Return Predictability in Africa's Emerging Equity Markets

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Abstract

This paper examined the dynamics of the first and second moment of stock return behaviour in Africa's emerging markets. After controlling for nonlinearity, conditional heteroscedasticity and time varying risk premium, we established that not only is the mean of returns predictable, but also, the variance. Further, long memory is found to be a major feature of African markets, while empirical stylized facts such as leverage effect and leptokurtosis are not peculiar to developed countries, but also prevalent in African stock returns.

Key words: Return predictability, volatility, long memory, nonlinearity, African stock markets
JEL: C22, C52, G10

1. Introduction

One of the conspicuous examples of globalisation is the ease with which financial capital moves around the world, especially to developing countries. Private capital flows to emerging markets have risen from $25 billion in 1990 to $491 billion by 2005 (see World Bank, 2006). Part of this expansion in financial flows has been brought about by the growth of equity funds dedicated to investing in publicly listed securities in developing countries. Available data from the International Finance Corporation (IFC) indicates that the number of developing countries with actively trading stock markets increased from 31 to 78 between 1989 and 1998. The number of domestic companies listed on emerging market stock indices rose by over 300%, from 8,709 to 26,354, and market capitalisation increased by 256% to $1.91 trillion within the same period. By the end of 2002, there were over 80 emerging stock markets and many more are being established each year. Sub-Saharan Africa (SSA) has also participated in this trend and, at the behest of national governments and, with the assistance of the World Bank and its private sector wing, the IFC, Africa has expanded the number of its domestic stock exchanges from six in the late 1980s to 26 today[1].

Stock markets have become an important conduit for raising long-term finance (see Khambata, 2000). Levine and Zervos (1995) argue that the two main channels of financial intermediation—banks and the stock market— should complement each other. Cho (1986) posits that credit markets need to be supplemented by well functioning equity markets, since equity finance does not experience adverse selection and moral hazard problems to the same extent as debt finance does in the presence of asymmetric

[1] In West Africa, the markets are located in Ghana, Nigeria, Cape Verde, Cote d'Ivoire, and Sierra Leone: East Africa has exchanges in Kenya, Rwanda, Tanzania and Uganda. The North African markets are in Algeria, Egypt, Libya, Morocco, Sudan and Tunisia, with Mauritius in the Indian Ocean. Apart from the well established markets of South Africa and Zimbabwe, there are now exchanges in Botswana, Namibia, Malawi, Mozambique, Zambia, Cameroon and Gabon. Angola is contemplating establishing one.

information. The existence of equity markets would thus enhance capital allocation and diversify investment risk.

The ability of stock markets to fulfil their roles in the pricing and allocation of capital and, in diversifying investment risk depends on their efficiency. Thus, in an efficient market prices of securities should '*fully reflect*' all available information, Fama (1965, 1970). Empirical evidence on the stochastic behaviour of stock returns has produced important stylized facts—the distribution of stock returns appears to be leptokurtic (Mandelbrot, 1963, Fama, 1965 and Nelson, 1991). Further, short-term stock returns exhibit volatility clustering. These processes have been modelled successfully by ARCH-type models (Engle, 1982, and Bollerslev, 1986). Moreover, changes in stock prices tend to be inversely related to changes in volatility (Black, 1976, Christie, 1982, and Bekaert and Wu, 2000).

Most of the empirical studies on these stylized facts have focused primarily on developed economies and the emerging markets in Asia and Latin America. With regards to African markets, there are only a few studies on the behaviour of stock returns (see Omran, 2007, Mecagni and Sourial, 1999, Appiah-Kusi and Menyah, 2003 and Smith and Jefferis, 2005 for evidence in African markets).

At the same time, interest has been rekindled in African stock markets in recent times on account of their fast growth and relatively low correlation with the more developed markets. For instance, in 1994 African stock markets posted the biggest gains in U.S. dollar terms among all markets world-wide — Kenya (75%), Ghana (70%), Zimbabwe (30%), Egypt (67%). In 1995, African stock exchanges gained about 40% on their indices, with the value of stocks on the Nigerian stock market and Côte d'Ivoire's bourse registering over 100% increases in dollar terms.[2] Average returns on African stocks in 2004 reached 44%. This compares favourably with a 30% return on the Morgan Stanley Capital International (MSCI) global index, 32% in Europe, 26% in the U.S. (Standard & Poor), and 36% in Japan (Nikkei)[3]. Additionally, African stock markets provide benefits of portfolio diversification as they tend to have zero, and sometimes negative, correlation with developed markets (see Harvey, 1995, for evidence on Nigeria and Zimbabwe).

