARCH model. The model not only provides a measure of expected or *ex ante* volatility but also

allows volatility shocks to persist over time. Such a framework is ideally suited to examining the returns of both developing and developed financial markets (see Bollerslev *et al.*, 1992). The main drawback of this model is that constraints have to be put on the coefficients to ensure non-negativity. In addition despite their popularity and apparent success in practical applications, GARCH models cannot capture the asymmetric response of volatility to news, since the sign of returns play no role in the specification of the model. In statistical terms, an asymmetric effect occurs when an unexpected decrease in price resulting from bad news increases volatility more than an unexpected increase in price of similar magnitude, following good news. However, we follow Nelson (1991) to allow for the asymmetric response of volatility to innovations and Engle *et al.* (1987) for ‘in Mean’ effects. A technique for incorporating asymmetries in the modeling of volatility is the EGARCH model developed by Nelson (1991). Nelson argues that returns may exhibit asymmetric conditional variance behavior in the sense that negative shocks generate volatility more than positive shocks of equal magnitude. This phenomenon has been attributed to the “leverage effect” (Black, 1976) and “volatility feedback” hypothesis (Koutmos, 1997). Accordingly, Nelson (1991) proposed an exponential GARCH or EGARCH (p, q) model to capture skewness and that asymmetry. In this formulation, the conditional variance is an exponential function of the previous conditional variances and excess returns. We introduce auto-regressive (AR) dynamics in the mean equation to capture the effect of nonsynchronous trading, which gives rise to a positive first order auto-correlation in market returns (Lo and MacKinlay (1988))⁴. The complete model to be estimated is as follows:

$$R_t = \phi_0 + \phi_1 R_{t-1} + \phi_2 R_{t-2} + \delta \sqrt{h_t} + \varepsilon_t \quad (2)$$

$$\varepsilon_t \mid \Omega_{t-1} \sim N(0, h_t) \quad (3)$$

$$\ln(h_t) = \alpha_0 + \alpha_1 \left\{ \left| \varepsilon_{t-1} / (h_{t-1})^{0.5} \right| - (2/\pi)^{0.5} \right\}_+ \gamma \varepsilon_{t-1} / (h_{t-1})^{0.5} + \beta \ln(h_{t-1}^2) \quad (4)$$

In the foregoing equations R_t represents the measure of market return. In the conditional mean equation (2), R_t is considered to be linearly related to the previous two days’ market returns and its

own standard deviation ($\sqrt{h_t}$). The error term is represented by ε_t and is assumed to follow a normal distribution in this study. Ω_{t-1} is the set of relevant information available at time $(t-1)$. The “in Mean” parameter, (δ) which follows Engel, *et al.* (1987) is introduced in the mean equation to determine whether investors are rewarded for their exposure to market risk. It measures the relationship between returns and volatility. It is the “reward to risk ratio” of Merton (1980, p.328), or as it is more generally termed, the index of relative risk aversion. Under the CAPM mean-variance hypothesis, large variances (or standard deviations) are expected to be associated with large returns, thus, (δ) is expected to be greater than zero. And, since R_t is the total market return, the term ϕ_0 is analogous to the risk-free rate in the CAPM. The $\phi_1 R_{t-1}$ and $\phi_2 R_{t-2}$ components are included in the mean equation to account for the auto-correlation potentially induced by non-synchronous trading in the assets that make up a market index. This problem can be particularly severe in emerging markets given their low level of liquidity (DeSantis and Imrohorglu, 1997). The parameterization we use follows Lo and MacKinlay (1988). Hence ϕ_1 and ϕ_2 are the AR(1) and AR(2) parameters respectively. However, the mean equation (2) differs from traditional CAPM in two respects. First, it includes auto-regressive components to take into account the effect of asynchronous trading. Second, it is inspired by Black’s (1972) version of the CAPM, which does not include a risk-free rate.

The conditional variance equation (4) is an exponential GARCH(EGARCH) process in the sense of Nelson (1991), which allows for time-varying heteroskedasticity in the errors. The EGARCH model is more general than the standard GARCH model in that it allows innovations of different signs to have a differential impact on volatility and allows bigger shocks to have a larger impact on volatility than does the standard GARCH model. Also, by modeling the logarithm of the conditional variance, it is not necessary to restrict parameter values to avoid negative variances. α , γ and β are parameters to be estimated. The parameter (α_1) measures the impact of innovation in equation (4) on conditional

volatility at time t . The parameter (β) is the auto-regressive term on lagged conditional volatility, reflecting the weight given to previous period's conditional volatility in the conditional volatility at time t . It measures the persistence of shocks to the conditional variance. The stationarity requirement is that the roots of the auto-regressive polynomial lie outside the unit circle for EGARCH (1,1) this translates into $\beta < 1$. The parameter (γ) permits the asymmetric response of conditional variance to innovations of differing sign. If (γ) is negative (positive), then negative realizations of the innovation in equation (2) generate more (less) volatility than do positive realizations. The presence of leverage effect can be tested by the hypothesis that $\gamma < 0$. The impact is asymmetric if $\gamma \neq 0$ and the most recent residual impact is exponential rather than quadratic. Good news ($\varepsilon_{t-1} > 0$) has an impact of $(\alpha + \gamma) / (h_{t-1})^{0.5}$ while bad news ($\varepsilon_{t-1} < 0$) has an impact of $(\alpha - \gamma) / (h_{t-1})^{0.5}$.

