The Day of The Week Effect in the Colombia Stock Exchange

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ABSTRACT

This study investigates the existence of day of the week effects on stock returns in the Colombian Stock Exchange (CSE) for the period between June 2001 and March 2005. The Bogotá Stock Exchange was established in 1928. However, the two other main bourses in the country merged with this in 2001 to create the CSE. Since then, the CSE is becoming a good diversification alternative for both domestic and foreign investors.

The modelling in the study begins with linear regression analyses, but the data generating process is shown to be non-linear. A non-linear GARCH model is then applied, achieving a good explanation for the modelled rates of return. Results obtained indicate the significant presence of day of the week effects in both returns and volatility. The maximum return is on Friday whereas the minimum is on Tuesday, with return variances at their highest on Monday.

CHAPTER 1.

INTRODUCTION

Calendar anomalies in stock market returns have been of considerable interest during the last three decades. The main anomalies can be listed briefly as the weekend effect, the day of the week effect, and the January effect.

In several empirical studies concentrating on daily stock returns, the distributions of stock returns are assumed to be identical for all weekdays. However, numerous studies document that this assumption is not correct. French (1980), Gibbons and Hess (1981), Kein and Stambaugh (1984), Lakonishok and Levi (1982), and Rogalski (1984) demonstrate that the distribution of stock returns varies according to the day of the week.

Sullivan et al. (2001) focus their attention on the case where among the social sciences, economics predominantly studies non-experimental data and thus does not have the advantage of being able to test hypothesis independently of the data that gave rise to them in the first instance. Therefore, they criticize the fact that none of the calendar effects were preceded by a theoretical model predicting their existence.

The findings of some studies have shown that the average return for Monday is significantly negative for countries like the United States, the United Kingdom, and Canada. On the other hand for several Pacific rim countries, the lowest rate of return tends to occur on Tuesday (Jaffe and Westerfield, 1985; Dobois and Louvet 1996).The day of the week effect has been explained by examining various kinds of measurement errors: the delay between trading and settlement in stocks and in clearing checks; specialist related biases; the distinction between trading and non-trading periods; the timing of corporate and government news releases; and time zone differences between relevant countries and markets. These are some of the possible explanations, but so far none of the suggested explanations is entirely adequate.

These day of the week findings appear to conflict with the Efficient Market Hypothesis since they imply that investors could develop a trading strategy to benefit from these seasonal regularities. In other words, any predictable pattern in stock returns and variances may provide investors with received returns different from the stock market average.

However, Berument and Kiymaz (2003) argue that for a rational financial decision market, returns constitute only one part of the decision-making process. Another part that must be taken into account when one makes investment decisions is the risk or volatility of returns. A formal test on the variations of volatility across days of the week is useful because that enables us to see whether the higher return on a particular day is just a reward for higher risk on that day.

The purpose of this study is analyze the day of the week effect in stock market returns and volatility by examining the Colombian Stock Exchange (CSE) index during the period of June 2001 and March 2005. In the emerging markets, with their unstable characteristics and relative few researches in this area, this study can be considered as one of the pioneering studies for CSE that examines data for the existence of a day of the week effect.

There exist two types of analysis for calendar anomalies. On the one hand, the most common is the study of the presence of the day of the week effect in stock market returns. Most of the studies investigating the day of the week effect in returns employ the standard OLS methodology by regressing returns on five daily dummy variables. On the other hand, GARCH (Generalized Autoregressive Conditional Heteroskedasticity) models are used for the time series behaviour of stock prices in terms of volatility. They take into account the possibility that the variance is time dependent: a feature that is common in stock return series and in financial time series in general.

Furthermore, the CSE will be modeled with linear and non-linear models in order to capture any possibility of non–linear structure in the data generating process. Accurate results will suggest the possibility of a trading strategy in order to take advantage of the market inefficiency, buying and selling strategies formulated accordingly to increase returns due to better timing. (For example, buy on Tuesday, sell on Friday).

Initially, the rate of return is tested for market efficiency. As the tests applied for efficiency show a departure from the random walk hypothesis, if efficiency is not achieved, the sample is further examined in a more general linear model to look for the presence of anomalies in the CSE returns. The usual linear regression method error assumptions on daily stock returns are violated and the Brock, Dechert and Scheinkman (1987) BDS test indicates that this model is inadequate in explaining rates of return. Therefore, GARCH models are fitted and tested; insignificant BDS statistics prove that these non-linear models explain all the structure in the CSE returns data.

Empirical findings show that the day of the week effect is interrupted by a structural change in the CSE on May 13th 2004, the day that the CSE had the largest fall in the last 5 years. So the data should be split and analysed in two sub-groups to achieve accurate results. The day of the week effect is presented in both the return and the volatility. While the highest and lowest returns are observed on Friday and Tuesday, the highest and the lowest volatilities are observed on Monday and Tuesday, respectively.

The dissertation is organized as follows: Chapter 2 presents the literature review; Chapter 3 describes the CSE; Chapter 4 introduces the data and methodology used; Chapter 5 presents and discusses the empirical results and, finally, Chapter 6 gives a summary of the findings of the study and offers some conclusions.

CHAPTER 2.

LITERATURE REVIEW

The Efficient Market Hypothesis (EMH) originated in the random walk theory that emerged in the security price literature in the 1950's. It states that the size and direction of a price change at a particular time is random with respect to the knowledge available at that point of time; future prices of a security are no more predictable than a series of random numbers. Therefore, Markiel (2003) argues that the logic of the random walk idea is that if the flow of information is immediately reflected in stock prices, then tomorrow's price change will reflect only tomorrow's news and will be independent of the price changes today. But news is by definition unpredictable and therefore resulting price changes must be unpredictable and random.

A number of researchers have found different and strange performance of the market in relation to the day of the week, public holidays, change of month, and even for the hour of the day; all of these peculiarities are known as "Calendar Anomalies".

French (1980) originally discussed two hypotheses. Firstly, the **calendar time hypothesis** suggests that the average Monday return (the day following the weekend) should be 3 times the average returns that occur on other days of the week. In contrast, **the trading time hypothesis** postulates that the Monday returns should not be significantly different from the return available on any other day of the week. He observed that stock returns are higher than average on the last trading day of the week and lower than average on the first, in the Standard and Poor's index over the 25 years from 1953 to 1977.

Many researchers have attempted to explain what has come to be known as the "weekend" or "day-of-the-week" effect. Contrary with French's findings, Rogalski (1984) discovers that all the average negative returns from Friday close to Monday close documented in the literature for stock market indexes occurs during the non-trading period from Friday close to Monday open. He calls these Monday effects, the non-trading weekend effect. His evidence also suggests a January effect; which was found by segmenting the day of the week returns into January's versus the rest of the year. It reveals that the Monday effect and the non-trading effects are on average positive in January and on average negative for the rest of the year. Finally, a relation between the Monday/January effect and firm size was found, where the close to close returns of small firms on Monday in January are on average positive (and greater than the corresponding positive returns of large firms), rather than the rest of the year where small and large firms have negative returns. However, a relation between Monday and firm size is not at all evident.

Furthermore, in response to previous results, Lakonishok and Levi (1982) presented an explanation based on the delay between trading and settlements in stocks, and in clearing checks. Basically, they propose an explanation to measure daily returns, that should depend on the day of the week and that adjustment for interest gains on certain days over adjacent business days that should be made. In the 1980´s, the United States settlement on traded stocks took place five business days after trading, nowadays it takes just three business days. Checks that clear via the United States Federal Reserve System take one business day from the time they are delivered to the commercial banks, to the time that usable funds are debited and credited. Normally, the in-clearing delay means that in weeks without a holiday, stocks purchased on business days other than Friday give the buyer eight calendar days before losing funds for stock purchases. These eight days are the five business days for settlement, the two weekend days, and the check clearing day. However, when the trade is taken on Friday the purchase will not actually occur until the second following Monday, ten calendar days after the trade. Consequently, it is important to understand the position of the buyer and seller of stocks; buyers should therefore be prepared to pay more on a Friday than on other days by the amount of two days interest. The sellers of stocks should also require a higher price for stocks sold on a Friday because of the two days extra delay before being paid.

Finally, the results pointed out that over earlier periods, unadjusted returns on Mondays are significantly negative, and returns on Fridays are positive; these findings are similar to those of previous studies. Further results found that taking into account interest earned during weekends and holidays, a calendar time is relevant for interest bearing securities and therefore also for the alternative of holding stocks.

Keim and Stambaugh (1984), for example, provide evidence of a double the length of the period examined by French (1980). The returns for one-day weekends (Saturday to Monday close) computed from historic New York Stock Exchange (NYSE)[1] data are more negative than returns for (the current) two-day weekends. They also investigate the possible relation between the weekend effect and firm size, and find that the smaller the firm the greater is the tendency for average returns to be high on Friday.

Connolly (1989) was concerned about the foundation of econometric models for the Day of the week effect. He cast doubt on the statistical significance of the day-of-the-week effect per se by showing that appropriate adjustments for sample size, heteroscedasticity, autocorrelation, and leptokurtosis greatly reduce the significance of regression F and t-values. Thus, in this model the error distribution may be conditionally heteroscedastic and non-normal.

[1] During much of the 25-year period from 1928 through 1952, the NYSE was open on Saturdays.

According to Connolly (1989) this is useful because the unconditional leptokurtosis may be traced to non-normality in the conditional error distribution and to time varying heteroscedasticity.

Hence, the evidence for a weekend anomaly is clearly dependent on the estimation method and the sample period. However, he shows that when transactions costs are taken into account, the probability that arbitrage profits are available from weekend-oriented trading strategies seems very small. Moreover, Chang et al. (1993), extend Connolly´s work by examining the robustness of the day-of-the-week effect in international markets, and emphasizes in the violation of the error terms in the OLS model, whereas the day-of-the-week effect has largely disappeared within most countries.

Nevertheless, compared to studies of the US market, few studies have been carried out on the day-of-the-week anomaly for non-US markets. There are some for Japanese stocks and some on major European markets. Solnik & Bousquet (1990) analyse the Paris Bourse, which exhibits a day-of-the week effect with a strong and persistent negative return on Tuesdays. Dobois and Louvet (1996) examine the day-of-the–week effect for eleven stock indices from nine countries; Canada, United States, Japan, Hong Kong, Australia, Germany, France, United Kingdom and Switzerland, during the 1969 – 1992 period. The standard methodology is the moving average. They found negative returns on Tuesdays for the Australian (1980-1992) and Japanese (1969 – 1988) indices. Non-synchronous trading may be an explanation for the one-day lag. However, some correlation analysis was made among daily returns with a one-day lag between Western and Eastern countries, where the correlation between Monday returns in the US market and Tuesday returns in the Japanese market is higher than other days of the week.

