Information Efficiency and Non-linear Modelling of Returns in an Emerging Stock Market in the Caribbean

By

Hyginus Leon
International Monetary Fund

Shelton Nicholls
Caribbean Centre for Monetary Studies
University of the West Indies, St. Augustine Campus, Trinidad and Tobago*

Dorian Noel
Petroleum Company of Trinidad and Tobago (PETROTRIN)

Abstract

It is generally recognized that volatility in the prices of securities is due, in part, to the continuous revision of the preference sets of traders in response to the arrival of unanticipated information. In particular, traders may update beliefs about the value of an asset in response to information on both market microstructure and the macro-economy. We argue that the microstructure characteristics of the Trinidad and Tobago Stock Exchange (TTSE) are consistent with serial correlation, volatility clustering and non-linearity in stock returns. The underlying behavioural patterns arise because informed traders may possess "long-lived" information sets arising from poor dissemination and disclosure of market information.

The paper has two objectives: (1) to investigate a price-volume relationship for stock returns, accounting for conditional heteroscedasticity and non-linearity; and (2) to determine whether volume is a sufficient proxy for information flow. Our results show that simple linear autoregressive models of stock returns display significant non-linearities that can partly be explained by functional and variable misspecification in the functions describing the mean and variance of returns. In particular, we find that prices and volume are not sufficient statistics for the conditioning information set of traders because both volume and the real effective exchange rate are significant predictors for the distribution of stock returns.

JEL Classification Numbers: G12, G14, C51.

Email addresses: hleon@imf.org; nicholls@tstt.net.tt; office@tstt.net.tt;

1. Introduction

It has long been recognised that the trading of securities in financial markets reflects the information sets of traders. Daily volatility in the price of securities is due, in part, to the continuous revision of the information sets of traders as "news or information" enters the market. Typically, the relationship between volatility of stock returns and order flow (especially trading volume and transaction arrivals) presumes that "information" or "news" is revealed in these observable variables (Lamourex and Lastrapes 1990, Lange 1999, Gallant *et al.* 1993 and Karpoff 1987). In fact, the literature posits that information has a critical role to play in the price formation process of efficient markets (Almedia *et al.* 1993, Locke and Sayers 1993, Fleming and Remolona 1999, Melvin and Yin 2000). However, most of this research focuses on mature markets in which the informational systems are well-developed.

In small emerging capital markets, especially in the Caribbean region, where the acquisition of information is more costly, there is a dearth of research on how "news events" impact on stock volatility, despite the obvious importance of this relationship for international portfolio diversification. In fact, previous research on the stock markets in the Caribbean has focused on: (i) an examination of the volatility of returns (Leon, Nicholls and Sergeant 2000 for the Trinidad and Tobago Stock Exchange); (ii) the relation between trading volume and the volatility of stock returns (Hamilton 1998 for the Jamaica Stock Exchange); and (iii) international spill-over effects (see Kim and Langrin 1996 for the Jamaica Stock Exchange). The unique characteristics of emerging stock markets provide excellent opportunities to study the effects of market of microstructure on stock returns and the efficiency of these markets. In particular, the high risk premium and clustering of volatility of stock returns observed in many of the emerging markets are due, in part, to the clustering of "news events" at fixed reporting intervals and the extended periods of time in which no "news" is revealed to the market.

As regards efficiency, the conventional tests that have been developed for advanced financial markets[1] are less reliable in emerging markets where typically liquidity is low, trading is shallow and investors utilise information which is often unreliable and sparse (Antoniou et al 1997). Also, efficiency assumes that investors are risk averse, respond instantaneously to new information, and are in a position to produce unbiased forecasts, thereby leading to a linear relationship between prices and information flow. In contrast, uninformed investors in emerging markets, respond with a delay to information flow either because the cost of acquiring information is high or because the information is unreliable. Therefore the relationship between prices and information flow in emerging markets may be non-linear.

If the true data generating process is non-linear, the use of a linear model can generate false inferences. In particular, conventional tests based on linear models may wrongly accept hypotheses of interest. For example, tests of efficiency based on the random walk hypothesis may erroneously fail to reject the null of no predictability since some non-linear systems can look like random walks but are predictable. On the other hand, evidence of predictability may not necessarily mean inefficiency, since this inefficiency may simply reflect the fact that information is not free or reliable, or that trades cannot be carried out at the observed prices. Further, both informational and allocative efficiency may be due to changes in the institutional and regulatory environment.

This paper has two objectives: The first is to investigate the price-volume relationship on the Trinidad and Tobago Stock Exchange accounting for conditional heteroscedasticity and non-linearity, and the second is to determine whether volume is a sufficient statistic to measure information flow. Our results show that simple linear autoregressive models of stock returns display significant non-linearity. This non-linearity can partly be explained by functional and variable misspecification in the mean and variance functions. Specifically, we find that both volume and the real effective exchange rate help predict

[1] These markets are characterised by high levels of liquidity, sophisticated investors, high quality and the rapid dissemination of data and few institutional impediments.

the moments of stock returns and that the process generating returns is non-linear in both the mean and the variance.

The rest of the paper is organised as follows: in section 2, the institutional characteristics stylised facts for the TTSE are summarized and linked to the literature on the price-volume relationship; the methodology used to model the non-linear relationship is outlined in Section 3. The empirical results are discussed in Section 4 and conclusions and recommendations are presented in Section 5.

2. Institutional Characteristics and Stylised Facts

The TTSE is characterized by (1) a trading system with temporal consolidation of trade orders; (2) brokers that can act in a dual capacity; and (3) information asymmetries.

2.1 Trading Mechanism and Trading Rules of the TTSE

The TTSE is a periodic call market. In such a market, trading in securities takes place at periodic (discrete) time intervals when "calls" are made for securities. The market is characterised by the temporal consolidation of transaction orders at fixed locations (brokerage houses). Orders detained are then brought to the floor of the TTSE to be executed in a multilateral transaction (batch) at a uniform (single) price when "calls" are made for securities. In contrast to developed capital markets such as the New York Stock Exchange, the time interval for trade in a security can be as much as five (5) minutes long.

The price discovery process of the TTSE is interactive. The method of communicating willingness to trade in a security on the floor of the TTSE is a hybrid system in which an open outcry system coexists with a "trading board", which is used to record the "calls" of brokers. The trading board is also used for the matching of orders of brokers. No bids and offers are binding until auction participants agree on the final price configuration. Trading on the floor of the exchange is restricted to brokers (members) and registered traders. Brokers are allowed to trade as principals or agents. Public orders (represented by orders of brokers) are brought to the floor of the exchange for execution. These orders are mainly of two types: (1) limit orders and (2) market orders.

Trading in listed securities begins at 9:30 am every Tuesday, Wednesday and Friday and continues until all securities are called for trading and dealt with by floor members. The market opens and closes with "calls" for securities. "Calls" for securities are done in a sequential alphabetical order. There is no minimum spread but a daily price limit is set at ten (10) percent. The sequence of matching orders follows the general rule of price, time and order size[2]. All trades struck during a "call" for a security are marked on the "Quotation Board". At the conclusion of the second "call" for securities, the closing prices for securities are set and the market is closed for the day.

The information system is underdeveloped.[3] The "Daily Official List," published by the TTSE, provides limited information on price and volume traded for each security; commercial vendors of information are non-existent; information on listed companies only becomes available at the end of reporting periods[4] and tends generally to provide only details on the operating performance of the firms[5]. Information on the future investment activities of listed companies is rarely made available to investors and the general public. Further, with few professional intermediaries continually assessing market activities and performance of listed companies, the cost of acquiring information is relatively high. Because of these related issues, investors often trade on noise.

---

[2] If competing bids and offers of equal size can not be satisfied in full, then priority is assigned in the time sequence in which they were called except client orders which are given priority over brokers orders for own account. If the timing of "calls" is unclear, then priority is given to the full satisfaction of clients' orders of 500 and less.

[3] In advanced financial centres such as New York, London and Tokyo, the information structures of the market are so well developed that traders have access to an abundance of real time information on which to conduct trades. Consequently, traders in these markets can assess their positions on a continuous basis and can make a fair assessment of the reservation price for various securities.

[4] For most firms, this reporting period is one calendar year. In a few instances, some firms do prepare quarterly reports.

Tables 1 and 2 summarize statistics and characteristics of the TTSE. Figure 1 includes a graph of the logarithm and first difference of the stock price index. Figure 2 shows descriptive statistics for the total stock returns, based on weekly data for the period 3/25/83 to 3/16/01. Figures 3-5 show scatter plots of the returns at period t against returns at period t-1 and illustrate clustering at typical periods of high volatility (the largest positive and negative are joined with the preceding and following points). Both positive and negative shocks cause returns to wander away from the central cluster before returning to the neighbourhood of their initial positions. Squared returns at time t are positively correlated with returns at time t-1 showing that large volatility often follows large negative returns. The distribution of returns is too peaked relative to samples from a Gaussian population and exhibit second-order temporal dependence (small and large changes are clustered together). Skewness is positive indicating relatively more positive returns. Quantile plots conform the departure from normality; in fact, a t-distribution with about 3 degrees of freedom seems more appropriate, at least suggesting the need for robust estimation. Since normality is better suited to modeling linear dependence and is not appropriate for data exhibiting significant leptokurtosis and second-order temporal dependence, our exploraratory data analysis suggests the need for a non-linear stochastic process, probably with a non-normal distribution.

