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THE GARCH AND VOLUME RELATIONSHIP WITH HETEROSCEDASTICITY IN STOCK RETURNS ON THE JAMAICA STOCK EXCHANGE

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ABSTRACT

The liberalization of the Jamaican Financial market in 1991 was accompanied by a significant expansion of the stock market trading volume, which continued as more information became available. At the same time returns appeared to become more volatile. This observed behaviour of the stock market raised questions of whether stock returns were in fact volatile, and if so, what are the factors causing such volatility.

The Generalized Autoregressive Conditional Heteroscedasticity (GARCH) methodology can be used to model such time varying volatility in stock returns and has been widely and well researched in developed stock markets, especially in the United States. Such research has shown that developed countries' stock returns are characterized by tranquil, as well as volatile periods. The factors causing volatility are unobservable, and are captured by GARCH. Some researchers hypothesised that the unobservable cause of the volatility is the time varying rates of information arrival. Further investigation has shown that once volume is introduced, the GARCH effect is significantly reduced, implying that volume may be a good proxy of the information arrival.

Research in developing stock markets, however, has not focused on this issue. This paper investigates the GARCH effect in the returns of three of the companies listed on the Jamaica Stock Exchange (JSE). The findings suggest that GARCH does not always model return volatility on the JSE well, and volume traded does not necessarily manifest the time varying volatility in stock returns.

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I. INTRODUCTION

The validity of the Generalized Autoregressive Conditional Heteroscedasticity (GARCH), in explaining variances in stock prices is well established (*cf.*, Bollerslev, Chou and Kroner (1992)). Research has been conducted to show the presence of the GARCH effect [Lamourex and Lastrapes (1990)], as well as to suggest possible explanation for its presence [Tauchen and Pitts (1983)].

Extensive research in developed stock markets reveal the uncertainty of speculative stock prices, measured by the changing variance over time. Engle (1982), introduced the Autoregressive Conditional Heteroscedasticity (ARCH) processes in the modeling of the variation in stock prices. He models changes in conditional variance over time as a function of past squared errors. Bollerslev (1986), extended the ARCH process to depend also on past conditional variances.

ARCH models the time variation in prices, but provides no theoretical explanation regarding the cause of such variation. It informs that there is some factor or set of factors which impact on returns, causing its variance to change over time, but does not specify what these factors are. Porterba and Summers (1986) explains that shocks which cause variations in returns had to persist for long periods of time in order to explain the large fluctuations observed in developed stock markets. If shocks are transitory, no significant risk premium will be required and no significant changes in stock prices will result. The rate of information arrival provides one possible explanation for the variation in the volatility of stock returns. Lamourex and Lastrapes (1990), using trading volume as a proxy for information arrival, found that it had significant explanatory power regarding the variance of stock returns. Including volume as an explanatory variable in the model results in a significant reduction of the GARCH effect. Other explanations for the variation in stock returns include the business cycle and financial crisis. Schwert (1989) found that stock volatility was higher on average during recessions and reacts strongly to banking crisis. He analyzed stock volatility using volatility in real and nominal macroeconomic variables, economic activity, financial leverage and stock trading activity covering the period of the depression when volatility was high. He found that aggregate leverage is significantly correlated with volatility, but provides explanation for little of the changes in stock return variability. There is, however a consensus that the arrival of information provides significant explanation for the presence of GARCH in stock returns. In fact, early research by French and Roll (1986), showed that stock prices vary more during trading hours and that the availability and the ability to trade on new information is the main reason for this.

All of the papers cited above examined stock markets which are more developed than the Jamaican market. Leon (1996) applied GARCH formulations to returns on the Jamaica Stock Exchange (JSE), and found that stock price returns are autocorrelated and negatively related to the Treasury Bill rate and that the volatility of the returns can be predicted using GARCH.

We go one step further and seek to explain why stock returns on the JSE exhibit time varying volatility. Variables which are likely to cause volatility in stock returns are unobservable, but the volatility itself can be modeled parsimoniously using GARCH. The question arises as to what effect is GARCH really capturing. As Tauchen and Pitts (1983) showed, one explanation for movements in stock return volatility is the arrival of information. As information becomes available it is incorporated into stock prices causing them to move up and down accordingly. If GARCH fits the data well, then the introduction of informational arrival into the model as an explanatory variable, should cause the GARCH effect to disappear or at least get smaller. This paper tests the presence of information effects in the returns of stocks listed on the JSE.