4.2 Estimating Procedure and Results

In the estimation of EGARCH model, we started with a general specification of the mean equation (2) and the variance equation (4). The orders of the variance equation and AR process in the mean equation were determined by the partial autocorrelation (PACF) and the autocorrelation function (ACF) of the return series of each market. In order to assess the relative fit of these models, Schwartz Criterion (SC) test was used. According to this test, the model that minimizes SC is chosen⁵. The final EGARCH specifications were decided by looking at the properties of standardized residuals and squared standardized residuals. The model was estimated using E-Views 4.0, and we employed the non-linear optimization of Berndt *et al.*, (1974) algorithm to compute maximum likelihood parameters. Bollerslev and Wooldridge (1992) note that maximizing a mis-specified likelihood function in a GARCH framework provides consistent parameter estimates, though the standard errors will be understated. Accordingly, we use the consistent variance-covariance estimator of Bollerslev and Wooldridge (1992) to correct the covariance matrix. Thus, we report asymptotic standard errors

(for parameters) that are robust to departures from normality. The estimation results are reported in Table 4.

4.3 Model Diagnostics

Estimates of normalized residuals and squared residuals of correctly specified EGARCH-M models will be white noise (Bollerslev and Mezrich, 1995). We use modified Box-Ljung test on the normalized residual series and squared normalized residuals to test for significant correlations. We also employ Arch LM test for ARCH effects on the normalized squared residuals (Engle, 1982)⁶. The LM test statistic is asymptotically $X^2(q)$ with q lags⁵. The results of the performed specification tests support our conditional mean and conditional volatility specification. We conclude that the models are well-specified. The results of the model diagnostics are reported in Tables 3A, 3B, 3C and 3D.

5. EMPIRICAL RESULTS AND DISCUSSION

5.1 Expected Returns and Predictability

Our empirical results are reported in Tables 3A, 3B, 3C and 3D. The first issue we investigate is whether expected returns are predictable in the JSE, NSE and LSE emerging markets. The magnitude and significance of AR(1) parameter in the mean equation show that there is time dependence in the daily returns even after correctly specifying the second moment dependencies. The ϕ_1 parameter is significant in all the markets. An examination of these results indicates that auto-regressive structure in the Nigerian Stock Exchange (NSE) is very high relative to the South African series. For Nigeria, the return series can reasonably be specified as AR(6)EGARCH(1,1)-M model. For the NSE (Kenya) returns, there is more auto-correlation structure and can only be reasonably modeled as AR(8)EGARCH(1,1)-M model. This implies that the Lagos and Nairobi Stock Exchanges have a higher percentage of stocks that do not trade in a time interval relative to the JSE (see Lo and MacKinlay, 1988). For South Africa, the model for all the series appears to be an AR(1). However,

GOLD has the lowest AR(1) parameter (ϕ_I) in all the three samples examined. Both ALSI and IND have the highest ϕ_I during the pre-announcement period (01/06/1988 – 09/20/1993). In contrast, GOLD has the lowest ϕ_I during this period, yet again reinforcing the evidence that the gold sector is driven more by global factors than by domestic factors. The estimated AR(1) parameters roughly correspond to a probability of non-trading (i.e. the percentage of stocks that do not trade in a time interval)⁷. Lo and MacKinlay (1988) suggests that asynchronous trading in a portfolio of stock can help explain the first-order auto-correlation in a time-series of portfolio returns.

5.2 *The Risk-Return Trade-off*

The hypothesis examined here is whether volatility is a significant factor in pricing domestic risk of the three Sub-Saharan African markets. Risk as measured by own conditional variance is a priced factor. If emerging markets are isolated from global markets, investors do not diversify their portfolios internationally. Therefore, they should be rewarded for their exposure to country-specific risk. In terms of our model, we should expect a positive relation between conditional expected return and conditional market volatility. In Tables 3A, 3B, 3C and 3D, we report point estimates of the price of market risk (δ) and other results. The point estimates vary considerably across the return series studied both in size and sign. It is positive and significantly different from zero for Nigeria. GOLD also displays a significant positive (δ) for the post-announcement sample, while the estimates for other samples are negative but insignificant. For IND return series, all the (δ) parameter estimates are negative, but only significant for the pre-announcement sample. All the (δ) estimates for ALSI samples are insignificant and negative (except for the pre-announcement sample). Kenya reports a negative but insignificant (δ). This finding of unstable (δ) parameter is consistent with the findings of Upsher and Smit (1994) who employed GARCH(1,1) in their analysis. Glosten, *et al.*, (1993) remark that even though it is generally agreed upon that investors, within a given time period would require a larger expected return from a security that is riskier, this relationship between risk and return may not

hold through time. They postulate that a positive or negative relationship between risk and return is consistent with theory. Backus and Gregory (1993) show that the relationship between risk premium and conditional variances can be increasing, decreasing, flat, or non-monotonic. The shape of the relationship depends on both the preferences of the representative agent and the stochastic structure of the economy. They also find that the lack of a theoretical structure between risk premiums and conditional variances may explain why this class of models works well for some assets but not for others. The extant literature provides conflicting results as to a risk premium for its own conditional variance⁸.