The observed serial correlation, volatility clustering, low market liquidity are consistent with the institutional characteristics of the TTSE. The temporal clustering of information at reporting intervals can provide explanations for the clustering of trade transactions and for the existence of "stock price volatility clusters" on the TTSE. When an information event occurs, the number of informed traders, the frequency of trade transactions, and the volatility of stock prices tend to increase. Informed traders on the TTSE market who possess long-lived information sets may have some discretion to determine the most appropriate time to actively trade a security. This may enable them to reap higher returns on their superior information sets by simply remaining in the market for a long enough period. Trading on these long-lived information sets may induce serial correlation in

[5] In Trinidad and Tobago, listed companies are required to report on a half-yearly and yearly basis. However, some companies do provide information on a quarterly basis.

stock prices (Kyle (1985) and Cho (1995)). Information asymmetry and inadequate disclosure suggests that informed traders could engage in trading practices that mask their information advantage, for example splitting orders among brokerage houses. Uninformed traders either build in risk premia for trading or wait to update their information sets before establishing positions in securities, thereby explaining why observed market prices are high, the liquidity of market is low and the volatility of stock prices tends to cluster around news events.

3. Literature Survey

3.1 Explanations for Non-linear Behaviour

The existence of non-linear behaviour in financial markets is well documented by Hsieh (1991), Savit (1988), Scheinkman and LeBaron (1989), Hiemstra and Jones (1994), and Peters (1991). In particular, Savit (1989) indicates that self-regulating systems are generally characterized by non-linear processes. To the extent that financial markets are self-regulating systems with feedback and feedforward loops, prices in these markets may be expected to exhibit non-linear behaviour. Granger (1989) also argues that the real world is "almost certainly non-linear." One of the many advantages of this feature is that it allows the development of richer and more representative models of asset behaviour (Hsieh (1991), Brock (1993)).

Antoniou et al (1997) discuss various reasons for the existence of non-linearity and list five arguments as to why non-linearity may be observed in financial markets: (1) difficulties in carrying out arbitrage transactions; (2) non-linear feedback adjustments (for example, overreaction to bad news (da Costa (1994)); (3) market imperfections like transactions costs; (4) differences in the frequency of important announcements relative to that of observations (monthly announcements may cause non-linearity in weekly but not in quarterly series); (5) investors may not be rational in the sense often assumed in capital market theory.

Table 1.1: Stylised Fact for the TTSE

Year End	No. Listed Companies	Market Capitalisation (TT$ Mn)	Ratio of GDP to Market Capitalisation	Average Daily Value of Stock Traded (TT$ Mn.)	Average Daily Volume (units)	Turnover Ratio %	Average Daily Transactions	Concentration Ratio (Capitalisation)	No. of Trading Days
1984	36	2,002.1	10.7	0.62	184,780	5.0	64	N/A	147
1985	36	1,667.6	9.2	0.50	162,536	4.0	38	N/A	150
1986	34	1,346.3	7.8	0.65	296,782	7.0	35	N/A	144
1987	34	1,397.9	8.4	0.31	234,041	3.0	23	N/A	147
1988	34	1,136.0	6.6	0.39	213,259	5.0	20	N/A	146
1989	31	1,748.4	9.5	0.97	471,059	8.0	19	N/A	151
1990	30	2,956.2	13.7	1.66	467,511	8.0	34	80	142
1991	29	2,851.7	12.6	2.27	694,468	12.0	44	84	149
1992	28	2,184.8	9.5	0.62	225,719	4.0	29	86	152
1993	26	2,850.9	11.6	1.98	512,972	11.0	31	90	152
1994	27	3,873.9	13.2	1.98	444,901	7.7	28	88	152
1995	27	6,750.7	21.3	5.42	877,697	12.0	42	87	150
1996	27	8,852.2	25.7	4.25	798,341	7.3	38	89	152
1997	24	19,636.9	53.7	5.64	671,640	4.3	44	91	150
1998	25	24,984.1	65.3	8.26	680,693	5.0	49	89	151
1999	27	27,513.5	67.0	3.99	493,396	2.7	21	87	152
2000	27	29,330.0	58.4	11.30	506,151	5.9	43	87	152

Source: The Annual Report of the Trinidad and Tobago Stock Exchange Limited (various years). GDP and No. denote Gross Domestic Product and number, respectively.

Table 2

Trinidad & Tobago: Traders Matrix

Index Name	*Sub-sectoral Indices*	*Trading Mechanism*	*Trading Hours*	*Secondary Market*
All Trinidad & Tobago Stock Price Index (Local listings) (01/01/99) Composite Index (All listed securities) (01/01/83=100)	Banking Conglomerates Manufacturing I Manufacturing II Property Trading	Periodic call Market (with two calls for securities)	Tuesday, Wednesday & Friday 9:30 am - Close	Second [illegible] (09/01/9[illegible])
Traded Securities	*Odd Lot*	*Round Lot*	*Options/Futures*	*Margin Trading*
Common Stock, Preference Shares, Corporation Bonds, Government Bonds	No	No	No	No
Short Sales	*Special Block Transactions*	*Off-Board Trading*	*Daily Price Limit*	*Minimum Spread*
No	Yes	Yes	10%	No
Settlement Period	*Foreign Restrictions*	*Reporting Threshold*	*Dividend Paid*	*Stamp Duty Act*
T+5	Non-approval limit is 30%. Beyond 30% requires the approval of MOF	10%	Quarterly, Semi-annually and Annually	No
Exchange Fees	*Capital Gains Tax*	*Dividend Withholding Tax*	*Commissions*	*Regional Listings*
0.1% or $1.00 whichever is higher for clients' orders. Members pay 2% on commission earned per month	No	No	1.5% for first $50,000. 1.25% for the next $50,000. 1.0% on the excess.	BST, BWIA, CIBC, GHL, GKC, LOB, NML, RBTT and TCL

---

[6] Margin Trading was introduced in 2000 to improve the liquidity of the TTSE.

[7] The Stamp Duty Act of 1908 (amended 1998) facilitates off-broad trading of listed securities of TTSE.

[8] Barbados Shipping and Trading Company Limited (BST), BWIA West Indies Airways (BWIA), Life of Barbados Limited, Neal and Massy Holdings Limited (NML) and RBTT Financial Holdings Limited (RBTT) are listed on both the Securities Exchange of Barbados and TTSE. Guardian Holdings Limited is listed on both the Jamaica Stock Exchange and TTSE. CIBC (West Indies) Limited (CIBC), Grace, Kennedy and Company Limited (GKC) and Trinidad Cement Limited (TCL) are listed on the Securities Exchange of Barbados, Jamaica Stock Exchange and TTSE.

Figure 1: Logarithm and first difference of the composite index and volume

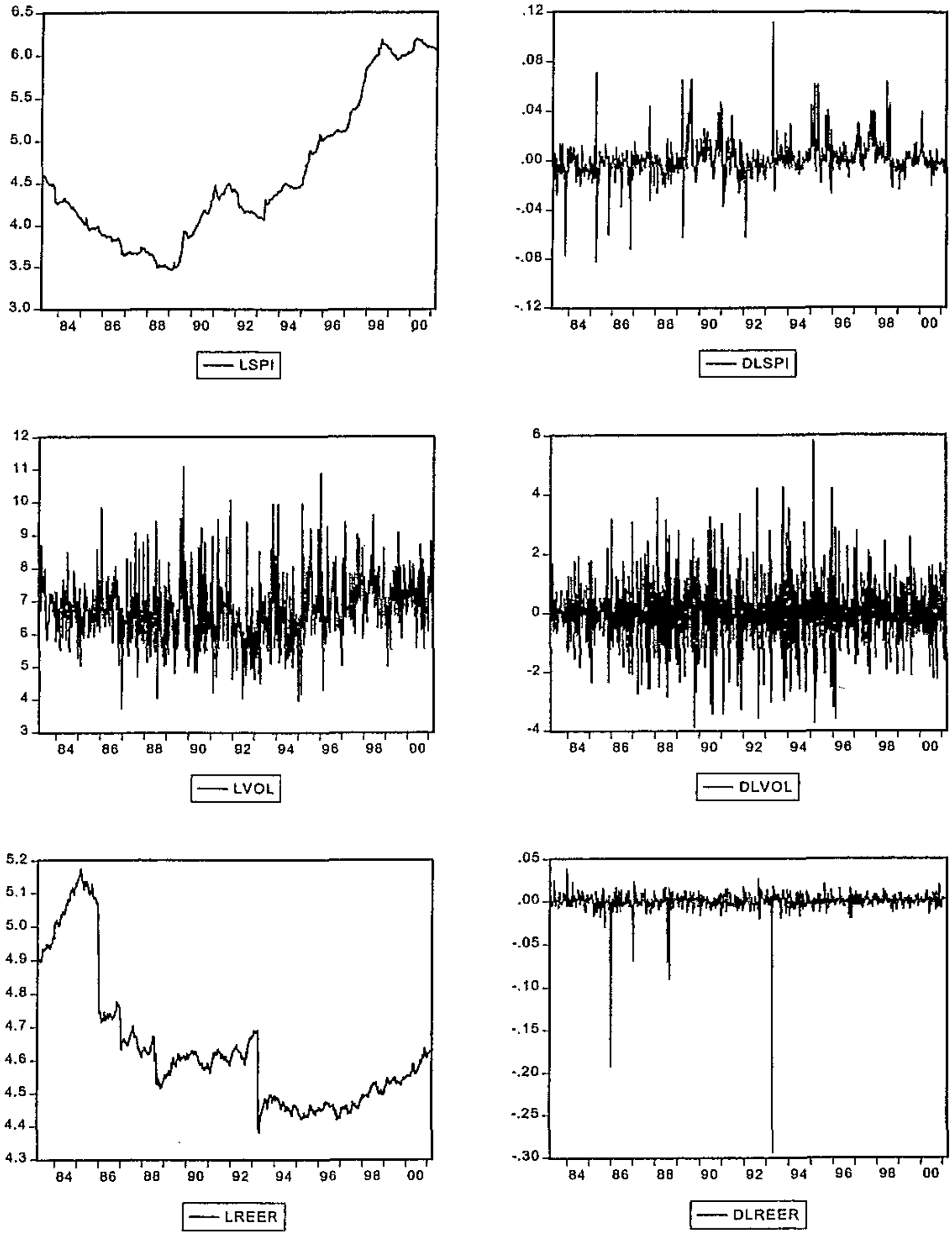
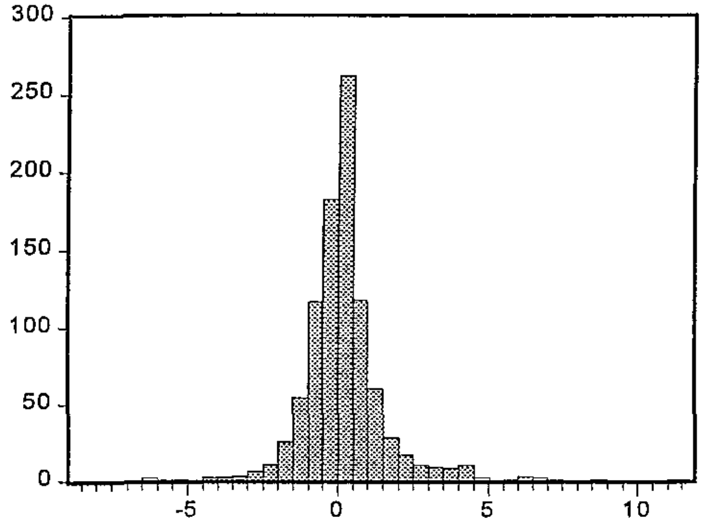


