CALENDAR ANOMALIES IN THE
PUERTO RICO'S STOCK INDEX

by

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A thesis submitted in partial fulfillment of the requirements for the degree of

MASTER IN BUSINESS ADMINISTRATION

in

FINANCE

UNIVERSITY OF PUERTO RICO
MAYAGÜEZ CAMPUS
2014

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Resumen

Esta investigación examinó los efectos del día-de-la-semana, lunes, mes-del-año y enero, en los rendimientos del Índice de Acciones de Puerto Rico (PRSI). El periodo de estudio abarcó del 1996 al 2013 y se subdividió según las etapas del ciclo económico de Estados Unidos. Se evaluó la media condicional de los rendimientos utilizando el método de los cuadrados mínimos (OLS, por sus siglas en inglés) y la prueba de Kruskal-Wallis (KW), mientras la varianza condicional de los rendimientos se analizó con el modelo de heteroscedasticidad condicional autorregresiva generalizada (GARCH, por sus siglas en inglés). Los resultados del OLS no revelaron anomalías de calendario en el PRSI, KW halló efectos negativos del lunes y jueves y el modelo GARCH encontró efectos del miércoles y viernes para el día-de-la-semana y efectos de septiembre y noviembre, para el mes-del-año. No obstante, los modelos OLS y GARCH, presentaron anomalías esporádicas y aisladas en los sub-periodos.

Abstract

This research examined the day-of-the-week (DOW) effect, the Monday effect, the month-of-the-year (MOY) effect and the January effect in the Puerto Rico Index (PRSI) returns. The period under study was from 1996 to 2013 and was divided into sub-periods based on the stages of the United States business cycle. The conditional mean of the returns was evaluated using the ordinary least squares (OLS) method and the Kruskal-Wallis (KW) test procedure, while the conditional variance of the returns was analyzed with the generalized autoregressive conditional heteroskedasticity (GARCH) model. According to OLS results, none of the calendar anomalies existed in the PRSI, the KW revealed a negative Monday and Thursday effects, and the GARCH model found a Wednesday and Friday effect for the DOW effect and, September and November effects for the MOY effect. However, OLS and GARCH models displayed sporadic and isolated calendar anomalies across sub-periods.

To my family…

Thank you for being my inspiration, strength and support in every step of my life.

I love you all.

Acknowledgments

In this special moment I would like to express my deepest thanks to my beloved husband, mom, father, sister, brother, nephew, mother-in-law and father-in-law, for all their love, support, and patience since I started my graduate studies and in every step of my life. All of you have been my greatest cheerleaders in this journey and this hard work is dedicated to you.

I would like to express my deep gratitude and appreciation to Dr. Yolanda Ruiz Vargas, for all her support, valuable time, excellent guidance, and contribution, from the beginning up to the end of my research and writing process.

Furthermore, I would like to thank my committee members, Prof. Eva Zoé Quiñones and Dr. Rosario Ortiz, for accepting to be part of this endeavor, and for their guidance and contribution to my research.

In addition, I would like to address special thanks to Dr. Saylisse Dávila, for her time and knowledge shared at the beginning of my investigation. Moreover, my gratitude to the Government Development Bank for Puerto Rico, for facilitating the data used in this research.

Last but not least, I want to thanks my MBA colleagues and my dearest friends in the Chemistry Department for all their support, love and laughs in stressful days. You have made all my years in graduate studies enjoyable and unforgettable.

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List of Abbreviations

ADF	Augmented Dickey Fuller
AIC	Akaike information criterion
AMEX	American Stock Exchange
ANOVA	Analysis Of Variance
ARCH	Autoregressive Conditional Heteroskedasticity
ARCH LM	ARCH Lagrange Multiplier test
AR	Autoregressive term
ARMA	Autoregressive Moving Average
DJIA	Dow Jones Industrial Average
DOW	Day-of-the-week Effect
EGARCH	Exponential General Autoregressive Conditional Heteroskedastic
EMH	Efficiency Market Hypothesis
GARCH	Generalized Autoregressive Conditional Heteroskedasticity
GDB	Government Development Bank for Puerto Rico
HAC	Heteroskedasticity and Autocorrelation Consistent Covariance
HQ	Hannan–Quinn information criterion.
JB	Jarque-Bera statistics
KW	Kruskal-Wallis test
LM	Lagrange Multiplier
MA	Moving Average term

