Management of Stock Price and It Effect on Economic Growth: Case Study of West African Financial Markets

Drama Bedi Guy Herve (Corresponding author)
School of International Business and Management, Shanghai University
99 Shangda Road, Shanghai 200444, China
E-mail: dramsiben@ yahoo.fr/ hotmail.com

Yao Shen
School of International Business and Management, Shanghai University
99 Shangda Road, Shanghai 200444, China
E-mail: yaoshen56@163.com

Abstract

This paper investigates the statistical properties of stock returns in the West African regional stock market and the link between the West African regional stock market and economic growth. To examine the nature of the distribution of West African regional stock returns, the daily closing prices of the two stock index of West African regional stock market, and eighteen of it sub-indices were utilized. Nine years data from 1998 to 2007 interval were employed. The analysis of our study shows that the distribution of the West African regional stock market returns is non-normal and non-*i.i.d* (independent, identically and normally distributed). The linear and non-linear dependencies in the returns appeared to be the main reasons for the data being non-*i.i.d.* The study also demonstrates the presence of the day-of-the-week effect in West African regional stock market.

Keywords: West Africa regional stock markets, Day of the week effects, Growth

1. Introduction

The rapid growth of capital markets in emerging market economies has come as a major event in recent financial history. According to the International Finance Corporation (IFC), portfolio flows to emerging countries has kept rising since the early 1980s and the trend has continued even after a number of financial crises (IFC, 2000). The stock markets in these countries have also grown considerably in size. The aggregate market capitalization of the countries classified by the IFC as emerging markets rose from US$488 billion in 1988 to US$3073 billion in 1999. Trading on these markets also rose in similar magnitude, growing from US$411 billion to US$2873 billion in that period (IFC, 2000).There is indeed a growing body of research which points towards capital market development and financial deepening in general and stock markets development in particular making positive contribution to economic growth. An array of financial instruments including stock market quoted shares and the bond market is almost certainly going to enhance the overall level of savings in an economy. Capital markets are the markets for long-term loanable funds as distinct from the money markets, which deals in short-term funds. However, there is no clear-cut distinction between the two markets. In principle, capital market loans are used by industry and commerce mainly for fixed investment. The capital market is an increasingly international one and in any country the market is not one institution but all those institutions that match the supply of and demand for long-term capital and claims on capital. In this respect, stock exchanges could be defined as the central point of the capital market. The evolution of capital markets in Africa in recent years has been rather dramatic, as countries have sought not only to mobilize domestic resources but also to attract foreign direct investment. Accordingly, activity in a number of capital markets that had been dormant for years picked-up significantly and a number of new markets have emerged. In a number of established stock exchanges, activity has been boosted by increased listings of companies; mostly made possible by privatization of state-owned enterprises. At present, there are about twenty six stock exchanges in the continent see annex. However, many African stock markets are characterized by a relatively limited number of scrip, which are held to a substantial extent in perpetuity by few insurance and pension funds. The participation by individual savers/investors is significantly limited in a number of markets. The result is that African stock markets (with the exception of Johannesburg) are illiquid. Widening stock market access beyond national boundaries to other stock markets in the region should enhance stock market liquidity and provide savers/investors with significantly more diversified risk opportunities. To this end, the establishment of the West African Regional Stock Exchange in Abidjan in 1994, whose scrip will encompass issues in the eight countries of the West African Monetary Union is already a very encouraging step forward. But in the context of West African Economic and Monetary Union financial market, not many studies can be traced in literature; This paper attempts to cover this gap by examining the causal relationship between growth and stock market indices in West African (UEMOA) financial market.

With more than forty years of the literature to consider, the remains part of our study is organized as follows. The next section (2) describes the Further Literature Review and the theoretical justification of the study. Section 3 presents the data and methodology, including a discussion of the impacts of stock market development on economic growth. The econometric methodology including a presentation of traditionally Granger causality test (Granger C. W., 1969) and subsequent improvements namely (Toda & Yamamoto, 1995) version is utilized to test the causal relationship between the stock market and growth. Section 4 presents the result and interpretations. It first illustrates statistical properties of the stock returns in West African Stock Market then; it secondly examines the causal effect relationship between stock market development and economic growth in West Africa Stock Market. This study closes with a summary, concluding remarks and policy in section 5.

2. Literature review and theoretical justification of the study

This section presents the literature on the statistical properties of the stock returns, and Finance, Investment and the real Economy. In this section, the literature on the stock return distribution is addressed. It provides the empirical evidence of the stock return distribution as well as its subsequent theoretical explanations.

As far as we know, the assumptions underlying the financial theories and empirical methods are that the security returns are independent, identically and normally distributed with parameters that are stationary over time. These assumptions are crucial due to the non-complicating properties of the normal distribution such as the stability under addition and the finite variance. Moreover, the assumptions of normality and stationary parameter are required for most of the econometric techniques typically exploited in empirical studies. However, the empirical evidence indicated that: 1) Stock return distribution is not normally distributed but it is found to be leptokurtic (Fama E. , 1965), (Westerfield, 1977), (Hagerman R., 1978), (Peiró, 1999), (Valkanov, 2006), (Ghysels, 2007) among others. 2) Linear as well as non-linear dependency exists in stock prices (French & Roll, 1986), (Errunza, Hogan, Kini, & Padmanabh, 1994), (Booth & al, 1994), (Corhay & Rad, Daily returns from European stock markets., 1994), (Yadav, Paudyal, & Pope, 1999), among others; 3) Anomalies/Seasonalities in return distribution such as the day of the week effect, January effect, the holiday effect, the size effect and others do exist (Keim & Stambaugh, 1984), (Rogalski, 1984), (Jaffe, Jeffery, & Westerfield, 1985, 1989), (Smirlock & Starks, 1986), Wong et al.(1992), (Cheung, Ho, & Draper, 1994), (Alexakis & Xanthakis, 1995), (Martikainen & Puttonen, 1990), among others. The main literature of characteristics of stock return was studied by (Hsieh D. , 1988). He examined the statistical properties of daily rate of change of five foreign currencies from 1974 to 1983. He found that the exchange rate distributions like the equity return distributions have similar characteristics. Specifically, both return distributions are leptokurtic (too small). Hsieh suggested that there are two competing explanations for the observed heavy tails of the distribution: (a) the data are identically distributed drawn from a heavy tail of distribution whose parameters remain fixed over time; (b) the data are not identically distributed but drawn from a distribution whose parameters vary over time. In addition, he documented the day-of-the-week effect for the exchange rate data. However, he concluded that the rejection of the *i.i.d.* hypotheses for the exchange rate data was not attributable to the presence of the day-of-the-week effect.

In spite of the typical assumption of normality, pioneering research by (Kendall, 1953), Osborne (1963), and (Fama E. F., 1965) reported the deviation from this presumption. These studies have concluded that stock price change behave like a random walk (The random walk theory is based on two assumptions: (1) price changes are independent random variables, and (2) the changes conform to some probability distribution.(no memory)) even though there is some evidence of leptokurtosis in the distribution of the stock price changes. In these studies, the empirical distributions of stock price changes over time yield a higher frequency of observations near the mean and the tails than would be expected for a normal distribution. The simple kurtosis is almost always found to be greater than 3 (the value expected for a normal distribution). This type of distribution is characterized as peaked and fat-tailed. Since the normality of the stock return distribution is the crucial assumption underlying financial theories and their empirical evaluations, the "fat-tailed" findings cast doubts on the validity of findings which assume the normal distribution of stock returns. At least two explanations of the observed kurtosis in stock returns are found in the literature. One suggests that stock returns are best described by a member of the class of distributions with infinite variance, "the stable paretian distribution" while the other suggests that stock returns are sampled form a mixture of distributions that have different variances "the mixture of distribution hypothesis" (Fama E. F., 1963) and (Mandelbrot, 1962) proposed that security returns follow a stable paretian distribution with an infinite variance. (Fama E. F., 1965) illustrated that stable paretian distribution has two crucial properties: 1) their stability under addition and; 2) their limited distributions for sums of independent, identically distributed random variable. Fama discussed that: "By definition, a stable paretian distribution is any distribution that is stable or invariant under addition. That is, the distribution of sums of independent, identically distributed, stable paretian variables is itself stable paretian and, except for origin and scale, has the same form as the distribution of the individual summands. Most simply, stability means that the values of the parameters α and β remain constant under addition" (Fama, 1965. p.43). (Blume, 1970), Roll (1970), and (Teichmoeller, 1971) have provided empirical support to this line of reasoning. A stable paretian distribution is defined by the log characteristic function as follows:

$$Log\,f(t) = Log \int_{-\infty}^{\infty} \exp(uit)\, dP(\tilde{u} < u) = i\delta t - \gamma |t|^{\alpha} \left[1 + i\beta (t/|t|) \tan\left(\frac{\alpha\pi}{2}\right)\right] \tag{1}$$