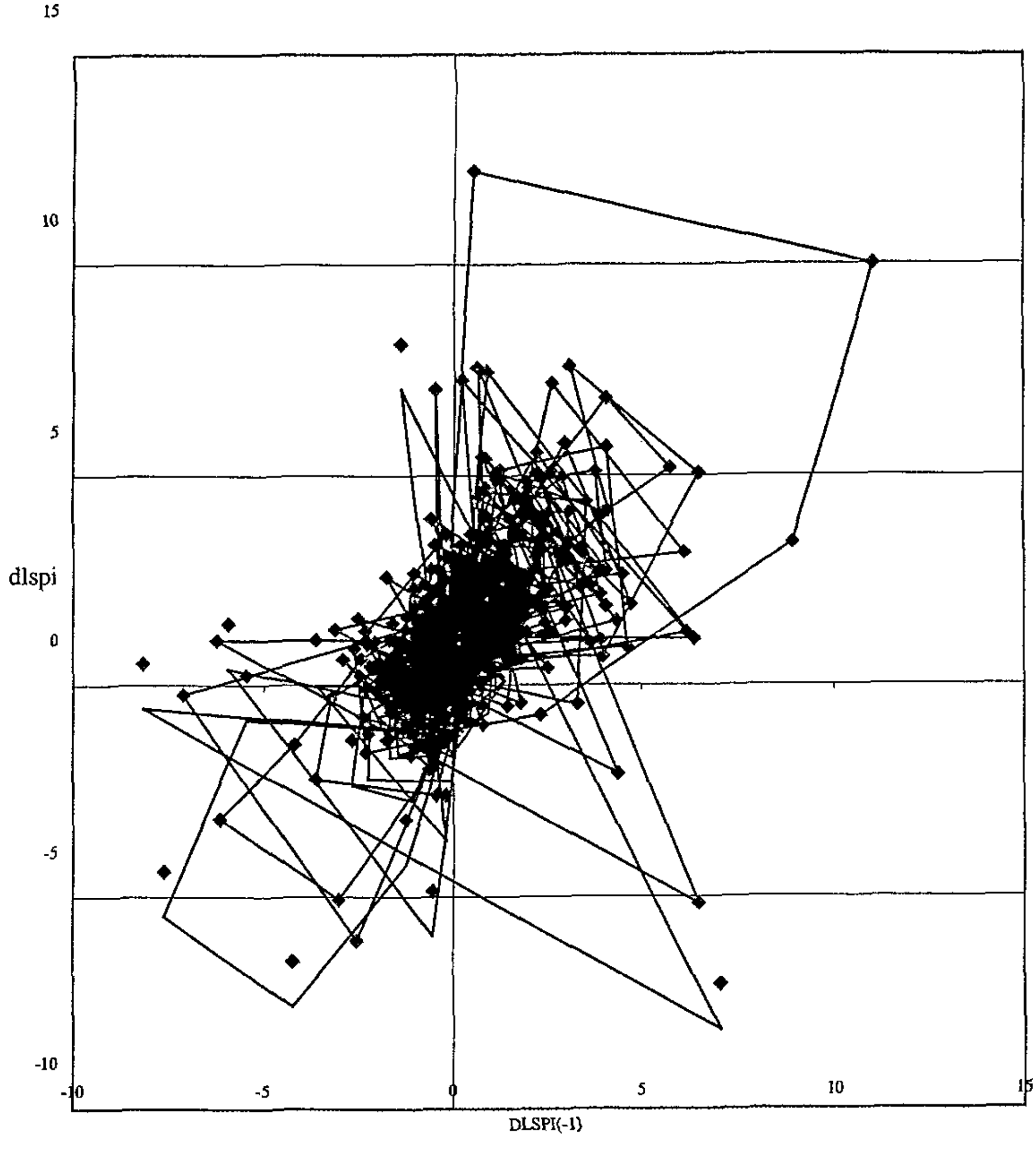
Figure 2: Empirical Moments for Trinidad Stock Return Series



Series: DLSPI
Sample 3/25/1983 3/16/2001
Observations 939

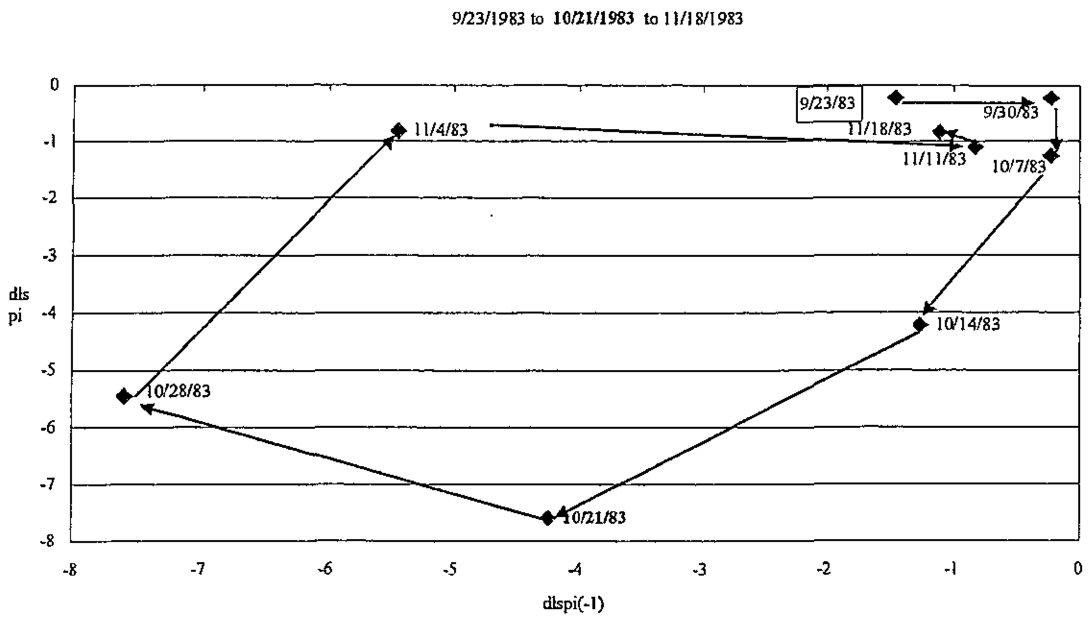
Mean	0.151804
Median	0.000000
Maximum	11.15806
Minimum	-8.157165
Std. Dev.	1.473820
Skewness	0.781639
Kurtosis	13.03194
Jarque-Bera	4033.146
Probability	0.000000