MOY	Month-of -the-year Effect
NASDAQ	National Association of Securities Dealers Automated Quotations
NBER	National Bureau of Economic Research
NYSE	New York Stock Exchange
OLS	Ordinary Least Squares
PR	Puerto Rico
PRSI	Puerto Rico Stock Index
S&P	Standard and Poor's composite
SC	Schwarz criterion
SPSS	Statistical Package for the Social Sciences
US	United States
VIF	Variance Inflation Factor

Chapter 1: Introduction

1.1 Introduction

Since the introduction of the efficient market hypothesis (EMH) in the 1970s, stock returns have attracted considerable interest of investigators. Researchers for decades have explored if past stocks return behavior exhibited a degree of predictability (e.g., Chang, Pinegar, & Ravichandran, 1993; French, 1980; Hamid & Tej, 2011; Keim & Stambaugh, 1984; Lakonisok & Smidt, 1988; Ritter, 1988; Rozeff & Kinney, 1976). As a result, different anomalies were proven to exist in many financial markets around the word, such as the day-of-the-week effect, Monday effect, month-of-the-year, January effect and many more. The existence of these anomalies contradicts the weak form of the efficient market hypothesis, in which historical price changes cannot be used to predict future price behaviors (Fama, 1970). Nonetheless, these unusual patterns are expected to eventually disappear soon after their discovery, preserving the efficiency of the market, although this has not been the case in some financial markets.

However, little is known about the financial anomalies manifested in the Puerto Rico Stock Index (PRSI). This index was created in 1995, by the Government Development Bank for Puerto Rico (GDB) and is solely composed of stocks of companies headquartered in Puerto Rico and/or with the island as their main place of business. According to GDB, its purpose is to emphasize the performance of Puerto Rico's equity markets and to attract the attention of equity investors abroad. Therefore, the aim of this investigation is to determine if common market anomalies, such as the day-of-the-week effect, Monday effect, month-of-the-year and January effect, are displayed in the PRSI. The findings of this study will provide a better picture of the efficiency of the index from 1996 to 2013 and will help investors develop strategies in accordance with this new information.

1.2 Justification

The study of the stock returns calendar anomalies has been well documented all over the world. However, this does not mean that all stock exchanges around the world exhibits the same anomalies during the same periods of time, reinforcing the importance of continued research to keep this information updated. Although there are other studies that analyzed the same calendar anomalies as in this investigation, its uniqueness rely in that the object of study is the Puerto Rico Stock Index (PRSI). For this reason, the resulting information may assist firms and individuals considering investing in the stocks listed in the PRSI~~,~~ as well as financial advisors and financial managers. Nonetheless, as French (1980) well acknowledged, for an individual to profit from the awareness of market anomalies is difficult and limited due to transaction costs, but this does not mean that this knowledge is irrelevant, because investors can beneficiate by altering the timing of their trades. For instance, if the Monday effect is present in an index, investors should buy securities on Monday or wait for any other day in the week, in the case they wanted to sell. Therefore, this research will contribute to the development of academic economic literature~~,~~ regarding Puerto Rico stocks returns behavior.

1.3 Objective

The main objective of this research is to empirically investigate whether calendar anomalies, such as the day-of-the-week effect, Monday effect, month-of-the-year and January effect are reflected in the returns of the Puerto Rico Stock Index (PRSI), from 1996 to 2013. Furthermore, it is expected to determine if the presence of these calendar anomalies is persistent during the United States (US) business cycles periods, in the specified time frame.

1.4 Limitations

The study concentrates on day-of-the-week effect, Monday effect, month-of-the-year and January effect calendar anomalies. Other seasonal anomalies and correlation between anomalies are excluded from the analysis. In addition, the data covers only the time period between January 1, 1996 and December 31, 2013.

1.5 Thesis Outline

The research is organized as follows. The second chapter outlines a review of the existent literature in areas related to the efficiency market hypotheses, calendar anomalies (day-of-the-week effect, Monday effect, month-of-the-year and January effect), in addition to a description of the Puerto Rico Stock Index (PRSI). Meanwhile, the third chapter explains the methodology used to demonstrate if calendar anomalies exist in the PRSI. In addition, the fourth chapter presents the empirical results and the corresponding analysis. Finally, chapter five states the conclusions and recommendations for further research.

Chapter 2: Literature Review

This section introduces different studies that have been conducted regarding anomalies of stock returns. First, explains the effect of anomalies in the efficient market hypothesis. Secondly, defines calendar anomalies and provides research evidence concerning the existence of the anomalies object of study in this investigation (day-of-the-week effect, Monday effect, month-of-the-year and January effect). Finally, it presents a description of the Puerto Rico Stock Index and related research.