In contrast, in Australia, there is a 14 hours difference between Sydney and New York and that the Australian Stock Exchange opens 3 and half hours on Tuesdays after U.S. markets close on Mondays. Therefore, one could conjecture that the U.S. negative Monday returns potentially cause the negative Tuesday returns in Australia as the average negative performances of the U.S.

markets on Mondays have immediate impact on the subsequent performance of the Australian market on Tuesdays, but studies conclude that the day-of-the-week effect in Australia is independent from the U.S. seasonal.

Oguzsoy and Guven (2003) investigate the existence of a day-of-the-week effect in the Istanbul Stock exchange (ISE) for the years 1988 and 1999. They observe that for most of the stocks among the 30 most heavily traded stocks of ISE, the maximum return is on Friday whereas the minimum return is either on Mondays or Tuesdays with return variances at their highest on Mondays.

Finally, Kiymaz and Berument (2003) include an analysis of a day-of-the-week effect in the volatility of the major stock markets indices of Canada, Germany, Japan, the United Kingdom, and the United States for the period of 1988 - 2002. They employ a GARCH model in order to capture the conditional heteroscedasticity and the day of the week effects.

In the financial field, the existence of a day-of-the-week effect seems to be a wide spread and well accepted phenomenon. However, there is a question remaining about the real possibility of enjoying abnormal returns, given the fact that there is nothing that guarantees the permanence of these anomalies in the future. Markiel (2003) argues that the anomalies are not dependable from period to period. Even more, it is well-known that Wall Street traders make a joke that the “January effect” is more likely to occur on the previous Thanksgiving. Moreover, these non-random effects are very small relative to the transactions costs involved in trying to exploit them.

2.1. UNCERTAINTY ASSOCIATED WITH THE FUTURE: THE ARCH MODEL

In the first part of the literature review, the day of the week in stock market returns was the subject of concern. However, there is a second issue, which has also been investigated, the time series behaviour of stock prices when volatility is time-varying. This has been investigated by employing a range of variants of the ARCH (Autoregressive, Conditional Heteroscedasticity) or GARCH (generalised ARCH) class of models. It is important to ascertain whether the higher return on a particular weekday is just a reward for higher risk on that day.

French et al. (1987) were also concerned with statistical approaches to investigate the relation between expected stock returns and volatility. They used daily returns to compute estimates of monthly volatility and reported that unexpected stock market returns are negatively related to the unexpected changes in volatility. It has been recognized for quite some time that uncertainty of speculative prices, as measured by the variances and covariances, are changing through time. One of the most prominent tools that has emerged for characterizing such changing variance is the ARCH model of Engle (1982). The importance of this model is that it enables one to quantify the variations in volatility across days of the week. As stated above, this is of interest because it is important to know if the higher return on a particular weekday is just a reward for higher risk on that day.

Since the introduction of the ARCH model, several hundred research papers applying this modelling strategy to financial time series data have already appeared. Engle (1982) proposes the following, ARCH(1), model to represent a series with changing volatility.

$$\begin{aligned} r_t &= \alpha + \varepsilon_t \\ \varepsilon_t &\sim N(0, \sigma_t^2) \end{aligned} \qquad (1) \qquad\qquad \sigma_t^2 = a + b\varepsilon_{t-1}^2 \qquad (2)$$

The assumption in (2) that volatility is a deterministic function of past returns is restrictive. However, the ARCH model is attractive, because the return and variance process are estimated jointly. Hence, it is a traditional econometric model which assumes a constant one-period forecast variance and, in particular, as far as the day-of-the-week is concerned, the variance of returns tends to be higher on days following closures of the market.

The contribution of French and Roll (1986), one of the first papers to use daily unconditional variances, remains significant among the low–order ARCH models for daily index returns presented in French et al (1987). Next, Bollerslev (1986) introduced a generalized autoregressive conditional heteroscedasticity (GARCH) model. This model is capable of capturing the three most important empirical features observed in stock return data: leptokurtosis, skewness and volatility clustering.

$$\sigma_t^2 = a + b\sigma_{t-1}^2 + C_1\varepsilon_{t-1}^2 + C_2\varepsilon_{t-2}^2 \qquad (3)$$

Engle, Lilien and Robins (1987) and Bollerslev, Engle and Wooldridge (1987) propose generalizations of the ARCH model that allow the conditional mean return to be a function of volatility and they refer to these as GARCH–in–mean models. An example is given in (4) and (5) below.

$$(Rm_t - Rf_t) = \alpha + \beta\sigma_t + \varepsilon_t - \theta\varepsilon_{t-1} \qquad (4)$$

$$(Rm_t - Rf_t) = \alpha + \beta\sigma_t^2 + \varepsilon_t - \theta\varepsilon_{t-1} \qquad (5)$$

Where $Rm_t - Rf_t$ is the daily excess holding period return of the S&P composite portfolio, and σ_t^2, the variance of the unexpected excess holding period return ε_t, follows the process in (3) above. The scope of the GARCH class of models is enormous and its fits the data rather better than other specifications for the variance.

Other authors analyse the international market using this methodology. Alexis and Xanthakis (1995), for example, provide evidence for a day-of-the-week effect in the Greek stock market which shows particular characteristics of uncertainty and risk. They test the day-of-the-week effect using a GARCH-M model. The period examined is split in two subgroups, 1985 – 87 and 1988 – 94. Results show different features of stock returns and the presence of a day-of-the-week effect. The first sub-period indicates high positive returns for Monday and negative returns on Tuesday while the second sub-period shows negative returns for Mondays, a reduction in the negative returns on Fridays, and lower returns on Mondays.

Al-Loughani and Chappell (2001) carry out an analysis where the series are highly leptokurtic relative to the normal distribution. This feature is used as a justification for the use of a GARCH model to investigate the presence of a day-of-the-week effect. They also test the independent and identically distributed IID assumptions through the application of the Brock, Dechert and Scheinkman (BDS) . If the residuals are not IID, then there is some structure in the data that have not been explaining. Therefore, through the study this issue will likely analyse.

Overall, results indicate that, during the 1980´s, this type of calendar anomaly was clearly evident in the vast majority of developed markets, but it appears to have faded away somewhat in the 1990´s. However, in the following chapters, the CSE will be analyse including the problems on variance unchanged over time and the possible nonlinear structure on the residuals.
Whereas the CSE is classified as an emerging market. Therefore it is plausible that we may uncover some market inefficiencies that investors could exploit as a trading strategy to benefit from these seasonal regularities.

CHAPTER 3.

THE COLOMBIAN STOCK EXCHANGE

The Colombian capital market and, in particular, the Bogotá Stock Exchange, were founded some 75 years ago in 1928. This coincides with the time that the industrialization of Colombia really took off. In the years subsequent to 1928 the Medellin Stock Exchange and the West Stock Exchange were founded and in 2001 all three exchanges were merged to create the Colombian Stock Exchange (CSE).

Generally, in industrialized countries, the returns from investment on the national stock exchange – and on other developed world stock exchanges - results in a valuable flow of income to investors. However, in Colombia, this has not always happened. Colombia, in recent years, has been dogged by criminality (often related to drug dealing) and political crises. For example, during the Samper Government (1994 – 1998) there was a political crisis generated by rumors of the presidential campaign being partly funded by the results of drug dealing. The last President (Pastrana, 1998 - 2002) was held to be at least partly responsible for an economic recession and widespread political violence in Colombia.

However, last year Colombia's economy expanded more than expected in the fourth quarter as a reduction in kidnappings and murders bolstered consumer confidence, helping fuel a surge in retail sales. The Gross Domestic Product, the broadest measure of a country's output of goods and services, grew by 4.28% over the year, up from 2.46% in the previous quarter. Furthermore, the improvements in national security, the low levels of FED rates and the revaluation of the Colombian peso against the dollar, helped to boost the domestic economy.

With the weak dollar policy by the U.S. in the short and medium term, with the local consolidation of the external sector, the environment was propitious for the peso-to-dollar exchange rate to continue appreciating during 2005. In fact, after one month and a half of the Central Bank's announced measure of intervening directly in the foreign exchange market (through buying up to US$1 billion), and during this period the FX rate had managed to remain relatively steady above COP$2,550 at the end of 2004, the local-currency appreciation trend managed to intensify in such a way that rapidly the Colombian peso strengthened to reach levels of COP$2,350 per dollar towards the end of the month of March 2005.

Also, this strengthening of the economy has continued. In addition to a generalized rise in investor appetite for emerging market assets and rising remittances from Colombians living abroad, the weakening of the US$ in international markets has served to bolster the Colombian currency, thereby establishing a steady foreign capital inflow and increasing private sector investment in both foreign and national markets.

In the international scenario, the economic situation in the U.S. played the starring role, given that appreciation in world currencies against the dollar intensified in November 2004. In the meantime, economic authorities of the U.S. (Secretary of Treasury John Snow and President of the Federal Reserve Alan Greenspan) reiterated that the closing of imbalances in the current and fiscal accounts of the largest economy in the world would necessarily have to go through further weakness in the U.S. currency.

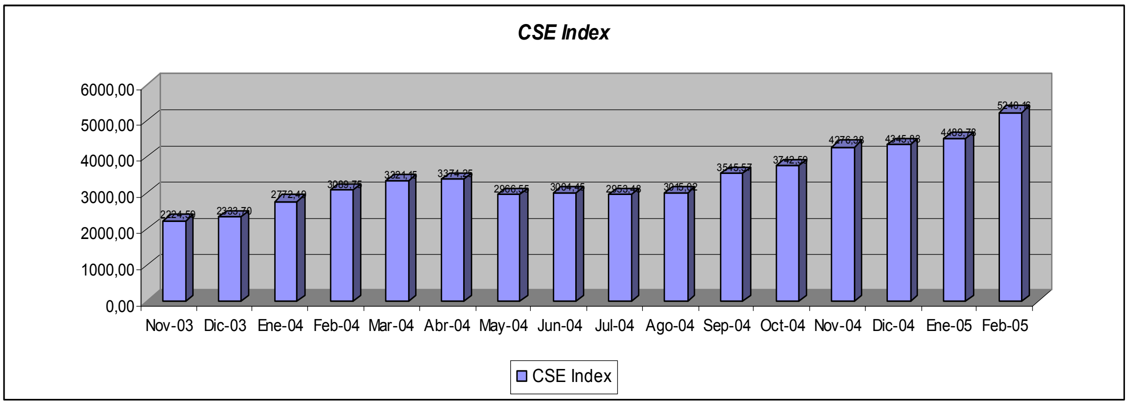
Simultaneously, the debate on the need for flexibility in China's foreign exchange system regained strength, precisely with the purpose of allowing for a correction, without major traumatisms, of the macroeconomic imbalances in the

U.S. Separately, it should be noted that the FED increased its reference rate for a fourth consecutive time. In fact, with the new 25-bp(basic points) hike on November 10, the accumulated increase in the year to date completed 100 bps, rising from 1.0% in June to 2.0% in November.