The rest of the paper is organized as follows: Section II provides background information and description of the data. Section III specifies the model used in the analysis. Section IV discusses the empirical results, while section V presents some concluding remarks.

II. BACKGROUND INFORMATION AND DATA ANALYSIS

The three companies examined in this study are Bank of Nova Scotia Jamaica Limited (BNS), National Commercial Bank (NCB) and Telecommunications of Jamaica Limited (TOJ). These three companies are dominant players on the JSE in terms of the fraction of total shares traded. Although this is so, the percentage of the total outstanding shares of these firms which are traded on the market is relatively small. Seventy percentage (70%) of TOJ is owned by Cable and Wireless with a further ten percent (10%) owned by large institutions which only infrequently trade on the market. The pattern is the same for both BNS and NCB. Seventy percent (70%) of BNS is owned by BNS Canada and another 10% by large institutions which tend to use the strategy of buy and hold. This is evident in the fact that the listing of the top ten share holders does not show much change in ownership structure over time. NCB is more diversified in terms of share holders. Mutual Life is the major share holder accounting for approximately sixty percent (60%). These large institutions normally do not liquidate through the stock market: they usually arrange private transactions with only the residuals coming onto the public market.

Although seventy percent (70%) of the shares of these companies essentially is non-traded, the remaining thirty percent (30%) constitutes a significant portion of the total activity on the stock market. Since the controlling ownership of these companies cannot change through normal daily activities on the JSE, it is possible that this fact could reduce the amount of volatility observed in the shares of these companies traded.

Trading on the JSE is done sequentially since 1993, with the shares of companies trading alphabetically. BNS is traded first. Given its relative importance to the market, the trading in BNS shares on any day has a major impact on the activities of the market which are to follow on that day.

The returns for the three stocks are calculated using daily close to close prices and are adjusted for bonuses, stock splits and dividends, in order to approximate the true return more accurately. These actively traded stocks are used in order to avoid problems that may impact on observed volatility such as those arising from non-synchronous trading, e.g. stale prices, and minimal trading.

Table I gives the summary statistics of returns used for the three companies. It shows the non-normality in the underlying distribution of these stock returns. All stocks show the presence of significant kurtosis. The table also shows that for all the stocks examined, their means were significantly different from zero. The Ljung Box Q test reveals the presence of significant higher order serial correlation in the returns of all three companies. The same is reported in the squared returns except for TOJ. This indicates that returns are generated by some autoregressive process, and that (except for TOJ), there is heteroscedasticity in the stock returns. The ARCH test at 6 and 9 lags, reported in the same table, confirms this observation.

Table II, provides the summary statistics for trading volume. The characteristics of these data are similar to those of returns except to the extent that for the most part, volume exhibits no volatility.

III. MODEL SPECIFICATION

As the Jamaica stock exchange grew, trading activity became more frequent, returns became more volatile as more information which is unobservable was incorporated into stock prices. In order to model this time variant volatility in stock returns in a parsimonious way, a GARCH(p,q) formulation is used as specified below.

$$r_t|\phi_t = \alpha_0 + \alpha_1 r_{t-1} + \alpha_2 h_t^{1/2} + \varepsilon_t, \quad (1)$$

$$\varepsilon_t|\phi_t \sim t(0, h_t, d), \quad (2)$$

$$h_t = \beta_0 + \beta_1\varepsilon^{2t}_{t-1} + \beta_2 h_{t-1} + \beta_3 V. \quad (3)$$

Where $r \equiv$ stock returns, $\phi \equiv$ information set, $h \equiv$ conditional variance, $d \equiv$ degree of freedom in the underlying studentised t distribution, $V \equiv$ daily trading volume.

Equation 1 (the conditional mean equation) is defined as an autoregressive process in order to capture the serial correlation in returns. The inclusion of $h_t^{1/2}$, which is the square root of the conditional variance takes account of the risk-return relationship. The conditional variance is generated by a GARCH(p,q) process such that the current observation, h_t, is generated by a weighted average of past observations going back q periods, as well as past squared residuals going back p periods. This system is estimated under the distribution assumption of the student t, with d degrees of freedom, to account for the excessive leptokurtosis reported in table I.