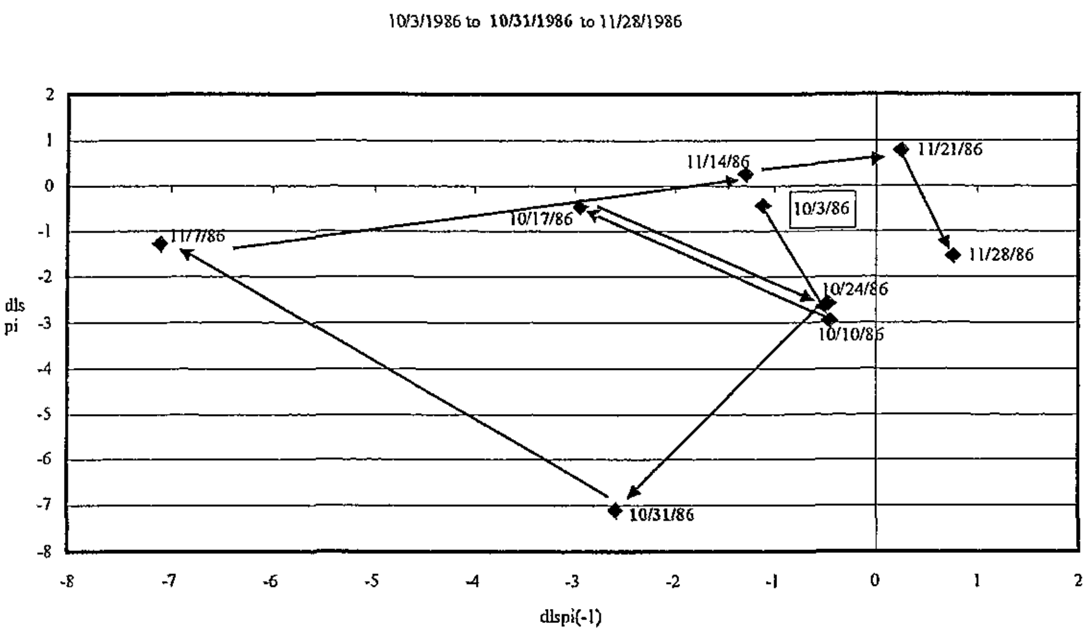
Figure 3: dlspi vs. dlspi(-1)



Source:

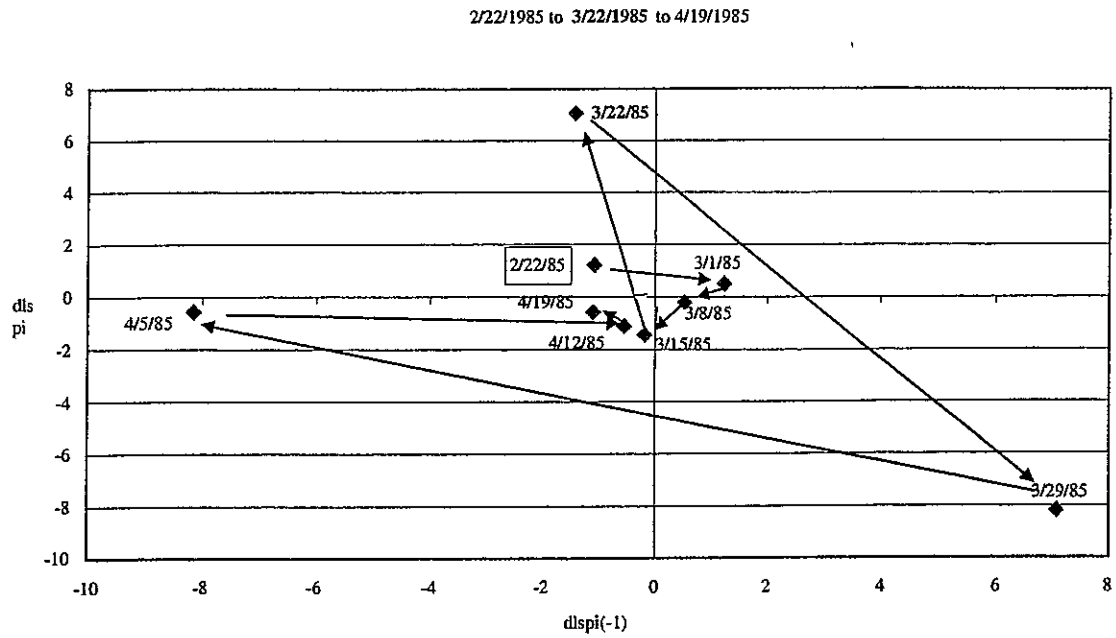
Figure 4: dlspi vs. dlspi(-1)

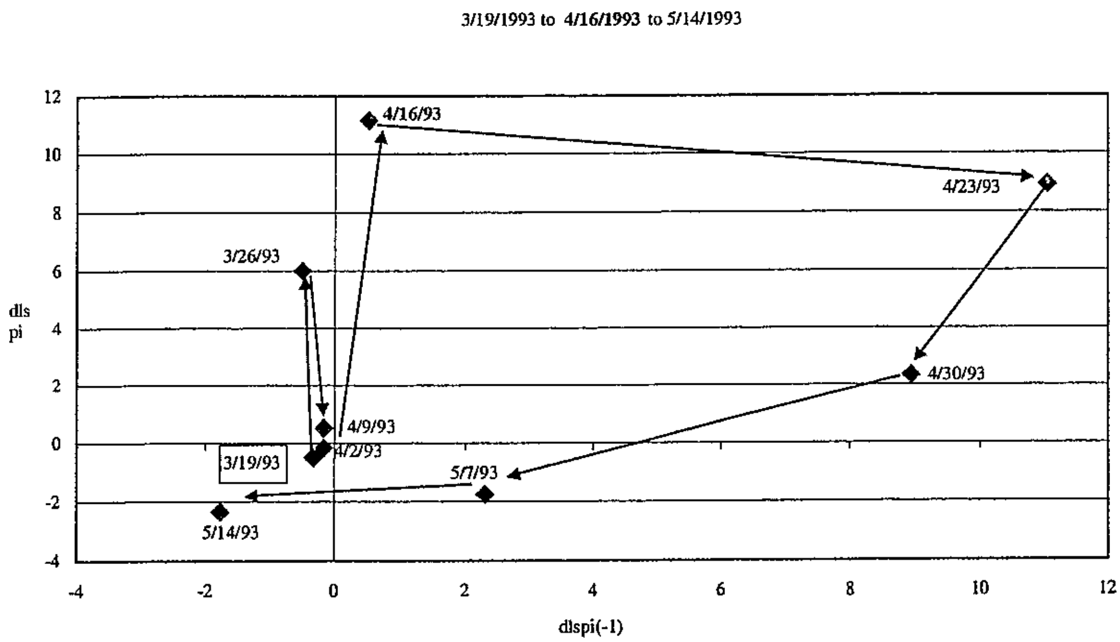




Source:

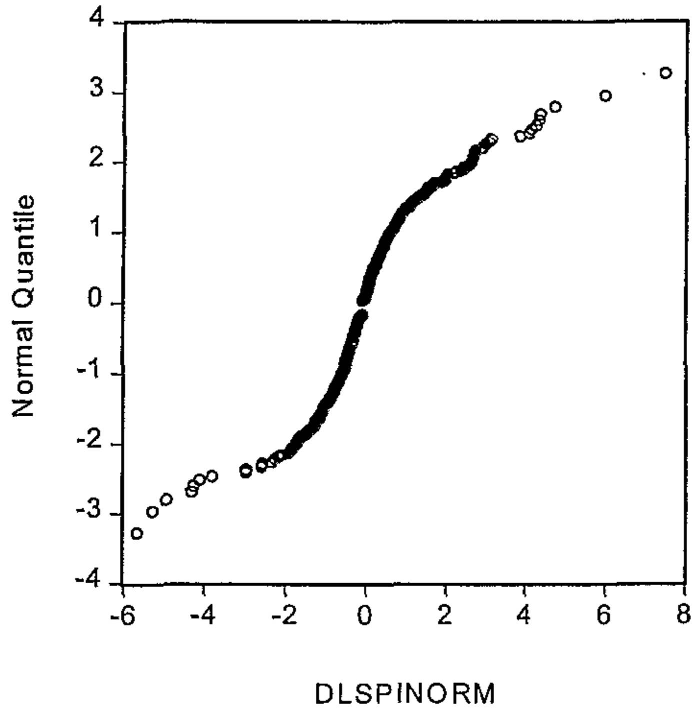
Figure 5: dlspi vs. dlspi(-1)

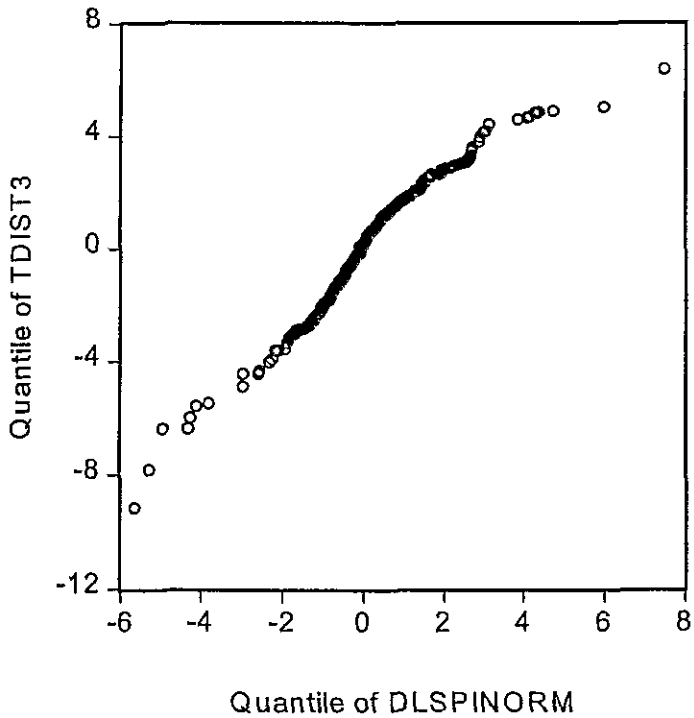




Source:

Figure 6: Quantile Plots for DLSPI





In addition, changes in the regulatory framework (information disclosure by companies, listing requirements), coupled with characteristics of unreliable information, uninformed traders, high transaction costs, and insider trading may also lead to non-linear behaviour in capital markets.