In response to the weak dollar policy and the decline in oil prices (which, after reaching historic highs in October), and considering the solid economic results of important emerging economies like the Brazilian increased capital inflows to the region, and country risk reached minimum levels during November.

In the case of Colombia, the spread over U.S. Treasury bonds narrowed to 331 bps, while at the same time local currencies and markets strengthened. In 2004, the CSE was the best investment opportunity in Colombia, experiencing a sharp increase in both value and size. In this context, the Index exhibited several historically high values. In January it started at 2335.98 units and increased to 4300 by the end of the year, an increase of 84%. The daily average in November was COP$342 billions per day. The total value in 2004 was around COP$4.77 billions, a massive increase from the COP$1.89 billions in 2003. These figures go a long way towards explaining why prestigious international agencies, such as Bloomberg and The Economist, chose the CSE as one of the best performers for stock exchange business around the world; helped also by the healthy economy and stable political scenario. The performance of the CSE over the period November 2003 to February 2005 is illustrated in the chart below.

GRAPH 1. CSE FROM NOVEMBER 2003 TO FEBRUARY 2005



Source: BVC

However, despite the relatively long stock exchange tradition in Colombia, the liquidity and the operations volume is not particularly high. This is due to high concentration and a modest stock-exchange culture in the country. There are 40 registered brokerage houses and 124 stocks traded, consisting of just those few those that are traded on a daily basis. But the trading volume has been strongly increasing over the last years, surging to a daily average of COP$7 million in 2004, up from about COP$500,000 the previous year. Some of the biggest increases in the index are connected to Grupo Empresarial Antioqueño such as Bancolombia, SurAmericana, Nacional de Chocolates, Cementos Argos, etc.

However, the players who have been most actively contributing to this growth are private citizens. Around 36% of the investors are private individuals, second are the pension funds with 20% of total participation, then the corporate sector with 17%, the mutual funds with 13% and the rest 14% is controls for foreign investors.

In contrast with the above, in the same year, on May 13, the CSE suffered the largest daily fall, of 6.17%, in the exchange's history. The accumulated loss of the previous two weeks (beginning April 27) in the CSE index was 21.5%. It was a taste of what can happen within two years, a vision of (as it has been described in Colombia) the end of the speculative surge. This will be a central issue in our data analysis, and it may prove to be a significant breakpoint that could indicate a structural change in the behavior of the CSE before and after the stock crisis.

Analysts attributed the May 13 drop in the stock index to the rumors of an interest rate increase in the US. This is undoubtedly a key factor in triggering the bursting of the bubble. Capital flies fast and massively. May 13 made it possible to see a little of what could happen: no one will want to buy more treasury bills (Titulos de Tesoreria or TES), they will just want out of the Colombian market. The crisis is illustrated by the figures in the following table.

TABLE 1. LARGEST FALL ON THE CSE

CSE Index 2004		
	Index	Var.%
May-05	3.343,46	
May-06	3.276,94	-1,99%
May-07	3.201,84	-2,29%
May-10	3.054,82	-4,59%
May-11	2.996,92	-1,90%
May-12	2.897,90	-3,30%
May-13	2.718,97	-6,17%

Source: BVC

Nevertheless, the nervousness in the CSE was stabilized the following day, and the index increased by 7%. During the rest of the year the index showed a clear recovery, closing at the end of December with wealthy, satisfied investors, who once again have faith in the Colombian Stock Market.

In conclusion, Colombia has moved forward on a number of fronts in its efforts to spur the growth of its securities market. There is currently a conducive environment for market development, which is in turn the result of:

1. A stable macroeconomic environment
2. Consolidation of a substantial base of institutional investors — and with it, a higher demand for capital market instruments

3. Implementation of numerous reforms aimed at establishing an appropriate regulatory and institutional framework, and
4. The launching of several initiatives aimed at creating an appropriate infrastructure to adequately support the market dynamics.

In addition, the Securities Commission is aiming to improve transparency standards through an accounting reform geared towards the adoption of international accounting and auditing standards. All of these features bode well for the future of the CSE.

CHAPTER 4.

DATA AND METHODOLOGY

4.1. DATA

The data utilized in this study was formally requested from and supplied by the CSE. It runs from 3 July 2001 (the day that the three regional Stock Exchanges in Colombia merged to form the CSE), to 16 March 2005. The CSE is open from Monday to Friday, and the data covers 906 trading days (after excluding the huge number of bank holidays and national holidays when the CSE is closed). The Daily rates of return for the CSE are expressed in local currency, Colombian Pesos (COP). Throughout the study all statistics are calculated and equations estimated using E-views 4.0 software.

The daily returns are the first differences of the natural logarithms daily closing prices of the CSE index and are defined by:

$$R_t = \ln (X_t / X_{t-1})$$

Where X_t and X_{t-1} are the daily closing prices of the index at time t and time t-1 respectively.

However, it is important to mention a well-known economic data problem that is related to the presence of calendar effects; the data mining or data-driving problem. Sullivan et al (2001) draw attention to the danger of data mining. It is the disadvantage of being able to test hypotheses independently of the data that gave rise to them in the first instance. Therefore, in general practice, the use of the same data set to formulate and test hypotheses introduces data-mining biases. They also argue that none of the calendar effects were preceded by a theoretical model predicting their existence. Conversely, when the observational evidence supports a theory the confirmation is much stronger when the evidence is new.

Some descriptive statistics for the data can be seen in table 2. It shows the minimum return which corresponded at the fall on 13th may, 2004, a maximum return that corresponded, the 28th December, 2001. Moreover, the series is leptokurtic: i.e. they all have distributions with high kurtosis. 'High' is usually taken to mean that the fourth central moment is greater than 3, the coefficient of kurtosis for any normal distribution. The shape of such a distribution is typified by a high degree of 'pointedness' and fat tails compared to a normal distribution.

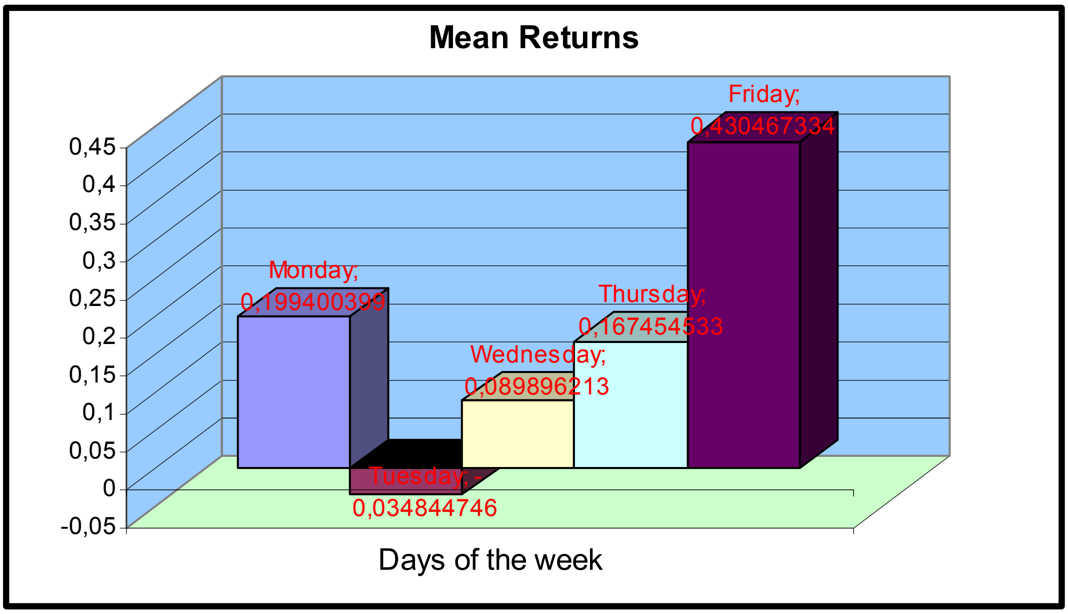
Table 2.

Summary Statistics for Daily Returns from July 2001 to March 2005	
Sample Period	July 3, 2001 to March 16 ,2005
Observations	906
Mean Return	0,1695
Median Return	0,1499
Maximun Return	8,8981
Minimun Return	-6,3733
Standard Deviation	1,1941
Skewness	0,4273
Kurtosis	11,6227

According to Adcock C, J (2000, p.18)[2] fat tails are of particular interest in finance because the presence of fat tails means, inevitably, that there is a high probability of extreme returns, leading to larger profits or losses, than what would be expected with a normal distribution.

If asset returns are normally distributed, then there is an exact linear regression relationship between the observed return on an individual asset and the observed return on the market. If returns are not normal then it is not always clear that these linear regression type relationships hold and, if they do hold, they may require modification and/or different procedures for estimation of model coefficients.

GRAPH 2. MEAN RETURN FOR THE CSE



Graph 2 also illustrates the mean stock return for each working day of the week. Mean returns for Mondays are positive (0.1994), contrary to several previous studies; i.e. Osborne (1962), Cross (1973), French (1980), Gibbons & Hess (1981), Keim & Stambaugh (1984), Jaffe & Westerfield (1985) all find strong evidence that Mondays' average returns are negative and Fridays' are positive.

However, in some other studies such Solnik & Bousqet (1990) in the French Market , Dobois & Louvet (1996) in the stock markets of Japan and Australia, and Jaffe & Westerfield (1985) in the stock markets of Australia and Japan. In the CSE, the negative average return is observed to occur on Tuesdays with a mean of –0.03484. Some authors have justified this observed behavior by the

[2] Adcock, Christopher J, "Fat tails and the capital asset pricing model" from Dunis, Christian, ed. Advances in quantitative asset management. Kluwer Academic, 2000. Chapter 2, p.17-39.

time difference ahead to New York. However, Jaffe & Westerfield (1985) tested the hypothesis and it was rejected. Nevertheless, for the CSE, the time difference with the NYSE is small; hence there is no justification to formally test a correlation between those stock exchanges.