The daily increment of prices is influenced by the stochastic rate at which information flows into the market. In an efficient market, the rate of information arrival influence returns to the extent that all available information will be incorporated into prices. Information arrival therefore reflects the time dependence in the generation of daily stock returns. Since the rate of information arrival is unobservable, a proxy has to be used to capture its effects. In this case, daily trading volume is the proxy used. The market activity of a stock will depend on what information the investor has about his capitalization. Information arrival[1] proxied by volume is also incorporated in the variance equation to test whether it has any explanatory power[2]. Volume when introduced is expected to capture at least some of the GARCH effect, thereby reducing it.

The model is estimated using maximum likelihood under the assumption that the random disturbance term ε_t follows a t distribution such that the log-likelihood function with parameter vector θ can be specified as:

$$l_t(\theta) = \ln\Gamma(0.5(d+1)) - \ln\Gamma(0.5d) - 0.5\ln(d-2) - 0.5\ln h_t - 0.5(d+1)\ln(1 + d_t^2/(h_{t(d-2)})) \quad (4)$$

IV. EMPIRICAL RESULTS

Table III reports the estimated coefficients and the associated asymptotic t-statistics of the restricted model, (the model without volume as an explanatory variable). Using the maximum likelihood procedure, the results obtained provide strong evidence that the time varying volatility in these stock returns can be characterised by the GARCH model when volume is left out of the equation. The Ljung

[1] The introduction of volume in the process is based on previous research done by Lamourex and Lastrapes (1990) in which they incorporated the rate of information arrival, proxied by trading volume, as an explanation for the presence of ARCH in stock returns.
[2] If the data series does not have heteroscedasticity, the estimation will indicate that we have a constant variance model i.e. $\beta_1 = \beta_2 = 0$ and hence $h_t = \beta o$, a constant.

Box Q tests rejects the presence of higher order serial correlation in the standardised residuals, indicating that the specification of the AR(1) model in the mean equation is adequate in accounting for the serial correlation in the stock returns. Higher order serial correlation was also rejected in the standardised squared residuals implying that the GARCH process is capturing all of the heteroscedasticity in the returns. NCB is the only stock which exhibits any form of serial correlation in the standardised residuals, suggesting that the mean equation could be better specified. In addition, the similarity in the closeness of the kurtosis in the standardised residuals and the implied kurtosis calculated from the degrees of freedom for the t distribution further supports the point that the GARCH formulation fits the data well.

The results of the unrestricted model are reported in Table IV. When volume was introduced as an explanatory variable into the model, the GARCH effect was not reduced for two of the three stocks (BNS and NCB). There is at least one other factor which is influencing the time varying volatility in these stock returns since some GARCH effect is still present in the data. The arrival of information is therefore one of the factors which directs the movements in stock returns for these two companies. The absence of higher order serial correlation in the squared residuals further supports the good fit of the unrestricted model to BNS's and NCB's data. The results for TOJ, are less straightforward and are inconsistent with the predictions which would follow from Lamourex and Lastrapes (1990). While the Likelihood Ratio test strongly rejects the null hypothesis of $\beta_3 = 0$ and the joint test for $\beta_1 = \beta_2 = 0$, suggesting a well specified model, the coefficients on all the parameters in the unrestricted model are insignificant, providing no explanations for the presence of heteroscedasticity in the stock returns. This is so because TOJ had little heteroscedasticity to begin with, as was shown in table I. Interestingly, the Ljung Box Q test of higher order serial correlation suggest that there remains heteroscedasticity in TOJ's data implying that GARCH may not be the best formulation for modeling heteroscedasticity in stock returns. Alternatively, volume may not be a good proxy for information arrival, and hence, even if GARCH fits the data well, none of the ARCH effect would be captured by volume. One reason for this is that there may be increased volume traded which has nothing to do with information flows.[3] If, on the other hand, volume is a good proxy for information arrival, then its insignificance as an explanatory variable would imply that the market is inefficient. If markets are efficient, all information which becomes available is incorporated into prices and are translated into movements in returns.

V. CONCLUSIONS

The paper found that the time varying volatility in stock returns may be manifested in the GARCH process when no explanatory variables are incorporated in the model. Data from one of the three companies studied, however, could not support the hypothesis that volume provides an explanation for the presence of time varying volatility in stock returns. The reason may be that volume does not serve as a good proxy for information arrival. An alternative explanation is that the JSE market may be inefficient. However, without further work we are unable to say definitively which of these two possibilities is more likely.