5.3 Time-Variation and Predictability in Volatility

We next study whether volatility in the three emerging markets under-study changes over time in a predictable pattern. The results are consistent with the empirical findings on time-varying volatility. First, the GARCH (β) parameter is statistically significant in all cases. Second, the (β) coefficient in the conditional variance is considerably larger than (α_1), the parameter of the lagged error term, implying that large market surprises induce relatively small revisions in future volatility. Additionally, the first order auto-regressive parameter of conditional variance (β) shows evidence of conditional variance persistence process -- historical stock price volatility is reflected in the present conditional variance. It is high and often close to Integrated GARCH of Engle and Bollerslev (1986). This implies that current information is relevant in predicting future volatility, also at long horizons.

However, we note some surprising results from South Africa data, especially in the pre-announcement period (01/01/1988 – 12/31/1993) of our sample. The coefficient of the lagged conditional variance declines dramatically, and becomes negative in the All-share Index (ALSI) and Industrial Index (IND). This implies that the impact of a shock on volatility declines rapidly as we move away from the shock. It is indicative of a market becoming more efficient in impounding

information flow (Ross, 1989). That is, the historical stock price volatility has no information value to construct prediction intervals of future expected returns. In contrast, the persistence coefficient for GOLD series is very high relative to other series. On average, the coefficient for GOLD series appears to be the same for all three samples. This result reinforces our earlier view that the global nature of the gold market will see GOLD Index reveal little, if any, impact of any structural change between our two sample periods.

5.4 *Asymmetric Conditional Heteroskedasticity*

Finally, this paper examines asymmetric nature of volatility (i.e. leverage effect). Generally, developed markets display a negative asymmetric parameter (Pagan and Schwert, 1990). In contrast to findings for developed markets, Koutmos (1992) and Koutmos, *et al.*, (1993) document a significant positive asymmetric parameter (γ), for Australia and Athens Stock Exchanges respectively. Our results also indicate that for Kenya the asymmetric parameter, (γ), is significant but positive, indicating that positive shocks increase volatility more than negative shocks of an equal magnitude. This is probably the result of the distributional features of the returns of the Kenyan market. It is conceivable that a few extreme observations may be responsible for the negative (γ). For Nigeria, (γ) is significant and negative. For South Africa, both ALSI and IND indexes have significant, negative asymmetric parameters, (γ), for the three samples under study. This is consistent with our earlier view that as the JSE gradually integrates with global markets it would eventually exhibit the “leverage effect,” particularly during the post-announcement period. For the GOLD index, the (γ) parameter is negative for all the samples, though insignificant. This is also consistent with our earlier expectation that the gold market will mirror the characteristics of developed markets.

6. SUMMARY AND CONCLUSION

This paper examines auto-regressive behavior of conditional mean and volatility; the predictability of returns from past observations; the asymmetric response of conditional volatility to innovations; and the conditional variance risk premium present in the stock returns of three Sub-Saharan African markets. An AR(2) EGARCH(1,1)-M model has been applied to daily stock returns of South Africa, Kenya and Nigeria. Our findings are mixed. Asymmetric volatility found in the U.S. and the U.K. does not appear to be a universal phenomenon. In one market, NSE (Kenya), the asymmetric volatility coefficient is significant but positive, suggesting that positive shocks increase volatility more than negative shocks of an equal magnitude. Asymmetric volatility exists in both South Africa and Nigerian stock markets. Additionally, a closer examination reveals that LSE (Nigeria), GOLD (the post-announcement sample) and IND (the pre-announcement sample) exhibit a significant and positive time-varying risk premium. Accordingly, the EGARCH test performed show that South African data exhibit the same general behavior as does the U.S. or the U.K. data. Differences include the higher persistence of volatility and inconclusive estimates for the index of risk aversion for South Africa. NSE (Kenya) and ALSI (South Africa) return series report negative but insignificant risk-premium parameters.

The results of the paper also indicate that expected returns in the emerging markets are predictable. The auto-regressive parameter (ϕ_1) is significant in all the markets. The auto-regressive structure is more severe in Nigeria and Kenya than in South Africa. This implies that the percentage of stocks that do not trade in a time interval in the Lagos and Nairobi Stock Exchanges are less than that of the Johannesburg Stock Exchange. Finally, the GARCH parameter (β) is statistically significant in all cases indicating that volatility persistence found in the developed markets is present in these three emerging markets. The behavior of (β) in the ALSI, IND and GOLD return series provides insight into how time series properties of an emerging market may be expected to change over time as it gradually integrates into the global markets.