2.1 Efficient Market Hypothesis

Every now and then, investors in their pursuit to generate the highest returns possible, seek opportunities to beat the market by analyzing past stock prices. Nonetheless, early investigations of the stock exchanges encountered that changes of securities prices did not follow any particular patterns; hence were random. As a result, the random walk hypothesis was developed, stating that returns distributions are not time-dependent (Stancu & Geambaşu, 2012), making impossible the forecasting of stock prices based on these changes. However, this theory failed to explain why securities prices were random until the efficient market hypothesis (EMH) was introduced by Eugene Fama in 1970.

The efficient market hypothesis (EMH) affirms that markets are rational and securities prices reflect all available information (Latif, Arshad, Fatima & Farooq, 2011). This implies that changes in securities prices are a result of adjustments due to the arrival of new information, and if information comes available randomly, the prices will be equally random. Consequently, in an efficient market is difficult to exploit trading activity based on new information because it should already incorporated in the securities price (Hamid & Tej, 2011). Still to this day, it is the most accepted theory to explain stock prices behavior.

Furthermore, the EMH subdivides into three categories based on the nature of the information incorporated in the security price, which can be past information, publicly available information, and/or private information (Latif et al., 2011). The three categories are: the weak form EMH, the semi-strong form EMH, and the strong form EMH. Following, all three are explained below as stated by Fama (1970):

1) The weak form EMH – assumes that stock prices adjust to historical prices and rates of returns sequences; that is, all market generated information.

2) The semi-strong form EMH – is concerned in whether securities prices adjust rapidly to the information publicly available. It covers the weak form hypothesis, because all market information considered by the weak form hypothesis is public, and also includes nonmarket information, such as earnings and dividends announcements, stocks splits, and more.

3) The strong form EMH – contends that investors have access to all relevant information from public and private sources (i.e., insider trader information) and that stock prices fully reflect all information as well. It encloses both the weak and the semi-strong form hypothesis.

Therefore, in order for the market to be efficient at least the historical price data should be reflected in the security price. If not, it contradicts the weak form of the EMH, thus contradicting the semi-strong and the strong form of EMH as well. Moreover, as explain by Nazari and Farzanegan (2011), for a market to be efficient, all the players need access to the same information, must process it in a similar way, and have similar financing opportunities.

However the reality is that not everyone has access to the same information nor the interpretation is the same and transactions costs differ, making it difficult for the existence of efficiency.

In the meantime, despite the popularity of the EMH, several studies have identified anomalies in stock returns, providing evidence against the EMH. Nonetheless, Keim (1988) argues that anomalies are not necessarily embarrassments for market efficiency (as cited in Fama, 1991). This is because it is extremely difficult for an investor to profit from them, since the variations generally are too small to compensate for the transactions cost (Fama, 1991).

2.2 Financial Markets Anomalies

According to the EMH, stock price behavior is random and historical price data cannot give insight about future price movements. Nonetheless, empirical researches have collected evidence sustaining that stock returns "depict methodical variations" (Rafique & Shah, 2012). These unexpected variations that contradict the EMH are called anomalies. When financial markets anomalies are present, provides opportunities for making abnormal returns.

In addition, anomalies can be divided into three different basic groups as suggested by Latif et al. (2011): fundamental anomalies, technical anomalies, and calendar or seasonal anomalies. The first category, fundamental anomalies, is based on the analysis of economic data to examine if securities prices reflect their intrinsic value. Some examples are value anomalies, small cap effect, low price to book, high dividend yield, low price to sales, and low price to earnings. Likewise, technical anomalies are those found by techniques used to forecast stock prices on the basis of past information and trends, like moving averages, resistant and support, and many others. Finally, calendar anomalies refer to "a deviation in normal behaviors of stocks with respect to time periods" (Latif et al., 2011). This very last category is the focal point of this investigation, concentrating in the day-of-the-week effect, Monday effect, month-of-the-year and January effect.