The characteristic function tells us that stable Paretian distributions have four parameters, α, β, δ, and γ. The location parameter is δ, and if α is greater than one, δ is equal to the expectation or mean of the distribution. The scale parameter is γ, while the parameter β is an index of skewness which can take any value in the interval $-1 \leq \beta \leq 1$. When β= 0 the distribution is symmetric. When β > 0 the distribution is skewed right (i.e., has a long tail to the right), and the degree of right skewness increases in the interval $0 < \beta \leq 1$ as β approaches 1. Similarly, when β< 0 the distribution is skewed left, with the degree of left skewness increasing in the interval $-1 \leq \beta < 0$ as β approaches -1. Of the four parameters of a stable Paretian distribution the characteristic exponent α is the most important for the purpose of comparing "the goodness of fit" of the Gaussian and stable Paretian hypotheses. The characteristic exponent α determines the height of, or total probability contained in, the extreme tails of the distribution, and can take any value in the interval $0 < \alpha \leq 2$. When $\alpha = 2$, the relevant stable Paretian distribution is the normal distribution (Note 1). When a is in the interval $0 < \alpha < 2$, the extreme tails of the stable Paretian distributions are higher than those of the normal distribution, with the total probability in the extreme tails increasing as a moves away from 2 and toward 0. The most important consequence of this is that the variance exists (i.e., is finite) only in the extreme case $\alpha = 2$. The mean, however, exists as long as $\alpha > 1$. Mandelbrot's stable Paretian hypothesis states that for distributions of price changes in speculative series α is in the interval $1 < \alpha < 2$, so that the distributions have means but heir variances are infinite. The Gaussian hypothesis, on the other hand, states that α is exactly equal to 2. In terms of empirical test, (Officer, 1972), (Barnea & Downes, June 1973), (Blattberg & Gonedes, 1974), and (Hagerman R., 1978) reported evidence in favor of the Stable paretian hypothesis. However, (Hagerman R., 1978) reported that the estimated characteristic exponents of individual securities and portfolios increase with the holding period. This finding is a clear violation of the properties of a stable paretian distribution.

The mixture of distribution hypothesis or the subordinated stochastic theory is an alternative explanation for the observed fat-tail in the empirical distribution of stock returns. This hypothesis asserts that stock returns are sampled from a mixture of distributions which have different conditional variances. The Heteroskedasticity associated with such mixtures of normal distributions will result in larger values of the sample kurtosis. As a result, this hypothesis implies that the distributions of underlying parameters are nonstationary over time. (Clark, 1973), (Epps & Epps, 1976), (Tauchen & Pitts, 1983), (Harris, 1986), (Lamoureux & Lastrapes, 1990), and (Richardson & Smith, 1994) have presented evidence supporting the mixture of distribution hypothesis from their studies of the stock return volatility-volume relationship. These findings have suggested that stock price data be generated by a conditional stochastic process with a changing variance parameter which can be proxied by volume. Also, several researchers including (Praetz, 1972) and (Blattberg & Gondeds, 1974), among others, have verified that if conditional variance follows an inverted gamma distribution, the resulting (posterior) distribution is the student t which is a distribution with fat-tailed properties. In this study, the scope of hypotheses is delineated as follows:

H_{0A}: The stock returns are normally distributed

H_{1A}: The stock returns are not normally distributed

The study employs two statistical tests to determine whether each return series is normally distributed: the chi-square goodness of fit test for normality of residuals by Klein (1974) and the Jarque-Bera statistic. According to (Jarque-Bera, 1987), the Jarque-Bera statistic is calculated as follows:

$$JB = n[s^2/6 + (k-3)^2/24] \tag{2}$$

Where n = the number of observations; s = skewness; and k = kurtosis.(Note 2) We begin with the assumption that log price Pt follows an RW1 without drift:

$$H_0: P_t = P_{t-1} + \varepsilon_t, \qquad \varepsilon_t \sim IID\ (0, \sigma^2) \tag{3}$$

Denote by I^t the following random variable:

$$I_t = \begin{cases} 1 & if \quad R_t = p_t - p_{t-1} > 0 \\ 0 & if \quad R_t = p_t - p_{t-1} \leq 0 \end{cases} \tag{4}$$

I_t is a indicator variable indicating whether the *Rt* is positive or negative. Define N_s and N_r as the numbers of sequences and reversals respectively in historical stock return, where the former are pairs of consecutive returns with the same sign, and the latter are pairs of consecutive returns with opposite signs. Given a simple of n+1 returns R_1, R_2, R_{n+1}, the N_s and N_r can be expresses a simple functions of I_t*'s:*

$$N_s = \sum_{t=1}^{n} y_t, \qquad y_t = I_t I_{t+1} + (1 - I_t)(1 - I_{t+1}) \tag{5}$$

Where $N_r = n - N_s$

If we add the further restriction that the distribution of increments is symmetric, then whether Rt is positive or negative should be equally likely, which implies that for any pair of consecutive returns, a sequence and reversal are equally probable; hence the ratio $\hat{C}J = N_s / N_r$ (Cowles & Jones, 1937) should be approximately equal to one. Since returns at different time are independent under H_0, $\hat{C}J$ can be interpreted as a consistent estimator of the ratio of the 1-π_s, which is

$$\hat{C}J = \frac{N_s}{N_r} = \frac{N_s/n}{N_r/n} = \frac{\hat{\pi}_s}{1-\hat{\pi}_s} \xrightarrow{pr} \frac{\pi_s}{1-\pi_s} = CJ \tag{6}$$

Under H_0, π_s =1/2, CJ=1.We need the asymptotic distribution of statistics $\hat{C}J = N_s / (n\text{-}N_r)$ which ban be derived by delta method from the distribution of N_s. *With* N_s being a binominal random variable, i.e. the sum of n Bernoulli random variable y_t where:

$$y_t = \begin{cases} 1 \ with\ probability\ \pi_s = \pi^2 + (1+\pi)^2 \\ \qquad 0 \ with\ probability\ 1+\pi \end{cases} \tag{7}$$

We may approximate the distribution of N_s for the large n by a normal distribution with mean $E(N_s) = n\pi_s$ and variance $Var(N_s)$. Because each pair for adjacent y_t 's will be dependent(Note 3),the $Var(N_s)$ *is:*

$$Var[N_s] = Var\left(\sum_{t=1}^{n} y_t\right) = nVar(y_t) + 2\sum_{t>s} Cov(y_t, y_s)$$

$$= n\pi_s(1-\pi_s) + 2nCov[y_t, y_{t+1}]$$

$$= n\pi_s(1-\pi_s) + 2(n-1)(\pi^3 + (1-\pi)^3 - \pi_s^2) \tag{8}$$

Since y_t is independent of y_{t+k} for k>2 and

$$Ey_t y_{t+k} = \begin{cases} P(y_t = 1, y_{t+1} = 1) & \\ = P(I_t = 1, I_{t+1} = 1, I_{t+2} = 1) + P(I_t = 0, I_{t+1} = 0, I_{t+2} = 0) & for \quad k = 1 \\ = \pi^3 + (1-\pi^3) & \\ P((y_t = 1, y_{t+k} = 1) = P(y_t = 1)P(y_{t+k} = 1) = \pi_s^2 & for \quad k \geq 2 \end{cases} \tag{9}$$

And then

$$Cov(y_t, y_{t-k}) = \begin{cases} \pi^3 + (1-\pi^3) - \pi_s^2 & for \ k = 1 \\ 0 & for \ k \geq 2 \end{cases} \tag{10}$$

Let $\bar{N}_s = N_s / s$.

$$E\bar{N} = \pi_s(1-\pi_s) \ \ and \ \ Var(\bar{N}_s) = \frac{1}{n^2}Var(N_s) = \frac{1}{n}[\pi_s(1-\pi_s) + 2(1-1/n)\left(\frac{1}{2}(3\pi_s - 1) - \pi_s^{\ 2}\right)]$$

$$= \frac{1}{n}[4\pi_s - 3\pi_s^{\ 2} - 1 + 0\left(\frac{1}{n}\right)] \tag{11}$$

The Central Limit Theorem (CLT) can be applied to $Y_1, Y_2, ..., Y_n, ...$ Although Y_t's are independent. $\sqrt{n}(\bar{N}_s - \pi_s)$ Follows normal distribution asymptotically*:*

$$\sqrt{n}(\bar{N}_s - \pi_s) \sim (.) N(0, 4\pi_s - 3\pi_s^2 - 1)$$

Doing the first order Taylor expansion of

$\hat{C}J = N_s / (n - N_s) = \bar{N}_s(n - \bar{N}_s)$ for $\bar{N}_s$ at $\bar{N}_s = \pi_s$

$$\hat{C}J \approx \frac{\pi_s}{1-\pi_s} + \frac{1}{(1-\pi_s)^2}(\bar{N}_s - \pi_s) \sim (\cdot)N\left(\frac{\pi_s}{1-\pi_s}, \frac{4\pi_s - 3\pi_s^{\ 2} - 1}{n(1-\pi_s)^4}\right). \tag{12}$$

We end up with conclusion that: Under H_0: π_s = ½, the test statistics $\hat{C}J \sim (\cdot)N(1, \frac{4}{n})$

According to (Hsieh D. , 1989), "There is no reason to believe that economic systems must be intrinsically linear". His finding that returns are uncorrelated is insufficient to prove that the data are statistically independent since it is possible for returns to be linearly uncorrelated and nonlinearly dependent simultaneously. The ARCH and GARCH models are examples of the nonlinear models describing the long term memory in the data series. Specifically, for common stock, these models capture the persistence in the volatility of stock returns. In empirical context, there is substantial evidence that stock returns show nonlinear dependency. For example, (Akgiray, 1989) found a strong evidence of autocorrelation in squared residual and return series of the S$P 500 index. Additional evidence has been presented by (Hinich & Patterson, 1985), Corhay and Rad (1994), (Booth, Martikainen, & Tse, 1997) and (Brorsen & Yang, 1994). (Hinich & Patterson, 1985) presented the evidence for

15 stocks listed on NYSE and AMEX. They reported that stock returns are generated by non-linear process. They also noted that the degree of dependence in stock returns is much higher than that suggested by the second order time series models. (Brorsen & Yang, 1994) examined the distribution of the three alternative models of daily stock index returns: a diffusion-jump process, an extended GARCH process, and a combination of the GARCH and jump process. The data are obtained from the Center for Research in Security Price (CTSP) and the S$P 500index. They found that there is evidence of nonlinear dependency in these indices. In addition, nonlinear dependence is not removed for the value-weighted index and the S$P 500 index when the indices are fitted into GARCH (1, 1) model. Corhay and Rad (1994) found strong evidence of nolinear dependency in daily returns of Franc, German, Italian and UK stock markets while (Booth, Martikainen, & Tse, 1997) documented that the Finnish stock returns exhibit non-linear dependence and the form of the dependence is not chaotic.