TABLE 1: DESCRIPTIVE STATISTICS FOR DAILY STOCK RETURNS

Statistics	South Africa			Kenya	Nigeria
	ALSI	IND	GOLD	NSE	LSE
Observations	2869	2869	2869	2340	1914
Mean	0.0382	0.0563	-0.0248	0.0299	0.1632
Max	6.6960	9.3633	14.5798	12.3941	6.3823
Min	-11.8514	-13.3468	-12.9392	-4.9495	-4.0069
Std. Dev.	1.0549	1.0020	2.2860	0.7448	0.4227
Skewness	-1.3520**	-2.2465**	0.4817**	2.5330**	3.1266**
Kurtosis	17.4693	35.5093	5.9486	40.5121**	47.8249**
Jarque-Bera	25901.39**	160703.20**	1150.34**	173490.9**	163358.1**
Q(12)	76.509**	157.28**	46.34**	1513.90**	212.50**
p-value	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Q ² (12)	438.41**	582.78**	341.60**	841.07**	39.52**
p-value	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
ADF Test	52.05**	-57.07**	-54.11**	-49.72**	-46.09**

B. AUTO-CORRELATIONS

$\rho(\text{lag})$	ALSI		GOLD		IND	
	Returns	Squared Returns	Returns	Squared Returns	Returns	Squared Returns
$\rho(1)$	0.140**	0.353**	0.158**	0.383**	0.102**	0.176**
$\rho(2)$	0.042**	0.149**	0.076**	0.145**	-0.033**	0.112**
$\rho(3)$	0.019**	0.202**	0.007**	0.195**	0.012**	0.091**
$\rho(4)$	-0.008**	0.106**	0.000**	0.139**	0.019**	0.140**
$\rho(5)$	0.003**	0.055**	0.050**	0.091**	0.023**	0.102**

$\rho(\text{lag})$	LSE		NSE	
	Returns	Squared Returns	Returns	Squared Returns
$\rho(1)$	-0.024**	0.062**	0.376**	0.296**
$\rho(2)$	0.093**	0.059**	0.334**	0.193**
$\rho(3)$	0.102**	0.091**	0.272**	0.146**
$\rho(4)$	0.069**	0.006**	0.266**	0.182**
$\rho(5)$	0.091**	0.032**	0.245**	0.235**

NOTES:

** and * denote statistical significance at 5% and 10% level respectively.

$Q(12)$ and $Q^2(12)$ are the Ljung-Box test statistics for the cumulative autocorrelation up to the twelfth-order autocorrelation in the return series and squared return series for each index respectively and are distributed as $\chi^2(12)$. Probability value is in parenthesis. Critical value (at 5% level) of χ^2 with twelve degrees of freedom is 21.02. ADF is the augmented Dickey-Fuller test for the stationarity of the return series. The critical value (at 5%) is -2.86. This test indicates that all returns series are stationary, i.e. $I(0)$.

Skewness estimate is zero in a normal distribution and excess kurtosis is three in a normal distribution.

Jarque-Bera is the LM test for normality. It tests whether the series is normally distributed. It has a χ^2 distribution with 2 degrees of freedom under the null hypothesis of normally distributed errors.

The critical value at 5% is 5.99.

TABLE 2: DESCRIPTIVE STATISTICS FOR DAILY STOCK RETURNS**A. ALL SHARE INDEX (ALSI)**

	Entire Period 01/16/1988 –12/31/1998	Pre-Announcement Period 1/6/1988 – 9/20/1993	Post-Announcement Period 9/30/1993-12/31/1998
Observations	2869	1491	1373
Mean	0.0382	0.0501	0.02610
Max	6.6960	5.8559	6.6960
Min	-11.8514	-11.1968	-11.8514
Std. Dev.	1.0549	1.0134	1.0984
Skewness	-1.3520**	-1.1568	-1.5153
Kurtosis	17.4693	15.9139	18.5217
Jarque-Bera	25901.39**	10693.05	14308.23**
Q(12)	76.509**	30.110	54.045**
<i>p-value</i>	(0.000)	(0.000)	(0.000)
Q ² (12)	438.41**	62.710	386.75**
<i>p-value</i>	(0.000)	(0.000)	(0.000)
ADF	52.05**	-37.14**	-36.33

B. INDUSTRIAL INDEX (IND)

	Entire Period 01/16/1988 –12/31/1998	Pre-Announcement Period 1/6/1988 – 9/20/1993	Post-Announcement Period 9/30/1993-12/31/1998
Observations	2869	1491	1373
Mean	0.0563	0.0755	0.0250
Max	9.3633	6.0574	6.9308
Min	-13.3468	-12.3836	-11.7495
Std. Dev.	1.0020	0.8288	1.0808
Skewness	-2.2465**	-2.3375	-1.4896
Kurtosis	35.5093	42.6303	19.7870
Jarque-Bera	160703.20**	98928.59	16629.20**
Q(12)	157.28**	60.336	59.60**
<i>p-value</i>	(0.000)	(0.000)	(0.000)
Q ² (12)	582.78**	79.899	419.58**
<i>p-value</i>	(0.000)	(0.000)	(0.000)
ADF	-57.07**	-36.63**	-37.78

NOTES:

** and * denote statistical significance at 5% and 10% level respectively.

Q(12) and Q²(12) are the Ljung-Box test statistics for the cumulative autocorrelation up to the twelfth-order autocorrelation in the return series and squared return series for each index respectively and are distributed as $\chi^2_{(12)}$. Probability value is in parenthesis. Critical value (at 5% level) of χ^2 with twelve degrees of freedom is 21.02.