This paper examines stock return behaviour in Africa's emerging stock markets, particularly, the evolution of returns over time, as knowledge on these features would be useful for regulators, academic research and professional fund managers. We draw comparison between return dynamics in African markets and their developed and emerging market economies counterparts.

The rest of the paper is organised as follows: the next section briefly examine the models employed. Section 3 describes the features of the data. We analyse and discuss the results in section 4.

2. Modelling Technique

Given the nature of the African data, we do not impose any specific data generating mechanism. Thus we first fit an AR(p) to the return series and examine whether the residuals are iid (independently and identically distributed). If we fail to explain the behaviour of the data and there is evidence against iid, we look beyond the linear model to explain the remaining structure of the series. Mills (1996) argues that, once the assumption of linearity is relaxed, a number of possible ways of modelling a time series

[2] See the Economist, June 11, 1994: "Stalking Africa's Fledgling Stock Markets."
[3] Databank Group Research, 2004, Accra, Ghana.

increases dramatically, covering such classes as chaotic dynamics (Hsieh, 1991) and conditional hetereroskedasticity models (Bollerslev et al, 1992).

Let $\Delta \log P_t$ be stock returns: the AR(p) model is then

$$\phi_p(L)\Delta \log P_t = \varepsilon_t \tag{1}$$

where the AR polynomial in L of order p is $\phi_p(L) = 1 - \phi_1 L - \ldots - \phi_p L^p$ and ε_t satisfies the white noise properties $E[\varepsilon_t] = 0$, $E\left[\varepsilon_t^{\,2}\right] = \sigma^2$ and $E[\varepsilon_t \varepsilon_s] = 0 \ \forall s \neq t$.

However, as Campbell et al (1997, p. 467) argue,

"*many aspects of economic behaviour may not be linear. Experimental evidence and casual introspection suggest that investor's attitudes towards risk and expected return are non-linear. And the strategic interactions among market participants, the process by which information is incorporated into security prices, and the dynamics of economy-wide fluctuations are all inherently non-linear. Therefore, a natural frontier for financial econometrics is the modelling of non-linear phenomena*".

Since nonlinearity occurs in many forms, there is no single test that dominates all others. For this reason, we consider five statistical tests—the McLeod and Li (1983) and Engle (1982) test for (G) ARCH), Brock et al's (1996) BDS test for randomness, Tsay's (1986) test for threshold effects and the Hinich and Patterson (1995) and Hinich (1995) bicovariance test. All these tests share a common principle—once any linear dependence is removed from the data, the remaining dependence must be due to nonlinearities in the data generating mechanism.

We fit an exponential GARCH-M, where the mean equation is specified as

$$\Delta \log P_t = \mu + \sum \phi_i \Delta \log P_{t-i} + \delta \sqrt{h}_t + \varepsilon_t ,\ \varepsilon_t | \Omega_{t-1} \sim \text{NID}\ (0, h_t) \tag{2}$$

$\varepsilon_t = z_t \sqrt{h_t}$, where z_t is iid with zero mean and unit variance, and the conditional variance $| h_t |$ takes the form

$$\ln(h_t) = \omega + \sum_{i=1}^{q} \alpha_i g(z_{t-i}) + \sum_{j=1}^{p} \beta_j \ln(h_{t-j}) \tag{3}$$

where $g(z_t) = \theta z_t + \gamma\left[|z_t| - E|z_t|\right], z_t = \varepsilon_t / \sqrt{h_t}$. The coefficient of the second term in (3), $g(z_t)$ is set to be 1 $(\gamma = 1)$. Note that $E|z_t| = (2/\pi)^{1/2}$ if $z_t \sim N(0,1)$. The function $g(z_t)$ is linear in z_t with slope coefficient $\theta+1$ if z_t is positive and $\theta-1$ if z_t is negative. By expressing the conditional mean in (2) as a function of the conditional variance, we are able to examine the risk premium hypothesis, i.e. whether investors are rewarded with extra return for taking on more risk. And by specifying an EGARCH model we account for asymmetry effects in the volatility process (see Black, 1976, and Christie, 1982, Glosten et al, 1993, and Nelson, 1991). For instance, suppose $\theta = 0$:large innovations increase the conditional variance if $|z_t| - E|z_t| > 0$, and decrease the conditional variance if $|z_t| - E|z_t| < 0$. Alternatively, suppose $\theta < 1$: the innovation in variance, $g(z_t)$, is positive if the innovations z_t are less than $(2/\pi)^{1/2}/(\theta-1)$. Therefore, negative innovations in returns cause the innovation to the conditional variance to be positive if $\theta < 1$. The natural log formulation ensures positive variances, thus dispensing with the need for parameter restrictions. Further, volatility at time t depends on both the size and sign of the normalized errors (see Nelson (1991).