On the other hand, anomalies have manifested in stock exchanges all around the world, as in the United States (e.g., French, 1980; Hamid &Tej, 2011; Keim & Stambaugh, 1984), Singapore (e.g., Hui, 2005), Australia (e.g., Jaffe & Westerfield, 1985; Marrett & Taube, 1995), and Japan (e.g., Hiraki, Maberly & Park, 1994; Jaffe & Westerfield, 1985). Even in emerging stock markets were proven to exist, like in China (e.g., Chen, Kwok & Rui, 2001), Chile (e.g., Kamath & Liu, 2011), and Hong Kong (e.g., Aggarwal & Rivoli, 1989, Chan et al., 1993). Nonetheless, anomalies are expected to disappear soon after are made public, as investor begin to try to exploit them and the market corrects itself. However, some persist for long periods of time without any known explanation.

Consistently, still to this day there is not a clear consensus on why anomalies take place, although there are very interesting theories that partially explain these phenomena. For instance, the delay of bad news until the market closes (Aggarwal & Rivoli, 1989), the tax-selling hypothesis (Asteriou & Kavetsos, 2006; Sias & Starks, 1997), window dressing hypothesis (Sias & Starks, 1997), and behavioral approaches like the herding behavior (Prechter, 2001), are among the most popular explanations.

Moreover, researchers have suggested that exploiting anomalies not necessarily realize higher returns due to transactions costs, but the importance of anomalies investigations in capital markets is to give insight to investors on when is more convenient to do their transactions (French, 1980). Therefore, this investigation aims to provide valuable information to the investors of the PRSI.

2.2.1 Calendar Anomalies

In financial literature, calendar effects are one of the most studied and well-known anomalies. Calendar anomalies have been defined as "a deviation in normal behaviors of stocks with respect to time periods" (Latif et al., 2011) and can be detected when the average returns of all periods are not the same (Nazari & Farzanegan, 2011). In addition, may be attributed to changes of investors' behavior, regarding their trading patterns relative to a time period (Rafique & Shah, 2012).

Particularly, the most well-known calendar irregularities are: the time of the day, the day-of-the-week, the time of month, month-of-the-year, and the turn of the month. Empirical evidence suggesting the presence of seasonality of stocks, can go back as far to the late 1800s (Hamid & Tej, 2011) and still continues to this day. However, it is a very debatable topic, with a lot of unanswered questions about the reasons behind these anomalies.

On the other hand, calendar anomalies go against the EMH rules because are based on the "assumption that past stock behavior is rich in information pertaining to its future behavior" (Stavarek & Heryan, 2012). As a result, investors could potentially forecast future stock behavior on a given time period, by analyzing historical price data. Nonetheless, previous research have suggested that some stock exchanges have been experiencing a decline or disappearance of these anomalies, proof that markets are becoming more efficient as times goes by, like is happening in Greece supported by the investigation of Mylonakis and Tserkezos (2008). Hence, the main objective of this investigation is to determine the degree of efficiency and predictability of the PRSI, by searching for the day-of-the-week effect, Monday effect, month-of-the-year and January effect.

2.2.1.1 Day-of-the-week effect

One of the most notorious calendar anomalies is the day-of-the-week effect (DOW). Different from the EMH, which state that daily average returns should be the same for all the days of the week, when DOW exist stock returns deviate from the average daily series on a particular day or days. This anomaly usually manifest with a display of significantly lower or higher returns on a particular day in the week (Abdalla, 2012). When the day-of-the-week effect prove to be present in a capital market, signals a degree of market inefficiency.

In addition, the DOW effect has been documented all over the world. In the United States, French (1980) found this effect for Standard and Poor's (S&P) composite portfolio from 1953 to 1977, as well as Keim and Stambaugh (1984), from data going back to the 1920s. Likewise, Smirlock and Starks (1986) found the same using the values of the Dow Jones Industrial Average from 1963-1983. Internationally, Jaffe and Westerfield (1985) discovered the DOW effect in Japan, Australia, Canada, and United Kingdom. Meanwhile, Aggarwal and Rivoli (1989) examined four emerging markets: Hong Kong, Singapore, Malaysia, and the Philippines, and drew the same conclusions for the time period of September 1976 to June 1988. Similarly, Chang et al. (1993) provided robust evidence regarding the presence of the DOW effect in Canada, Hong Kong, France, Italy, the Netherlands, Spain, and Sweden from 1985 to 1992. Consequently, every stock exchange has a chance of experiencing the DOW effect, because is not an anomaly for just one region or a specified type of capital market.