Since financial markets are capable of generating non-linear behaviour, it is equally important that theoretical models, which seek to characterise market behaviour, employ richer specifications that capture the stylised facts that are commonly observed in financial series. These stylised facts, in general, include serially correlated volatility, volume-volatility correlation, skewness and excess kurtosis of returns[9], large volatility followed by large negative returns.

3.1 *Theoretical notions*

Karpoff (1987) identifies two main reasons why the price-volume relationship is important for capital markets. First, it provides a useful insight into the structure of the market and second, it makes trade more competitive. The ability to predict price variability has direct implications for the efficiency of the capital market. If lagged volume is a useful predictor of price variability, then this implies the existence of some inefficiency. **Further, technical analysts have always used volume measures to augment their information sets. Specifically, they place less emphasis on price changes with low volume than to similar changes with substantial volume, suggesting a non-linear relationship.**

The following four broad classes of models have been utilised to explore the relationship between stock prices and volume: mixture of distribution models, sequential information, models of tax related motives for trading, and noise trader models.

[9] Large returns are often negative, tend to cluster, and occur more frequently than expected.

(a) Mixture of Distributions Model

In Clark's (1973) mixture of distribution model (MDM), trading volume is a proxy for the speed of information flow, a latent factor that affects both returns and trading volume. The MDM assumes (a) that the joint distribution of price change and volume is bivariate normal, conditional upon the arrival of information variable, and (b) that the number of information events per period is random (Harris, 1987). The mean and covariance of the conditional joint distribution are both proportional to the conditioning variable, the information arrival process. Price changes and trading volume are both related to the information process, but the relation depends on the market microstructure, the information dissemination process, and on how trades process information. This model predicts contemporaneous change of both prices and volume.

In Epps and Epps (1976), trading volume measures the disagreement among traders as they interpret the new information received. In that model, volume increases with the degree of disagreement and affects absolute stock returns. In contrast, herd behaviour, while minimizing disagreement, may increase trading volume and affect absolute stock returns.

Bikhchandani and Sharma (2000) argue that informationally inefficient herd behaviour may occur and can lead to price bubbles and mis-pricing when the accuracy (or lack thereof) of the information with market participants is not common knowledge. Information cascades and reputation herding are also more likely to arise in emerging markets where there is weak reporting requirements, lower accounting standards, lax enforcement of regulations, and costly information acquisition. Also, since information is likely to be revealed and absorbed more slowly, momentum investment strategies could be potentially more profitable.

(b) Sequential Information Models

Copeland (1976) and Jennings, Starks, and Fellingham (1981) assume that information arrival and dissemination generate a sequence of momentary equilibria before a final information equilibrium is achieved. Because of this sequential flow, lagged volume may help predict absolute stock returns and lagged absolute returns may help predict trading volume. Information signals are not received by all traders simultaneously, but are observed by each trader.

Easley and O'Hara (1992) also develop a sequential model in which bid-ask prices depend on time itself and may change even in the absence of trades. Traders learn from trades and lack of trades because each may be correlated with a different aspect of information. While trade provides signals on the direction of new information, the lack of trade provides a signal of the existence of new information. In their sequential trading model, the market maker learns from the lack of trade as well as from actual transactions, and bid-ask prices move in response to the absence of trade. Since the sequence of trading outcomes (buys, sales, and no trades) matters, total trade or volume affects price behaviour (prices at time t+1 depend on volume of trade at time t). In this framework, past prices are not sufficient statistics for all past market information.

These authors conclude that the level of trade volume, inventory, and time, all matter in the adjustment of prices to information. Given these findings, a GARCH process is quite appropriate to model the adjustment, since it can adequately describe time dependence in the rate of information arrival (Lamoureux and Lastrapes (1990)). Although this rate of information is not directly observable, trading volume has been used as a proxy for the directing variable (if prices and volume are jointly determined, there may be some simultaneity bias). In fact, a significant variance-volume relationship, in that framework, is more a test of whether volume is a valid proxy for information rather that a test of the volatility-volume relationship (Foster (1990) Wong and Yau (2000)).

(c) Models of Tax related Motives for Trading

These models are associated with the optimal timing of capital gains and losses realized during the tax year; non-tax motives including portfolio rebalancing, window dressing, and contrarian strategies. Lakonishok and Smidt (1989, 1986) find evidence that past prices are positively related to trading volume, possibly due to rebalancing of incompletely diversified portfolios, trading strategies based on past prices and psychological motives that inhibit investors from realizing losses. This model predicts that returns affect future volume.

(d) Noise Trader Models

In noise trader models, traders do not trade on the basis of economic fundamentals, thereby inducing mispricing in stock returns in the short run. In the long run, stock price changes revert to their means. In these models, volume may predict returns and price returns may also predict volume due to positive-feedback effects (DeLong et al (1990)).

Recent theoretical models of the price-volume relationship have placed greater emphasis on endogenous volume as an important determinant of asset price determination, (see Admati and Pfleiderer (1988, 1989) and Huffman (1987)). In Brock (1993), stock price changes and volatility are related to volumes of different groups of traders. Campbell, Grossman, and Wang (1993) also develop a model in which the autocorrelation of stock returns is a non-linear function of trading volume. Easley et al (1994) provide a model, based on the assumption that traders receive pricing signals of differing precision, which describes the informational role of volume. The model demonstrates how volume can affect market behaviour rather than describing the correlation of volume with price, as earlier studies had done. They postulate that both the *quality (precision) and quantity (dispersion) of information affect the price-volume relationship*. The price-volume relationship is less discernible the lower the precision (quality) and the higher the dispersion (quantity)[10]. They show that volume provides information about the quality of information that cannot be deduced from the price statistic alone. In fact, their model shows that for specific parameters, the relationship between price and volume may be convex which suggests the existence of some degree of non-linearity. Since traders use volume statistics to update their beliefs, volume is informative in that it complements information provided by price (characteristic common to technical analysis). Traders can therefore do better if they condition on volume and past prices rather than on past prices alone.

In this paper, we extend the conditioning information set to include the real effective exchange rate. Our reason for doing so is based on one of the core features commonly observed in economic activity in Caribbean type economies – that is, openness. In these small highly open economies, trade information provides the fulcrum upon which economic activity is based. The real effective exchange rate, which is one of the more important macroeconomic indicators in developing countries, provides an important signal of the underlying state of the macro-economy[11]. Changes in this rate, for instance, impact on the competitiveness of domestic goods relative to foreign goods, thereby affecting aggregate demand and output and consequently, the future expected cash flows of firms. An increase in the real effective exchange rate thus impacts negatively on the stock price. However, an increase may also raise the stock prices of firms in the domestic economy, depending on whether they are exporters or users of intermediate inputs.

4. Modeling Methodology

4.1 Empirical results on non-linearity in the price-volume relationship

There is a growing body of evidence that economic processes in futures, exchange rates and capital markets may be non-linear (see for instance the special issue of Journal of

[10] With high event uncertainty, high information dispersion may encourage herd behaviour by uninformed traders. Also, if quality is proportional to intensity, the variance of the price-volume relationship may depend on the intensity of information arrival.

Econometrics, 1996). For futures markets, Moosa and Silvapulle (2000) find bidirectional non-linear causation in oil futures, indicating evidence for both sequential information arrival and noise trading models. In the foreign exchange market, Hsieh (1989, 1991), Bajo-Rubio et al (1992,1997), Brooks (1996) and Ma (2000) find evidence of non-linearity in foreign exchange markets.

For capital markets, Tauchen et al (1996), using dynamic impulse response analysis to investigate the interrelationship among price volatility, trading volume, and the leverage effect, find that volume responds non-linearly to price shocks. Scheicher (1999) also finds evidence of non-linearity in the small Austrian Stock market. Fujihara and Mougove (1997) find evidence of bidirectional non-linear Granger causality after adjusting for volatility effects and conclude that the non-linear process may influence both the mean and variance of futures returns and volume.

In causation studies, Hiemstra and Jones (1994) and Gallant et al (1993) find unidirectional linear causation from volume to stock returns but bidirectional non-linear Granger causality between stock returns and volume, even after controlling for volatility persistence. Abhyankar (1998) finds that even after accounting for volatility persistence, linear causality is unidirectional from futures to cash but non-linear causation is bidirectional between futures and cash.