In empirical research it is often the case that (3) produces evidence that the conditional volatility process is highly persistent and possibly not covariance-stationary, suggesting that a model in which shocks have a permanent effect on volatility might be more appropriate. We apply fractionally integrated GARCH (FIGARCH) to examine long memory and persistence in the variance. Following Baillie et al. (1996), the FIGARCH (p, d, q) model of the conditional variance can be motivated as an ARFIMA model applied to squared innovations,

$$(1-\alpha(L))(1-L)^d \varepsilon_t^2 = \omega + (1-\beta(L))v_t \tag{4}$$

with $\alpha(L)$ and $\beta(L)$ being polynomials of order q and p, and $0 < d < 1$ is the fractional integration parameter. Defining $v_t = \varepsilon_t^2 - h_t$ and rearranging (4), the FIGARCH (p, d, q) model can be expressed as

$$h_t = \omega + \beta(L)h_t + \left(1 - \beta(L) - (1 - \alpha(L))(1 - L)^d\right)\varepsilon_t^2 \tag{5}$$

The chief advantage of the FIGARCH is that it parsimoniously decouples the long-run and short-run movements in volatility. The long-run component is captured by the fractional differencing parameter **d** and the short-run component by the lag polynomials. For the case of $d = 0$, the FIGARCH reduces to the standard GARCH model.

3. Summary Features of African Indices

Previous empirical studies on stock return behaviour in African stock markets were mostly based on monthly and/or weekly data (see Magnussen and Wydick, 2002, and Appiah-Kusi and Menyah, 2003). In this study, we use daily index data obtained from DataStream. Daily data enable us to capture the dynamic evolution of returns, and to understand volatility, which may be overlooked when using monthly observations. We use indices from six African stock markets: CASE 30 (Egypt), NSE 20 (Kenya), TUNINDEX (Tunisia), MASI (Morocco), FTSE/JSE (South Africa) and NSE All Share Index (Nigeria). The stocks included in the indices are selected based on market size, trading volume and sector representation. These represent the largest stock markets in Africa, and account for over 90% of total market capitalisation and domestic company listings. All the indices are daily closing values. Table 1 gives a summary of the key return features of African markets.

INSERT Table 1

The highest daily mean return occurs in Egypt (0.116), with Kenya having the lowest mean return (0.034). Interestingly, the lowest mean return for Kenya coincides with the highest standard deviation. The risk/return trade-off is the balance between the desire for the lowest possible risk and the highest possible return: if there are expectations of higher levels of risk associated with a particular investment then greater returns are required as compensation for that higher expected risk. Alternatively, an investment with relatively lower levels of expected risk would require investors settle for relatively lower returns. This standard postulate in the finance literature does not generally hold in all cases. Table 1 indicates that, for Kenya, just as risk means higher potential returns, it also means higher potential losses. Generally, the standard deviations appear high in Table 1 for the rest of the countries (1.66 for Egypt, and 1.17 for South Africa); implying investors in Africa's emerging markets must be ready to accept high risk in exchange for possible higher returns.

The distributional properties of returns appear to show extreme observations. The highest kurtosis in the sample occurs in Kenya and Tunisia, with Egypt and Nigeria having the lowest. However, the kurtosis for all countries exceeds the threshold of 3, implying that the returns have fatter tails than would be expected from a normally distributed variable. With the exception of South Africa, all the return series are positively skewed. The Jarque-Bera (JB) test rejects the normality assumption for all countries.

Deviations from normality could be induced in part by temporal dependencies in returns, especially second moment temporal dependence; an indication that assuming a linear process for returns may leave important features of the data unexplained. The presence of second moment dependence is reinforced by Ljung-Box (LB) statistics calculated for 12 lags. The hypothesis that all autocorrelations up to the 12^{th} lag are jointly zero is rejected. A possible reason for autocorrelation in the returns is non-synchronous trading, a common feature of African markets. The majority of the stocks scarcely trade, and even the most active ones trade for just a few hours in the working week.

4. Preliminary Evidence: AR(p) Model

As a prelude to our modelling outlined earlier, an AR (p) model was fitted to the returns of all countries to pre-whiten the residuals before testing for evidence of nonlinearity. Fitting an AR(p) model to the series by ordinary least squares regression yielded the results in Table 2.