(Sewell, Lee, & Pan, 1993) documented nonlinear dependencies in the stock markets of South Korea, Japan, Hong Kong, Taiwan, and Singapore whereas (Errunza & al, 1994) identified nonlinear dependencies in the markets of Japan, Germany, and the emerging markets of Brazil, India, Chili, Mexico, and Argentina. Their findings are similar to (Yadav, Paudyal, & Pope, 1999)'s examination that nonlinear dependence in stock returns for an exclusive sample of UK stocks for a 21-year period is highly significant in all cases for both individual stocks and stock portfolios formed on the basis of trading frequency. Following in Hsieh's footsteps (Hsieh D. , 1988), the i.i.d. hypotheses next offered are:

H_{0B} : The stock returns exhibit no serial dependence

H_{1B} : The stock returns exhibit a serial dependence

H_{0C} : The stock returns exhibit no nonlinear dependence

H_{1C} : The stock returns exhibit a nonlinear dependence

To investigate if the BRVM stock price changes exhibit nonlinear dependence, we will use three tests such us the autocorrelation coefficients and Box-Pierce Q-statistics of the square residual of an ARMA model are examined. In a step by step process utilized by (Hsieh D., 1988) to uncover the possible causes of the rejection of the *i.i.d.* hypothesis for the five exchange rates, be documented the day-of-the-week effect. However, he concluded that the rejection of the *i.i.d.* hypotheses for exchange rates was not attributable to the presence of the day-of-the-week effect. To test the day-of-the-week effect in stock returns this study, we follow 3 steps. i) investigates whether the day-of-the-week effect is present in the West African Regional stock market, ii) tests whether the distribution of stock returns changes across days of the week, and iii) Examines if the rejection of the *i.i.d.* hypothesis is attributable to the day-of-the-week effect.

As a preliminary test, the study conducts a test of whether the day-of-the-week effect exists in the stock returns of the West African Regional stock market, by running the following regression with binary dummy variables for each index to test whether there is any statistically significant difference among stock market returns, on different days of the week. The model which he estimated can be represented as follows:

$$R_t = \sum_{i=1}^{5} B_i D_{it} + \mu_t \tag{13}$$

Where D_{1t} = 1 if day t is a Monday and 0 otherwise; D_{2t} = 1 if day t is a Tuesday and 0 otherwise; and so on. The coefficients $B1$ to $B5$ are the mean returns for Monday through Friday, respectively. The stochastic error term is given by u_t .Using the regression in equation (13), the following hypotheses are proposed and tested to determine the existence of the day-of-the-week effect in the West African Regional stock market.

H_{0D} : Mean returns of each trading day are equal. (Days before and after holidays are included in the data set)

（$B1= B2= B3= B4= B5$）

H_{1D} : At least one trading day has a significantly different mean return.

In order to test whether the distribution of stock returns actually changes across the days-of-the-week, the data are categorized into five groups (Monday through Friday) in accordance with days of the week. We test the following null hypothesis of equal mean returns across days of the week:

（$B1= B2= B3= B4= B5$）

If the daily returns are drawn from an identical distribution, they will be expected to be equal. However, the rejection of the null hypothesis would indicate a specific observable pattern in the stock market returns, thus violation of weak-form market efficiency.

3. Econometric framework and data.

There was a significant difference in the statistical test of the multiple unit root test. Although their asymptotic distribution seems to be the same, the distribution of limited simple is still exhibit significant difference. Dissimilarity of the data Generating Process (DGP) in the data sample will produce different unit root result. Hence, from the practical point view, we should review the methodology of the multiple unit root test and implement the tests according to the different circumstances. Applying one or two unit root test that having similar tests power to economic or financial research may outcomes bias conclusion. The unit root test basically assumes the GDP having the characteristic as bellows:

$$y_t = d_t + u_t \tag{14}$$

$$u_t = \alpha u_{t-1} + v_t \tag{15}$$

Where d_t (t=1,…, T) is the time trend, u_t is the stochastic disturbance, the stochastic residual variable can be expressed as the first order autoregressive model as equation above, $\{v_t\}$ represent the stable stochastic process. If the null hypothesis of α =1 is not rejected, the time series of $\{u_t\}$ is an unstable unit root process. If the alternative hypothesis of $\alpha < 1$ is accepted, the time series of $\{u_t\}$ is stable process with trend. The ADF unit root test is proposed by (Dickey & Fuller, 1979) and (Phillips–Perron, 1988). They assume that the stochastic process $\{v_t\}$ is an AR (p) process and it is OLS regression as follow:

$$\Delta y_t = \delta_0 \delta_1 t + (\alpha - 1) y_{t-1} + \sum_{j=1}^{p} a_j \Delta y_{t-j} + e_t \, , \qquad t = 1....T \tag{16}$$

The null hypothesis is α =1. The ADF use the statistical test T ($\hat{\alpha}$ -1) and the t-test, $t_{\hat{\alpha}-1}$ of the coefficient ($\hat{\alpha}$ -1) to examine the null hypothesis. If the null hypothesis is rejected, the time series is a stable process. It necessary for us to determine the appropriate lag length (k) before the cointegration tests is conducted. We use the criteria developed by using the Akaike Information criterion (AIC) and Schwarz Bayesian Criterion (SBC) in this form:

$$AIC(p) = Ln\left(\frac{SSR(p)}{p}\right) + (p+1)\frac{2}{T} \tag{17}$$

$$BIC(p) = Ln\left(\frac{SSR(p)}{T}\right) + (p+1)\frac{LnT}{T} \tag{18}$$

Where $SSR(p)$ is the sum of square residuals of the estimated $AR(p)$ the BIC estimator of $\hat{p}, p$ is the value that minimizes $BIC(p)$ among the possible choices $p = 0,1 \ldots, p_{max}$ is the largest value of p value considered. Because the regression decreases when add lag. In contrast, the second term increases when you add a lag. The BIC trades off these two forces so that the number of lag that minimizes the BIC is a constant estimator of the true lag length (Waston, 1994).The difference between the AIC and the BIC is that the term "LnT" in the BIC is replace by "2" in the AIC, so the second in the AIC is smaller then T represent the simple.

Traditionally (Granger C. W., 1969) and subsequent improvements, namely, (Toda & Yamamoto, 1995) version of Granger causality (Granger C. W., 1969) is employed to test for the causal relationship between two variables. This test states that, if past values of a variable *y* significantly contribute to forecast the future value of another variable *x* then *y* is said to Granger cause *x* . Conversely, if past values of *x* statistically improve the prediction of *y,* then we can conclude that *x* Granger causes *y.* The test is based on the following regressions:

$$y_t = \beta_0 + \sum_{k=1}^{M} \beta_k y_{t-k} + \sum_{l=1}^{N} \alpha_l x_{t-l} + u_t \tag{19}$$

$$x_t = \gamma_0 + \sum_{k=1}^{M} \delta_k x_{t-k} + \sum_{l=1}^{N} \gamma_l x_{t-l} + v_t \tag{20}$$

Where y_t and x_t are the two variables, u_t and v_t are mutually uncorrelated error terms, t denotes the time period and *'k'* and *'l'* are the number of lags. The null hypothesis is $\alpha_l = 0$ for all l's and $\delta_k = 0$ for all k's versus the alternative hypothesis that $\alpha_l \neq 0$ l and $\delta_k \neq 0$ for at least some l's and k's. If the coefficient α_l's are statistically significant but δ_k's are not, then x causes y. In the reverse case, y causes x. But if both α_l and δ_k are significant, then causality runs both ways. The F-statistics are the Wald statistics

$$F = \frac{(RSS_r - RSS_u)/l}{RSS_u/(T-2l-1)} \quad (21)$$

Where RSS_r is the restricted sum of squared-residual while RSS_u is the unrestricted sum of squared-residual, T is the number of observations; l is the lagged order and degree of freedom of the statistics is (*T-2l-1*). The joint hypothesis is $\beta_1 = \beta_2 = \ldots = \beta_l = 0$ for each equation. The null hypothesis is that x does not Granger-cause y in the first regression and that y does not Granger-cause x in the second regression. Recent studies on time-series econometrics have highlighted several crux issues pertaining to Granger causality test. *First*, the direction of causality depends critically on the number of the lagged terms included. If the chosen lag length is smaller than the true lag length, the omission of relevant lags may cause bias. Conversely, the inclusion of extraneous lags in the equation may cause the estimates to be inefficient. In our model, we have used the Akaike and Schwarz information criterion (AIC / BIC) to fix the choice of lag length. *Secondly,* traditional Granger causality (Granger C. W., 1969) test is based on the assumption that the variables are stationary, or even if non-stationary must have the same order of integration. As observed by Toda and Phillips (1993), any causal inference in Granger jargon is questionable when there are stochastic trends and the F – test is not valid unless the variables in levels are cointegrated.