Nonetheless, the first empirical evidence regarding DOW effect was based on US indexes data. Their findings usually reported that securities prices exhibited high average returns on

Friday close prices, while negative returns on Monday close prices[1]. Specifically, French (1980) investigated this irregularity and found that the effect was a weekend effect rather than a general "closed market effect". He concluded this after analyzing stock returns following a holiday and finding that only Tuesdays' average returns, were lower than the non-holidays returns. As a result literature began to call the DOW effect, the weekend effect; although is important to clarify, that the weekend effect only consists of the period from Friday close to Monday open.

Moreover, another popular term to refer to the DOW effect is the Monday effect, precisely because Monday usually is the day which exhibits more negative returns in comparison with the other days of the week. Aggarwal and Rivoli (1989), suggested that this anomaly results as firms tend to delay negative announcements after the market closes. However in order to determine the Monday effect, daily close to close stock returns data must be use. Nonetheless, researchers in early investigations were evaluating daily close to close stock returns and still were calling it the weekend effect. Not was until Rogalski (1984) decomposed daily close to close stock returns into trading period (Monday open to Monday close return) and non-trading period (Friday close to Monday open return), that a difference between the weekend and Monday effect was established. In addition, he discovered that negative returns occurred during the non-trading period after the examination of data from October of 1974 to April of 1984. Likewise, Smirlock and Starks (1986) got similar results from the post-1974 period. Nevertheless, Maberly and Taube (1995) after analyzing close to close and close Friday to open Monday records, found that both the weekend effect and the Monday effect persisted for 1975-1991.

Conversely, although Monday is usually the day with the lowest returns of the week, other days had been reported to display the DOW effect, as well. For instance, Aggarwal and Rivoli

[1]See French (1980) and Keim and Stambaugh (1984).

(1989) found that Hong Kong, Singapore, Malaysia, and Philippines exhibited negative returns on Tuesday. Likewise, this situation also manifested within stock exchanges in China (e.g., Chen et al., 2001), Australia (e.g., Jaffe & Westerfield, 1985), and Japan (e.g., Jaffe & Westerfield, 1985; Hiraki et al., 1994). Though for Japan, this effect disappeared after 1990 and ultimately, was replaced by the Monday effect (Boynton, Oppenheimer, & Reid, 2009). Furthermore, there is evidence of a Wednesday effect in the Moroccan Stock Exchange of Casablanca, from 2008 to 2010 (Derbali & Khadraoui, 2011).

Additionally, sometimes the Tuesday effect is associated with a spillover effect, that is, a reaction of what happened in US stock exchanges the day before (Monday). For instance, Chen et al. (2001) suggested that information flows primarily from America to Europe and Asia, in which America lead Europe and the Pacific by one day, but the same was not true for the opposite direction. Furthermore, Hiraki et al. (1994) stated that the spillover effect is a result of financial markets integration.

Moreover, some investigations have contradicted previous findings. In fact, Connolly (1989) reported that the DOW effect disappeared by 1975 in the US. Similarly, Chang et al. (1993) empirical work concluded that US DOW effect was not statistically significant in their analysis. In contrast, Maberly and Taube (1995) sustained that the DOW effect persisted at least until 1991. In response, some researchers argue that these inconsistencies are due to differences on the estimation methods and sample periods (e.g., Connolly, 1989; Chen et al., 2001). Some recent empirical investigations did not find evidence of the DOW effect. For example, the researches of the Khartoum Stock Exchange from Sudan (Abdalla, 2012), the Muscat Securities Market of Oman (Al-Jafari, 2012), and the Central European stock markets (Stavarek & Heryan, 2012), all rejected any difference regarding the means of the days in the week.

Finally, is important to understand the purpose of the DOW effect research. The intention is to generate relevant information, enabling investors to make informed decisions regarding their investments transactions. For example, if one day-of-the-week resulted in a higher daily average return than the other four, investors should wait for that particular day to sell securities or avoid it, in the case they wanted to buy securities. Therefore, it is not to profit from the anomaly, because it is almost impossible to make a profit from the abnormal returns due to transactions costs. Moreover, the DOW effect can change over time as illustrated in Smirlock and Starks (1986), when was found that the weekend effect shifted from being present in the active trading period from 1963-1968, to the non-trading period. Similarly, Kamath and Liu (2011) Chilean Stock Market investigation, from January of 2003 through August of 2008, showed a traditional Monday-Friday effect during the first half of the data period, whereas only a positive Wednesday effect on the second half. For this reason regularly investigations are needed to keep this information updated.