INSERT Table 2

With the exception of Nigeria and, to some extent, Kenya the countries follow low order autoregressive processes. Egypt follows an AR(1) process, while an AR(2) is sufficient to model the South African and Tunisian series. From Table 2, it is seen that the series appear to be stationary around a constant mean, $\hat{\mu} = \hat{\phi}_0 \Big/ \left(1 - \hat{\phi}_1, \ldots, \hat{\phi}_p\right)$ for all countries. Daily mean returns range from 0.136% for Egypt to 0.035% for Tunisia. Between January 2001 and April 2006, the return on the FTSE/JSE index of South Africa was estimated to be 0.78% per annum. Around the same period the returns on the CASE 30 of Egypt and NSE 20 of Kenya were 1.63% and 1.09% respectively.

Having fitted an AR(p) model, it is now necessary to examine whether such a model is adequate. As a diagnostic check, we look at the properties of the residuals $\hat{\varepsilon}_t$ to see whether they are approximately white noise. Table 2 indicates that there is no higher order serial correlation as shown by the Breusch-Godfrey test for up to 5 lags (Nigeria appears to be significant at 5 lags but not at 2 or 3). To check whether the autocorrelations are approximately zero, we applied the Ljung-Box statistic. With the exception of 24 lags in Tunisia and South Africa (which may, in fact, be a statistical artefact), the residuals of the AR(p) appear to be white noise. In order to examine further the properties of the data, we employed the nonlinear diagnostic tests for evidence of iid. The results are shown in Table 3.

INSERT Table 3

The entire set of tests rejects the null of linearity at the 1% level. Almost all p-values in Table 3 are zero, indicating strong departures from the iid condition. In a simulation study of the power of the tests, Patterson and Ashley (2000) found the BDS to perform better under different conditions. It is, however, instructive to note that, by rejecting linearity, the BDS is silent as to which data generating mechanism would be appropriate to model the data. To this end, the other tests are instrumental in pointing to the specific type of nonlinearity in our series. For instance, the McLeod-Li and Engle LM tests indicate the presence of (G) ARCH effects. The Tsay test points to a TAR model, while the bicovariance test indicates the presence of third order nonlinear dependence.

The dependence in the residuals of the AR (p) indicates the inadequacy of the model to explain the (more complex) behaviour of index returns. The presence of nonlinearities in the series could imply evidence of return predictability. Neftci (1991) demonstrates that technical trading rules require some form of nonlinearity in prices to be successful and Mills (1997) argues that the presence of nonlinearity is a necessary condition for trading rules to have potential predictive power. Although we do not consider the possibility of employing trading rules in the observed nonlinearity in the data, the evidence nonetheless could shed important light on the predictability of return means and variances in subsequent sections.

The nonlinearity observed in the African series is, however, not entirely surprising, and can be due to different reactions of investors to price sensitive information or delayed response of investors to information, or simply the result of market inefficiency. In the sections that follow, we examine various empirical stylized facts in African stock returns.

4.1. Results of Fitting GARCH Models

The estimates of the volatility models are reported in Tables 4 and 5. The estimates are obtained by assuming a student t-distribution for the normalised residuals to account for fat tails (the evidence of excess peakedness observed in Table 1). Estimates of the parameters are obtained by maximising the likelihood function over the sample period.

INSERT Table 4

4.1.1. Return Predictability

This section focuses on the predictability of the first and second moments. It is conjectured in this framework that, since ϕ_i (equations 2 and 3) measures the relationship between current and past returns, a statistically significant ϕ_i would indicate that past returns are important in forecasting current and future returns; evidence inconsistent with weak form efficiency. As shown in Table 4, this parameter is significantly different from zero in all the markets. With the exception of Egypt, up to three lags of the previous returns are predictable. Two possibilities may account for the return predictability observed in our sample; a) predictability can arise as a consequence of market inefficiency and, b) predictability can also arise as a result of the risk-averse behaviour of investors and, of time-varying risk premia. A close look at Table 4 reveals that not only is the mean of returns predictable, but also that there is a high degree of persistence in the conditional variance. In fact, a closer examination of the last row of Table 4 shows that $\alpha + \beta > 1$ for Kenya, and close to unity in all other cases. For Kenya the second and fourth unconditional moments do not exist, but the conditional distribution is still well defined. In contrast to the stationary variance, the impacts of shocks remain forever. An appropriate way to model this could be to use the FIGARCH to capture the long memory in the return series (see section 4.1.4). Further, from Table 4, the β coefficient in the conditional variance equation is considerably larger than α. A large sum of these coefficients implies that a large positive or negative return causes future forecasts of the variance to be high; this is useful in considering these models for forecasting.