4.2 Smooth Transition Model with GARCH Type Conditional variances (STR-GARCH)

Smooth Transition Regression (STR) models are a general class of state-dependent non-linear time series models, in which the transition between states is endogenously generated (see survey in van Dijk et al (2001)). One interpretation is of a regime-switching model, where the transition between regime is smooth. The STR model of order r, for variable z, has the following specification:

[11] In a statistical sense, one can think of this term as a principal component, encompassing much of the variation in macroeconomic activity.

$$y = \beta_t' \tilde{x}_t + \theta' \tilde{x}_t F(z_{t-d}, \gamma, c) + \mu_t$$

$$y = \beta_t' \tilde{x}_t + \theta' \tilde{x}_t F(z_{t-d}, \gamma, c) + \mu_t$$

where:

$$\tilde{x}_t = \left(1, y_{t-1}, y_{t-2}, \ldots, y_{t-r}; \tilde{w}_{t-1}, \ldots, \tilde{w}_{t-q}\right)'; \quad \beta = \left(\beta_0, \beta_1, \ldots, \beta_p\right)';$$

$$\theta = \left(\theta_0, \theta_1, \ldots, \theta_p\right)';$$

μ_t is a martingale sequence with constant variance; w_t is a vector of exogenous variables; d is the delay parameter; z_{t-d} is a scalar or vector;[12] y_t is stationary and ergodic; and F, the transition function, is at least fourth-order continuously differentiable with respect to the scale parameter γ. Non-linearity is introduced in this model via the form of the transition function. The STR model can be viewed as a weighted average of two linear models (typically autoregressive), with weights determined by the value of the transition function. It is clear that a variety of regime-switching behaviors can be generated by alternative choices of F. Popular forms of this function are the logistic and exponential functions. Indeed, one may even consider a more general class of non-linear transition functions that may contain the logistic or exponential functions as special cases. The logistic function can be defined as (Escribano and Jordá, 1999):

$$F(z_{t-d}, \gamma, c) = \left[\left(1 + \exp\{-\gamma(z_{t-d} - c)\}\right)^{-1} - \frac{1}{2}\right]$$

while the exponential function can be represented as:

$$F(z_{t-d}, \gamma, c) = \left[1 - \exp\{-\gamma(z_{t-d} - c)^2\}\right]$$

γ measures the speed of transition from one regime to the next while c is the halfway point between the two regimes. It is simple to depict the logistic STR (LSTR) and

[12] The transition variable can be a variable not included in x, a function of linear time trend, or even a linear combination of several variables rather than own lags.

exponential STR (ESTR) models by replacing the transition function in the STR model with the logistic and exponential functions, respectively. Thus the LSTR model can be represented as follows:

$$y = \beta_t' X\%p + \theta' X\%p \left[1+\exp\left\{-\gamma\left(y_{t-d}-c\right)\right\}\right]^{-1} + \mu_t$$

$$y = \beta_t' \tilde{x}_t + \theta' \tilde{x}_t \left[1 + e\left\{-\gamma\left(y_{t-d}-c\right)\right\}\right]^{-1} + \mu_t$$

while the ESTR model has the following form:

$$\beta_t' \tilde{x}_t + \theta' \tilde{x}_t$$

$$y = \cancel{\beta_t' X\%p + \theta' X\%p}\left(1-\exp\left\{-\gamma\left(y_{t-d}-c\right)^2\right\}\right) + \mu_t$$

The models imply two distinct regimes; the regimes (say expansion and contraction) in the LSTR have different dynamics, while the two regimes in the ESTR have similar dynamics but the transition period can have different dynamics. The ESTR is symmetrically distributed around the threshold c. When $|y_{t-1}| > c$, $F(z_{t-d}, \gamma, c) \approx 1$, and behaviour is characterised by the "upper" linear regime. When $|y_{t-1}| = c$, $F(z_{t-d}, \gamma, c) \approx 0$ and the dynamics of the lower regime holds. For the LSTR model, $|y_{t-1}| < c$, $F(z_{t-d}, \gamma, c) \approx 0$ implies the dynamics of the lower regime and when $|y_{t-1}| > c$, $F(z_{t-d}, \gamma, c) \approx 1$, we have the dynamics of the upper regime. These models can be used to describe the transition periods between different regimes on the stock market. For example, the LSTR model implies that bullish and bearish regimes have different dynamics, with the transition from one to the other being smooth. In contrast, the ESTR model suggests that dynamics are similar in the two regimes but differ for the transition period. The conventional STAR model is a special case of the smooth transition model when $z_{t-d} = y_{t-d}$ and $w_t = 0$.

The form of the conditional variance utilised in this study is the EGARCH (p, q). Following Hsieh (1991), EGARCH is chosen over the simple GARCH model for two reasons: (a) EGARCH does not impose any restrictions on the signs of the parameters to guarantee estimated variances are positive; and (b) EGARCH can accommodate conditional skewness, which is not allowed in the GARCH model. The EGARCH (p, q) specification (Nelson (1991), which captures asymmetric effects in the conditional variance, is:

$$\log(h_t) = \alpha_0 + \sum_{j=1}^{p} \beta_j \log(h_{t-j}) + \sum_{i=1}^{q} \omega_j \left(\gamma \frac{\varepsilon_{t-j}}{\sqrt{h_{t-j}}} + \alpha \left[\frac{|\varepsilon_{t-j}|}{\sqrt{h_{t-j}}} - E\left\{ \frac{|\varepsilon_{t-j}|}{\sqrt{h_{t-j}}} \right\} \right] \right) \quad (3)$$

$\omega_j, \beta_j, \gamma$, and α are constant parameters; the terms $\varepsilon_{t-1}/\sqrt{h_{t-1}}$ in the equation ensure asymmetry through their coefficients. If a coefficient is negative, the variance increases (decreases) when the error innovation is negative (positive). Stationarity requires that the reciprocal of the roots of the autoregressive polynomial lie inside the unit circle. The LSTR-GARCH and the ESTR-GARCH are estimated by maximum likelihood.

4.3. Modeling Strategy

Granger (1993) argues in favor of a specific-to-general approach for non-linear modeling when the specification is not completely given by economic theory. The first phase requires a test for linearity; if rejected, choose a particular non-linear model for estimation[13] and evaluation; third evaluate both linear and non-linear models for in-sample and out-of-sample forecasting accuracy. The methodology we follow (see Terasvirta and coauthors) includes:

(a) Test for unit roots;

(b) Estimate linear model, AR(p) chosen according to AIC criterion;

(c) Test for non-linearity, using each potential transition variable;

(d) Determine and estimate model of choice (LSTAR, ESTAR);

[13] There are many possible non-linear models that the researcher may consider. Granger (1993) identifies Bilinear, Flexible Fourier Form; Neural Network; Projection Pursuit; Smooth Transition Switching; and Time Varying Parameter.

(i) Run the following regression of the dependent variable against the vector of independent variables and the interactions of the independent variables with the transition variables;

$$\tilde{\delta}\tilde{x}_t + \beta_1'\tilde{x}_t z_{t-d} + \beta'\tilde{x}_t z_{t-d}^2 + \beta_3'\tilde{x}_t z_{t-d}^3 + \beta_4'\tilde{x}_t z_{t-d}^4 + v_t$$

$$Y = \delta_0 + \cancel{\delta' x_t} + \beta_1' x z_{t-d} + \beta_2' x z_{t-d}^2 + \beta_3' x z_{t-d}^3 + \beta_4' x z_{t-d}^4 + \upsilon_t \tag{4}$$

where β' are parameters, x is a vector of independent variables and z is the delay factor.

(ii) Test the null hypothesis, H_{oc}: $\beta_2' = \beta_4' = 0$ with an F-test (F_e).

(iii) Test the null hypothesis, H_{ol}: $\beta_1' = \beta_3' = 0$ with an F-test (F_L).

(iv) Compare the relative strength of the rejection of each hypothesis. If the minimum p-value corresponds to F_L, select a Logistic Smooth transition; otherwise if it corresponds to F_e, select an Exponential Smooth Transition model. Homoscedasticity may be rejected due to neglected serial correlation, non-linearity, or omitted variables in the conditional mean. In this paper we augment the mean for omitted variables, include lagged dependent variables for neglected serial correlation, and address possible non-linearity through the use of a specific non-linear alternative, the ESTAR/LSTAR model.

Terasvirta et al (2001) state that estimation of γ may be problematic and advocate scaling the transition function. In addition, we conduct an initial grid search on c and γ, with the c ranging from the first to the third quartile of z_{t-d}, to obtain starting values. All models are estimated by non-linear least squares, using the Marquardt algorithm in Eviews 4.0.

5: Results

In this section, the statistical properties of the various data sets as well as the estimation results from the ESTAR-GARCH (p, q) and LSTAR-GARCH (p, q) model are presented along with a number of diagnostic tests that were conducted to gauge the goodness of fit of the models.

The data are weekly end-of-period total stock returns, obtained from the TTSE; volume is the total volume for each period; nominal weekly effective exchange rates are computed according to the methodology outlined in IMF (1997); real price relatives are obtained from monthly real and nominal effective exchange rates and one month lagged values are used to deflate the weekly nominal effective exchange rate; company news is an information intensity variable that measures the number of times during each week that a news event was reported about a company trading on the TTSE.

Both the Phillips-Perron and Augmented Dickey Fuller tests were computed for the various data sets. The results form these tests confirm that log stock prices and log effective exchange rates are I(1) or contain a unit root whereas log volume is an I(0) or stationary process. The logarithmic differences for the stock price index and the effective exchange rate series are therefore stationary series.

To determine the appropriate form of the lag polynomial, we fitted an autoregressive model of the log differences of stock prices with a maximum lag length equal to 12 and utilized Akaike's information criterion to decide on the optimal lag-length for this process. The minimum AIC value corresponded to a maximum lag-length of three. Given that the tendency of the AIC to over-parameterize and the fact that the third lag was not significant at the10% level, an autoregressive process of order 2 was chosen as the best fitting model.