2.2.1.2 Month-of-the-year effect

Calendar anomalies are not limited to the day-of-the-week effect. There is evidence that monthly seasonality has been and/or still is present in capital stocks markets in the US and around the world. Nonetheless, there is more than one anomaly related to monthly patterns but the ones to be discussed in this research are the month-of-the-year anomaly and the January effect.

The month-of-the-year anomaly manifest when one month experiences different returns than the average mean for the twelve months. Therefore, as stated by Nazari and Farzanegan (2011), there will be a month-of-the-year effect, when some months have higher or lower returns than other months. Usually, the month that generates the maximum returns is January, making the month-of-the-year anomaly popularly known as the January effect. This anomaly usually manifests with a boost of financial securities prices during the first month in the year (Rafique & Shah, 2012). Moreover, sometimes it is also referred as to the turn of the year effect. One of the pioneers' who works regarding this type of anomaly is Rozeff and Kinney (1976). Their findings showed superior returns in the month of January, based on US data from the period of 1904 to 1974, specifically from the aggregated returns on the New York Stock Exchange (NYSE).

Internationally, Aggarwal and Rivoli (1989) tested for the January effect in Hong Kong, Malaysia, Philippines, and Singapore, over the period from 1976 to 1988 and documented the presence of the January effect in all these countries, except the Philippines. More recently, Georgantopoulos, Kenourgios, and Tsamis (2011) investigated the former Yugoslav Republic of Macedonia Stock Exchange during the period 2002 to 2008, by both mean (ordinary least squares [OLS]) and variance regressions (Generalized Autoregressive Conditional Heteroskedasticity [GARCH]), in which the results indicated the presence of the mentioned anomaly. The same was the case for Sannassee, Boopen, and Sewraj (2011) investigation, regarding the Stock Exchange of Mauritius for the period from January 1998 to December 2008, with the use of the OLS method, the GARCH specification, and exponential general autoregressive conditional heteroskedastic (EGARCH) model.

Furthermore, the January effect is often linked to small capitalizations firms. Even Latif et al. (2012) defined the January effect as "the phenomenon of small-company stocks to generate more returns than other asset classes and market, in the first two to three weeks of January". Meanwhile, Keim (1983) reported in his paper that "the relation with abnormal returns and size is always negative and more pronounce in the month of January". Similarly, Reinganum (1983) documented that small firms experience large returns on January, especially during the first few days on the month. In addition, Marrett and Worthington (2011) results by a regression approach, not only were consistent with the manifestation of significantly higher January returns for small cap firms in the Australian market, but also evidenced higher August and December returns.

Despite the popularity of the January Effect, in other countries the month in which the month-of-the-year anomaly manifest, varies. For example, Marrett and Worthington (2011), through a regression analysis, found an April effect in Tunis Stock Exchange over the period of 2003 to 2008. Likewise, Rafique and Shah (2012), found a May effect in the Pakistan Stock Exchange, using a regression analysis of daily data of the KSE 100 index from 1997 to 2011. However, some researches like Stancu and Geambaşu (2012), state that the month-of-the-year effect is linked to the first month of the financial year, implying that if the financial year does not start in January, it will manifest in the month that it does. As proof, an investigation confirmed high stock returns in August and September for the Tehran Stock Exchange of Iran from 1997 to 2010, country with a tax year ending in July (Nazari & Farzanegan, 2011).

Furthermore, in certain capital markets more than one month has exhibited superior and/or inferior returns, when compare with the remaining months of the year. This is the case for Athens Stock Exchange for the period of 1985 to 2001, which presented significantly higher returns in January, while lower returns in November (Mylonakis & Tserkezos, 2008). The results were determined using the parametric one-way analysis of variance (ANOVA) and the non-parametric Kruskal-Wallis (KW) statistic. Another example is the Marrett and Worthington (2011) study on the Australian market, were results reported significantly higher returns in April, July, and December while using regression analysis.

On the other hand, not every stock market displays anomalous monthly patterns. Yakob, Beal and Delpachitra (2005) examined this issue by employing the GARCH (1,1) and GARCH(1,1)-M models in ten Asia Pacific countries: Australia, China, Hong Kong, Japan, India, Indonesia, Malaysia, Singapore, South Korea, and Taiwan, but detected the month-of-the-year effect in only eight countries, with the exceptions being Japan and Singapore. Similarly, Asteriou and Kavetsos (2006), found the existence of the January effect in four out of eight countries (namely in Hungary, Poland, Romania, and Slovakia). Not long after, Swami (2011) investigated monthly anomalies in India, Pakistan, Sri Lanka, Bangladesh, and Nepal, and postulated that the month-of-the-year was not found on any of the countries mentioned, although, found other monthly related anomalies such as the turn of the month and intra month anomalies, only on India.