ADF is the augmented Dickey-Fuller test for the stationarity of the return series. The critical value (at 5%) is -2.86. This test indicates that all returns series are stationary, i.e. I(0).

Skewness estimate is zero in a normal distribution and excess kurtosis is three in a normal distribution.

Jarque-Bera is the LM test for normality. It tests whether the series is normally distributed. It has a χ^2 distribution with 2 degrees of freedom under the null hypothesis of normally distributed errors.

The critical value at 5% is 5.99.

C. GOLD INDEX (GOLD)

	Entire Period 01/16/1988 – 12/31/1998	Pre-Announcement Period 1/6/1988 – 9/20/1993	Post-Announcement Period 9/30/1993-12/31/1998
Observations	2869	1491	1373
Mean	-0.0248	-0.0053	-0.0441
Max	14.5798	12.4837	14.5798
Min	-12.9392	-12.9392	-7.7632
Std. Dev.	2.2860	2.2065	2.3728
Skewness	0.4817**	0.2845	0.6547
Kurtosis	5.9486	6.1861	5.7045
Jarque-Bera	1150.34**	650.78**	516.52**
Q(12)	46.34**	16.835	41.75**
<i>p-value</i>	(0.000)	(0.156)	(0.000)
Q ² (12)	341.60**	85.92	323.17**
<i>p-value</i>	(0.000)	(0.000)	(0.000)
ADF	-54.11**	-39.13**	-37.13

NOTES:

** and * denote statistical significance at 5% and 10% level respectively.

$Q(12)$ and $Q^2(12)$ are the Ljung-Box test statistics for the cumulative autocorrelation up to the twelfth-order autocorrelation in the return series and squared return series for each index respectively and are distributed as $\chi^2_{(12)}$. Probability value is in parenthesis. Critical value (at 5% level) of χ^2 with twelve degrees of freedom is 21.02.

ADF is the augmented Dickey-Fuller test for the stationarity of the return series. The critical value (at 5%) is -2.86 . This test indicates that all returns series are stationary, i.e. $I(0)$.

Skewness estimate is zero in a normal distribution and excess kurtosis is three in a normal distribution.

Jarque-Bera is the LM test for normality. It tests whether the series is normally distributed. It has a χ^2 distribution with 2 degrees of freedom under the null hypothesis of normally distributed errors.

The critical value at 5% is 5.99.

TABLE 3: RESULTS OF ESTIMATION OF JSE, LSE AND NSE INDEX DAILY RETURN SERIES USING AR(2)EGARCH(1,1)-M MODEL

Estimated Model:

$$R_t = \varnothing_0 + \varnothing_1 R_{t-1} + \varnothing_2 R_{t-2} + \delta \sqrt{h_t} + \varepsilon_t, \quad \varepsilon_t | \Omega_{t-1} \sim N(0, h_t)$$

$$\ln(h_t) = \alpha_0 + \alpha_1 \left\{ \left| \varepsilon_{t-1} / (h_{t-1})^{0.5} \right| - (2/\pi)^{0.5} \right\} + \gamma \varepsilon_{t-1} / (h_{t-1})^{0.5} + \beta \ln(h_{t-1}^2)$$

A. All-Share Index

PARAMETERS	Entire Period 01/06/1988 – 12/31/1998	Pre-Announcement Period 01/06/1988 - 09/20/1993	Post-Announcement Period 09/30/1993 - 12/31/1998
\varnothing_0	0.1697* (0.1070)	-0.1645 (0.3649)	0.0933 (0.0697)
\varnothing_1	0.1807* (0.02232)	0.1775** (0.0315)	0.1746** (0.0325)
\varnothing_2	0.0267 (0.0234)	0.0035 (0.0265)	0.0381 (0.0332)
δ	-0.1476 (0.2076)	0.2030 (0.3701)	-0.0626 (0.0835)
α_0	-0.1635** (0.0364)	-0.1854 (0.1352)	-0.2324** (0.0436)
α_1	0.2160** (0.0515)	0.1718** (0.0764)	0.2953** (0.0600)
γ	-0.0809** (0.0388)	-0.1138** (0.0516)	-0.0873** (0.0472)
β_1	0.9470** (0.0119)	-0.6049** (0.2683)	0.9479** (0.0135)
n	2869	1491	1371
Log Likelihood	-3859.52	-2081.15	-1765.31
SC	2.7146	2.8346	2.6174

