Return Volatility and Equity Pricing: A Frontier Market Perspective

Theuri Chege[a], Ferdinand Othieno[a] and Odongo Kodongo[b,*]

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[a] School of Finance and Applied Economics, Strathmore University, Nairobi, Kenya.
[b] University of the Witwatersrand, Johannesburg, South Africa.
[*] Corresponding author. Tel +27 11 717 3806
Email addresses: theuri.chege@gmail.com (Theuri); fokoth@gmail.com (Ferdinand);
kodongo03@gmail.com (Odongo).

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Abstract

Using both monthly and weekly return series between 1999:01 and 2013:12, we investigate the dynamics of stock returns and volatility in a Kenya's fledgling equity market – the Nairobi Securities Exchange. Both the GARCH-in-mean and E-GARCH models yield positive and significant conditional variance parameters. We also find that shocks to equity returns of conditional volatility are highly persistent. Our results also indicate that conditional variance is driven more by the past conditional variance than it is driven by new disturbances. Finally, we find evidence of volatility clustering in the stock markets around major world and domestic economic episodes. Results are consistent with the inference that investors require larger risk premia on equities if they anticipate greater price volatility in future.

Key words: Volatility; equity returns; Nairobi Securities Exchange; GARCH

JEL Classification: G12, G17

1.   Introduction

Asset pricing models generally hypothesize a positive relationship between expected returns on and risk of equity. Many of the traditional asset pricing models rest on the simplistic premise of static volatility and normality in the distribution of asset returns, the elegance of which are still relevant today. However, while the assumption of normally distributed asset returns allows for simple variance and covariance techniques to be employed for measuring risk, some recent studies (e.g., Nyamongo and Misati, 2010, and Tortorice, 2014) have shown that volatility is not constant but varies with time. Such studies document unique characteristics of volatility of asset returns including clustering, asymmetry and excess kurtosis. Mandelbrot (1963) describes volatility clustering as the phenomenon whereby "large asset price changes tend to be followed by large price changes of either sign and small changes tend to be followed by small changes." Given such findings on the nature of return volatility, the normal distribution assumption is no longer considered tenable and return volatility is generally viewed as a stochastic process in modern asset pricing (see, e.g., Dupire, 1994 and Dumas, Fleming, and Whaley, 1998).

Two important relationships between stock returns and volatility have been addressed in the asset pricing literature. The first is the hypothesis that negative association between unexpected returns and unexpected volatility is observed during financial recessions, where lower than average returns provoke speculative activity and therefore increase market volatility. This hypothesis has been supported by several studies (French et al., 1987; Poon and Taylor, 1992; Choudhry, 1996; Shin, 2005; Nikkinen et al., 2008). The second hypothesis is positive association in which the equity risk premium provides more compensation for risk when volatility is high. This hypothesis is the more widely held in empirical research (French et al., 1987; De Santis and

İmrohoroğlu, 1997; Kim, Morley, and Nelson, 2004). However, the hypothesis holds more strongly in emerging markets than mature markets (Er and Fidan, 2013). Other studies either fail to support these hypotheses (Baillie and DeGennaro, 1990) or find no significant relationship of expected returns and conditional volatility (e.g., Shawky and Marathe, 1995).

GARCH-type models are the most prevalent among empirical studies on stock market volatility (Poon and Taylor, 1992; Choudhry, 1996; De Santis and İmrohoroğlu, 1997; Christofi and Pericli, 1999; Shin, 2005; Nikkinen, *et al.*, 2008; Karunanayake, 2011; and Er and Fidan, 2013). In general, empirical studies have presented mixed results on the pricing of volatility in the stock market with studies in advanced markets reporting a weak relationship between risk and return, implying that volatility is not priced (Poon and Taylor, 1992; Baillie and DeGennaro, 1990) while emerging markets studies generally report a stronger risk-reward relationship (Shin, 2005; De Santis and İmrohoroğlu, 1997; Choudhry, 1996). In the Kenyan context, conditional variance techniques have been employed by Nyamongo and Misati (2010) to assess leverage effects and the impact of news on stock prices. Tah (2013) also uses similar techniques to test the degree of vulnerability of stock market to external shocks. However, our study is the first to examine the nexus between return volatility and the pricing of equity claims in Kenya.