Consequently, the literature gives mixed results about the existence of monthly anomalies. However, researchers had developed several hypotheses to explain these phenomena. According to Rafique and Shah (2012), the most accepted justifications that relate to institutional investors are: window dressing hypothesis, tax-loss selling hypothesis, and risk shifting hypothesis. The first one, window dressing hypothesis, establish that agency problems persuade institutional investors to “dress up” or make look better their portfolios before the compulsory portfolio disclosure dates by selling underperforming stocks in December. Secondly, the institutional tax loss selling hypothesis suggests that losing stocks are put up for sale in December, in order reduce tax liabilities. Finally, the risk shifting hypothesis affirms that institutions buy small risky stocks in January, to increase expected returns, while avoiding investors’ inspections.

Nevertheless, the most popular rationalization regarding individual investors for this effect is the tax-loss selling hypothesis, which implies that individual investors sell losing stocks in December in order to reduce their tax liabilities (Ariel, 1987; Asteriou & Kavetsos, 2006; Rafique & Shah, 2012; Reinganum, 1983). Nonetheless, to give more insight to the tax loss hypothesis in an attempt to explain the monthly anomalies, Ritter (1988) proposed the "parking the proceeds" hypothesis, stating that when stocks are sold for tax purposes the proceeds are parked until January. Therefore, the January Effect is cause by the buying and selling behavior of individual investor who own a greater share of small firms than large firms, which switch from selling in December to buying in January, as opposed to the original theory which state that January experiments a recovery from the previous month. However none of the mentioned possible explanations fully accounts for this effect.

2.3 Puerto Rico Stock Index

The Puerto Rico Stock Index (PRSI) was introduced in October 1995 by the Government Development Bank for Puerto Rico (GDB). The PRSI is the first index comprised exclusively by stocks of local companies, trading in U.S. stock markets [e.g., New York Stock Exchange (NYSE), American Stock Exchange (AMEX), and National Association of Securities Dealers Automated Quotations (NASDAQ)]. It is a capitalization weighted (or market value weighted) index composed of five companies by the end of this investigation, headquartered in Puerto Rico and/or with the island as their main place of business. The main purpose for its establishment was "to emphasize the performance of Puerto Rico's equity markets and to attract the attention of equity investors abroad" (Government Development Bank for Puerto Rico (GDB), 2008). Accordingly, the objectives specified by the GDB (2008) are:

> (a) serve as a fundamental analytical tool to measure the strength and fluctuations of Puerto Rico's financial markets and economy; (b) allow flexibility to analyze the investment in local equity as a separate asset category in comparison to other markets and asset categories; (c) provide the local and foreign investment communities with a passive benchmark to measure the returns of active portfolios composed of local stocks; and (d) to encourage the growth of an equity-oriented market structure and present stock issues as a viable alternative to finance the expansion of local companies.

For the companies to be included in the PRSI specific requirements need to be met as remarked by Cortés-Santiago (2011). Some of the requirements are:

> (a) the companies' securities must trade in a national stock market, in over-the-counter markets, or international security exchanges; (b) the companies must have Puerto Rico as their principal place of business; (c) they do not have to be incorporated in Puerto Rico, but they must be registered to do business in Puerto Rico; (d) the companies must have total assets of at least $5 million (for continued inclusion, the company must have total assets of at least $3 million); (e) their common stock needs to have a minimum bid price of three dollars ($3.00) per share; (f) they must be subject to the reporting requirements established by the Commission pursuant to the Securities Act of 1934.

The final decision to determine if a company qualifies to be included as part of the value of the Puerto Rico Stock Index relies on the PRSI Committee. Also, the Committee oversees the necessary adjustments need to be made to account for additions and deletions to the index, corporate actions and weight changes (Cortés-Santiago, 2011). The PRSI is primarily composed by commercial banks stocks and small cap firms. Table 2.1 presents the composition of the

Puerto Rico Stock Index as of March 20, 2014, before the latest composition change with the inclusion of Evertec.