[3] Lamourex and Lastrapes (1990), found that some companies for which dividends are paid out exhibits increased trading activity around the ex-date. They conclude that it is the taxation of dividends which induces trading and not the arrival of new information.

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Table I
Descriptive Statistics for BNS, NCB, and TOJ Returns

Full Period

	BNS	NCB	TOJ
Observations	978	926	1024
Mean	3.361*	4.264*	0.311*
Variance	18.306	30.43	11.888
Skewness	.919*	1.242*	2.262*
Kurtosis	4.52*	11.137*	17.596*
Q(20)	584.651*	267.934*	135.210*
Q^2(20)	413.324*	32.479*	23.017
ARCH(6)	199.410*	17.514*	11.285
ARCH(9)	201.789*	18.402	11.787

Sub-period 1 (Oct. 1988 - Sept 1991)

	BNS	NCB	TOJ
Observations	365	365	365
Mean	4.700*	5.515*	0.426*
Variance	10.698	29.546	9.844
Skewness	1.505*	2.552*	4.531*
Kurtosis	6.015*	22.288*	50.117*
Q(20)	162.798*	32.916*	65.895*
Q^2(20)	116.998*	11.288	7.128
ARCH(6)	63.827*	1.831	0.829
ARCH(9)	63.695*	2.607	1.317

Sub-period 2 (Sept 1991 - Oct 1994)

	BNS	NCB	TOJ
Observations	613	561	659
Mean	2.564*	3.451*	.0247**
Variance	21.157	29.379	13.026
Skewness	1.110*	0.489*	1.439*
Kurtosis	4.715*	4.011*	6.978*
Q(20)[1]	223.982*	152.892*	103.856*
Q^2(20)[2]	323.739*	74.434*	65.604*
ARCH(6)	136.381*	59.872*	27.189*
ARCH(9)	139.959*	60.250*	290.692*

* significance at 5%
**significance at 10%
[1]Jung Box Q test for higher order serial correlation in the residuals at 20 lags
[2] Jung Box Q test for higher order serial correlation in the squared residuals at 20 lags

Table II
Descriptive Statistics for BNS, NCB, and TOJ Trading Volume

Full Period

	BNS	NCB	TOJ
Observations	978	926	1024
Mean	52,888*	117,070*	242,316*
Variance	1.21×10^{10}	1.48×10^{11}	$3.83{*}10^{11}$
Skewness	8.386*	11.038*	8.345*
Kurtosis	115.200*	143.467*	90.057*
Q(20)	476.409*	97.468*	109.207*
ARCH(6)	5.887	0.892	0.178
ARCH(9)	5.871	0.996	0.935

Sub-period 1 (Oct. 1988 - Sept 1991)

	BNS	NCB	TOJ
Observations	365	365	365
Mean	20,627*	43,290*	110,082*
Variance	8.05×10^{8}	6.17×10^{9}	8.19×10^{10}
Skewness	3.3241*	5.424*	9.811*
Kurtosis	15.391*	41.834*	125.769*
Q(20)	115.869*	231.303*	56.410*
ARCH(6)	24.589*	0.536	2.443
ARCH(9)	25.497*	0.604	3.744

Sub-period 2 (Sept 1991 - Oct 1994)

	BNS	NCB	TOJ
Observations	613	561	659
Mean	72,097*	165,073*	315,558*
Variance	1.78×10^{10}	2.34×10^{11}	5.35×10^{11}
Skewness	7.057*	8.845*	7.288*
Kurtosis	79.827*	90.094*	66.918*
Q(20)[1]	165.926*	36.837*	33.141*
ARCH(6)	2.968	0.569	0.259
ARCH(9)	3.027	0.765	0.589

* significance at 5%
**significance at 10%
[1]Jung Box Q test for higher order serial correlation in the residuals at 20 lags