Moreover, in Appendix 1, histograms of daily percentage close-to-close returns for each day separately are illustrated. The relative higher dispersion of Tuesday returns can be seen at a glance. The frequency axis is informative for both observing the dispersion on Tuesdays and the dominant positive returns on Fridays.

Table 3. Number of days with more than 0%,1%,2%,3%,4% increase/decrease in returns.

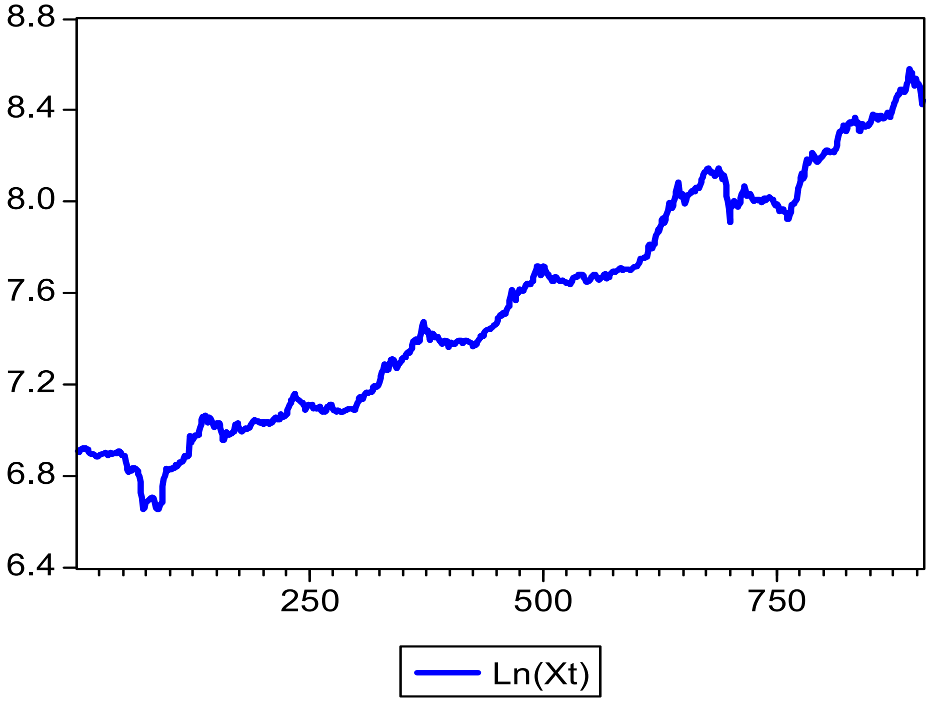
Criteria	Mondays	Tuesdays	Wednesday	Thursdays	Friday	All Days
Rt>0%	93	101	96	114	124	528
Rt>1%	30	29	31	32	38	160
Rt>2%	10	7	7	5	10	39
Rt>3%	4	0	1	2	3	10
Rt>4%	0	0	1	0	3	4
Rt<0%	64	87	91	72	64	378
Rt<-1%	12	34	23	19	12	100
Rt<-2%	0	13	7	8	3	31
Rt<-3%	2	4	1	3	0	10
Rt<-4%	1	3	0	2	0	6

Table 3 presents the attractive behaviour of the CSE. As can be observed from the table, in 528 (378) of 906 observations the index increased (decreased) between 0% and 1% in a day, and 160 (100) days it increased (decreased) more than 1% in a day. Friday is the day with the highest number of positive jumps and Tuesday with negative ones.

4.2. METHODOLOGY

The natural logarithms, ln (X_t), of the closing prices of the CSE index, X_t, for the period 3rd July 2001 to 16th March 2005 are given in Fig. 3 below.

GRAPH 3. FULL PERIOD LN (X_T)



At a first glance the graph shows that ln (X_t) appears to is non-stationary. If the data is non-stationary the mean and variance change over time and the data has to be differenced one or more times to achieve stationarity. However, the formal way to determine whether the series is stationary is by carrying out a unit root test; the Augmented Dickey – Fuller (ADF) test, for example.

If the data are non-stationary, the transformation is the first difference of ln(X_t) is the daily rate of return R_t=ln(X_t/X_{t-1}). This is depicted in Fig. 4 below.

GRAPH 4 .FULL PERIOD R_t

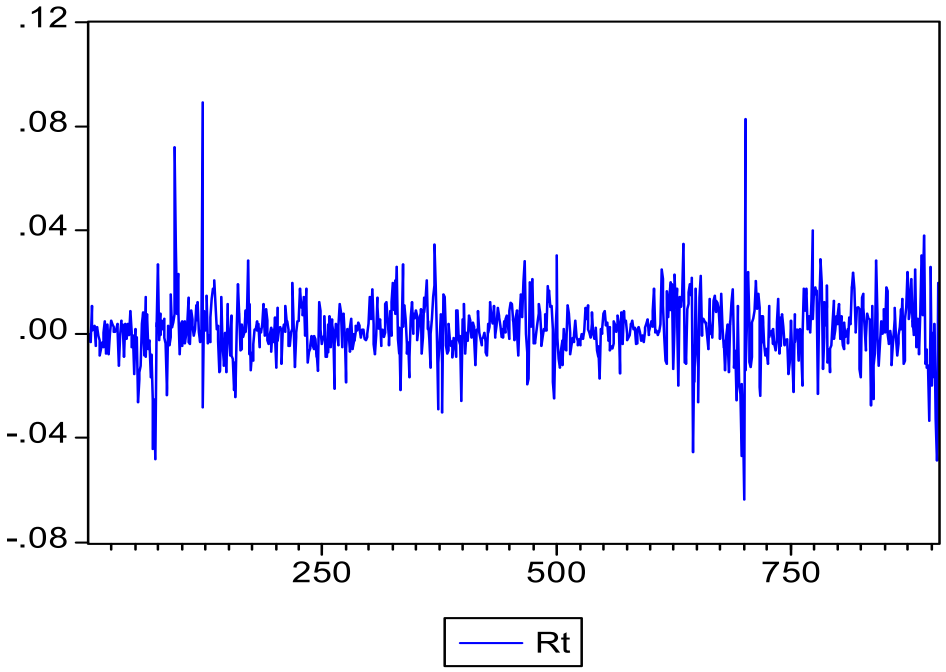


Fig. 4 appears to illustrate a stationary series with the trend around the mean. However, The formal test to check for stationarity is the unit root, (ADF) statistic. Series with a unit root are non-stationary. A first order autoregressive AR(1) process with a unit root is defined as a random walk. In equation 7 below, the X_t are optional exogenous regressors which may contain a constant, or a constant and trend: ρ and δ are parameters to be estimated, and the ε_t are assumed to be white noise. If $|\rho| \geq 1$, R_t is a non-stationary series and the variance of R_t increases with time and approaches infinity. If $|\rho| < 1$, R_t is a stationary series. Thus, the hypothesis of stationarity can be evaluated by testing whether the absolute value of ρ is strictly less than one.

$$R_t = \rho R_{t-1} + X'\delta + \varepsilon_t \qquad (7)$$

Dickey and Fuller (1979) show that under the null hypothesis of a unit root, this statistic does not follow the conventional Student's t-distribution, and they derive asymptotic results and simulate critical values for various test and sample sizes.

The econometrics software package, E-views 4.0, gives the critical values of this test at the 1%, 5% and 10% levels. Note that, when the t-value statistic is *greater than* the critical value, we accept the null at the chosen level of significance.

Furthermore, as we commented earlier on, there is the possibility of a structural change in the CSE on May 13th 2004, the day that the CSE had the largest fall in the last 5 years. This could be tested by carrying out a Chow breakpoint test. The Chow test fits the equation separately for each sub sample and shows whether there are significant differences in the estimated equations, or not.

To carry out the test, we partition the data into two or more sub samples, in our case, pre-fall and post- fall respectively. Each sub sample must contain more observations than the number of coefficients in the equation in order for the equation to be estimated. The Chow breakpoint test compares the sum of squared residuals obtained by fitting a single equation to the entire sample with the sum of squared residuals obtained when separate equations are fit to each sub sample of the data. An F-statistic is used to test the null hypothesis of no structural change. Hence, a significant F-statistic indicates a structural change in the relationship.

4.2.1. Random Walk

The concept of an efficient market was developed in the finance literature by authors such as Fama(1970) who introduced the concept of efficient market hypothesis, which is closely related to the data following a random walk. This hypothesis asserts that movements in daily rates of return will not follow any patterns or trends and that past price movements cannot be used to predict future price movements.

Firstly, in order to test the random walk hypothesis that states that the size and direction of price changes are random with respect to the knowledge available in any point of time, the variables $\ln(X_t)$ and R_t must be examined for the presence of unit roots by calculating ADF statistics. However, as is well documented in the literature, the natural logarithms of stock prices (or index values) may well be expected to follow simple random walks.

If this is the case, the series R_t may be examined further by using ordinary least squares to estimate the equation:

$$R_t = \alpha + \mu_t$$

Under the random walk hypothesis, the constant term should be insignificantly different from zero and the resultant residuals should be IID.

4.2.2. Randomness

The existence of a random walk in a series necessarily excludes the possibility of non–linear structure in the data; if the first difference of the series is stationary, the next step is to examine the series to see if its elements are IID. The BDS test can be utilised here since its null hypothesis is that the data under examination is IID.

The BDS statistic was proposed by Brock, Dechert and Scheinkman(1987) and can be applied to a series of estimated residuals to check whether they are IID. The distribution of the statistic, which is defined by:

$$W_m(\varepsilon)\frac{\sqrt{n}\left\{C_m(\varepsilon)-C_1(\varepsilon)^m\right\}}{\sigma\,(\varepsilon)} \qquad (6)$$

is asymptotically N(0,1) under the null. $W_m(\varepsilon)$ is known as the BDS statistic and $\sigma_m(\varepsilon)$ is an estimate of the standard deviation under the null hypothesis of IID. (Chappell,D(1997)).

The test is carried out using the E-views 4.1 econometric package with embedding dimensions, m, from 2 to 6 and distance, ε, between 0.5 and 2 times the standard deviation of the data. Chappell et all (1998) claim that this range of values is suitable in as much as it avoids the situation where ε is too small and no m-histories are within ε of each other, or too big and so that all m-histories are within a distance ε of each other.

Consequently, if the residuals appear to be non-IID as indicated by the results of the BDS test, then there is a possible inefficiency in the market and this may be our starting point to test for the presence of the a daily calendar anomaly in the CSE.