An augmented autoregressive model incorporating the optimal lag-length was then fitted in which log-differenced prices were determined by own lagged differences and the log differences of the real effective exchange rate. The residual diagnostics from this model indicate that the residuals were positively skewed, leptokurtic and serially correlated. The Jarque-Bera test statistic rejected the null of normality, confirming that the residuals were non-normal. The Ramsey Reset test also confirmed that the augmented model was functionally misspecified. An ARCH test for the presence of heteroscedasticity was also conducted using the residuals of the augmented model and found heteroscedastic errors for lags of order 2, confirming that the variance of the residuals was not constant. As indicated earlier, the existence of heteroscedasticity in the residuals may be indicative of either one or all of the following: omitted variables, the presence of serial correlation and functional non-linearity in the conditional mean.

Given that we have attempted in the augmented model to account for (i) omitted variables, by including the real effective exchange rate term and (ii) for serial correlation, by including additional lags of the dependent variable in the augmented model specification, it seems reasonable to argue that the remaining heteroscedastic effects might be the consequence of some type of functional non-linearity. We therefore utilized the BDS statistic to test for the presence of non-linear dependence in the residuals, noting its low power in the presence of heteroscedasticity.[16] The BDS statistic rejected the null hypothesis, at the 5% level, that the residuals were independent and identically distributed (i.i.d.), confirming that the lack of independently distributed residuals could have arisen from the presence of functional non-linearity or heteroscedasticity in the residual error process.

The sign and size test developed by Engle and Ng (1993) was also utilized to test for non-linearity in the variance. Essentially, this test attempts to gauge whether negative and positive values in the residual data set have a symmetric influence on the squared

[16] It is necessary to pre-whiten the residuals using a GARCH filter to remove heteroscedastic effects from the variance.

residuals or variances. The results indicate that positive residuals have a much stronger influence than negative residuals on the estimated variances, confirming the existence of asymmetric sign effects in the estimated variance function.

The artificial neural network (ANN) test developed by Terasvirta, Lin and Granger (1993) was also employed to test for generic non-linearity. This test replaces the activation function in the hidden layer of an artificial neural network by third order Taylor series expansions around the null hypothesis. The results from this test show that the second and third order cross-products are generally significant indicating the importance of non-linear interactions. As expected, the null hypothesis of linearity is rejected in favour of generic non-linearity. The major difficulty with the ANN test results, however, is that we can make no definitive statement about the form of the non-linearity.

Further attempts were made to test for non-linearity in the variances using the E-J test procedure. Our results are (see equation 4):

	DLSPI(-1)	*DLSPI(-2)*	*DLSPI(-3)*	*DLREERB*
F-values H_{oe}: $\beta_1' = \beta_3' = 0$	7.22	1.78	1.29	4.9
F-Values H_{ol}: $\beta_2' = \beta_4' = 0$	16.47	2.26	1.51	5.26
Model	*ESTAR*	*ESTAR*	*ESTAR*	*ESTAR*

Note: *DLSPI(-1) was chosen as the delay factor.*

The E-J test rejected the null of linearity in favour of a non-linear exponential smooth transition model. Not withstanding the rejection of linearity in favor of the ESTAR, we estimate both ESTAR and LSTAR models, following the recommendation of Terasvirta (1999). A final choice could then be effected on the basis of residual diagnostics and economic interpretation.

In regressors in the linear part of both the ESTAR and LSTAR models include a constant term; a dummy variable that captures the impact of the floatation of the Trinidad and

Figure 7: ESTAR Transition Function versus Transition Variable

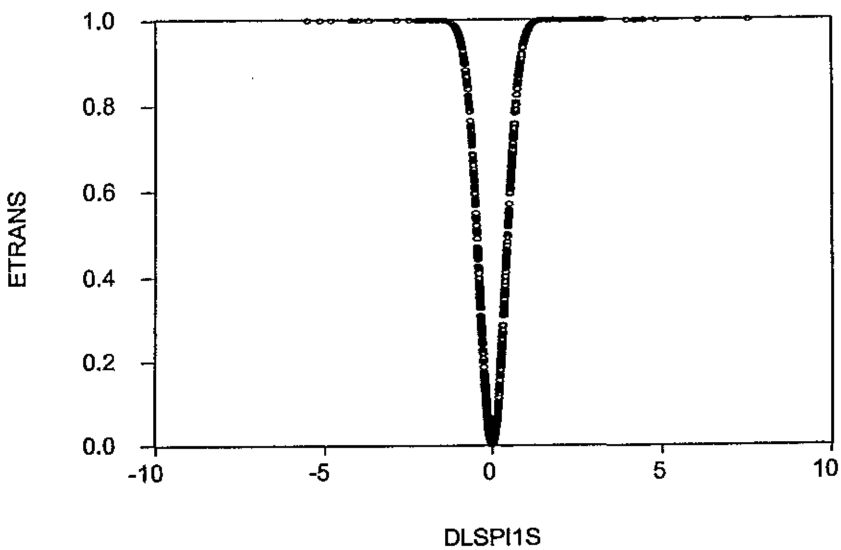
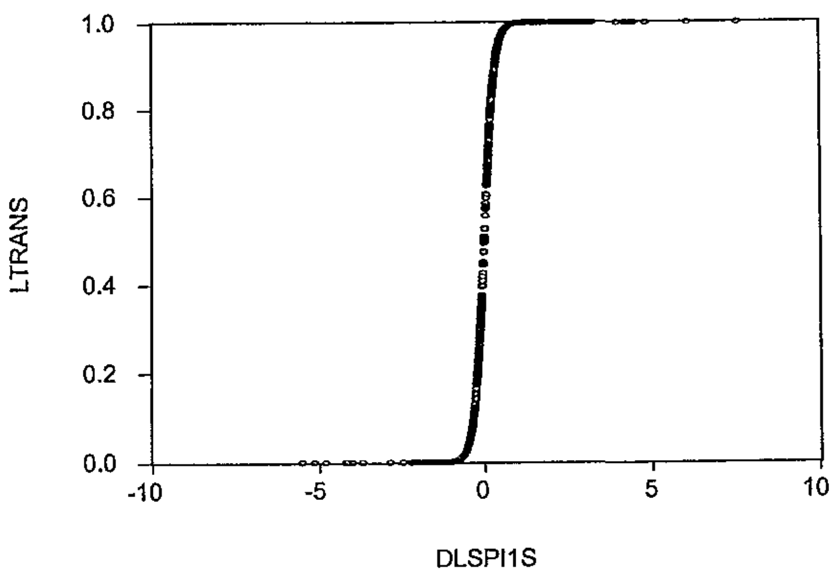


Figure 8: LSTAR Transition Function versus Transition Variable



6. Summary and concluding remarks

This paper estimated a price-volume relationship for stock returns on the TTSE, accounting for conditional heteroscedasticity and non-linearity. We find that the real effective exchange rate is a significant determinant of the conditional mean while the intensity of company news and the percentage change in volume help explain the conditional variance. Our results show that simple linear autoregressive models of stock returns are not sufficient for explaining the distributions of returns; these models display significant non-linearity, which can partly be explained by functional and variable misspecification in the functions describing the mean and variance of returns. In particular, we find that prices and volume are not sufficient statistics for the conditioning information set of traders because both volume and the real effective exchange rate are significant predictors for the distribution of stock returns.

The implications of our results are that the TTSE may be informationally inefficient. Further, improvements in the disclosure and dissemination of information could reduce volatility; standards for and frequency of financial reporting could be enhanced; and the speed and frequency of transmitting market information increased.

References

Abhyankar, A. (1998), "Linear and Non-linear Granger Causality: Evidence from the U.K. Stock Index Futures Market," *The Journal of Futures Markets*, 18 (5), 519-40.

Admati, A. R., and Pfleiderer, P. (1988), "A Theory of Intraday Patterns: Volume and Price Variability," *Review of Financial Studies*, 1 (1), 3-40.

Antoniou, A. et al (1997), "Market Efficiency, Thin Trading and Non-Linear Behaviour: Evidence From an Emerging Market," *European Financial Management*, 3 (2), 175-90.

Bikhchandani, S, and Sharma, S (2000), "Herd Behaviour in Financial Markets: A Review," IMF Working Paper 00/48, (Washington: International Monetary Fund).

Blume, L, et al (1994), "Market Statistics and Technical Analysis: The Role of Volume," *Journal of Finance*, 49 (1), 153-81.

Bollerslev, T.P. (1986), "Generalized Autoregressive Conditional Heteroscedasticity," *Journal of Econometrics*, 31, 307-327.

Brock, W. (1993), "Beyond Randomness: Emergent Noise," Working paper, University of Wisconsin, Madison.

Brooks, C. (1996), "Testing for Non-Linearity in Daily Sterling Exchange Rates," *Applied Financial Econometrics*. 6, 307-17.

Campbell, J., Grossman, S., and Wang, J., (1993), "Trading Volume and Serial Correlation in Stock Returns," *Quarterly Journal of Economics*, 108, 905-39.

Caporale, G. M. and Pittis, N. (1997), "Causality and Forecasting in Incomplete Systems," *Journal of Forecasting*, 16, 425-37.

Clark, P. K. (1973), "A Subordinated Stochastic Process Model with Finite Variance for Speculative Prices," *Econometrica*, 41 (1), 135-55.