Table III

Maximum Likelihood Estimate of the GARCH(1,1) Restricted Model

Model: $r_t|\phi_t = \alpha_0 + \alpha_1 r_{t-1} + \alpha_2 h_t^{1/2} + \varepsilon_t$

$$h_t = \beta_0 + \beta_1 \varepsilon^2_{t-l} + \beta_2 h_{t-l}$$

	BNS		NCB		TOJ	
Coefficient	Estimate	Asymptotic T-Stat	Estimate	Asymptotic T -Stat	Estimate	T- Stat
α_0	0.838	3.991	-0.472	-0.323	0.0003	0.034
α_1	0.588	21.525	0.397	12.282	0.062	13.369
α_2	0.113	1.473	0.214	3.254	-0.016	-3.462
β_0	2.159	6.363	0.725	4.012	0.009	14.714
β_1	0.643	5.936	0.689	9.439	0.250	12.168
β_2	0.324	5.901	0.311	8.923	-0.0008	-4.354
1/d	0.213	45.316	0.224	11.321	0.215	81.642
Q(20)	34.251		31.567		37.645**	
Q^2(20)	3.670		26.554		13.554	

** significantly different from zero at the 10% level

Q(20) is the Ljung Box Q test for the presence of higher order serial correlation in the standardized residuals at 20 lags.

Q^2(20) is the Ljung Box Q test for the presence of higher order serial correlation in the standardized squared residuals at 20 lags.

The implied Kurtosis is calculated from the estimated value of d.

Table IV
Maximum Likelihood Estimates of the GARCH(1,1) Unrestricted Model

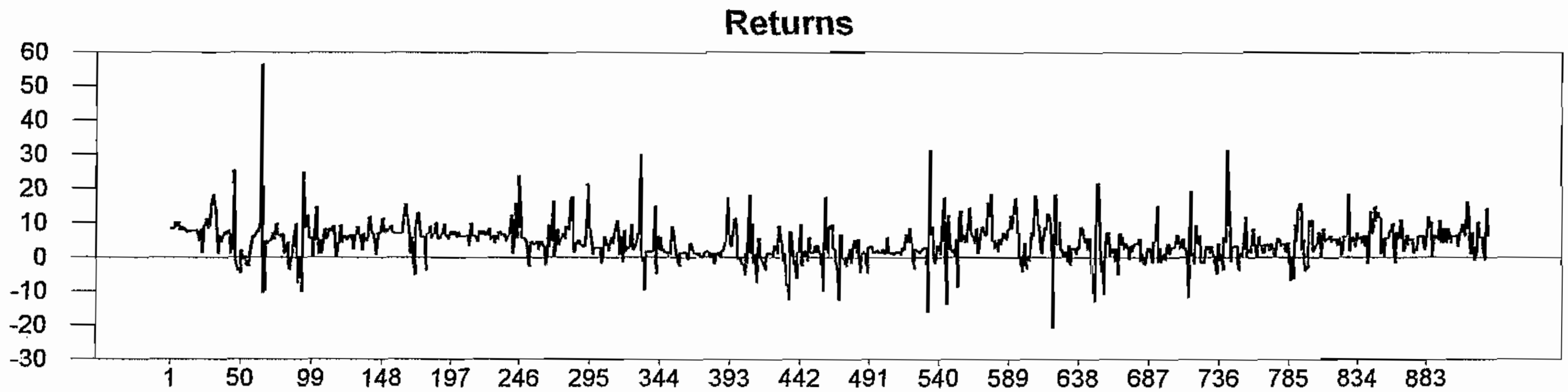
Model : $r_t|\phi_t = \alpha_0 + \alpha_1 r_{t-1} + \alpha_2 h_t^{1/2} + \varepsilon_t$

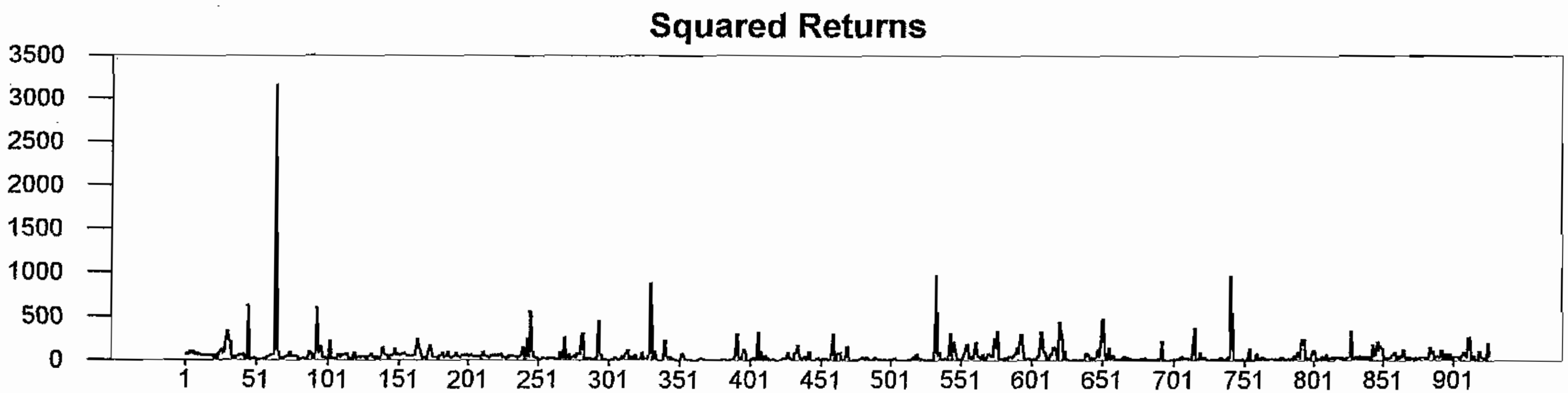
$$h_t = \beta_0 + \beta_1\varepsilon^2_{t-l} + \beta_2 h_{t-l} + \beta_3 v_t$$