4.2.3. Univariate time series

The foregoing discussion suggests as a first step a test for whether the variable R_t in either of the sub-series is IID or not. If one, or both, of the series is not IID, we should fit a linear ARMA model to the particular sub-set of the data using the well-known general-to–specific (GTS) methodology to decide the order of the ARMA. The (GTS) methodology was introduced by D.F. Hendry (2001)[3] as "the concept of general-to-specific modelling: starting from a general dynamic statistical model, which captures the essential characteristics of the underlying data set, standard testing procedures are used to reduce its complexity by eliminating statistically insignificant variables, checking the validity of the reductions at every stage to ensure the congruence of the selected model".

The correlogram may be used to obtain an approximation to the number of lags that should be included in the model in order to get a good fit to the data. Hence, the final model after such reductions contain only significant lagged variables and the residuals should be saved and tested for IIDness by means of the BDS test. As discussed above, embedding dimensions m from 2 to 6 and a

[3] H.-M. Krolzig, D.F. Hendry," Computer automation of general-to-specific model selection procedures" Journal of Economic Dynamics and Control, Vol 25, pag. 831-866 (2001)

range of values for ε from 0.5 to 2 times of the standard deviation of the series should be used for the BDS tests. If this model does not give IID residuals, then we will proceed as follows.

Our next step is to fit the model again, but now also including the four dummy variables for Tuesday to Friday, Monday's return is captured by the constant in the regression. Firstly, however, a simpler methodology, as summarised in the following equation, is commonly used for testing for a day-of-the-week effect. This model is as follows.

$$R_t = c + \beta_2 D_2 + \beta_3 D_3 + \beta_4 D_4 + \beta_5 D_5 + \mu_t$$

The regression is run to test for differences among returns on the trading days, where the four *D*'s are dummy variables (one for each weekday from Tuesday to Friday) that take the value of 1 for the corresponding day-of-the-week and zero otherwise e.g. D_2=1 if it is Tuesday and 0 if not; and μ_t is the zero mean stochastic disturbance term. β_1 captures the mean return for Monday and β_2, β_3, β_4 and β_5 are parameters used to estimated means returns for Tuesday to Friday respectively. If the day-of-the-week effect is to exist, at least two of these coefficients must be statistically significant and different from one another.

Under the null hypothesis of no day-of-the-week effect; $\beta_2 = \beta_3 = \beta_4 = \beta_5 = 0$, residuals should be IID random variables. This will be tested for in the empirical results with standard Ordinary Least Squared (OLS) and using the ANOVA process to test the significance and equality of mean returns. However, the daily stock returns are very likely to violate conventional assumptions about the OLS error terms. Chang et al. (1993), focussed their attention on the weakness of this method to estimated day-of-the-week effects, hence the statistics should be calculated under the assumption that regression errors are homoskedastic, serially uncorrelated and normally distributed. Thereby, they demonstrate - as in Connolly´s contributions - (1989), (1990) for the United States market, that in foreign markets the usual daily stock returns error assumptions are violated.

If the results from this model indicate that the residuals are still not IID, then the previous ARMA model including the (GTS) methodology should be repeated, but should now also include the four dummy variables for Tuesday to Friday. When the GTS methodology gives a reduced model in which each of the remaining variables is statistically significant, the residuals should be saved and test for IIDness by again using BDS statistics.

If the BDS statistics are still significant, it is appropriate at this stage to fit a non-linear model. However, in order to fit an appropriate non-linear model, it should be noted that there are various different models that may well explain the expected non-linearity of the data generating process: Examples include Threshold auto regression models (TAR), generalised autoregressive conditional Heteroscedasticity (GARCH) models and the Smooth transition autoregressive models.

Kiymaz and Berument (2003) identify some problems in the standard OLS approach. Firstly, the model could have misleading inferences resulting from autocorrelations. When autocorrelation of any order is found, the OLS estimates are unbiased but they are inefficient and we cannot rely on the standard errors because they are not correctly estimated. Nevertheless, they propose a solution that addresses the autocorrelation problem: include lagged values of the return variable in the equation. Secondly, there is a problem when the error variances may not be constant over time; this is known as heteroscedasticity. The direct consequences are on the variability of the errors, which may depend on the size of (one of) the exogenous variables and the standard errors of the OLS estimates will be biased downwards. The estimator is not efficient; one estimator is defined to be more efficient than another if it has lower variance. Gujarati (2003) argues that heteroscedasticity may well be a problem where important explanatory variables are omitted from the model.

If the null Hypothesis of no ARCH effects in residuals is rejected, standard OLS estimates are not invalidated, but it may well be the case that more efficient estimators exist. In spite of that, If the null hypothesis of IID cannot be accepted in the previous ARMA model, the implications is that the residuals may well contain some non-linear structure.

Chappell and Padmore (1995) have drawn attention to the fact that there is strong evidence for the presence of conditional heteroscedasticity in exchange rate innovations. However, there are several different types of model for conditional variances suggested in the literature review. See, for example, Engle (1982), Bollerslev (1986), Engle, Lilien and Robins (1987) and Bollerslev, Engle and Wooldridge (1987).

The importance of such models in the investigation of a day-of-the-week effect is in the conditional variance of the CSE returns. Such models are also capable of capturing the three most empirical features observed in stock returns data: leptokurtosis, skewness and volatility clustering. Also, according to Connolly (1989), the problem created by the fat tailed distributions described above, is that test statistics based on non-robust standard error estimates cannot be interpreted in the usual way. The GARCH class of models are capable of dealing with non-normal error terms and make the interpretation of the t-statistics more robust.

The GARCH (p,q) model that is applied to the study of the day-of-the-week effect on the CSE returns and volatility is as follows:

$$R_t = \beta_1 + \beta_2 D_{2t} + \beta_3 D_{3t} + \beta_4 D_{4t} + \beta_5 D_{5t} + \varepsilon_t$$

$$\varepsilon_t / \Psi_{t-1} \sim t.d.(0, h_t, v) \qquad (8)$$

$$h_t = c + \gamma_2 D_{2t} + \gamma_3 D_{3t} + \gamma_4 D_{4t} + \gamma_5 D_{5t} + \sum_{j=1}^{p} \delta_j h_{t-j} + \sum_{j=1}^{\alpha} \alpha_j \varepsilon_{t-j}^2$$

Where R_t is the stock return considered to be linearly related to a vector of explanatory dummy variables (D_t) and an error term (ε_t) which depends on past information (Ψ_{t-1}); h_t is the conditional variance. The error terms are assumed to follow a conditional student-t density (t.d.) with v degrees of freedom. The t-distribution approaches a normal distribution with variance *(h_t)* as 1/*v* approaches zero. Choudhry (2000) comments that the error distribution may well be conditionally heteroscedastic and non-normal. Furthermore, Connolly (1989) finds that this feature very useful because the unconditional leptokurtosis may be traced to non-normality in the conditional error distribution and to time varying heteroscedasticity.

The coefficients β_1 to β_5 in equations (8) represent the size and the direction of the effect of each working day of the week on stock returns. Similarly, coefficients γ_1 to γ_2 represent the size and direction of the day-of-the-week effect on volatility. Some of the previous studies have found that the coefficient on the Monday dummy (β_1) should be negative and significantly different from zero, and the coefficient on the Friday dummy (β_5) should be positive. In contrast, the volatility coefficient for the Monday dummy (γ_1) is positive but the Friday effect (γ_5) is negative.

If the standardised residuals from this model are still not IID, our methodology suggests that the GARCH model should be fitted again ***using all the lags in R_t and the dummy variables*** and again following the (GTS) methodology. One hopes that this model will result in a good fit with all the coefficients in the mean and variance equations statistically significant. The standardised residual series should be saved and BDS tests then carried out to check for any remaining unexplained structure. The standardized residuals should become more and more conservative, while the size distortion correction provided by the transformation on the residuals improves and there is no clear dominant measure of effective sample size. Thus, if these residuals turn out to be IID, then this final model will be used to derive the equations for the day-of-week effect.

CHAPTER 5.

EMPIRICAL RESULTS

Table 4 reports the preliminary statistics for returns for each day of the week on the CSE. The first column of table 4 reports the daily mean, standard deviation, Skewness, and kurtosis. The second through sixth columns of table 4 show the same measures for each day of the week.

TABLE 4. SUMMARY STATISTICS FOR DAILY CSE RETURNS

Statistics	All Days	Monday	Tuesday	Wednesday	Thursday	Friday
Observations	906	157	188	187	186	188
Mean	0,170	0,199	-0,0348	0,089	0,1773	0,4305
Std. Dev	1,1941	1,127	1,2035	1,067	1,1702	1,3368
Skewness	0,427	-0,182	-1,0051	-0,0046	-1,2727	3,0192
Kurtosis	11,623	5,829	5,8213	4,2774	9,3372	19,5118

The average return for the entire study period is 0,17 percent, the standard deviation is 1,194, and the skewness is 0,427. The kurtosis is 11,623, which is significantly larger than the value of 3 for a normal distribution. The Jarque-Bera normality test rejects normality of returns for each of the five days; see Appendix 1.

When the returns for each day are examined, the findings indicate that Friday has the highest mean return with 0,4305, while Tuesday has the lowest mean return with -0,034. The signs of the findings are in line with some of the day of the week effect literature (Solnik & Bousqet 1990, Dobois & Louvet 1996, Jaffe & Westerfield 1985).

Table 4 also reports standard deviation, skewness, and kurtosis for each day. Friday has the highest standard deviation of 1,3368 and Wednesday has the lowest with 1,067. Moreover, all sample distributions are negatively skewed, indicating that they are non-symmetric. They also exhibit high levels of kurtosis, indicating that these distributions have thicker tails than a normal distribution. Thus, the CSE daily returns are clearly not normally distributed, as indicated by the Jarque - Bera statistics for each of the five days.

The natural logs of the CSE data, $Ln(X_t)$, and the rate of the return (R_t) were plotted in the previous section. However, in order to ascertain the stationarity of these series, ADF tests will be carried out.

The results of the ADF tests for the two series are given in Appendix 2. The null hypothesis that the series $Ln(X_t)$ has a unit root is accepted at the 1% and 5% significance levels but is rejected at the 10% level. For the returns series, R_t, the null hypothesis of a unit root is rejected at all significance levels. Hence, $ln(X_t)$ is a non-stationary, $I(1)$, variable and R_t is stationary, ($I(0)$). So in what follows, this study will analyse the rate of return, R_t.

However, on May 13th 2004 the CSE suffered the largest one-day fall in the last 5 years. The existence of a structural break on that date was tested by carrying out a Chow breakpoint test. The results are given in Table 5 below.