Diagnostics on Standardized Residuals from each Period's Stock Return Equation

	Entire Period 01/06/1988 – 12/31/1998	Pre-Announcement Period 01/06/1988 - 09/20/1993	Post-Announcement Period 09/30/1993 - 12/31/1998
$Q(12)$	11.544	10.883	7.893
<i>p-value</i>	(0.483)	(0.539)	(0.793)
$Q^2(12)$	9.60	5.658	8.310
<i>p-value</i>	(0.651)	(9.322)	(0.760)
<i>Mean</i>	-0.0037	0.0046	-0.0158
<i>Std. Dev.</i>	1.0018	0.9996	0.9995
<i>Skewness</i>	-0.6168**	-0.9870**	-0.5254**
<i>Kurtosis</i>	10.0571**	43.2369**	6.9388**

NOTES:

All returns are measured in local currencies and expressed in percentage form. The sample for the South African indexes covers the period 01/16/1988 – 12/31/1998 (2869 observations). The sample for Kenya has 2340 observations from 01/12/1990 – 12/31/1998. Nigerian index covers the period 11/15/1988 – 03/15/1996 (1914 observations). ** and * denote statistical significance at 5% and 10% respectively. SC = Schwarz Criterion. The test statistics for skewness and excess kurtosis is the conventional t-statistic. Jarque-Bera is the LM test for normality. It tests whether the series is normally distributed. It has a χ^2 distribution with 2 degrees of freedom under the null hypothesis of normally distributed errors. The critical value at 5% is 5.99. Skewness estimate is zero in a normal distribution and excess kurtosis is three in a normal distribution. $Q(12)$ and $Q^2(12)$ are the Ljung-Box statistics (of order 12) applied to standardized and squared standardized residuals respectively. *p-value* is in parenthesis. Critical value (at 5% level) of χ^2 with twelve degrees of freedom is 21.0. Robust standard errors derived by Bollerslev and Wooldridge (1992) are in parentheses. Robust standard errors allow for non-normality of the standardized residuals.

TABLE 3B: Industrial Index

PARAMETERS	Entire Period 01/06/1988 – 12/31/1998	Pre-Announcement Period 01/06/1988 – 09/20/1993	Post-Announcement Period 09/30/1993 – 12/31/1998
\emptyset_0	0.3492 (0.3417)	0.6767** (0.3207)	0.0983* (0.0537)
\emptyset_1	0.1785* (0.0563)	0.2470** (0.0847)	0.2302** (0.0340)
\emptyset_2	0.0762** (0.0295)	0.0723** (0.0277)	0.0672** (0.0315)
δ	-0.2971 (0.3811)	-0.9024** (0.4190)	-0.0888 (0.0759)
α_0	-0.3079** (0.0603)	-1.1944** (0.1747)	-0.2355** (0.0432)
α_1	0.3600** (0.0752)	0.4918 (0.0630)	0.2985** (0.0574)
γ	-0.1174* (0.0876)	-0.0497 (0.0681)	-0.0793* (0.0449)
β_1	0.8060** (0.0759)	-0.4132 (0.2886)	0.9561** (0.0100)
n	3579	1491	1371
Log Likelihood	-4425.98	-1677.56	-1648.55
SC	2.4939	2.2925	2.4470

Diagnostics on Standardized Residuals from each Period's Stock Return Equation

	Entire Period 01/06/1988 – 12/31/1998	Pre-Announcement Period 01/06/1988 – 09/20/1993	Post-Announcement Period 09/30/1993 – 12/31/1998
$Q(12)$	18.122	9.372	10.910
p -value	(0.112)	(0.671)	(0.537)
$Q^2(12)$	0.469	3.607	6.572
p -value	(1.000)	(0.990)	(0.885)
Mean	-0.0709	0.0202	-0.0020
Std. Dev.	0.9971	1.0151	0.9986
Skewness	-2.9089**	-2.2777**	-0.3894**
Kurtosis	78.7223**	31.6449**	6.9427**

NOTES:

All returns are measured in local currencies and expressed in percentage form. The sample for the South African indexes covers the period 01/16/1988 – 12/31/1998 (2869 observations). The sample for Kenya has 2340 observations from 01/12/1990 – 12/31/1998. Nigerian index covers the period 11/15/1988 – 03/15/1996 (1914 observations). ** and * denote statistical significance at 5% and 10% respectively. SC = Schwarz Criterion. The test statistics for skewness and excess kurtosis is the conventional t-statistic. Jarque-Bera is the LM test for normality. It tests whether the series is normally distributed. It has a χ^2 distribution with 2 degrees of freedom under the null hypothesis of normally distributed errors. The critical value at 5% is 5.99. Skewness estimate is zero in a normal distribution and excess kurtosis is three in a normal distribution. $Q(12)$ and $Q^2(12)$ are the Ljung-Box statistics (of order 12) applied to standardized and squared standardized residuals respectively. p -value is in parenthesis. Critical value (at 5% level) of χ^2 with twelve degrees of freedom is 21.0. Robust standard errors derived by Bollerslev and Wooldridge (1992) are in parentheses. Robust standard errors allow for non-normality of the standardized residuals.