The returns on equities listed on the Nairobi Securities Exchange (NSE), have exhibited a great deal of volatility in the recent past. Figure 1 shows time series plots of monthly and weekly returns on the Nairobi Securities Exchange 20-share index (NSE-20). A visual examination of the monthly returns plot reveals anecdotal evidence of volatility clustering in monthly returns, during 2002/2003 and 2008/2009. These periods coincide with important economic episodes,

such as, in the first instance, the period during which the world economy was emerging from the recession of 2001/2002, where we see large positive returns being followed by large positive returns on the NSE 20-share index and, in the second instance, the recent global financial crisis as well as the violence that followed a disputed presidential election in Kenya in 2008, where large negative returns are followed by large negative returns. Also evident in the weekly returns plot is clustering in 2003 and 2007, although the relatively 'noisy' weekly returns tend to mask it.

(*FIGURE 1 ABOUT HERE*)

The Nairobi Securities Exchange had 62 listed companies as of December 2013. The exchange recently got a boost through an increment in its weight in the MSCI frontier markets portfolio index to 4.8% from 3.0%, a move that is expected to boost its visibility and, perhaps, enhanced volumes of portfolio and foreign direct investment flows. The exchange therefore provides a suitable platform to measure the relationship between return and volatility in the frontier markets. Our analysis uses GARCH-in-mean to model and examine return volatility with the NSE 20-Share Index (NSE-20) as the market proxy. NSE-20, the oldest and most widely used of the NSE's performance barometers, is a geometrically-weighted average of the largest 20 listed companies, measured by market capitalisation. The index is constructed from stock price data (excluding dividends), adjusted for corporate actions, such as stock splits, and changes in firms' market capitalization over time. The NSE-20 index is a good proxy for the whole market because its 20 companies represent over 80% of the market capitalisation of the entire exchange.[1] The 20 stocks constitute a fairly well-diversified portfolio.

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[1] Another of Kenya's stock market indices is the Nairobi All Share Index (NASI), introduced in 2008, and which, therefore, does not have a long history. The NASI includes counters that are not actively trading, due to suspension or lack of liquidity and is unsuitable for our study because illiquidity may distort the underlying volatility.

Our findings suggest that returns volatility is priced in Kenya's stock market with time-varying premia and that shocks to equity prices arising from volatility are highly persistent. The findings have important implications for stock returns predictability and volatility trading strategies that might be useful to asset price researchers and practitioners in the frontier stock markets.

2.   Data and preliminary analysis

We obtain daily NSE-20 index values from the Nairobi Securities Exchange database for January 1999 through December 2013. We then extract end-of-month and end-of-week index values, which we use to compute monthly and weekly returns respectively. We compute returns as $\ln(P_t) - \ln(P_{t-1})$ where P_t is the index value at time t. In our baseline empirical analysis, we use monthly returns because, as shown in Figure 1, monthly returns are less noisy and appear to have better ability to reveal volatility clustering; similarly, monthly frequency is the most popular in the stock volatility literature (see, e.g., Poon and Taylor, 1992; Choudhry, 1996; Kim et al., 2004; Tah, 2013). Nonetheless, we also analyze weekly returns to check the robustness of our findings from monthly returns.

(*TABLE 1 ABOUT HERE*)

Preliminary statistics for our returns series are presented in Table 1. The table shows that the mean return is positive for both monthly returns and weekly returns. Returns are positively skewed with excess kurtosis, as also evidenced by the Jarque-Bera statistics, clearly violating the hypothesis of normal distribution. The tests for autocorrelation show that the monthly data fail to

reject the hypothesis of serial independence at lags 1 and 2 and at lag 24. This can be interpreted as weak evidence of return predictability, a finding that is common for young equities markets. For the weekly returns, however, there is no evidence of serial independence.

Empirical work based on time series data assumes that the underlying time series is stationary. Spurious regressions can result if time series have unit roots. Although stock returns data are generally known to be stationary in levels, as the visual observation in Figure 1 shows, we run two tests of stationarity to confirm our visual observations. Both the Augmented Dickey-Fuller and the Phillips-Perron tests show that the series are stationary in levels. Results are presented in Panel C of Table 1.