We consider two measure of stock market development namely size and liquidity: SIZE denotes market capitalization as a % of GDP at constant price whereas LIQUIDITY denotes total value of share traded as a % of GDP at constant price. We build our model based on the following augmented production.

$$Y_t = \beta_1 FDI_t + \beta_2 HUMAN_t + \beta_3 MD_t + \mu_t \quad (22)$$

Where *Y*t denotes real GDP per capita; FDI denotes foreign direct investment, HUMAN denotes human capital and MD denotes stock market development. The econometric model can write as reduced form logarithm equation for SIZE and LIQUIDITY;

$$LnY_t = \beta_0 + \beta_1 LnFDI + \beta_2 LnHUMAN + \beta_3 LnSIZE + \mu_1 \quad (23)$$

$$LnY_t = \beta_0 + \beta_1 LnFDI + \beta_2 LnHUMAN + \beta_3 LnLIQUIDITY + \mu_1 \quad (24)$$

Over the years, the country has experienced sustain and consistent growth. Many factors have contributed to this namely successful trade liberalization, political stability, institutional factors among others. However, it can be argued two main factors that have help the country in the attainment of sustained growth is FDI and human capital.

To test the nature of the distribution of West African Regional stock returns data, the daily closing prices of Brvm Composite Index, Brvm 10 Index as well as its eighteen (18) sub-indices are utilized. These indices are Nestle, Solibra, Uniwax, Ciec, Sdcc, Snts, Bicc, Safca, Sgbci, Sdvc, Sdv-Saga, Sivom, Ph Ci, Sicor, Sogb, Shec, Ttlc, Bnbc. Table 1 displayed the West African Regional Stock Price Indices and eighteen of its sub-indices. This data stream results in a total of 2000 daily observations on prices. The return from the index, R_t, is computed as follows the log return.

$$R_t = \log(p_t / p_{t-1}) * 100 \quad (25)$$

Where p_t is the current closing price and p_{t-1} is the previous closing price. Log Return Throughout this paper, we will use these notations

Price change	price return	log return	
$ct = p_t - p_{t-1}$	$rt = (p_t - p_{t-1})/p_{t-1}$	$R_t = 100$ rt	(26)

Where log is the natural logarithm , p_t is the close price of the security at time t , p_{t-1} is the close price of the security at time t – 1 and τ is the time lag (τ =1). In financial literature, people often use log return rather than simple return. If stock price at time t, the log return R_t over time interval [t, t+1] is defined as the first order difference logarithm of p_t over [t, t+1],

$$R_t = log\, p_t - log\, p_{t-1} = log\,(p_t / p_{t-1}) \tag{27}$$

We will usually use the log return, mainly for these reasons: First and most important is that, empirical evidence shows that the distribution of stock price tends to have a thicker tail than that of normal distribution. Using normal distribution to calculate the probability of extreme events is most likely misleading. Log normal distribution has a thicker tail than normal distribution and can be employed to describe the tail features of stock prices. The second reason is normal distribution permits a random variable to take negative values and then is not obviously suitable for nonnegative stock price. Log price that can be negative overcomes this difficulty. The third reason for using log return is it's summability over time interval [t-1, t] and [t, t+1] respectively. The log return over [t, t+2], $R_t(2)$ is the sum of $R_t(1)$ and $R_{t+1}(t)$:

$$R_t(2) = log\, p_{t+2} - log\, p_t = log\, p_{t+2} - log\, p_t + log\, p_t - log\, p_t = R_t(1) + R_{t+1}(1). \tag{28}$$

In the same way, we have

$$R_t(k) = R_t(1) + R_{t+1}(1) + \ldots R_{t+k}(1), \tag{29}$$

Finally financially, it corresponds to the continuously compounded return of the asset S.

The current study focuses on West African Monetary union economy spanning over a period of more than eleven years (1995-2006). Any study on stock market development should preferably be based on daily (or monthly) frequency, given the dynamic nature of the market. But given the fact that monthly GDP figures in West African Monetary union economy are not available only year and quarter GDP. In the present study, we have used quarterly data on output and indicators of stock market development for the period 1995:Q1 – 2006:Q4. i) Economic development is measured by the growth rate of real GDP; ii) Stock market development is measured by two proxies: real market capitalization ratio (*size proxy*) defined by the ratio of market capitalization to real GDP, and real value traded ratio (*activity proxy*) defined by the ratio of trading volume to real GDP. MCR means Market Capitalization Ratio. This measure equals the value of listed shares divided by GDP. The assumption behind this measure is that overall market size is positively correlated with the ability to mobilize capital and diversify risk on an economy-wide basis. STR signifies Total Value of Shares Traded Ratio. This measure equals total value of shares traded on the stock market exchange divided by GDP. The total value traded ratio measures the organized trading of firm equity as a share of national output and therefore should positively reflect liquidity on an economy-wide basis. The total value traded ratio complements the market capitalization ratio: although a market may be large, there may be little trading. For other variables we have**:** Foreign Direct Investment (FDI); Foreign direct investment is used as a control variable since it is presumed that FDI is a determinant of economic growth. Data was obtained from different source. The data on market capitalization and total trade value is collected from the Brvm stock market; while that of real GDP and FDI was obtained from Brvm-Togo; the data on stock development measures namely SIZE and LIQUIDITY was obtained from Stock Market of West African various bulletin, HUMAN (proxied by secondary enrollment ratio was obtained from Central Statistical Office, UEMOA.

4. Empirical results and interpretations.

This section presents the empirical result of the study. First Statistical Properties of the Stock Returns in West African stock market are reported. Descriptive statistics of the daily returns on the West African Regional Market along with its two Stocks Index as well as its eighteen sub-indices are reported in table 2. The Jarque-Bera statistics exhibited in table 2 indicate that all of the return series are significantly non-normally distributed. One possible explanation for the rejection of the hypothesis is that the distributions of the stock returns are leptokurtic. Specifically, they are fat-tailed and peaked. These characteristics can be clearly observed from the values of the coefficients of the excess kurtosis and the coefficients of the skewness. The level of excess kurtosis ranking from 18.62 to 309.18 indicates fatter tails than the normal distribution.

The results of tests of independence and identical distributions for the sample series under consideration are summarized in table 3. For the entire period (1997-2007), the Cowles and Jones statistics indicate that the null hypotheses are rejected for the BRVM tow indices and as well as its 18 sub-indices choose. In order to examine whether the rejection of the hypothesis is predominantly attributable to a particular time period within the ten (10) year study, this paper devides the sample into three periods (1998-2003, 2004-2007, Jan 2007- Dec 2007. The Cowles and Jones results strongly suggest the rejection of the null hypothesis of independence and identical distribution for the Brvm indices and its fifteen sub-indices returns for all periods evaluated. As already noted, the rejection of the *i.i.d.* hypothesis could be caused by several reasons. Some of the reasons could be a changing distribution of returns across days of the week, dependency within the data, or time-varying means and variances. In order to determine the possible causes underlying the rejection of the *i.i.d.* hypothesis, the subsequent tests are conducted.

The autocorrelation coefficients for the Brvm Composite Index, Brvm 10 Index as well as eighteen (18) of is sub-indices returns series up to 23 lags are reported in table 4. The autocorrelation coefficients indicate that most return series exhibit significant positive serial dependence for lags of 1 day. The magnitude of the first order autocorrelations is large; ranging from -0.057 to 0.154. The Box-Pierce Q (23) statistics of the Brvm Composite Index, Brvm 10 Index as well as eighteen (18) of is sub-indices are also presented in table 4. However, except for SDCC and SNTS the statistically significant Q (23) values in the table suggest the presence of a long term linear dependency in the Brvm Composite Index, Brvm 10 Index as well as its eighteen (18) sub-indices. The Box-Pierce statistics for that squared return series up to 23 lags, Q (23), are presented in table 5. The null hypothesis of conditional homoskedasticity is easily rejected at the 5 percent significance level in the Brvm Composite Index, Brvm 10 Index as well as eighteen (18) of is sub-indices. This strong evidence of linear as well as nonlinear dependencies in the Brvm Composite Index, Brvm 10 Index as well as its eighteen (18) indices is similar to that reported for Australia, Belgium, Canada, France, Italy, Switzerland and Germany by (Theodossiou & Lee, 1995), for Thailand by (Kamath & al, 1998) and (Jirayuth & Ravindra, 2002). The findings indicate that the rejections of serial independence using the standard testing procedure had resulted from the presence of the heteroskedasticity in the data. In spite of the evidence of the serial correlation in the data, its magnitude is too small to be responsible for the rejections of the *i.i.d.* hypothesis. Therefore, to validate the result, this study investigates whether changing distributions of the data (across days of the week) can explain the Average daily returns over the trading period of 1998-2007 for the West African Regional stock market two indices and eighteen of is sub-indices along with their t-values are presented in Table 4 and Table 5 (all days of the week are included). With the exceptions of Brvm-10, Brvm-Composite, Nestle, Solibra, Uniwax, Snts, Sdv_Saga, Sivom, and Sicor the presented evidence shows that the H_{0D} can be rejected. In fact, the insignificance of all F1 values in table 4 and table 5 of the West African Regional stock market two indices and is eighteen sub-indices support the conclusion that the distribution of returns for each day of the week might be *i.i.d.* The coefficient of variation (CV), standard deviation divided by mean return, is used as a measure of risk per unit return. The highest CV values are observed on Thursday among days of the week. Moreover, the lowest CV values appear towards the end of the week (Friday) returns. The lowest standard deviations returns on Mondays is does not conform to the studies: (Fama E. F., 1965), (Gibbons & Hess, (October 1981)), (Agrawal & Kishore, 1994), and (Balaban, (1995,1996)). However, it is interesting to observe the lowest standard deviations returns on Tuesdays, just after Mondays with the lowest standard deviations. As illustrated in table 6 the highest daily mean returns in SNTS index.