Predictability in the mean and variance of returns in all the African markets considered may establish that weak form efficiency is rejected. Our results thus contradict the findings by Classens et al (1995), Appiah-Kusi, and Menyah (2003) who conclude that Kenya, Egypt and Morocco are weak form efficient. Our results also contrast Magnussen and Wydick (2002), Appiah-Kusi and Menyah (2003) and Smith and Jefferis (2005), who find mixed evidence for weak form efficiency.

Theoretical work by LeRoy (1973, 1989), Rubinstein (1976) and Lucas (1978) conclude that, in a market peopled by risk averse investors, tests of excess returns cannot on their own confirm or falsify the efficient market hypothesis. Intuitively, unforecastable prices do not necessarily imply a well functioning stock market with rational investors, and forecastable prices need not imply the opposite.

To gain further insight into return predictability of African markets, we look beyond the statistical evidence for explanation: institutional bottlenecks. While considerable financial reform in terms of dismantling exchange controls and investment restrictions has taken place since the 1980s, African markets suffer from several imperfections—absence of accurate legal and regulatory frameworks, lower standards of transparency and internal controls, and generally undeveloped financial systems (see Alagidede, 2009 and, Irving, 2005). For instance, lax legislation is the main cause of insider trading in Africa's most advanced capital market, the Johannesburg Securities Exchange. Thus underdeveloped legal and information systems affect the price discovery process, and inhibit the speed at which new information can be reflected in prices, and or become public.

Moreover, a stylized fact of African markets is the vicious cycle of low trading volume, low liquidity and low turnover. Buy and hold is the dominant feature of trading. There are limited instruments; trading is limited to stocks and bonds (only South Africa has a derivative market and, arguably, other investment vehicles such as mutual funds, country funds and unit trusts). Turnover is very low, with less than 10% of market capitalisation trading annually in exchanges such as Kenya, Morocco and Tunisia. The stock market forms just a minute part of the entire economies of the countries under investigation (less than 5% of total value traded as a percentage of GDP is recorded in countries such as Kenya and Morocco).

4.1.2. Risk Return Trade-Off in African Markets

The nominal risk-free rate provides a useful benchmark against which risk in a particular investment can be assessed. However, since we do not have reliable estimates of daily nominal risk-free rates, we rely on the EGARCH-M specification. The δ parameter in the mean equation may be interpreted as the coefficient of relative risk aversion of a representative investor, while the value $\sqrt{h_t}$ relates to the time-varying risk premium. A positive δ implies that investors are compensated for any additional risk (see Chou, 1987, and French et al, 1987). From Table 4, the risk premium is significant and positive for Kenya and Tunisia at the 5% level. The estimates are about 0.07 for daily and 0.84 for monthly returns. The estimates for Tunisia are higher than Kenya, 0.2 for daily returns and 2.64 for monthly returns. For these countries, we can argue that higher risk, proxied by the conditional standard deviation, might lead to higher returns. Such results imply that the Tunisian and Kenyan markets provide returns that compensate investors for time-varying risk premium.

The magnitude of the risk premium as important as the sign. Whereas the risk premium is negative for Egypt and Morocco, it is positive for South Africa and Nigeria. However, the relationship between mean returns and own variance or standard deviation is insignificant. These results may suggest that investors in these markets consider some other risk measure to be more important than the variance (conditional standard deviation) of portfolio returns. For instance, Omran (2007) employed sectoral data for Egypt and found that market risk, as measured by beta tend to play a significant role in the return dynamics of the Egyptian stock market. In particular, the risk-return relationship indicates that portfolios constructed from consumer staples outperformed bank based portfolios.

4.1.3. Asymmetry in African Stock Returns

Next, we examine the question of asymmetry in volatility. The notion of asymmetry has its origins in the work of Black (1976), French et al (1987), Nelson (1991) and Schwert (1990). It has been argued that a negative shock to a financial time series is likely to cause volatility to rise by more than a positive shock of the same magnitude. In the case of equity returns, such asymmetries are typically attributed to leverage effects, whereby a fall in the value of a firm's stock causes the debt-to-equity ratio to rise. This leads shareholders, who bear the residual risk of the firm, to perceive their future cash flow stream as being relatively more risky. The γ parameter captures this in the EGARCH-M, hence for the leverage effect $\gamma > 0$ and significant. From Table 4, γ is significantly positive for Kenya, Morocco, and Nigeria. However, the sign and magnitude of the asymmetry term differs across markets. These results could imply different reactions of investors to new information, possibly because of frictions, such as transactions cost and/or the existence of taxes, which may affect the ease with which information is reflected in prices. The findings are also consistent with the existence of leverage effect in these markets.