3. Empirical design

We model the rate of return at time t, r_t, as a function of a constant mean, μ, and conditional variance, $ln(\sigma^2_{t|t-1})$ with a co-efficient δ:

$$r_t = \mu + \delta \, ln(\sigma^2_{t|t-1}) + \vartheta_t \tag{1}$$

where $\vartheta_t = \epsilon_{t|t-1}\varepsilon_t$ is the random component of return such that $\epsilon_{t|t-1}$ is positive and ε_t is a white noise process, a sequence of independent and identically distributed random variables with zero mean and variance equal to one. Modelling returns as a function of conditional volatility provides a way to directly study the explicit trade-off between risk and return. Equation (1) forms the basis for GARCH-in-mean model suggested by Bollerslev, Engle, and Wooldridge (1988). The coefficient, δ, is the time varying volatility risk premium and represents relative risk

aversion (Choudhry, 1996). A significant and positive δ coefficient implies that investors are compensated with higher returns for bearing higher levels of volatility. A significant negative δ indicates that investors are being penalized for bearing risk.

Under the GARCH $(1, 1)$ process, conditional volatility is modelled as:

$$\sigma^2_{t|t-1} = \omega + \alpha \vartheta^2_{t-1} + \beta \sigma^2_{t-1|t-2} \qquad (2)$$

The parameters of the GARCH $(1, 1)$ process must be non-negative ($\omega > 0$, $\alpha \geq 0$ and $\beta \geq 0$) to ensure that $\sigma^2_{t|t-1}$ is positive for all values of the white noise process, ε_t. The new information at time $t - 1$ is embodied in the ARCH term, the squared residual, ϑ^2_{t-1}. The carrier of the old information at time $t - 1$ is the GARCH term, $\sigma^2_{t-1|t-2}$ (Rachev et al., 2008). Persistence of shocks to volatility becomes greater as the sum $(\alpha + \beta)$ approaches unity. A significant impact of volatility on the stock prices can only take place if shocks to volatility persist over a long time (Porteba & Summers, 1986). A value less than unity implies that shocks decay with time (Chou, 1988). The closer to unity the value of the persistence measure, the slower is the decay rate.

A major shortcoming of the "plain vanilla" GARCH $(1, 1)$ model is that it does not capture the volatility asymmetry typically observed in practice. Both positive return shocks (when $\vartheta_{t-1} > 0$) and negative return shocks (when $\vartheta_{t-1} < 0$) have an identical impact on the conditional variance, $\sigma^2_{t|t-1}$, since the residual ϑ_{t-1} appears in squared form. To solve this problem, the exponential GARCH (E-GARCH) process has been proposed (Nelson, 1991). Following the definition of return in equation (1), volatility is specified under E-GARCH thus:

$$ln(\sigma_t^2) = \omega + \beta \, ln(\sigma_{t-1}^2) + \gamma \frac{\vartheta_{t-1}}{\sqrt{\sigma_{t-1}^2}} + \alpha \left| \frac{\vartheta_{t-1}}{\sqrt{\sigma_{t-1}^2}} \right| \tag{3}$$

The E-GARCH process has two advantages over the pure GARCH process. Modelling $ln(\sigma_t^2)$ results in a positive variance even if the parameters are negative. This obviates the need to artificially impose non-negativity constraints on the model parameters. Second, asymmetries are allowed for under the E-GARCH formulation, since if the relationship between volatility and returns is negative, γ will be negative. However, Giannopoulos (2000) and Rachev et al. (2008) have shown that a GARCH $(1,1)$ process is sufficient for most financial time series; Poon and Taylor (1992) demonstrate that GARCH $(1,1)$-in-mean performs better than other methods. In this study, we use both the GARCH $(1,1)$-in-mean and the E-GARCH. This allows us to directly compare our results to others in the literature.