	BNS		NCB		TOJ	
Coefficient	Estimate	Asymptotic T-Stat	Estimate	Asymptotic T-Stat	Estimate	T-Stat
α_0	1.138	9.121	0.833	0.322	0.022	2.265
α_1	0.631	22.364	0.427	11.14	0.138	8.805
α_2	0	0	0.022	2.795	0.0002	0.045
β_0	1.621	4.166	10163	2.291	0.019	0.103
β_1	0.671	5.242	0.717	5.981	0.064	0.108
β_2	0.328	5.640	0.283	5.236	$0.6x10^6$	0.034
β_3	0.329	3.765	0.066	4.510	0.003	0.106
1/d	0.238	8.289	0.239	7.341	0.496	12.964
Q(20)	38.979*		104.586*		133.59*	
$Q^2(20)$	6.081		16.445		80.705*	
LR Test (β_3=0)	27.446*		173.624*		1843.064*	
LR Test ($\beta_1 = \beta_2$ =0)	327.05*		3413.226*		216.693*	

* significantly different from zero at the 5% level.
Q(20) is the Jung Box Q test of higher order serial correlation in the standardized residuals at 20 lags.
$Q^2(20)$ is the Jung Box Q test for higher order serial correlation in the standardized squared residuals at 20 lags.
The implied Kurtosis is calculated from the estimated value of d.

CHART 1 NCB


Returns
60
50
40
30
20
10
0
-10
-20
-30
1 50 99 148 197 246 295 344 393 442 491 540 589 638 687 736 785 834 883


Squared Returns
3500
3000
2500
2000
1500
1000
500
0
1 51 101 151 201 251 301 351 401 451 501 551 601 651 701 751 801 851 901

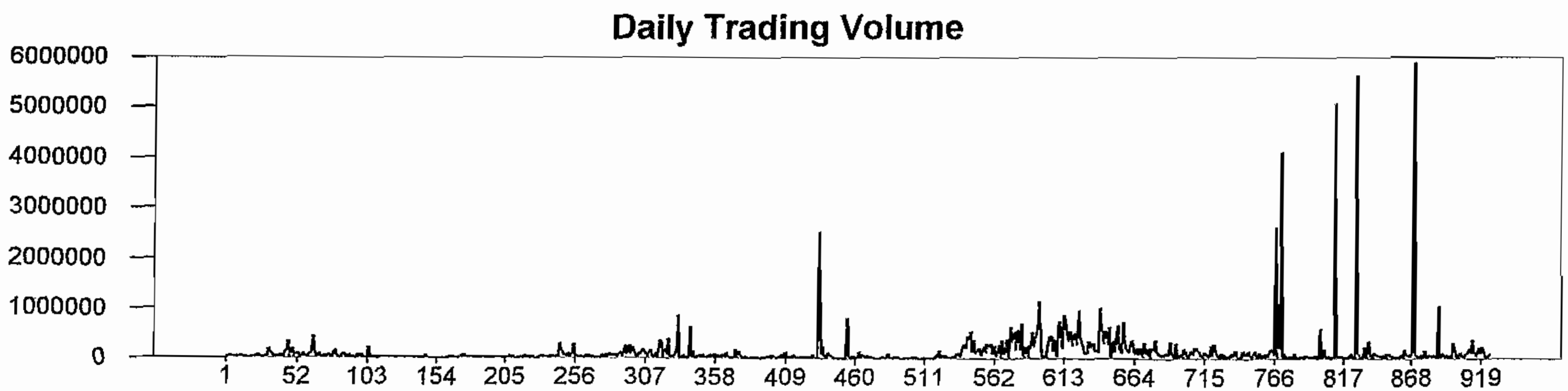

Daily Trading Volume
6000000
5000000
4000000
3000000
2000000
1000000
0
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CHART 2 BNS