4.1.4. Long-Memory in African Stock Returns

We examine the long-memory properties of African stock returns by fitting a FIGARCH. If asset returns display long-memory, or long-term dependence, they exhibit significant autocorrelation between observations widely separated in time. Since the series realisations are not independent over time, realisations from the remote past can help predict future returns, giving rise to the possibility of consistent speculative profits. The presence of long-memory in asset returns provides further evidence that contradicts the weak form market efficiency hypothesis, which states that, conditioning on historical returns, future asset returns are unpredictable. The estimates of the fractional differencing parameter are shown in Table 5.

INSERT Table 5

The FIGARCH estimates indicate the presence of long-memory in all return series. As Table 5 reports, there is evidence that African stock returns exhibit fractional dynamics with long-memory features. The fractional differencing parameters range from 0.12 for Tunisia to 1.06 for Kenya. The long-memory parameter is highly significant for all countries, with return series that exhibit exponential decay (except Kenya). However, the series are clearly covariance stationary as the **d** estimates lie below the 0.5 threshold of stationarity for all but Morocco and Kenya. The presence of long memory is yet another indication that it should be possible to forecast returns over the range of dependence. Hence long memory in returns is synonymous to weak form inefficiency since a shock will have a lasting impact for a long period of time (see Henry, 2002).

4.2. Robustness Checks

We analysed the robustness of our results to ensure model adequacy. The Ljung-Box statistics on the standardized residuals and the standardized squared residuals of the estimated EGARCH-M and FIGARCH models in Tables 4 and 5 respectively find that there is no evidence of serial correlation. Furthermore, the ARCH (10) tests indicate that there is no evidence of conditional heteroscedasticity in the residuals. Thus, we find that our models have successfully taken care of the nonlinear dependence and that there is no significant autocorrelation among the squared residuals. This implies that the fitted volatility models are adequate.

5. Conclusion

This paper examined the predictability of stock returns in Africa's largest markets—South Africa, Egypt, Nigeria, Kenya, Morocco and Tunisia. These markets account for over 90% of stock market capitalisation and domestic company listing in Africa. Their fast growth and impressive performance, coupled with their low correlation with the more developed markets make them agents for global risk reduction and potential investment avenues for investors seeking to diversify risk. However, evidence regarding the behaviour of returns is lacking. This paper fills an important gap by using various time series tools to uncover the dynamics of the first and second moment of return distribution. After controlling for nonlinearity, conditional heteroscedasticity and time varying risk premia, we find that returns are predictable, both in the mean and variance. Further, long memory is a major feature of African countries. In Tunisia and Kenya, we find that investors may be compensated for assuming risk, while empirical stylised facts such as leverage effect and leptokurtosis are not peculiar to developed countries, but also prevalent in African stock returns.

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Appendix

Table 1: Descriptive Statistics (Logarithmic Returns)

	EGYPT	KENYA	MOROCCO	NIGERIA	TUNISIA	SOUTH_AFRICA
Sample	4/04/2001 to 1/02/2006	8/11/1997 to 11/16/2006	1/10/1995 to 11/13/2006	7/17/1995 to 11/09/2006	1/06/1998 to 11/10/2006	7/05/1995 to 5/16/2006
Observations	1239	2455	3129	3000	2346	2870
Mean	0.116	0.034	0.042	0.094	0.037	0.058
Std. Dev.	1.663	1.739	0.734	0.884	0.472	1.174
Skewness	0.200	14.731	0.353	0.160	0.947	-0.598
Kurtosis	8.641	798.726	10.974	7.890	15.375	11.127
JB	0.000	0.000	0.000	0.000	0.000	0.000
LBQ(12)	74.83*** [0.00]	220.2*** [0.00]	300*** [0.00]	835.5*** [0.00]	263.8*** [0.00]	44.4*** [0.00]

*** Denotes statistical significance at 1% level. LBQ is the Ljung-Box test statistic for autocorrelation. JB is the p-values of Jarque-Berra statistic for normality.