4. Results

4.1 GARCH-in-mean estimation results

The mean and conditional variance equations under the GARCH-in-mean model are those given in equation (1) and equation (2) respectively. Estimates for the model's parameters are presented in Table 2. The volatility coefficient, δ, is positive and significant (at the 10% level for monthly returns and 5% for weekly returns). This finding suggests that conditional standard deviation (volatility) is important in explaining returns on equities listed on the NSE. Table 2 also shows that the coefficients of the conditional variance equation, α and β, are both highly statistically significant. The fact that β is relatively larger than α suggests that the conditional variance is fuelled more by the past conditional variance than by new disturbances. The sum of the

coefficients (α + β) is close to unity, implying that shocks to the conditional variance are highly persistent. Results for monthly and weekly data are qualitatively similar.

(*INSERT TABLE 2 HERE*)

Next, we graph the conditional standard deviations, in Figure 2. The figure shows that the conditional standard deviations adequately capture key episodes that impact on volatility: the 2003 recovery from the world recession of 2001/2, and the effects of the global financial crisis in 2008/2009 and violence that followed a disputed presidential election in 2008. These episodes show in both monthly returns (panel A) and weekly returns (panel B), although the 2003 events are fairly subdued when weekly returns are considered.

(*FIGURE 2 ABOUT HERE*)

4.2   E-GARCH estimation results

Equation (1) and equation (3) respectively outline the mean and conditional variance for the E-GARCH model. Estimation results are displayed in Table 3. The equation for the mean monthly returns indicates a positive risk-return relationship with the coefficient of δ significant at 5%. The value of the coefficient is 0.0169, which is only 2.98% different from the 0.0164 (Table 2) estimated using the GARCH-in-mean model. In the conditional variance equation, the GARCH coefficient, β, is highly significant and is considerably larger than the other coefficients, just like in the GARCH-in-mean model. There is a marginal improvement of 0.16% in the log likelihood function in the E-GARCH relative to that in GARCH-in-mean specification (249.1613 and 248.7627 respectively), indicating that asymmetry does not affect the relationship between risk

and return in the monthly series. Weekly returns series provide results qualitatively similar to monthly returns.

(*TABLE 3 ABOUT HERE*)

5. Conclusions

This study finds that volatility is important in explaining returns of stocks listed on the Nairobi Securities Exchange, Kenya. Both the GARCH-in-mean and E-GARCH model specifications yield positive, significant volatility parameters. Results are robust to alternative return frequencies. Our findings are consistent with various asset pricing theories, which postulate a positive relationship between volatility and asset returns. Conditional variance is driven by the past conditional variance to a larger extent than they are driven by new disturbances. We also find results consistent with volatility clustering: the violence following presidential elections in 2008 and the global financial crisis in Kenya had a statistically significant effect on monthly and weekly NSE-20 returns volatilities; similarly, the aftermath of the world recession of 2001/2 had a significant effect on return volatilities. Our results are comparable with several others in the empirical literature especially for the emerging markets (Poon and Taylor, 1992; Shin, 2005; Baillie and DeGennaro, 1990; and De Santis and İmrohoroğlu, 1997). However, they contradict those of Choudhry (1996) who reports a negative relationship across several emerging markets.