TABLE 5.CHOW TEST FOR A STRUCTURAL CHANGE IN R_T

Chow Breakpoint Test: 702, May 13th 2004			
F-statistic	3.430468	Probability	0.002355
Log likelihood ratio	20.62265	Probability	0.002144

The null hypothesis for the test in Table 5 is that there is ***not*** a structural break. The test result shows quite clearly that we must reject the null and conclude that there was indeed a structural break on May 13th 2004. The consequence of this is the necessary subdivision of the series into two, "pre-fall" and "post-fall", series in order to be able to construct an adequate model for this data.

Following the results of the break-point test, the data was split into two subgroups corresponding to 'before' and 'after' the structural break. ADF tests were carried out on the R_t data for the two sub-groups. The results are given in Appendix 3 and they show quite clearly that Rt is stationary in both sub-periods.

Our investigation proceeds by examining whether the CSE is an efficient market. If the market is efficient, the series $\ln(X_t)$ will follow a random walk and the R_t will be a purely random IID series. This may be tested for by means of BDS statistics. Under the null of IID, BDS statistics are distributed as N(0, 1). Statistics were calculated for each sub-sample for a range of values of M (the embedding dimension) and for critical distances ranging from 0.5 to 2 standard deviations of the data. The results are given in Table 6.

TABLE 6. BDS TESTS FOR R_T

6.1. Pre-fall period -BDS statistics for R_t					
	M				
values	**2**	**3**	**4**	**5**	**6**
0,5	10,4133	12,7906	14,3016	16,9029	20,7837
1	9,8217	11,2709	12,1023	13,5370	14,7856
1,5	9,1697	9,8059	10,1873	10,7891	11,0292
2	8,5956	8,2364	7,9501	8,1540	7,6353

Note: all significant at the 5%

6.2. Post-fall period -BDS statistics for R_t					
	M				
values	**2**	**3**	**4**	**5**	**6**
0,5	5,5952	6,4190	7,1364	8,7359	9,3053
1	4,9453	5,6232	5,7906	6,6529	6,9868
1,5	3,5637	3,4354	3,4054	4,2764	4,6067
2	2,7711	1,5774*	1,1499*	2,1371**	2,6354

Not significant at the 1% level* and 5% level** respectively

The overwhelming evidence for the pre-fall period indicates the R_t are not IID, and it follows that the CSE was not an efficient market during this period. For the post-fall period the evidence is mixed. We accept the null for embedding dimensions 3 & 4 and distance 2 standard deviations at the 5% level and we accept it at the 1% level for **M** = 5 and distance 2 standard deviations. We reject the null for other combinations of embedding dimension and distance. Faced with this evidence we will, on balance, accept the null for the post-fall period and conclude that there is some evidence that the market was efficient during this period. Our attention will now focus exclusively on the pre-fall period.

We proceed by fitting a linear ARMA model using General-to-Specific (GTS) methodology that ultimately gives a reduced model in which each of the remaining variables are statistically significant. We then test the residuals from this model for to ascertain whether they are IID by means of BDS statistics. All these results are given in Appendix 4. Firstly, the correlogram is used to indicate the number of lags that we should include in the model. At a first glance, the graph shows (see appendix 4.1) that just two lags should be included in the model. However, we decided to fit a more general model which, following GTS methodology, results in the ARMA (5,4) given in Appendix 4.2.
Furthermore, the BDS statistics (Appendix 4.3) on the saved residuals show that the residual are still not IID. So our next step is to test for the presence of a daily calendar anomaly in the CSE during the pre-fall period.

The previous ARMA model is now re-estimated with the four dummy variables added. After applying the GTS procedure, the fitted model is ARMA(4, 4). The results are given in Appendix 5.1. The residual are saved and tested for IIDness and the results are given in Appendix 5.2. However, the BDS statistics are still significant, and we again have to conclude that the residuals are not IID and the model still contains some unexplained component. It is now clear that a non-linear model is needed.

Appendices 6 and 7 report the results of tests for heteroscedasticity and ARCH effects in the residuals of the lineal OLS model. It is clear that we must reject the null hypotheses of homoscedastic disturbances and no ARCH effects. So our next step will be to fit a GARCH model with the daily dummies in both the mean equation and the variance equation. However, we will first estimate, for comparison purposes, an OLS model containing just the daily dummies and lagged R_t.

Table 7 below reports on the day of the week effects and stock market volatility during the pre-fall period, using three different models: Standard OLS, GARCH(1,1) and Modified GARCH(1,1) using GTS methodology. The first column reports the results from the OLS estimation.

The results of the OLS estimation show that Tuesday has the lowest return (-0.000814), while Friday has the highest return(0.003552). This result is consistent with the previous finding reported in table 4. We include a lag value of order one on the return variable to the equation to minimise the possibility of having autocorrelated errors. This improved the estimation with a Durbin-Watson statistic closer to 2.

One of the assumptions made up until now is that the errors, u_t in the regression equations have a common variance σ^2. Using the White test allows us to discover whether errors are heteroscedastic. Under the null the errors are homoscedastic. However, in Appendix 6, the null hypothesis is rejected at the 1% level of significance, thus the errors are heteroscedastic. Therefore, a GARCH model is felt to be appropriate.

The second column of Table 7 reports the result of the GARCH(1,1) estimation. In this estimation, we allow the time varying conditional variance to follow a GARCH(1,1) specification and the model also reports the estimates of the dummy terms that are included for each day. The results indicate that the highest return is observed on Friday (0.002035) and the lowest return is on Wednesday (-0.000349). Monday has the second highest rate of return

(0.000931), followed by Thursday (0.000476). Nevertheless, the entire set of coefficients are all statistically insignificant.

Additionally, the lowest volatility is observed on Tuesday (-0.00006.89) and the highest volatility on Monday (0.0000249) after controlling the persistence effect with the lag values of the conditional variance $\sum_{j=1}^{p}\delta_j h_{t-j}$ and the squared lag values of the residual term $\sum_{j=1}^{\alpha}\alpha_j \varepsilon_{t-j}^2$. All the day-of-the-week dummy variables in the conditional variance equation are statistically significant.

TABLE 7. DAY OF THE WEEK EFFECT AND STOCK MARKET VOLATILITY IN THE CSE

		OLS	GARCH(1,1)	GARCH modified
Return Equation	Monday(B_1)	0.000384	0.000931	0.001183**
		(0.001035)	(0.001196)	(0.000414)
	Tuesday(B_2)	-0.000814	-0.001179	-0.001633*
		(0.001394)	(0.001268)	(0.000737)
	Wednesday(B_3)	0.000208	-0.000349	
		(0.001399)	(0.001357)	
	Thursday(B_4)	0.000940	0.000476	
		(0.001402)	(0.001284)	
	Friday(B_5)	0.003552*	0.002035	0.001806*
		(0.001391)	(0.001603)	(0.000993)
	Rt-1	0.248985**	0.326817**	0.311568**
		(0.038073)	(0.036238)	(0.036466)
Volatility Equation	Monday($\gamma 1$)		2.49E-05**	2.34E-05**
			(4.17E-06)	(3.58E-06)
	Tuesday($\gamma 2$)		-6.89E-05**	-4.87E-05**
			(7.83E-06)	(8.55E-06)
	Wednesday($\gamma 3$)		-2.35E-05**	-3.18E-05**
			(8.15E-06)	(6.82E-06)
	Thursday($\gamma 4$)		-3.20E-05**	-2.12E-05**
			(4.61E-07)	(6.47E-06)
	Friday($\gamma 5$)		2.27E-05**	
			(7.39E-06)	
	ARCH(α)		0.118029**	0.108418**
			(0.014467)	(0.013170)
	GARCH(δ)		0.871827**	0.890384**
			(0.013088)	(0.010862)
	Durbin-Watson	1,9281	2,0637	2,03890
	Prob(F-statistic)	0.000000	0.000004	0.000000

Notes: Standard errors are reported under the corresponding estimated coefficients.
** and * indicate the level of significance at the 1 percent and 5 percent level, respectively.

The sum of the coefficients of the GARCH equation without a constant term is less than one, and both of them are positive and statistically significant. Hence, we do not have either negative or explosive implied variances as suggested by Bollerslev(1986) for the specification test. On the other hand, since the summation of these two coefficients is close to one, it indicates that the volatility is persistent. However, this second model does not reach the expectations in terms of the return, the standard error remain almost the same.

The estimation results for the third specification of the model are reported in the third column of Table 7. We apply GTS methodology to the model in column 3. Following with the (GTS) methodology, the insignificant variables are deleted one-by-one, until everything remaining is significant. This third model, which we call Modified GARCH(1,1), also reports the estimates of the five dummy terms that are included for each day.

When the Modified GARCH (1,1) is estimated, Tuesday has the lowest rate of return (-0.001633), and Friday has the highest rate of return (0.001806), both statistically significant at the 5% level. Clearly, using the (GTS) methodology and allowing time varying variance in the estimation process provides more efficient estimates for the return. In contrast, this can be easily observed with the lower standard errors for the estimated parameters of the return equation. In sum, the third model specification increases the efficiency of the estimates compared to the previous models.

The lowest volatility is observed on Tuesday (-0.0000487) and the highest volatility is on Monday (0.0000234), a significant positive effect implies that stock return volatility is increased, although the size of the coefficient (γ_1) is very small. A significant positive influence by Monday on volatilities provides some evidence in favour of the information oriented theories of French and Roll(1986) and Foster and Viswanathan (1990). In the case of Tuesday, a significant negative effect is found. This indicates that volatility is reduced on Tuesdays, in line with some of the findings in Solnik & Bousqet (1990), Dobois & Louvet (1996), and Jaffe & Westerfield (1985).

For all five days with the exception of Friday, dummy variables in the conditional variance equation are statistically significant. Consistent with the second model, GARCH coefficients for these two parameters sum to less than one, but quite close to one as reported in the former model. In addition, they are both positive and statistically significant. Results from the GARCH model, OLS and mean returns based on the day of the week are not identical, but are similar.

In Appendix 7.1, the autocorrelation Q statistics are reported for the OLS specification at 30 and 35-day lags. The coefficients are statistically significant at the 10% level. Nevertheless, in the GARCH models, we cannot reject the null hypothesis that the residuals are uncorrelated. On the other hand, the ARCH-LM test in Appendix 7.2 does not indicate the presence of a significant ARCH effect in any of the GARCH models. These findings indicate that the standardised residual terms have constant variance and do not exhibit autocorrelation.

In the final step, the results provide ample evidence of a day-of-the-week effect in stock market volatility. Table 9 reports the results of applying the BDS test to the standardised residuals in order to determine whether any remaining non-linear structure was present.