Table 2: AR (p) Pre-Whitening MODEL

	Egypt	Kenya	Morocco	Nigeria	Tunisia	South Africa
μ	0.119(2.28)	0.069(1.708)	-0.004(-0.12)	0.087(3.039)	0.024(1.53)	0.056(2.241)
ϕ_1	0.125**(2.513)	0.103***(3.66)	0.28***(8.98)	0.389***(20.4)	0.27***(11.9)	0.09***(5.28)
ϕ_2				0.14***(6.62)	0.054**(2.38)	0.055**(2.94)
ϕ_3				-0.065***(-3.19)		
ϕ_4		0.139***(4.96)		-0.036*(-1.76)		
ϕ_5				-0.051**(-2.56)		
ϕ_7				0.039*(1.99)		
ϕ_8				0.04**(2.166)		
ϕ_{10}				0.039**(2.207)		
DW	2.003	2.011	2.012	2.001	1.995	1.995
B.G(5)	0.681[0.638]	0.397[0.851]	1.163[0.325]	3.51[0.03]	0.924[0.464]	
LBQ(12)	8.631[0.656]	4.169[0.939]	12.23[0.347]	5.25[0.26]	3.38[0.641]	1.179[0.316]
LBQ(24)	20.04[0.639]	14.247[0.892]	19.34[0.681]	21.55[0.158]	38.2***[0.017]	14.048[0.171]

Notes: *, **, and *** indicates significance at 10%, 5% and 1% levels respectively, μ is the constant. ϕ indicate the AR coefficients. B.G is Breusch-Godfrey test for higher order serial correlation; D.W is the Durbin-Watson test for autocorrelation; LBQ (12), LBQ (24) indicates the Ljung-Box statistics for 12 and 24th lags respectively. Test statistics are shown in ( ) while p-values are shown in [ ]. For sample size, see table 4.1.Lag length of AR(p) is based on AIC. We reserve the last 30 observations for out-of-sample forecast.

Table 3.A: Nonlinearity Test on AR (p) Residuals

	Egypt		Kenya		Morocco		Nigeria		South Africa		Tunisia	
	Asymptotic	Bootstrap	Asymptotic	Bootstrap	Asymptotic	Bootstrap	Asymptotic	Bootstrap	Asymptotic	Bootstrap	Asymptotic	Bootstrap
McLeod-LI (20 lags)	0.000	0.000	0.019	0.019	0.000	0.013	0.000	0.000	0.000	0.03	0.000	0.001
McLeod-LI(24 lags)	0.000	0.000	0.000	0.000	0.000	0.016	0.000	0.000	0.000	0.033	0.000	0.000
Bicovariance(17 lags)	0.000	0.001	0.000	0.002	0.000	0.002	0.000	0.000	0.000	0.012	0.000	0.000
Engle LM												
1	0.000	0.000	0.000	0.002	0.000	0.005	0.005	0.014	0.034	0.022	0.000	0.001
2	0.000	0.000	0.000	0.004	0.000	0.007	0.000	0.005	0.000	0.004	0.000	0.002
3	0.000	0.000	0.000	0.005	0.000	0.001	0.000	0.007	0.000	0.007	0.000	0.001
4	0.000	0.000	0.000	0.008	0.000	0.011	0.000	0.003	0.000	0.008	0.000	0.001
5	0.000	0.000	0.000	0.011	0.000	0.016	0.000	0.003	0.000	0.008	0.000	0.001
Tsay	0.000	0.000	0.010	0.02	0.010	0.029	0.001	0.005	0.000	0.011	0.000	0.001

Table 3.B: BDS Test on AR (p) Residuals

	Egypt			Kenya			Morocco			Nigeria			South Africa			Tunisia		
Dimension	EPS=.5	EPS=1	EPS=2	EPS=.5	EPS=1	EPS=2	EPS=.5	EPS=1	EPS=2	EPS=.5	EPS=1	EPS=2	EPS=.5	EPS=1	EPS=2	EPS=.5	EPS=1	EPS=2
									Bootstrap									
2	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.001	0.002	0.000	0.000	0.000
3	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
4	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
									Asymptotic									
2	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.002	0.001	0.000	0.000	0.000
3	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
4	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Notes: only p-values are reported under the null hypothesis that the time series is a serially iid process. All calculations are done using the non-linear toolkit by Patterson and Ashley (2000).