TABLE 3C: Gold Index

PARAMETERS	Entire Period 01/06/1988 – 12/31/1998	Pre-Announcement Period 01/06/1988 – 09/20/1993	Post-Announcement Period 09/30/1993 – 12/31/1998
\emptyset_0	-0.1523 (0.1500)	0.1282 (0.2329)	-0.4195** (0.1887)
\emptyset_1	0.1124** (0.0202)	0.0788** (0.0285)	0.1433** (0.0297)
\emptyset_2	-0.0085 (0.0200)	-0.0018 (0.0263)	-0.0235 (0.0304)
δ	0.0586 (0.0739)	-0.0647 (0.1154)	0.1738** (0.0947)
α_0	-0.0730** (0.0141)	-0.0517** (0.0128)	-0.0832** (0.0247)
α_1	0.1223** (0.0218)	0.0842** (0.0209)	0.1333** (0.0346)
γ	-0.0006 (0.0145)	0.0100 (0.0176)	-0.0210 (0.0186)
β_1	0.9876** (0.0049)	0.9929** (0.0057)	0.9882** (0.0058)
n	2869	1489	1371
Log Likelihood	-6241.86	-3223.59	-2997.92
SC	4.3765	4.3691	4.4155

Diagnostics on Standardized Residuals from each Period's Stock Return Equation

	Entire Period 01/06/1988 – 12/31/1998	Pre-Announcement Period 01/06/1988 - 09/20/1993	Post-Announcement Period 09/30/1993 - 12/31/1998
$Q(12)$	12.242	8.035	9.791
p -value	(0.426)	(0.782)	(0.634)
$Q^2(12)$	11.245	15.264	12.664
p -value	(0.508)	(0.227)	(0.394)
Mean	-0.0001	-0.0059	-0.0024
Std. Dev.	1.0003	1.0013	1.0011
Skewness	0.3054**	0.2521**	0.3807**
Kurtosis	4.6994**	4.6573**	4.1759**

NOTES:

All returns are measured in local currencies and expressed in percentage form. The sample for the South African indexes covers the period 01/16/1988 – 12/31/1998 (2869 observations). The sample for Kenya has 2340 observations from 01/12/1990 – 12/31/1998. Nigerian index covers the period 11/15/1988 – 03/15/1996 (1914 observations). ** and * denote statistical significance at 5% and 10% respectively. SC = Schwarz Criterion. The test statistics for skewness and excess kurtosis is the conventional t-statistic. Jarque-Bera is the LM test for normality. It tests whether the series is normally distributed. It has a χ^2 distribution with 2 degrees of freedom under the null hypothesis of normally distributed errors. The critical value at 5% is 5.99. Skewness estimate is zero in a normal distribution and excess kurtosis is three in a normal distribution. $Q(12)$ and $Q^2(12)$ are the Ljung-Box statistics (of order 12) applied to standardized and squared standardized residuals respectively. p -value is in parenthesis. Critical value (at 5% level) of χ^2 with twelve degrees of freedom is 21.0. Robust standard errors derived by Bollerslev and Wooldridge (1992) are in parentheses. Robust standard errors allow for non-normality of the standardized residuals.

TABLE 3D: NSE AND LSE INDEXES

KENYA (NSE): 01/24/1990 - 12/31/1998		NIGERIA (LSE): 11/28/1988 – 03/15/1996	
PARAMETERS		PARAMETERS	
\emptyset_0	-0.0052 (0.0421)	\emptyset_0	-0.0518** (0.0269)
\emptyset_1	0.1355** (0.0304)	\emptyset_1	-0.0513 (0.0406)
\emptyset_2	0.1385** (0.0285)	\emptyset_2	0.1141** (0.0332)
\emptyset_3	0.1067** (0.0305)	\emptyset_3	0.0960** (0.0351)
\emptyset_4	0.1023** (0.0261)	\emptyset_4	0.0627** (0.0325)
\emptyset_5	0.0202 (0.0350)	\emptyset_5	0.0906** (0.0361)
\emptyset_6	0.0036 (0.0229)	\emptyset_6	0.1252** (0.0384)
\emptyset_7	0.0477* (0.0284)	--	--
\emptyset_8	0.0593** (0.0309)	--	--
δ	-0.0031 (0.0862)	δ	0.5093** (0.1334)
α_0	-0.3391** (0.0836)	α_0	-0.8754** (0.1073)
α_1	0.3436** (0.0794)	α_1	0.5829** (0.0679)
γ	0.1005** (0.0464)	γ	-0.3236** (0.0632)
β_1	0.8982** (0.0378)	β_1	0.7800** (0.0401)
n	2332	n	1910
Log Likelihood	-2074.51	Log Likelihood	-592.287
SC	1.8257	SC	0.6684