TABLE 9.

Pre-fall period -BDS test on GARCH (1,1) standardised residuals					
	M				
values	**2**	**3**	**4**	**5**	6
0,5	2.073702*	2.773529	3.036908	3.622360	3.861715
1	1.802251*	2.622949*	3.093071*	4.101888	4.521770
1,5	0.998249*	1.507987*	1.944140*	2.844155	3.001099
2	0.250216*	0.182273*	0.645599*	1.512018*	1.297233*

Note: *Not significant

Under the null hypothesis there are strong indications that for the pre-fall series all non-linear structure has been removed and the residuals are IID. This result indicates that the Modified GARCH(1,1) model can adequately describe the daily return process of the CSE stock price index in the pre-fall period.

CHAPTER 6.

CONCLUSIONS

The day of the week findings appear to conflict with the Efficient Market Hypothesis. Hence, any predictable pattern in stock returns and variances may provide investors with returns in excess of the stock market average. This study indicates that there is a substantial day-of-the-week effect in the Colombia Stock Exchange between June 2001 and March 2005 based on our statistical analysis of the CSE stock index.

In 2004, the CSE was the best investment opportunity in Colombia, experiencing a sharp increase in both value and size. Moreover, the Index exhibited several historically high values. The total value in 2004 was around COP$4.77 billions, a massive increase from the COP$1.89 billions in 2003.

Empirical findings show that the day-of-the-week effect is interrupted by a structural change in the CSE on May 13th 2004, the day that the CSE had the largest fall in the last 5 years. So the series was split and analysed in two sub-groups to achieve more accurate results. However, we found some evidence that for the post-fall period the market was efficient, whilst the pre-fall was successfully explained by a (non-linear) GARCH model.

Three different models were considered. The first, which assumes the constancy of the residual term's variance, is the standard OLS. However, all sample distributions are negatively skewed, indicating that they are non-symmetric. They also exhibit high levels of kurtosis, indicating that these distributions have thicker tails than a normal distribution. Thus, the CSE daily returns are clearly not normally distributed. The findings based on this model indicate a flawed evidence of the day-of-the-week effect in the return equation with Friday with highest return and unique significant dummy variable. In the second model, a GARCH (1,1), volatility changes over time, and the capability of this model to deal with non-normal error terms makes the interpretation of the t-statistics more robust. The results are similar to those of the first model with most of the coefficients statistically insignificant.

Finally, the third model employed is the modified GARCH(1,1), in which we apply general-to–specific (GTS) methodology, which captures the essential characteristics of the underlying data set but eliminates all statistically insignificant variables one-by-one.

Under the null hypothesis of IID residuals, there are strong indications that for the pre-fall series all non-linear structure has been removed and the residuals are IID. This result indicates that the Modified GARCH(1,1) model can adequately describe the day-of-the-week effect in the CSE stock price index in the pre-fall period.

Tuesday has the lowest rate of return (-0.001633), and Friday has the highest (0.001806), both statistically significant at the 5% level. Clearly, using the (GTS) methodology and allowing time varying variance in the estimation process provides more efficient estimates for the returns compared to the previous models. The findings show that the day-of-the-week effect is present in both the volatility and the mean equations.

Tuesday has the lowest significant day-of-the-week effect for the returns and Friday has the highest. These findings are in line with some of the findings in Solnik & Bousqet (1990), Dobois & Louvet (1996), and Jaffe & Westerfield (1985). Oguzsoy and Guven (2003) also observe that for most of the stocks among the 30 most heavily traded stocks in the Istanbul Stock Exchange, the maximum return is on Friday whereas the minimum return is either on Monday or Tuesday, with return variances at their highest on Mondays.

For Tuesday, non-synchronous trading may be an explanation for the one-day lag. However, some correlation analysis was made among daily returns with a one-day lag between Western and Eastern countries, where the correlation between Monday returns in the US market and Tuesday returns in the Japanese market is higher than other days of the week. In contrast, no significant differences appear between US market and Australian market. However, in the CSE, this theory is inconsistent; there are only a few hours of time difference with the New York Stock Exchange.

Moreover, the significant day of the week effect in volatility is maybe in line with the information availability theory. In the CSE variance equations, Monday has the highest variance, with 0.0000234, according with French and Roll (1986) and Foster and Viswanathan (1990), who point out that the stock return variance should be highest on Monday, when the informed trader has the maximum information advantage. The variance should decline through the week with the arrival of publicly available information. Chaudhry (2000) also points out, that in a situation when private information is available throughout the week while public information is available only during weekdays, traders are more sensitive to changes in order flow at the beginning of the week. Consequently, the variance of prices changes would be higher at the beginning of the week than at the end of the trading week.

The non-synchronous trading time zones and the information availability theory are some possible explanations for the day-of-the-week effect on the Colombian Stock Exchange, but clearly indicate the necessity for further research in stock markets; e.g. distinction between trading and non-trading periods, settlement periods, size of the companies, measurement error, etc.

In the financial field, the existence of a day-of-the-week effect seems to be a widespread and well-accepted phenomenon. However, there is a question remaining about the real possibility of enjoying abnormal returns, given the fact that there is nothing that guarantees the permanence of these anomalies in the future.

Overall, results indicate that, during the 1980´s, this type of calendar anomaly was clearly evident in the vast majority of developed markets, but it appears to have faded away somewhat in the 1990´s. Moreover, Connolly (1989) shows that when transactions costs are taken into account, the probability that arbitrage profits are available from weekend-oriented trading strategies seems very small.

The Colombia Stock Exchange is classified as an emerging market. Therefore it is plausible that we may uncover some market inefficiencies that investors could exploit as a trading strategy to benefit from these seasonal regularities. As a final conclusion it is important to remark that accurate results will suggest the possibility of a trading strategy in order to take advantage of the market inefficiency, buying and selling strategies formulated accordingly to increase returns due to better timing. (For example, buy on Tuesday, sell on Friday).

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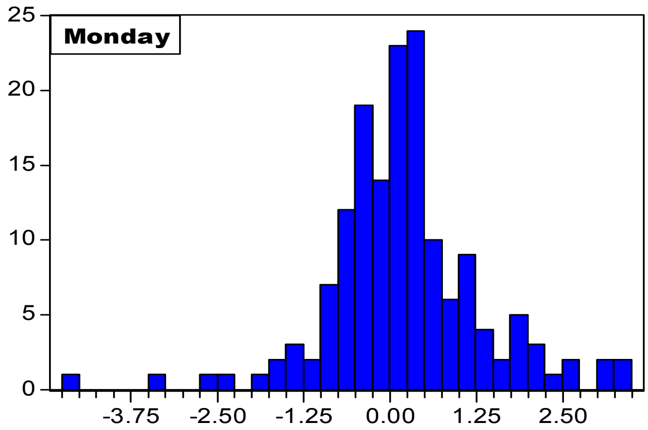
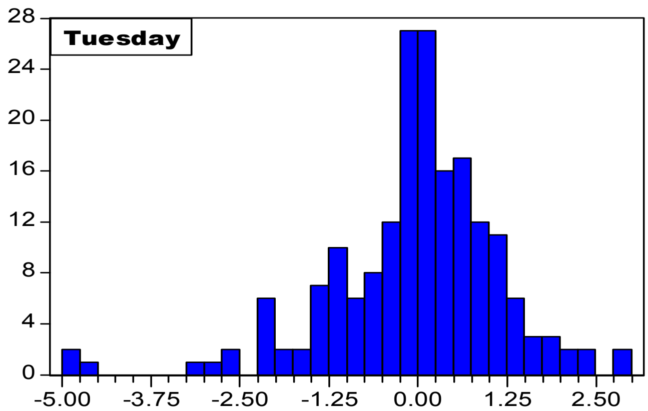
APPENDICES

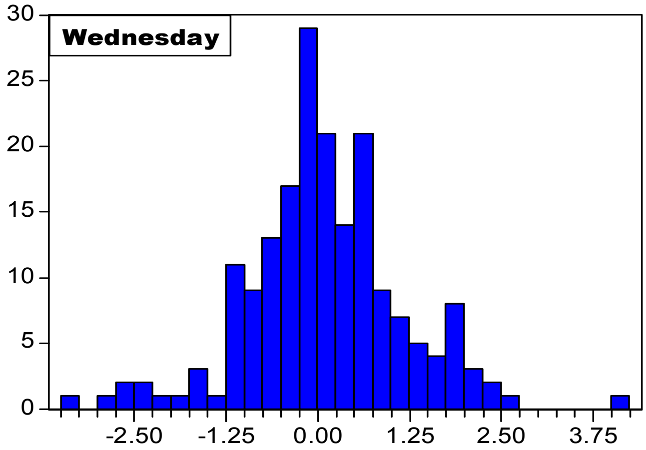
APPENDIX 1



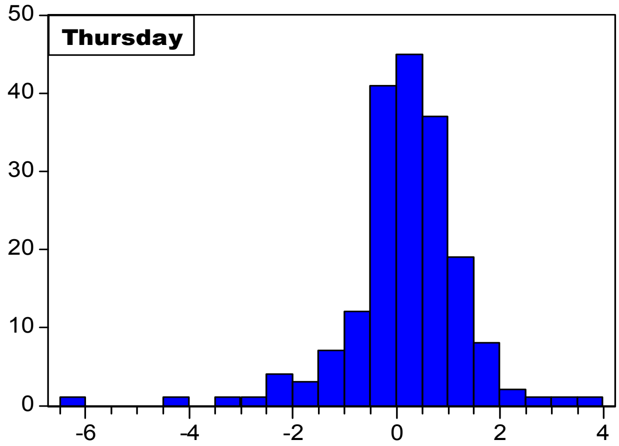
Series: MONDAYS	
Sample 1 157	
Observations 157	
Mean	0.199400
Median	0.117515
Maximum	3.480829
Minimum	-4.700497
Std. Dev.	1.126712
Skewness	-0.182471
Kurtosis	5.829102
Jarque-Bera	53.22956
Probability	0.000000