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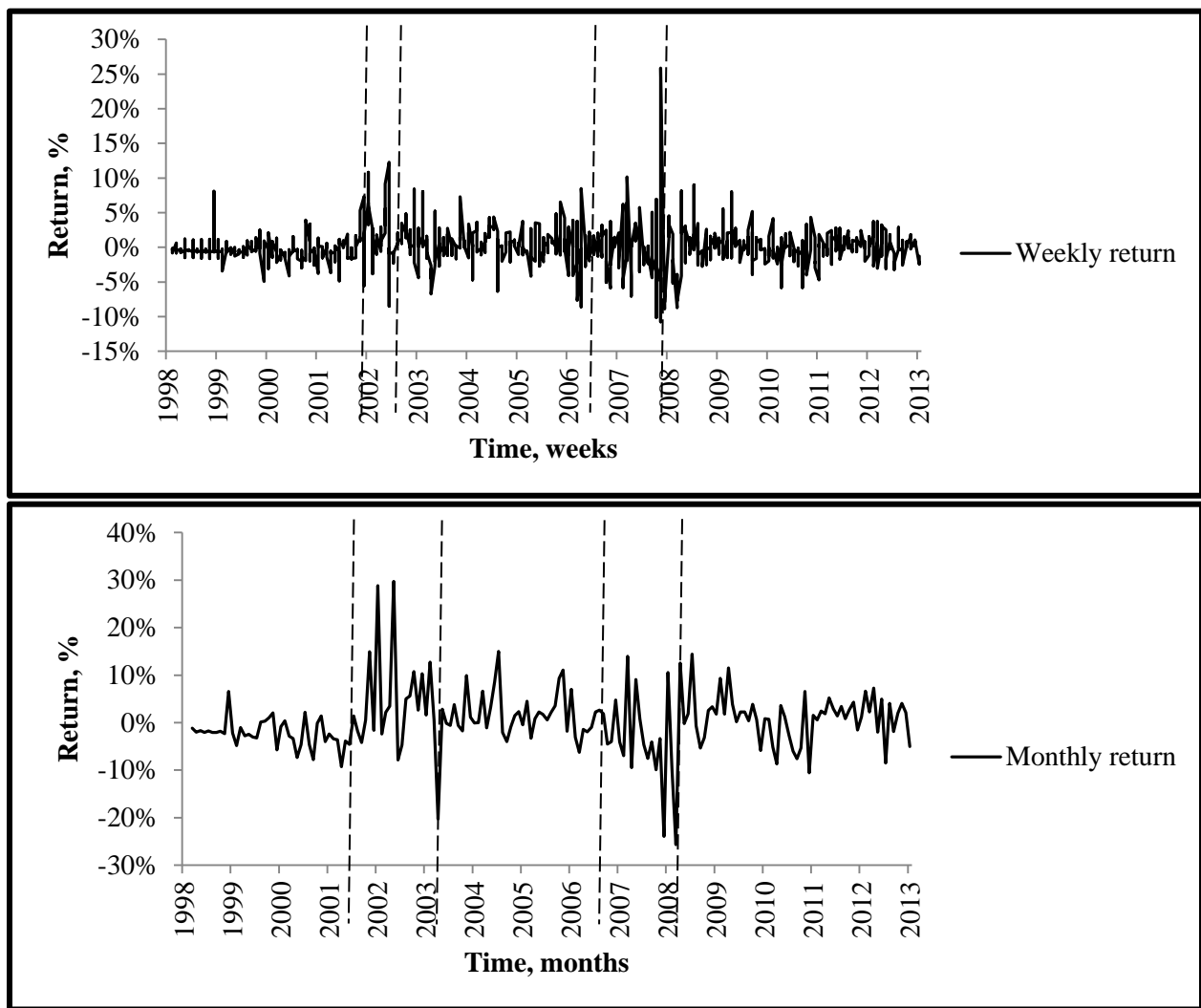
The 'dashed' lines in the figure identifies periods of volatility clustering in the returns series.

Figure 1: Time series plots of NSE 20-share index returns, 1999 – 2013.

Table 1: Preliminary statistics

Panel A: Summary statistics

	Obs.	Mean	SD	Min	Max	Skew	Kurt	Jarque-Bera
Monthly data	179	0.0034	0.0669	-0.2567	0.2973	0.414	7.950	>99***
Weekly data	781	0.0007	0.0268	-0.1077	0.2588	1.265	16.286	>99***

Panel B: Autocorrelation (Ljung-Box Q-test)

Lag	1	2	3	4	5	6	12	24
Monthly data	0.017	2.493	9.754	11.816	12.008	14.063	19.287	31.797
	(0.90)	(0.29)	(0.02)	(0.02)	(0.03)	(0.03)	(0.08)	(0.13)
Weekly data	9.924	10.076	13.216	13.606	13.609	28.036	35.842	53.620
	(0.00)	(0.01)	(0.00)	(0.01)	(0.02)	(0.00)	(0.00)	(0.00)

Panel C: Stationarity tests

	Augmented Dickey Fuller test	Phillips-Perron test
Monthly data	-13.388***	-13.756***
Weekly data	-24.900***	-25.330***

Obs. is number of observations; SD is standard deviation; Min is the minimum value of return; Max is maximum value of return; in square brackets are p-values of the Jarque-Bera statistic for test for normality. *** indicates statistical independence at 1%. P-values of the Ljung-Box Q-test are in brackets.