Diagnostics on Standardized Residuals from Stock Return Equation

<i>Q(12)</i>	12.54	<i>Q(12)</i>	11.346
<i>p-value</i>	(0.403)	<i>p-value</i>	(0.500)
<i>Q²(12)</i>	69.07	<i>Q²(12)</i>	0.9650
<i>p-value</i>	(0.123)	<i>p-value</i>	(0.998)
<i>Mean</i>	0.0037	<i>Mean</i>	-0.0083
<i>Std. Dev.</i>	1.0009	<i>Std. Dev.</i>	0.9978
<i>Skewness</i>	0.020**	<i>Skewness</i>	2.1500**
<i>Kurtosis</i>	11.5333**	<i>Kurtosis</i>	37.1934**

NOTES:

All returns are measured in local currencies and expressed in percentage form. The sample for the South African indexes covers the period 01/16/1988 – 12/31/1998 (2869 observations). The sample for Kenya has 2340 observations from 01/12/1990 – 12/31/1998. Nigerian index covers the period 11/15/1988 – 03/15/1996 (1914 observations). ** and * denote statistical significance at 5% and 10% respectively. SC = Schwarz Criterion. The test statistics for skewness and excess kurtosis is the conventional t-statistic. Jarque-Bera is the LM test for normality. It tests whether the series is normally distributed. It has a χ^2 distribution with 2 degrees of freedom under the null hypothesis of normally distributed errors. The critical value at 5% is 5.99. Skewness estimate is zero in a normal distribution and excess kurtosis is three in a normal distribution. $Q(12)$ and $Q^2(12)$ are the Ljung-Box statistics (of order 12) applied to standardized and squared standardized residuals respectively. *p-value* is in parenthesis. Critical value (at 5% level) of χ^2 with twelve degrees of freedom is 21.0. Robust standard errors derived by Bollerslev and Wooldridge (1992) are in parentheses. Robust standard errors allow for non-normality of the standardized residuals.

NOTES:

1. For example, if a volatility model could be used to forecast when a high volatility period is likely to occur, then a trading strategy would be to engage in an option (bottom) straddle. That is, the investor simultaneously buys a put and a call option on the market index, with the same exercise price and maturity date. If the prediction of high volatility is accurate then either the put or the call will provide a large positive return, and it does not depend upon the direction of price movement. Alternatively, forecasts of low volatility would imply an option (top) straddle trading strategy.
2. According to Mills and Coutts (1995, p.81) lack of information about dividends payments in the daily return series does not invalidate the results. On a similar note, French *et al.* (1987) have also concluded that monthly returns series that do not include dividends have little effect on the returns estimation.
3. Engle (1982) introduced a class of models which he termed ‘autoregressive conditionally heteroscedastic’ (ARCH) where the conditional variance is a function of past squared errors. Bollerslev (1986) extended the analysis by developing a generalized class of ARCH or (GARCH) models where the conditional variance is not only a function of past errors but past conditional variances as well. Engle *et al.* (1987) provided an extension to the GARCH model where the conditional mean is an explicit function of the conditional variance. Such a model is known as the GARCH-in-the-mean or GARCH-M model.
4. I would like to thank an anonymous colleague for suggesting the inclusion of the error correction terms in the conditional mean equation. Following Lo and MacKinlay (1988) our model incorporates RA(2) term in the mean equation to capture market inefficiencies like autocorrelation and non-synchronous trading. Nicholls and Tonuri, (1995) indicate that with small values of first order autocorrelation using AR(1) or MA(1) in the mean equation does not alter the results. For this paper, MA(1) structure is adopted for the mean equation. Poon and Taylor (1992) argue that the consequences of ignoring a relevant MA term can be severe, while the inclusion of insignificant MA term is unlikely to affect the reliability of any inferences.
5. Schwarz’s (1978) information criteria (SIC) imposes a greater penalty for additional parameters than the AIC. This technique generally leads to a more parsimonious model. It involves choosing p and q that minimizes the value of SIC. The SIC values suggest AR(2)EGARCH(1,1)-M. The reader should note that the application of AIC to distinguished between variance models is not universally accepted, since the orders of probabilities are not what Akaike originally presented (Brailsford and Faff, 1993).
6. Engle’s test statistic is computed as the number of observations times R^2 from the test regression. To test the null hypothesis that there is no ARCH up to order q in the residuals we run the regression $e^2_{t-1} = \beta_0 + \beta_1 e^2_{t-1} + \beta_2 e^2_{t-2} \dots \beta_q e^2_{t-q}$, where e is the residual.
7. See Table 4 of Lo and Mackinlay (1988).
8. Concerning the sign of the risk-return tradeoff parameter, δ , note that this measure differs from the equilibrium price of systematic risk commonly discussed in the literature. Since volatility is a measure of total risk, the increase in it need not always be accompanied by an increase in the risk premium. Indeed, if fluctuations in volatility are mostly due to shocks to the unsystematic risk the tradeoff coefficient δ can have any sign. This could explain why GJR, and French, Schwert and Stambaugh (1987), Nelson (1991), and Kim and Kon (1994), have found such varied results, both positive and negative, for the risk aversion parameter (δ).

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