However, the lowest risk per unit return in BICC index where all the days have not significantly positive mean returns. The highest risk per unit return in SDVC index among the West African Regional stock market two indices and eighteen of its sub-indices which exhibit daily seasonality. For all the two indices and eighteen sub-indices of West African Regional stock market return, the highest risk per unit return is observed in the SDVC index. This study presents evidence for the existence of the day of the week effects for a recent period of time West African Regional stock market return. The daily effects are analyzed in stock market returns of the West African Regional stock market two indices and eighteen of its sub-indices. A daily pattern in stock markets is observed for the two indices of West African Regional stock market return and five of its eighteen sub-indices. We believe that our empirical results detecting significant and different daily patterns of mean returns and their volatility in West African Regional stock market return terms have useful implications for international portfolio diversification.

In summary the study finds the following characteristics in the West African Regional Stock data as follow: 1) The distribution of the BRVM indices and eighteen of its sub-indices returns is distinctly fat-tailed non-normal, and leptokurtic; 2) The returns of the West African Regional Stock Price Indices and eighteen of its sub-indices are not independent and identically distributed; 3) The conclusion that the distribution of returns is not *i.i.d.* across different days of the week in the West African Regional Stock Price Indices and eighteen of its sub-indices during 1998-2007 is not strongly validated; 4)There is evidence of both linear and nonlinear dependency in the West African Regional stock market data; 5) The dependency of the stock return data is found to be one of the causes that might have led to the rejection of the i.i.d. hypothesis. The overall conclusion of comprehensive investigation of this study indicates that West African Regional stock market return data is non-normal and *non-i.i.d.* The linear and non-linear dependency in the data appears to be the primary cause of the data being non-*i.i.d*. Consequently, the GARCH methodology, which does not require the assumption of normality, can overcome the problem of dependency and is the preferred choice.

Second, using the Toda and Yamamoto (1995) Test, the result on the Stock Market Activity and Economic Growth Causality Testing in West African Monetary Union are reported. As discussed in the earlier section, we first check whether the series under consideration are stationary or not. In the latter case, we also determine their order of integration. The results of Augmented Dickey Fuller (Dickey & Fuller, 1979) unit root test are depicted in table 7. The results suggest all variables, real market capitalization ratio (MCR), real value traded ratio (VTR) and real GDP growth rate (GDPGR) has a unit root, but the first difference of each is stationary. Thus the four variables in our model are not cointegrated and hence F-test in Granger causality may not be reliable in inferring leads and lags among such variables, with different orders of integration (Toda and Phillips, 1993).

Given that the maximum order of integration ($d_{\max}$) equals 1, we next determine the number of lagged terms (*k*) to be included using AIC / SIC rule and find it to be 2. Finally, we construct a VAR in levels, similar to that depicted in (5) with a total of (k + $d_{\max}$) equaling 3 lags.

$$\begin{bmatrix} GDP \\ MCR \\ TTV \end{bmatrix} = B_0 + B_1 \begin{bmatrix} GDP_{t-1} \\ MCR_{t-1} \\ TTV_{t-1} \end{bmatrix} + B_2 \begin{bmatrix} GDP_{t-2} \\ MCR_{t-2} \\ TTV_{t-2} \end{bmatrix} + B_3 \begin{bmatrix} GDP_{t-3} \\ MCR_{t-3} \\ TTV_{t-3} \end{bmatrix} + E_t \tag{30}$$

The results in table 8 suggest unidirectional causality between economic growth proxied by GDP and stock market proxied by market capitalization and Total trade value. The research makes a modest attempt to explore the causal relationship between stock market development and economic growth in the West African monetary union for the period from 1995:Q1– 2006:Q4. The study primarily revolved around two major questions: first whether at all any relationship exists between stock market development and economic growth and secondly, what could be the nature and direction of the causal relationship, if any i.e. does development of stock market promote economic growth or vice versa? To test this hypothesis, we employ the methodology of *Granger non-causality* proposed by (Toda & Yamamoto, 1995). In this study, the Brvm Index is used as a proxy for the West African stock market. The two important indicators for stock market development variables included in the study are real market capitalization ratio and, real value traded ratio. Real GDP growth rate is used as a proxy for economic development. In the Toda-Yamamoto sense, the causality test suggests that stock market development proxied by market capitalization and Total trade value causes economic growth without a feedback. These two outcomes suggest stock market development led “economic growth” in the West African monetary union. This empirical result validates (Levine & al, 1999) and (Jung, 1986) but fails to validate (Waqabaca, 2004) and (Kar & Pentecost, 2000). The empirical results suggest that financial sector development and economic growth is positively cointegrated indicating a stable long-run equilibrium relationship between “market-based” financial deepening and economic growth. This means that high but sustainable economic growth would lead to financial sector development. Also, a unidirectional causality between financial deepening and economic growth exists running from financial deepening to economic growth. This suggests that financial sector development would lead to high but sustainable economic growth in West African monetary union. Therefore, the performance of financial intermediaries influences real sector development as well as real economic activity.

Table 9 and table 10 reports result for the Long Run Equation of model (24). The results indicate that all the independent variables have the expected positive sign and are highly significant. Both measures of stock market development demonstrate the importance of stock market development to growth. A 10% increase in SIZE leads to a 1.75% increase in RGDPPC whereas a 10% increase in LIQUIDITY leads to a 6.33% increase in RGDPPC. These results suggest that development of the stock market is an important ingredient for economic growth. However, LIQUIDITY has a greater impact on growth rather than SIZE. We check for the presence of multicollinearity using the variance inflation factor (VIF). As a rule of thumb, a variable whose VIF values are greater than 10 may merit further investigation when it comes to multicollinearity. Equation (23) produces a VIF of 4.88 and equation (24) 3.37. Table 11 and table 12 depict results from the short run equations. The results are replicated compared to the long run ones. The Adjusted R^2 is 0.7635 and 0.7954 which indicate the ability of the model to fit the data reasonably well. The lagged error terms have the required negative sign and are significant at 1%. This reinforces the finding of along run relationship among the variables.

The results in table 9 and table 10 indicate that the immediate effect of SIZE as well as LIQUIDITY is positive and significant. In fact, the immediate impact of all other variables namely HUMAN and FDI is positive and significant. The size of the coefficient of the error correction terms, namely -0755 and -0.635 for equation (23) and (24) suggests a high speed adjustment from the short run deviation to the long run equilibrium in RGDPPC. It indicates that 75% (for equation 23) and 63% (equation 24) of the deviation is corrected every year. The model analyzes relationship between stock market development and economic growth in West African monetary Union over the period of time 1995 to 2006. Using two measures of stock market development namely Size and Liquidity, we found that stock market development is an important ingredient for growth in West African monetary Union since the stock market gives a general idea of an economy's health. We adopt the simple two step procedure of Engle and Granger when it comes to the econometric methodology. Given the small size of our sample and the number of parameters to be estimated, the Engle-Granger approach is more attractive than the Johansen approach which would require the estimation of a system of 3 equations, implicitly there is a loss of degree of freedoms. The positive relationship between stock market development and economic growth is replicated in both the long run and short run equations. Our two controlling variables have the expected positive result and are highly significant. Both FDI and HUMAN are crucial determinants of growth in West African monetary Union. The emerging literature on FDI stipulates that FDI's positive impact on growth depends on local conditions and absorptive capacities. Essential among these capacities is financial development. This model provides support for this hypothesis in the context of West African monetary Union. Like FDI, the importance of human capital to economic growth in not a doubt.

5. Conclusion

This study has investigated the statistical properties of stock returns in the West African regional stock market and the link between the West African regional stock market and economic growth. In all the two areas, the study has made important contributions to the finance literature. We first started by investigated the statistical properties of the West African Regional stock market. To examine the nature of the distribution of West African regional stock returns, the daily closing prices of the two stock index (brvm-10 and brvm-composite) of West African regional stock market, and eighteen of it sub-indices were utilized. Nine years data from 1998 to 2007 interval were employed. The primary conclusion of this study indicated that the distribution of the West African regional stock market returns is non-normal and non-*i.i.d.* The linear and non-linear dependencies in the returns appeared to be the main reasons for the data being non-*i.i.d.* Accordingly, the GARCH methodology, which does not require the assumption of normality, is the appropriate methodology for the West African regional stock market. The existence of the Day-of-the-week-effect in the stock returns implies that the stock market is not efficient since investors can earn excess returns by buying stocks on Monday and selling them on Friday afternoon.