Table 2: GARCH (1, 1)-in-mean results

	μ	δ	ω	α	β	$(\alpha + \beta)$	Log-L
Monthly data	0.0970^{*}	0.0165^{*}	0.0003^{*}	0.2380^{***}	0.7387^{***}	0.9767	248.8
	(0.09)	(0.08)	(0.08)	(0.00)	(0.00)		
Weekly data	0.0235^{*}	0.0030^{*}	0.0001^{***}	0.4483^{***}	0.4547^{***}	0.9030	1,869.3
	(0.05)	(0.05)	(0.00)	(0.00)	(0.00)		

This table presents coefficient (p-values in brackets) estimates for the equations $r_t = \mu + \delta \ln(\sigma^2_{t|t-1}) + \vartheta_t$ and

$\sigma^2_{t|t-1} = \omega + \alpha\vartheta^2_{t-1} + \beta\sigma^2_{t-1|t-2}$. ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively.

Log-L is the log-likelihood function. Data are for the period January 1999 through December 2013.
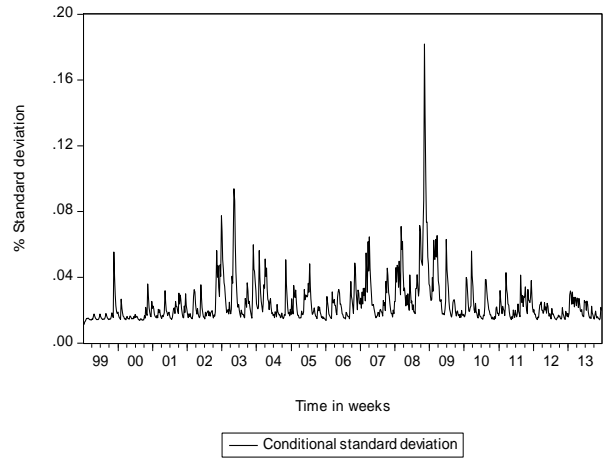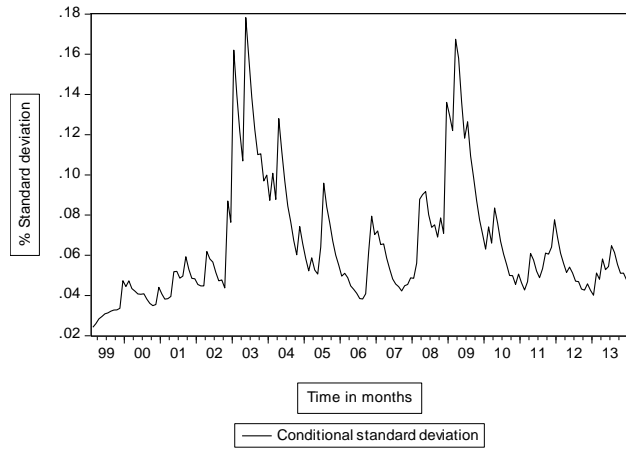
Figure 2: Conditional standard deviations

Table 3: E-GARCH results

	μ	δ	ω	β	γ	α	Log-L
Monthly data	0.1016**	0.0169**	-0.5537***	0.9527***	0.0655*	0.3978***	249.2
	(0.05)	(0.05)	(0.00)	(0.00)	(0.06)	(0.00)	
Weekly data	0.0309***	0.0039***	-1.7514***	0.8269***	0.0409	0.5902***	1,873.4
	(0.00)	(0.00)	(0.00)	(0.00)	(0.14)	(0.00)	

This table presents coefficient estimates (p-values in parentheses) for the equations $r_t = \mu + \delta\, ln\left(\sigma^2_{t|t-1}\right) + \vartheta_t$ and

$ln(\sigma_t^2) = \omega + \beta\, ln(\sigma^2_{t-1}) + \gamma\left(u_{t-1}/\sqrt{\sigma^2_{t-1}}\right) + \alpha\left|u_{t-1}/\sqrt{\sigma^2_{t-1}}\right|.$ ***, ** and * refer to significance at the 1%, 5% and

10% levels, respectively. Log-L is the log-likelihood function. Data are for the period 1999:01 through 2013:12.