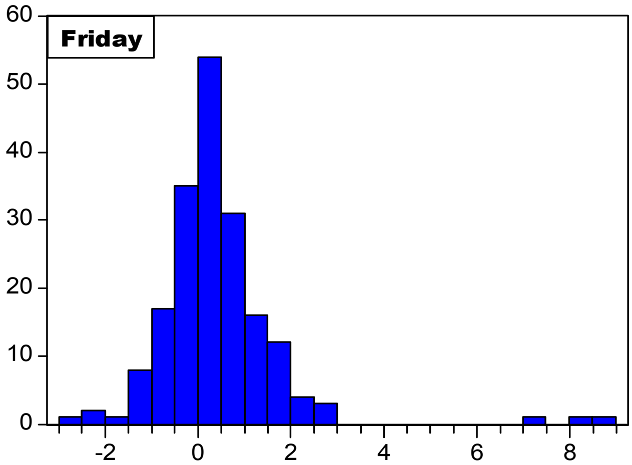
Series: TUESDAY	
Sample 1 188	
Observations 188	
Mean	-0.034845
Median	0.060260
Maximum	2.859596
Minimum	-4.864521
Std. Dev.	1.203504
Skewness	-1.005162
Kurtosis	5.821351
Jarque-Bera	94.01117
Probability	0.000000



Series: WEDNESDAY	
Sample 1 187	
Observations 187	
Mean	0.089896
Median	0.055682
Maximum	4.003336
Minimum	-3.359876
Std. Dev.	1.067035
Skewness	-0.004610
Kurtosis	4.277471
Jarque-Bera	12.71613
Probability	0.001733



Series: THURSDAY	
Sample 1 185	
Observations 185	
Mean	0.177334
Median	0.270717
Maximum	3.780647
Minimum	-6.373320
Std. Dev.	1.170266
Skewness	-1.272779
Kurtosis	9.337220
Jarque-Bera	359.5185
Probability	0.000000



Series: FRIDAY	
Sample 1 187	
Observations 187	
Mean	0.430523
Median	0.238758
Maximum	8.898115
Minimum	-2.522364
Std. Dev.	1.336873
Skewness	3.019217
Kurtosis	19.51184
Jarque-Bera	2408.432
Probability	0.000000

APPENDIX 2

2.1. Unit root test for variable Ln (X_t)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-3.247281	0.0760
Test critical values:	1% level	-3.968211	
	5% level	-3.414782	
	10% level	-3.129555	
*MacKinnon (1996) one-sided p-values.			

2.2. Unit root test for R_t

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-23.81719	0.0000
Test critical values:	1% level	-3.968211	
	5% level	-3.414782	
	10% level	-3.129555	
*MacKinnon (1996) one-sided p-values.			

APPENDIX 3

3.1. Unit root test for R_t Pre–fall

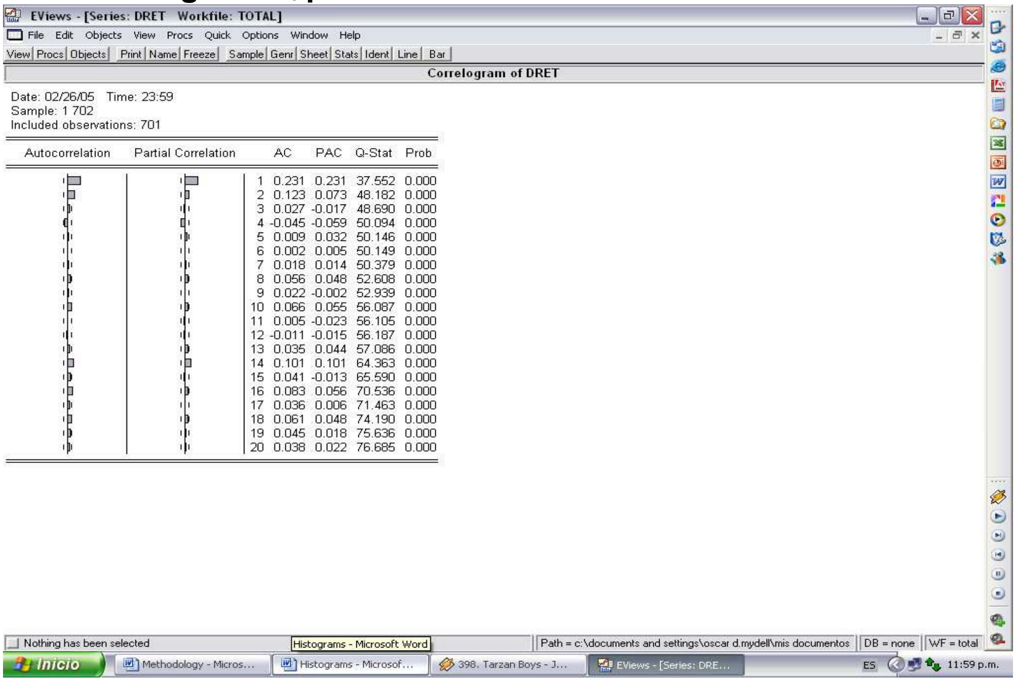
		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-19.76802	0.0000
Test critical values:	1% level	-3.971217	
	5% level	-3.416250	
	10% level	-3.130425	
*MacKinnon (1996) one-sided p-values.			

3.2. Unit root test for R_t Post–fall

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-12.92353	0.0000
Test critical values:	1% level	-4.003226	
	5% level	-3.431789	
	10% level	-3.139601	
*MacKinnon (1996) one-sided p-values.			

APPENDIX 4, ARMA model Rt variable

4.1. Correlogram R_t pre- fall


EViews - [Series: DRET Workfile: TOTAL]

Correlogram of DRET

Date: 02/26/05 Time: 23:59
Sample: 1 702
Included observations: 701

	AC	PAC	Q-Stat	Prob
1	0.231	0.231	37.552	0.000
2	0.123	0.073	48.182	0.000
3	0.027	-0.017	48.690	0.000
4	-0.045	-0.059	50.094	0.000
5	0.009	0.032	50.146	0.000
6	0.002	0.005	50.149	0.000
7	0.018	0.014	50.379	0.000
8	0.056	0.048	52.608	0.000
9	0.022	-0.002	52.939	0.000
10	0.066	0.055	56.087	0.000
11	0.005	-0.023	56.105	0.000
12	-0.011	-0.015	56.187	0.000
13	0.035	0.044	57.086	0.000
14	0.101	0.101	64.363	0.000
15	0.041	-0.013	65.590	0.000
16	0.083	0.056	70.536	0.000
17	0.036	0.006	71.463	0.000
18	0.061	0.048	74.190	0.000
19	0.045	0.018	75.636	0.000
20	0.038	0.022	76.685	0.000

4.2. R_t pre- fall, ARMA(5,4)

Dependent Variable: RT
Sample(adjusted): 7 702

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.003009	0.001133	2.655938	0.0081
RT(-1)	0.223987	0.036272	6.175205	0.0000
RT(-2)	-0.533678	0.029217	-18.26607	0.0000
RT(-4)	-0.822902	0.026993	-30.48524	0.0000
RT(-5)	0.233104	0.038076	6.122136	0.0000
MA(2)	0.621838	0.024348	25.53972	0.0000
MA(3)	0.133768	0.027328	4.894965	0.0000
MA(4)	0.863936	0.024807	34.82648	0.0000

R-squared	0.086425	Mean dependent var	0.001541
Log likelihood	2137.277	F-statistic	9.297876
Durbin-Watson stat	1.897375	Prob(F-statistic)	0.000000

4.3.Pre-fall period -BDS test (ARMA (5,4)) residuals

	M				
values	**2**	**3**	**4**	**5**	6
0,5	9.179427	12.01744	13.67564	16.56853	21.01244
1	7.364463	9.180985	10.20432	11.79021	13.00783
1,5	6.511607	7.468624	8.095228	9.181802	9.468418
2	5.762196	5.973314	6.186023	6.997851	6.547275

Note: all significant at the 5%

APPENDIX 5

5.1 .ARMA(4,4) model Rt variable and dummy variables

Dependent Variable: RT				
Sample(adjusted): 6 702				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.003002	0.000806	3.723666	0.0002
D2	-0.003413	0.000690	-4.948837	0.0000
D3	-0.003012	0.000565	-5.334700	0.0000
D5	0.002251	0.000450	4.997426	0.0000
RT(-1)	-0.355702	0.077934	-4.564147	0.0000
RT(-3)	0.413716	0.072097	5.738344	0.0000
RT(-4)	-0.411976	0.104781	-3.931775	0.0001
MA(1)	0.613081	0.092963	6.594875	0.0000
MA(2)	0.233085	0.045006	5.178960	0.0000
MA(3)	-0.342225	0.072664	-4.709700	0.0000
MA(4)	0.297492	0.109317	2.721373	0.0067
R-squared	0.109847	Mean dependent var		0.001541
Log likelihood	2149.899	F-statistic		8.465391
Durbin-Watson stat	1.905867	Prob(F-statistic)		0.000000

5.2.Pre-fall period -BDS test (ARMA (4,4)) residuals

	M				
values	**2**	**3**	**4**	**5**	6
0,5	7.956710	9.843892	11.55930	13.88170	16.00100
1	7.155499	9.048985	10.39730	12.14669	13.34134
1,5	6.729682	7.760945	8.437321	9.651089	9.941559
2	6.440150	6.462428	6.674425	7.462068	6.936580

Note: all significant at the 5%

APPENDIX 6. White Heteroskedasticity Test on the OLS model

White Heteroskedasticity Test:			
F-statistic	29.88064	Probability	0.000000
Obs*R-squared	143.8737	Probability	0.000000

APPENDIX 7

7.1 Autocorrelation Q statistics			
Lags	**OLS**	**GARCH(1,1)**	**Modified GARCH(1,1)**
5	6,3010	3,6618	4,3905
	(0.278)	(0.599)	(0.495)
10	10.815	7,5722	9,4989
	(0.372)	(0.671)	(0.485)
15	17.496	14.892	16.305
	(0.290)	(0.459)	(0.362)
20	24.677	21.356	22.938
	(0.214)	(0.376)	(0.292)
25	33.026	25.484	26.813
	(0.130)	(0.436)	(0.365)
30	43.632*	37.715	38.741
	(0.051)	(0.157)	(0.132)
35	46.929*	42.290	43.214
	(0.086)	(0.185)	(0.134)
Note: p values in parenthesis,* statistically significant at the 10 percent level			

7.2.ARCH LM			
Lags	**OLS**	**GARCH(1,1)**	**Modified GARCH(1,1)**
5	22,5857**	0.1893	4,3905
	(0.0000)	(0.9666)	(0.495)
10	11,288**	0.2566	9,4989
	(0.0000)	(0.9897)	(0.485)
15	7,4186**	0.2518	16.305
	(0.0000)	(0.9983)	(0.362)
20	5,5015**	0.2471	22.938
	(0.0000)	(0.9997)	(0.292)
25	4,5146**	0.2516	26.813
	(0.0000)	(0.9999)	(0.365)
Note: p values in parenthesis,** statistically significant at the 1 percent level			