Therefore, a study of the Day-of-the-week-effect in West African regional monetary union helps in uncovering the trends and evidence from the market. This examination helps to better understand this phenomenon in a market with different institutional, political, and regulatory environments. We also demonstrate the presence of the day-of-the-week effect in West African regional stock market. This paper has provided a comprehensive empirical investigation on the days-of-the-week effect in West African regional stock market both for the overall index (brvm-10, brvm-composite) and eighteen sub-indices from September 1998 to December 2007.

This study presents evidence for the existence of the day of the week effects for a recent period of time in West African Regional stock market return. The daily effects are analyzed in stock market returns of the West African Regional stock market two indices and eighteen of its sub-indices. A daily pattern in stock markets is observed for the two indices of West African Regional stock market return and five of its eighteen sub-indices. We believe that our empirical results detecting significant and different daily patterns of mean returns and their volatility in West African Regional stock market return terms have useful implications for international portfolio diversification.

References

Agrawal, A., & Kishore, T. (1994). Anomalies or Illusions? Evidence from Stock Markets in Eighteen Countries. *Journal of International Money and Finance,* Vol. 13, pp. 83–106.

Akgiray, V. (1989). Conditional Heteroscedasticity in Time Series of Stock Returns:Evidence and Forecasts. *Journal of Business*, Vol. 62, No.1, pp 55-80.

Alexakis, P., & Xanthakis, M. (1995). Day of the week effect on the Greek stock market. *Applied Financial Economics,* 5, 43-50.

Balaban, E. (1995, 1996). Day of the Week Effects: New Evidence from an Emerging Stock Market. *Applied Economics Letters,* 2, 139-143.

Barnea, A., & Downes, D. (June 1973). A re-examination of the empirical Distribution of Stock Price Change. *Journal of the American Statistical Association*.

Blattberg, R., & Gondeds, N. (1974). A Comparison of the Stable and Student Distribution as statistical models for stock prices. *Journal of Business*, 47 April 244-80.

Blume, M. (1970). Portfolio Theory: A Step Towards Its Practical Application. *Journal of Business,* 43:2, pp. 152-174.

Booth, & al, e. (1994). On the Idea of the Moral Economy. *The American Political Science Review*, Vol 88, No 3: 653667.

Booth, G., Martikainen, T., & Tse, Y. (1997). Price and volatility spillovers in Scandinavian stock markets. *Journal of Banking and Finance*, 21, pp. 811-823.

Brorsen, B., & Yang, R. S. (1994). Nonlinear Dynamics and the Distribution of Daily Stock Index Returns. *Journal of Financial Research,* 17, 187-203.

Cheung, Y., Ho, P. Y.-k., & Draper, P. (1994). Intraday Stock Return Volatility:the Hong Kong Evidence. *Pacific-Basin Finance Journal,* 2, 261-276,.

Clark, P. (1973). A Subordinated Stochastic Process Model with Finite Variance for Speculative Prices. *Econometrica,* 41, 135—155.

Corhay, A., & Rad, A. (1994). Daily returns from European stock markets. *Journal of Business and Finance and Accounting,* 21, 271-281.

Corhay, A., & Rad, T. (1994). Statistical Properties of Daily Returns: Evidence from European Stock Markets. *Journal of Business Finance and Accounting*, 21, pp 271-282.

Corhay, A., & Rad, T. (1994). Statistical Properties of Daily Returns: Evidence from European Stock Markets. *Journal of Business Finance and Accounting*, 21, pp 271-282.

Cowles, A., & Jones, H. (1937). Some A Posteriori Probabilities in Stock Market Action. *Econometrica,* 5, 280-294.

Dickey, D., & Fuller, W. (1979). Distribution of the Estimators for Autoregressive Time Series with a Unit Root. *Journal of the American Statistical Association*, 74, p. 427–431.

Epps, M. L., & Epps, T. W. (1976). The Stochastic Dependence of Security Prices Changes and Transaction Volumes: Implications for the Mixture-of-Distributions Hypothesis. *Econometrica,* 44(2), pp. 305-321.

Errunza, Hogan, Kini, & Padmanabh. (1994). Conditional Heteroskedasticity and Global Stock Return Distributions. *Financial Review*, 29(3), 293-317.

Errunza, V. R., & al. (1994). Conditional heteroskedasticity and global stock return distribution. *Financial Review,* 29, 293−317.

Fama, E. (1965). The Behaviors of Stock Price. *Journal of Business*.

Fama, E. F. (1963). Mandelbrot and the Stable Paretian Hypothesis. *Journal of Business*, XXXVI (October, 1963), 420-29.

Fama, E. F. (1965). Portfolio Analysis in a Stable Paretian Market. *Management Science Science* (January).

French, & Roll. (1986). Stock return variances: The arrival of information and the reaction of traders. *Journal of Financial Economics,* 17, 5-26.

Ghysels, e. a. (2007). Handbook of financial time series. *Business & Economics* - 1050 pages.

Gibbons, M., & Hess, P. ((October 1981)). Day of the Week Effects and Asset Returns. *Journal of Business*, pp. 579-596.

Granger, C. W. (1969). Investigating causal relations by econometric models and cross-spectral methods. *Econometrica,* 37, 424-438.

Hagerman, R. (1978). More evidence on the distribution of security returns. *Journal of Finance,* 33. 1213-1221.

Harris, L. (1986). Transaction Data Study of Weekly and Internal Patterns in Stock Returns. *Journal of Financial Economics*, 16: 99-117.

Hinich, M., & Patterson, D. (1985). Evidence of nonlinearity in daily stock returns. *Journal of Business and Economic Statistics*, 3, 69-77.

Hsieh, D. (1988). Statistical Properties of Daily Exchange Rates. *Journal of International Economics*, 24 (1988), 129-145.

Hsieh, D. (1989). Modeling heteroscedasticity in daily foreign-exchange rates. *Journal of Business and Economic Statistics*, 7, 307-317.

Hsieh, D. (1988). The statistical properties of daily exchange rates: 1974-1983. *Journal of International Economics*, 24, 129-145.

Jaffe, Jeffery, & Westerfield. (1985, 1989). The Week-End Effect in Common Stock Returns: The International Evidence. *Journal of Finance,* Vol. 40, June 1985, pp. 433-454.

Jarque-Bera. (1987). A test for normality of observations and regression residuals. *International Statistical Review*, 55, 163–172.

Jirayuth, C., & Ravindra, K. (2002). An Investigation of the Day-of-the-week Effect in Korea: Has the Anomalous Effect Vanished in the 1990's? *International Journal of Business,* 7(1), 2002 ISSN:1083-4346.

Jung, W. (1986). Financial Development & Economic Growth: International Evidence. *Economic Development and Cultural Change*, 34, PP. 333-46.

Kamath, R., & al. (1998). Return distribution and the Day-of-the-Week Effects in the Stock Exchange of Thailand. *Journal of Economics and Finance*, Vol. 22, No. 2-3, 97-106.

Kar, M., & Pentecost, E. (2000). Financial development and economic growth in turkey. *Further evidence on the causality issue*, 00/27.

Keim, D., & Stambaugh, R. (1984). A future investigation of the weekend effect in stock returns. *Journal of Finance*, 39,819-835.

Kendall, M. (1953). The Analysis of Economic Time Series-Part I: Prices. *ROYAL STATISTICAL SOCIETY journal*, Series A,Vol. cxvI, Part I,.

Lamoureux, C., & Lastrapes, W. (1990). Persistence in variance, structural change, and the GARCH model. *Journal of Business and Economic Statistics*, 8, 225-234.

Levine, R., & al. (1999). Law Finance and Economic Growth. *Journal of Finance Intermediation,* 8(1/2),36-67.

Mandelbrot, B. (1962). A Class of Long-taileg Probability Distributions and the Empirical Distribution of City Sizes. *Research note*, Thomas J. Watson Research Center, Yorktown Heights, N.Y., May 23,.

Martikainen, T., & Puttonen, V. (1990). Sequential Information arrival in stock and stock index derivatives markets. *European Journal of Finance,* 2:2 207-217.

Officer, R. (1972). The Distribution of Stock Returns. *Journal of the American Statistical Association*, 340, (67), pp.807-12.

Peiró, A. (1999). Skewness in financial returns. *Journal of Banking & Finance*, 23, 847-862.

Phillips–Perron. (1988). Testing for a Unit Root in Time Series Regression. *Biometrika,* 75, 335–346.

Praetz, P. (1972). The Distribution of Share Price Change. *Journal of business,* 45 january, 49-55.

Richardson, M., & Smith, T. (1994). A Unified Approach to testing for Serial Correlation in Stock Returns. *Journal of Business*, 67 (3).

Rogalski, R. (1984). New findings regarding day of the week returns over trading and non trading periods: A note. *Journal of Finance,* December, pp. 1603-1614.

Sewell, S. R., Lee, S. I., & Pan, M. (1993). Nonlinearities in emerging foreign capital markets. *Journal of Business Finance & Accounting*, 20, 237-248.

Smirlock, M., & Starks, L. (1986). Day of the week and intraday effects in stock returns. *Journal of Financial Economics*, Vol.17, pp197-210.