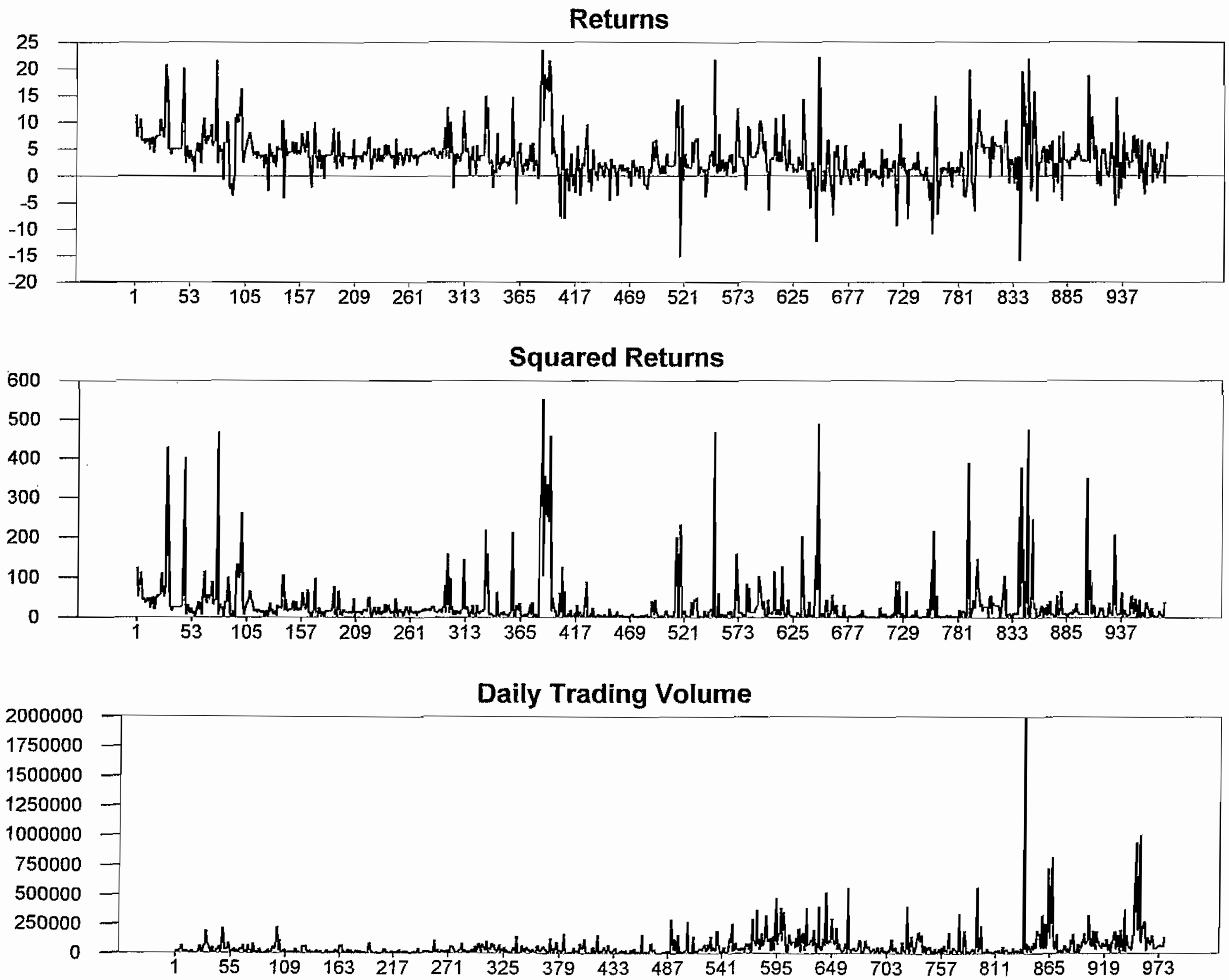
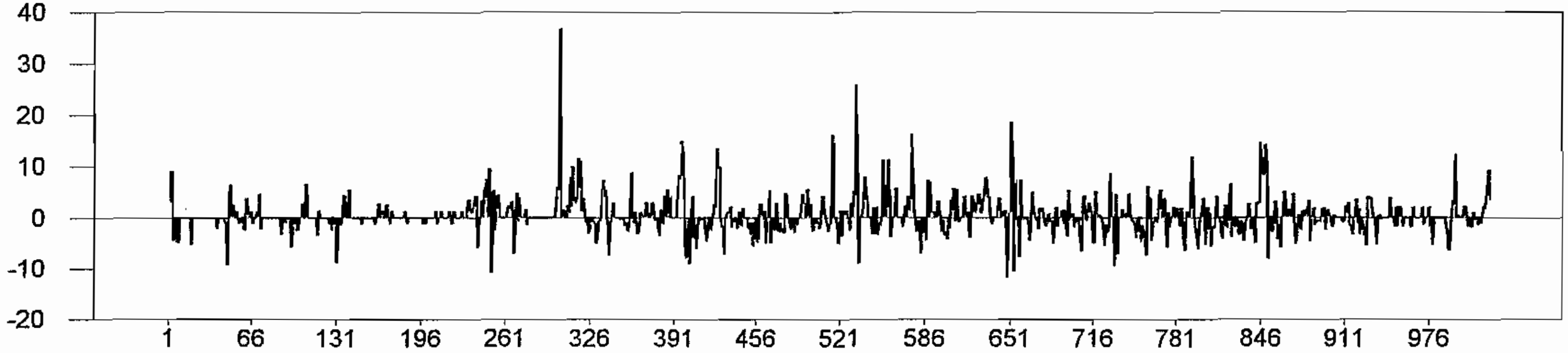
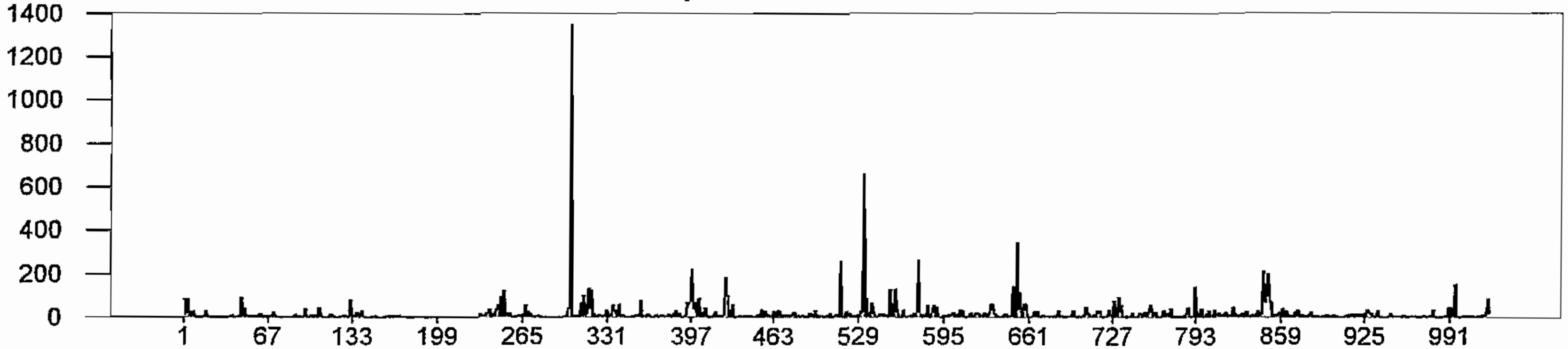

Returns
25
20
15
10
5
0
-5
-10
-15
-20
1
53
105
157
209
261
313
365
417
469
521
573
625
677
729
781
833
885
937
Squared Returns
600
500
400
300
200
100
0
1
53
105
157
209
261
313
365
417
469
521
573
625
677
729
781
833
885
937
Daily Trading Volume
2000000
1750000
1500000
1250000
1000000
750000
500000
250000
0
1
55
109
163
217
271
325
379
433
487
541
595
649
703
757
811
865
919
973

CHART 3 TOJ

Returns



Squared Returns



Daily Trading Volume