Table 4: Estimated EGARCH Model

	Egypt	Kenya	Morocco	Nigeria	South Africa	TUNISIA
	EGARCH-M	EGARCH-M	EGARCH-M	EGARCH-M	EGARCH-M	EGARCH-M
μ	0.064*(1.656)	0.0053(0.1426)	-0.0126(-0.53)	0.055***(5.035)	0.063**(2.311)	-0.022(-1.517)
δ	-0.007(-0.401)	0.062**(2.855)	-0.016(-1.511)	0.035(1.371)	0.0212(0.803)	0.222**(2.546)
ϕ_1	0.1325***(4.537)	0.108***(5.912)	0.228***(12.45)	0.307***(17.26)	0.099***(5.139)	0.192***(9.01)
ϕ_2		0.091***(5.321)	0.059***(3.247)	0.139***(7.27)	0.047**(2.531)	0.105***(4.86)
ϕ_3		0.075***(4.349)	0.055***(3.185)	0.049**(2.813)	-0.032*(-1.699)	-0.037*(-1.82)
ω	-0.271***(-8.713)	-0.205***(-4.54)	-0.409***(-13.86)	-0.253***(-14.1)	0.018***(3.58)	-0.382***(-9.02)
α_1	0.239***(8.39)	0.389***(4.484)	0.310***(11.965)	0.23***(13.5)	0.094***(7.95)	0.273***(9.61)
β_1	0.747***(74.02)	0.799***(52.69)	0.608***(78.34)	0.701***(297.5)	0.896***(77.6)	0.716***(58.3)
γ	0.029(0.931)	0.124**(2.831)	0.119**(2.544)	0.057*(1.98)	-0.049***(-4.38)	-0.001(-0.061)
AIC	3.378	1.749	1.598	1.748	2.798	0.894
SBC	3.412	1.774	1.617	1.768	2.817	0.919
$LBQ^2(12)$	8.872[0.634]	2.8359[0.970]	2.675[0.97]	1.775[0.955]	14.68[0.100]	1.982[0.992]
$LBQ^2(24)$	19.45[0.674]	4.1037[1.000]	3.721[3.720]	7.291[0.997]	24.98[0.248]	5.347[1.000]
ARCH(10)	0.7416[0.685]	0.266[0.988]	0.273[0.98]	0.155[0.99]	1.385[0.181]	0.182[0.997]
v	3.913	2.282	3.365	4.809	6.191	4.142
LL	-2030.646	-2083.193	-2460.263	-2577.379	-3950.235	-1023.337
$\alpha+\beta$	0.98	1.18	0.92	0.93	0.984	0.98

***, **, * indicates significance at 1%, 5% and 10% levels respectively. AIC, SBC represent the Akaike and Schwartz criterion. LBQ is the Ljung-Box statistic. Test statistics are. reported in ( ) while p-values are reported in [ ] beside the calculated coefficient. v is the scale parameter of the distribution of the error term(i.e., the student t-distribution).

Table 5: Long Memory in Stock Returns

	Egypt	Kenya	Morocco	Nigeria	South Africa	Tunisia
Constant	0.0012**(2.97)	0.004(0.051)	0.0008**(2.697)	0.009*(1.783)	0.0007***(4.848)	0.002***(3.121)
Alpha	0.459**(2.281)	0.011***(7.96)	0.169***(11.12)	0.562***(7.984)	0.079***(11.35)	0.344***(4.782)
Beta	0.665***(4.480)	0.562***(4.480)	0.391***(5.412)	0.068***(12.349)	0.470***(4.139)	0.067***(3.892)
Std t	4.287	2.462	3.742	4.7871	6.112	5.232
LL	3863.6	4766.6	4483	4323.39	9181	4213.10
AIC	-5.681	-7.296	-7.635	-5.456	-6.3917	-5.5643
SBC	-5.6464	-7.2612	-7.5961	-5.745	-6.373	-5.7641
LBQ(12)	6.698[0.569]	10.918[0.363]	11.764[0.3011]	10.45[0.897]	11.736[0.303]	9.457[0.112]
LBQ(24)	10.416[0.917]	30.015[0.118]	19.186[0.6337]	23.98[0.323]	22.444[0.4336]	12.69[0.232]
ARCH(10)	0.681[0.742]	0.119[0.999]	0.281[0.992]	0.342[0.876]	0.728[0.7244]	0.323[0.989]
d	**0.486***(3.774)**	**1.061***(5.641)**	**0.867***(5.485)**	**0.2742***(15.43)**	**0.471***(5.500)**	**0.119***(3.912)**

***, **, * indicates significance at 1%, 5% and 10% levels respectively. AIC, SBC represent the Akaike and Schwartz criterion. LBQ is the Ljung-Box statistic. Test statistics are. reported in ( ) while p-values are reported in [ ] beside the calculated coefficient, and **d** is the fractional differencing parameter.