Tauchen, G., & Pitts, M. (1983). The price variability-volume relationship on speculative markets. *Econometrica*, vol. 51, pp. 485–505.

Teichmoeller, J. (1971). A Note on the Distribution of Stock Price Changes. *Journal of the American Statistical Association*, 66: 282-284.

Theodossiou, P., & Lee, U. (1995). Relationship Between Volatility and Expected Returns Across International Stock Markets. *Journal of Business Finance and Accounting,* 22: 289-300.

Toda, H., & Yamamoto, T. (1995). Statistical inference in vector autoregressions with possibly integrated processes. *Journal of Econometrics,* 66,225-250.

Valkanov, a. a. (2006). Forecasting Realized Volatility: A Bayesian Model Averaging Approach. *Forthcoming in Handbook of Economic Forecasting.*

Waqabaca, C. (2004). Financial Development and Economic Growth in Fiji. *Economics Department*, Reserve Bank of Fiji, WP 03.

Waston, M. W. (1994). *Vector Autoregression and Cointegration Chap.14 Hand book of econometrics Volume IV.* Amsterdam: Edit by Robert Engel and Daniel McFadden.

Westerfield, R. (1977). The distribution of common stock price changes: An application of transactions time and subordinated stochastic models. *Journal of Financial and Quantitative Analysis*, Vol. 12, pp. 743-765.

Notes

Note 1. The logarithm of the characteristic function of a normal distribution is log f(t) = i μ t- $\frac{\sigma^2}{2}$ t ^{2} This is the logarithm of the characteristic function of a stable Paretian distribution with parameters α= 2, **δ**=μ, and **γ**= $\frac{\sigma^2}{2}$ **.**

Note 2. The expected value of kurtosis for normal distribution random variable is 3. Consequently, a value of zero for the excess kurtosis corresponds to normality (Nanjand and Yang 1991).

Note 3. In fact y_t is a two-state Markov chain with probabilities Pr(y_t =1)/ $y_{t-1} = 1) = (p^3 + (1-p)^3)/p_s$ and $\Pr(y_t = 0 / y_{t-1} = 0) = 1/2$

Table 1. The West African Regional stock market two indices and is eighteen sub-indices

INDICES	-BRVM-10
	-BRVM COMPOSITE
INDUSTRIE	-NESTLE
	-SOLIBRA beer
	-UNIWAX
	-CIEC Compagnie Ivoriene d'electricite
SERVICES PUBLICS	-SDCC Ste de Distribution d'eau de la cote d'ivoire
	SNTS Société Nationale de Télécommunication - Sonatel
	BICC BICICI, Banque Internationale pour le Commerce et l'Industrie de Côte d'Ivoire
BANQUES	SAFCA Société Africaine de Crédit Automobile
	SGBCI Société Générale de Banque en Cote d'Ivoire
	SDVC Delmas Vieljeux Cote d'Ivoire
TRANSPORT	SDV-SAGA company specialized in transport and logistics services
	SIVOM Société Ivoirienne d'Operations Maritimes
	PH CI Plantation et Huileries de Côte d'Ivoire
AGRICULTURE	SICOR Société Ivoirienne de Coco Rape
	SOGB Société des Caoutchoucs de Grand Bereby
	SHEC Shell Cote d'Ivoire
DISTRIBUTION	TTLC Total Fina Elf Oil Côte d'Ivoire
	BNBC BERNABE-Côte d'Ivoire (huilerie)

Source: Banque Régionale des Valeurs Mobilières Cote d'Ivoire

Table 2. Summary Statistics of Daily stock Returns Indices of West African Regional Stock Exchange. From 16 September 1998 to 31 December 2007

	Mean	Maximum	Minimum	Std. Dev.	Skewness	Kurtosis	Jarque-Bera	Observations
BICC	-0.002721	8.702956	-16.96567	0.883087	-4.143558	92.91484	678766.9	1998
BRVM_10	0.017381	2.233289	-4.791725	0.420602	-0.991576	18.62458	20661.36	1999
BRVM_COMPOSITE	0.014878	3.945388	-4.640333	0.362723	-0.661692	37.11805	97100.83	1999
CIEC	-0.006129	9.376961	-10.13005	1.133793	-1.233620	23.70759	36222.85	1999
NESTLE	-0.010432	4.800773	-8.006193	0.624769	-1.920570	42.39773	130447.4	1998
PH_CI	-0.012327	13.00784	-20.67174	0.975260	-1.166816	156.3558	1959307.	1999
SAFCA	-0.014665	3.621217	-7.449562	0.408341	-6.144954	124.8404	1247178.	1996
SDCC	-0.008181	9.390450	-12.49387	0.928435	-1.376496	49.36357	179673.4	1999
SDV_SAGA	0.016568	9.014532	-10.13498	0.709001	-0.060885	65.80318	327866.1	1995
SDVC	0.005952	6.280641	-15.91158	0.866415	-4.663198	95.55244	659786.3	1830
SGBCI	0.010534	10.91922	-14.73571	1.068094	-1.475844	45.30972	149752.2	1998
SHEC	-0.010193	9.375679	-6.069784	0.788373	0.830814	30.60563	63704.10	1999
SICOR	-0.027158	6.821406	-20.08458	0.761997	-10.13188	272.3075	6075055.	1999
SIVOM	-0.018563	9.342169	-23.64658	0.916812	-9.510714	274.9679	6190933.	1999
SNTS	0.042276	3.140846	-5.551733	0.624869	-0.528760	18.69275	20604.76	1999
SOGB	0.011753	9.315516	-13.51924	1.096374	-1.705146	33.66173	79274.66	1999
SOLIBRA	0.023612	12.73671	-25.04939	0.926703	-8.570164	309.1878	7821390.	1996
TTLC	0.021290	9.422357	-5.270635	0.704084	1.736847	37.84004	102106.8	1999
UNIWAX	-0.043376	3.385827	-7.918125	0.467600	-5.584672	77.97955	478651.1	1999

Source: Own computation by Eview 3.1

Note: 1) Return $R^t = \log(P^t/P^{t-1})*100$; 2) Normality test is a Jaque-Bera Asymptotic LM Normality test.

Table 3. Statistic of Cowles and Jones (CJ)

Index	1998-2007	1998- 2003	2004-2007	01/2007-12/2007
Brvm_10	0.95117	0.99602	0.90805	0.93701
BRVM_Composite	0.96847	1.02424	0.91538	0.98387
UNIWAX	0.05158	0.08795	0.01736	0.04681
CIEC	0.26376	0.33600	0.19856	0.30851
SDCC	0.11933	0.13477	0.10421	0.15493
SNTS	0.43431	0.47570	0.39496	0.50000
SIVOM	0.03096	0.01933	0.04293	0.06034
PH_CI	0.05658	0.06369	0.04953	0.12329
SICOR	0.05603	0.09508	0.01945	0.05579
SOGB	0.18435	0.15571	0.21463	0.36667
SHEC	0.18929	0.21308	0.16628	0.20588
TTLC	0.17946	0.19570	0.16355	0.18841
NESTLE	0.12191	0.14009	0.10421	0.16038
BICC	0.11068	0.09879	0.12289	0.14419
SGBCI	0.14376	0.13235	0.15545	0.17703
SDVC	0.11564	0.10730	0.12415	0.01653
BNBC	0.08474	0.11346	0.05732	0.12329
SOLIBRA	0.09136	0.08587	0.09692	0.12329
SAFCA	0.01994	0.01835	0.02154	0.02500
SDV_SAGA	0.07780	0.04171	0.11659	0.23000

Note: 1. Return $R_t = \log(P_t/P_{t-1})*100$; CJ= $\hat{C}J \sim (\cdot) N(1, \frac{4}{n})$

Table 4. Average Daily returns over trading periods of 1998-2007, for the BRVM index and, 18 of its indices (All days are included)

INDEX	B1	B2	B3	B4	B5	R^2-Adj	F-value	P-value	DW
BRVM_10	0.0161	0.0072	0.0032	0.0228	0.0357	-0.0012	0.4192	0.7949	1.8154
	(0.8072)	(0.3035)	(0.1657)	(0.9468)	(1.8504)*				
BRVM_COMPOSITE	0.0180	0.0033	0.0038	0.0344	0.0194	-0.0011	0.4297	0.7873	1.6862
	(1.0419)	(0.1588)	(0.2264)	(1.6568)*	(1.1680)				
NESTLE	0.0279	-0.0010	-0.0785	0.0178	-0.0029	0.0020	2.0125	0.0902	1.8867
	(0.9409)	(-0.0281)	(-2.7233)**	(0.4992)	(-0.1029)				
SOLIBRA	0.0875	-0.0537	-0.0387	0.0816	0.0387	0.0019	1.9418	0.1014	1.9025
	(1.9864)	(-1.0258)	(-0.9048)	(1.5413)	(0.9115)				
UNIWAX	-0.0312	-0.0407	-0.0655	-0.0418	-0.0350	-0.0012	0.3815	0.8220	1.7516
	(-1.4012)	(-1.5402)	(-3.0295)**	(-1.5626)	(-1.6319)				
CIEC	-0.0544	-0.0806	0.0349	0.0771	-0.0061	0.0002	1.1093	0.3504	1.7726
	(-1.0103)	(-1.2573)	(0.6675)	(1.1889)	(-0.1168)				
SDCC	-0.0245	-0.0452	-0.0687	0.0719	0.0396	0.0011	1.5501	0.1851	1.8601
	(-0.5556)	(-0.8614)	(-1.6044)	(1.3548)	(0.9316)				
SNTS	0.0609	0.0418	0.0093	0.0377	0.0598	-0.0010	0.5210	0.7203	2.1127
	(2.0508)**	(1.1824)	(0.3235)	(1.0541)	(2.0862)**				
BICC	-0.0482	0.0677	0.0222	0.0017	-0.0339	0.0001	1.0380	0.3861	1.8416
	(-1.1485)	(1.3555)	(0.5437)	(0.0330)	(-0.8375)				
SAFCA	-0.0180	0.0056	-0.0077	-0.0091	-0.0352	-0.0009	0.5525	0.6973	1.8623
	(-0.9244)	(0.2435)	(-0.4062)	(-0.3890)	(-1.8800)				

Note: 1.the Equity of means tests are based in the $R_t = \sum_{i=1}^{5} B_i D_{it} + \mu_t$, where t=1, 2, 3….N. R_t is the return from the index i on the day 1. B_{1t} = 1 for the day j and zero otherwise. u_t is the disturbance term 2. The values in parentheses denote the t-value of the coefficients. *, **, and *** denote statistical significance of given coefficients at 10%, 5% and 1% respectively.