Copeland, T., (1976), "A Model of Asset Trading Under the Assumption of Sequential Information Arrival," *Journal of Finance*, 31 (4), 1149-68.

Cornell, B. (1981), "The Relationship Between Volume and Price Variability in Futures Markets," *The Journal of Futures Markets*," 20 (1), 5-18.

Da Costa, N. C. A., (1994), "Overreaction in the Brazilian Stock Market," *Journal of Banking and Finance*, 18, 633-42.

DeLong, J., and et al (1990), "Positive Feedback Investment Strategies and Destabilizing Speculation," *Journal of Finance*, 45 (2), 379-95.

Easley, D., and O'Hara, M., "Time and the Process of Security Price Adjustment," *Journal of Finance*, 47 (2), 1992, 577-605.

Engle, R.F. (1982), "Autoregressive Conditional Heteroscedasticity with Estimates of the Variance of U.K. Inflation," *Econometrica*, 50, 987-1008.

Engle, R. F., and Ng, V. K. (1993), "Measuring and Testing the Impact of News on Volatility," *Journal of Finance*, 48 (5), 1749-78.

Epps, T. W., and Epps, M. L. (1976), "The Stochastic Dependence of Security Price Changes and Transaction Volumes: Implications for the Mixture-of-Distributions Hypothessis," *Econometrica*, 44 (2), 302-21.

Escribano, a. and Jorda, O. (1999), "Improved Testing and Specification of Smooth Transition Regression Models, in *Non-linear Time Series Analysis of Economic and Financial Data,* ed by P. Rothman, (Boston: Kluwer).

Fleming, M. and Remolona, M. (1999), "What Moves Bond Prices?" *Journal of Portfolio Management,*" 25 (4), 28-38.

Foster, A. (1995), "Volume-Volatility Relationships for Crude Oil Futures Markets, *Journal of Futures Markets,* 15, 929-951

Fujihara, R. and Mougoué, M (1997), "An Examination of Linear and Non-linear Causal Relationships Between Price Variability and Variability and Volume in Petroleum Futures Markets," *The Journal of Futures Markets*, 17 (4), 385-417.

Gallant, A.R., Rossi, P.E., Tauchen, G., (1992), "Stock Prices and Volume," *Review of Financial Studies,* 5, 199-242.

Gallant, A.R., Rossi, P.E., Tauchen, G., (1993), "Non-Linear Dynamic Structures," *Econometrica* 61, (4), 871–908.

Granger, C., (1989), *Forecasting in Business and Economics*, 2nd ed. (San Diego: Academic Press).

Granger, C., and Terasvirta, T. (1993), *Modelling Non-linear Economic Relationships.* Oxford University Press.

Grossman, S. J. (1975), "The Existence of Future Markets, Noisy Rationale Expectations and Information Externalities," Chapter 2 of unpublished Ph.D. Dissertation, University of Chicago.

Grossman, S. J. (1977), "The Existence of Future Markets, Noisy Rationale Expectations and Inforamation Externalities," *Review of Economic Studies*, 44 (3), 431-49.

Hamilton, J. (1998), "The GARCH and Volume Relationship with Heteroscedasticity in Stock Returns on the Jamaica Stock Exchange." In *Econometric Modelling of Issues in Caribbean Economics and Finance, (eds.)* S. Kim and T. Agbeyegbe, Caribbean Centre for Monetary Studies, St. Augustine, Trinidad.

Harris, L., (1987), "Transaction Data Tests of the Mixture of Distributions Hypothesis," *Journal of Financial and Quantitative Analysis*, 22 (2), 127-41.

Hiemstra, C. and Jones, J. (1994), "Testing for Linear and Non-linear Granger Causality in the Stock Price-Volume Relation," *Journal of Finance,* 49 (5), 1639-64.

Hsieh, D.A., 1991, "Chaos and Non-linear Dynamics: Application to Financial Markets," *Journal of Finance*, 46 (5), 1839-77.

Hsieh, D.A., (1989), "Testing for Non-Linear Dependence in Foreign Exchange Rates," *Journal of Business*, 62, 339-68.

Huffman, G. W. (1987), "A Dynamic Equilibrium Model of Asset Prices and Transactions Volume," *Journal of Political Economy*, 95 (1), 138-59.

Jansen, E. S. and T. Terasvirta (1996), "Testing parameter constancy and super exogeneity in econometric equations," *Oxford Bulletin of Economics and Statistics*, 58, 735-63.

Jennings, R. et al (1981), "An Equilibrium Model of Asset Trading with Sequential Information Arrival," *The Journal of Finance*, 36 (1), 143-61.

Karpoff, J.K (1987), "The Relation Between Price Changes and Trading Volume: A Survey," *Journal of Financial and Quantitative Analysis*, 22 (1), 109-26.

Kim, S. and R. Langrin (1996), "Stock Return Volatility Spillovers under Foreign Exchange Market Liberalisation: Case of Jamaica, Trinidad and Tobago, and the United States." Paper presented at the 28th Annual Conference on Monetary Studies, Central Bank of Trinidad and Tobago, Trinidad.

Kyle, A. (1985), "Continuous Auctions and Insider Trading," *Econometrica*, 53 (6), 1315-35.

Lakonishok, J. and Smidt, S. (1989), "Past Price Changes and Current Trading Volume," *The Journal of Portfolio Management*," 15 (4), 18-24.

Lamoureux, C.G and Lastrapes, W.D (1990), "Heteroscedasdicity in Stock Return Data: Volume versus GARCH Effects," *Journal of Finance*, 45, 221-229.

Lange, S. (1999), "Modelling Asset Market Volatility in a Small Market: Accounting for Non-synchronous Trading Effects," *Journal of International Financial Markets, Institutions, and Money*, 9, 1-18.

Leon, H., Nicholls, S., and K. Sergeant (2000), "Testing volatility on the Trinidad and Tobago Stock Exchange," *Applied Financial Economics*, 10, 207-220.

Lin, C.-F. J. and T. Terasvirta (1994), "Testing the Constancy of Regression Parameters Against Continuous Structural Change," *Journal of Econometrics*, 62, 211-28.

Locke, P. and C. Sayers, (1993), "Intrra-Day Futures Price Volatility: Information Effects and Variance Persistence." In *Non-linear Dynamics, Chaos, and Econometrics, (eds.)* M. Pesaran and S. Potter, John Wiley and Sons, Chichester, England.

Ma, Y., and Kanas, A. (2000), "Testing for a Non-linear Relationship Among Fundamentals and Exchange Rates in the ERM," *Journal of International Money and Finance*, 19 (1), 135-52.

Malliaris, A., and Urrutia, J. (1998), "Volume and Price Relationships: Hypotheses and Testing For Agricultural Futures," *The Journal of Futures Markets*, 18 (1), 53-72.

McQueen, G. and Roley, V. (1993), "Stock Prices, News, and Business Conditions," *The Review of Financial Studies*, 6 (3), 683-707.

Moosa, I. And Silvapulle, P. (2000), "The Price-Volume Relationship in the Crude Oil Futures Market: Some Results based on Linear and Non-linear Causality Testing," *International Review of Economics and Finance*, 9 (1), 11-30.

Nelson, D.B (1991) "Conditional Heteroscedasticity In Asset Returns: A New Approach" *Econometrica*, 59, 347 -370.

Peters, E. E. (1991), *Chaos and Order in Capital Markets*, (New York: Wiley).

Phillips, P.C.B. (1987), "Time Series Regression with a Unit Root," *Econometrica*, 55 (2), 277-301.

Savit, R. (1998), "When Random is not Random: An Introduction to Chaos in Market Prices," *Journal of Futures Markets*, 8, 271-89.

Savit, R. (1989), "Non-linearities and Chaotic Effects in Option Prices, *Journal of Futures Markets*, 9, 507-518.

Scheicher, M. (1999), "Non-linear Dynamics: Evidence for a Small Stock Exchange," *Empirical Economics*, 24 (1), 45-59.

Scheinkman, J, LeBaron, B., 1989, "Non-linear Dynamics and Stock Returns," *Journal of Business*, 62 (3), 311-37.

Schwert, G.W. (1989), "Why Does Stock Volatility Change Over Time?" *Journal of Finance*, 44 (5), 1115-54.

Smirlock, M. and Starks, L. (1984), "A Transactions Approach to Testing Information Arrival Models," Working Paper, Washington University.

Smirlock, M. and Starks, L. (1988), "An Empirical Analysis of the Stock Price-Voolume Relationship, *Journal of Financial Research*, 8, 31-41.

Tauchen, G. et al (1996), "Volume, Volatility, and Leverage: A Dynamic Analysis," *Journal of Econometrics*, 74 (1), 177-208.

Terasvirta, T. (1998), "Modelling Economic Relationships with Smooth Transition Regressions," in *Handbook of Applied Economic Statistics*, ed. A. Ullah and D. E. A. Giles, pp. 507-552, (New York: Marcel Dekker).

Terasvirta, T. (1994), "Specification, Estimation and Evaluation of Smooth Transition Autoregressive Models," *Journal of the American Statistical Association*, 89 (425), 208–218.

Terasvirta, T., Anderson, H.M. (1992), "Characterising non-linearities in business cycles using smooth transition autoregressive models," *Journal of Applied Econometrics*, 7, 119-39.

Wang, G. and Yau, J. (2000), "Trading Volume, Bid-Ask Spread, and Price Volatility in Futures Markets," *The Journal of Futures Markets*, 20 (10), 943-70.