Table 5. Average Daily returns over trading periods of 1998-2007, for the BRVM index and, 18 of its indices (All days are included)

INDEX	B1	B2	B3	B4	B5	R^2 -Adj	F-value	P-value	DW
SGBCI	0.0430	0.0303	0.0267	0.0069	-0.0465	-0.0010	0.4964	0.7384	1.8638
	(0.8460)	(0.5014)	(0.5410)	(0.1134)	(-0.9488)				
SDVC	-0.0449	0.0208	0.0537	0.0329	-0.0198	-0.0003	0.8707	0.4807	1.9735
	(-1.0489)	(0.4028)	(1.2922)	(0.6280)	(-0.4782)				
SDV_SAGA	0.0289	0.0084	0.0590	0.0099	-0.0273	-0.0001	0.9274	0.4470	1.8413
	(0.8559)	(0.2088)	(1.8012)*	(0.2451)	(-0.8389)				
SIVOM	-0.0294	-0.0004	0.0195	-0.1175	0.0059	0.0005	1.2316	0.2953	2.0153
	(-0.6753)	(-0.0074)	(0.4609)	(-2.2418)**	(0.1400)				
PH_CI	-0.0228	0.0250	-0.0479	0.0110	-0.0068	-0.0013	0.3318	0.8567	1.8745
	(-0.4907)	(0.4523)	(-1.0636)	(0.1980)	(-0.1531)				
SICOR	-0.0358	-0.0013	-0.0579	0.0053	-0.0262	-0.0011	0.4341	0.7841	2.0256
	(-0.9871)	(-0.0311)	(-1.6444)	(0.1215)	(-0.7491)				
SOGB	-0.0207	0.0698	-0.0184	0.0321	0.0205	-0.0011	0.4415	0.7787	1.8501
	(-0.3976)	(1.1258)	(-0.3641)	(0.5117)	(0.4074)				
SHEC	-0.0265	0.0322	-0.0361	0.0098	-0.0101	-0.0011	0.4502	0.7723	1.8712
	(-0.7059)	(0.7215)	(-0.9910)	(0.2181)	(-0.2789)				
TTLC	0.0497	0.0511	-0.0093	0.0029	0.0168	-0.0008	0.5997	0.6629	1.9203
	(1.4857)	(1.2837)	(-0.2851)	(0.0714)	(0.5198)				
BNBC	-0.0248	-0.0191	-0.0134	-0.0014	0.0110	-0.0016	0.2056	0.9354	1.7673
	(-0.7896)	(-0.5116)	(-0.4374)	(-0.0371)	(0.3619)				

Note: 1.the Equity of means tests are based in the $R_t = \sum_{i=1}^{5} B_i D_{it} + \mu_t$, where t=1, 2, 3….N. R_t is the return from the index i on the day 1. B_{1t} = 1 for the day j and zero otherwise. u_t is the disturbance term ; 2)The values in parentheses denote the t-value of the coefficients. *, **, and *** denote statistical significance of given coefficients at 10%, 5% and 1% respectively.

Table 6. Summary Statistics for the Returns

Index	Mean	Std. Dev.	Skewness	Kurtosis	CV
BRVM_10	0.0173	0.4206	-0.9908	18.6120	24.2713
BRVM_COMPOSITE	0.0149	0.3628	-0.6611	37.1225	24.3931
NESTLE	-0.0105	0.6248	-1.9211	42.4232	-59.7855
SOLIBRA	0.0236	0.9266	-8.5727	309.3277	39.2770
UNIWAX	-0.0434	0.4676	-5.5859	78.0109	-10.7823
CIEC	-0.0061	1.1339	-1.2325	23.7037	-184.9785
SDCC	-0.0082	0.9284	-1.3773	49.3565	-113.3552
SNTS	0.0422	0.6250	-0.5277	18.6718	14.7958
BICC	-0.0027	0.8832	-4.1453	92.9313	-328.3387
SAFCA	-0.0147	0.4084	-6.1514	124.8979	-27.8365
SGBCI	0.0105	1.0682	-1.4760	45.3174	101.3815
SDVC	0.0059	0.8663	-4.6649	95.5638	145.7188
SDV_SAGA	0.0166	0.7090	-0.0582	65.7475	42.7358
SIVOM	-0.0186	0.9169	-9.5134	274.9876	-49.3502
PH_CI	-0.0123	0.9753	-1.1660	156.3316	-79.1611
SICOR	-0.0271	0.7620	-10.1273	272.1330	-28.0751
SOGB	0.0118	1.0964	-1.7044	33.6641	92.9056
SHEC	-0.0102	0.7884	0.8321	30.6215	-77.3717
TTLC	0.0213	0.7042	1.7373	37.8233	33.0845
BNBC	-0.0092	0.6613	-1.0642	37.1637	-71.5721

Table 7. Results for the Unit Root Test in First Difference

Variables	Augmented Dickey-Fuller			Phillips-Perron		
	ADF statistic	Critical Value		P-P Statistic	Critical Value	
GDP	-4.9737*	1%	-3,5814	-7.001*	1%	-3,5778
		5%	-2,9271		5%	-2,9256
		10%	-2,6013		10%	-2,6005
MCR	-5.0178*	1%	-3,5814	-7.0472*	1%	-3,5778
		5%	-2,9271		5%	-2,9256
		10%	-2,6013		10%	-2,6005
TTV	-4.6462*	1%	-3,5814	-6.6924*	1%	-3,5778
		5%	-2,9271		5%	-2,9256
		10%	-2,6013		10%	-2,6005
FDI	-3.737*	1%	-3,5814	-5.6924*	1%	-3,5778
		5%	-2,9271		5%	-2,9256
		10%	-2,6013		10%	-2,6005
SE	-3.501**	1%	-3,5814	-5.0175*	1%	-3,5778
		5%	-2,9271		5%	-2,9256
		10%	-2,6013		10%	-2,6005

Note: Asterisk (*), (**), (***) denote statistically significant at 1%, 5% and 10% levels respectively

Table 8. Result of Long Run Causality due to Toda-Yamamoto (1995) Procedure

Null Hypothesis:	MWALD Statistics	p-value
Real GDP Growth(GDPGR) versus Market Capitalization Ratio(MCR)		
MCR does not Granger Cause GDP	4.82296**	0,01329
GDP does not Granger Cause MCR	1,94993	0,15557
Real GDP Growth(GDPGR) versus Value Traded Ratio(TTV)		
GDP does not Granger Cause TTV	2.12485	0.47842
TTV does not Granger Cause GDP	6.75402*	0,00023
Market Capitalization Ratio(MCR) versus Value Traded Ratio(VTR)		
TTV does not Granger Cause MCR	1,8796	0,12658
MCR does not Granger Cause TTV	5.7271*	0,00074
Note: Asterisk (*), (**), (***) denote statistically significant at 1%, 5% and 10% levels respectively.		

Table 9. The Long Run Equation, Equation (23)

Variables	*Coefficient*	*t-ratios*	*p-value*
FDI	0,221	6,822	0
SIZE	0,175	4,423	0
HUMAN	2,033	5,237	0
Constant	-6,111	-3 435	0

Table 10. The Long Run Equation, Equation (24)

Variables	*Coefficient*	*t-ratios*	*p-value*
FDI	0,121	6,822	0
LIQUIDITY	0,633	4,423	0,011
HUMAN	2,537	5,237	0
Constant	-8,435	-3 435	0

Table 11. The Short Run Equation, Equation (23)

Variables	*Coefficient*	*t-ratios*	*p-value*
FDI	0.102	2.467	0.029
SIZE	0.132	3.211	0.007
HUMAN	1.846	3.773	0.002
u_{t-1}	-0.755	-3.321	0.010

Table 12. The Short Run Equation, Equation (24)

Variables	*Coefficients*	*t-ratios*	*p-value*
FDI	0.102	2.467	0.029
SIZE	0.132	3.211	0.007
HUMAN	1.846	3.773	0.002
μ_{t-1}	-0.755	-3.321	0.010