Table 2.1: Composition of the Puerto Rico Stock Index

Quote	Description	Market	Market Cap (March 20, 2014)
DRL	Doral Financial Corp.	NYSE	**75.48M**
FBP	First BanCorp	NYSE	**1.20B**
BPOP	Popular, Inc.	NASDAQ	**3.24B**
OFG	Oriental Financial Group	NYSE	**804.81M**
GTS	Triple S MGMT Corp – B	NYSE	**494.46M**
Source: Yahoo! Finance			

At its beginnings the PRSI was doing extremely well, even outperforming some of the major US stock indexes (Cimadevilla, 2001). Experts suggest that this growth was due to overconfidence in PR stocks (Torres & Alameda, n.d.), hence, the value was overpriced. Nonetheless, by 2004 the PRSI value began plummeting, mainly due to fiscal problems and policies (e.g., implementing more taxes and crediting agencies downgrading the national debt), slowdown of the local economy, and fierce competition on the island's banking sector (Márquez, 2005). Also, the Credit Crisis of 2008 affected many sectors, especially the financial area (Tong & Wei, 2009). These factors contributed, in a way, to the closing of three financial institutions by the Federal Deposit Insurance Corporation in April 30, 2010: W Holding, Inc., R-G Financial Corp., and Eurobank shares, Inc. Consequently, they were eliminated from the PRSI and were the latest composition change for the time frame of this investigation. Torres and Alameda (n.d.) stated that the PRSI is not representative of the Puerto Rico aggregate economy nor to the real equity returns of commercial banks, because it only measures a group of stocks in the financial sector, which is not the only sector in the local economy, and besides have a high relative weight of Popular Bank of Puerto Rico stocks.

On the other hand, previous studies have analyzed monthly series of the PRSI. First, Alameda (1999) using Dickey-Fuller test statistic on monthly series from 1995 to 1998 implied that PRSI returns behave as a random walk. In contrast, using Bayesian techniques on monthly series from December 1995 to August 2006, Álvarez and Rodríguez (2006) tested the mean reversion and it was found for short term lags of 3 and 12 months, suggesting that PRSI display some degree of predictability. However, little is known about the behavior of daily series or specifics calendar anomalies concerning the PRSI. Although the PRSI cannot be compared to traditional US stock market indexes, is important to remember that PRSI stocks are listed in US national stock markets, and as such this stretch the importance of analyzing whether calendar anomalies can be found in the PRSI.

Chapter 3: Methodology

This chapter describes the data and methodology applied to evaluate the main objective of this research, which is identifying calendar anomalies in the Puerto Rico Stock Index (PRSI). Specifically, the anomalies that were examined are the day-of-the-week, Monday effect, month-of-the-year and January effect. To test PRSI mean returns, two parametric models were used: the ordinary least squares (OLS) and the generalized autoregressive conditional heteroskedasticity (GARCH) model, the latter incorporating the variance of the returns in the estimation. Moreover, the Kruskal-Wallis (KW) test non-parametric procedure was also employed, because financial time series are likely to not follow a normal distribution.

3.1 Data

The data employed in this study consisted of daily closing prices of the PRSI from January 1, 1996 to December 31, 2013, obtained from the Government Development Bank for Puerto Rico (GDB). Thus the daily time series consists of 4697 observations. The investigation examined the full sample and also divided the data into several sub-periods centered on the phases of the US business cycles obtained from National Bureau of Economic Research (NBER, n.d.). Business cycles are the changes in the economic activity, and the period of time in which the economic activity goes from a trough to a peak is the expansion stage, and when the economic activity goes from a peak to a trough is the contraction stage (Federal Reserve Bank of San Francisco (FRBSF), 2002). Consequently, the data was divided in expansion and contraction periods.

The division of the data allowed the examination of the returns for anomalies and at the same time the detection of persistent patterns over time. Therefore, the resulting five sub-periods to test daily anomalies are presented in Table 3.1 and the three sub-periods to test monthly anomalies, are presented in Table 3.2. The difference in the amount of periods is due to the fact that after dividing the data into the phases of the US business cycles, two of the resulting periods contained less than 24 months, preventing the examination of a monthly anomaly. Therefore, these periods with insufficient months were incorporated into the subsequent period, resulting in fewer sub-periods for the monthly series.

Table 3.1: Daily Series sub-periods

Daily anomalies	Full Period	First sub-period	Second sub-period	Third sub-period	Fourth sub-period	Fifth sub-period
Dates	Jan. 1, 1996 to Dec. 31, 2013	Jan. 1, 1996 to Feb. 28, 2001	Mar. 1, 2001 to Oct. 31, 2001	Nov. 1, 2001 to Nov. 30, 2007	Dec. 1, 2007 to May 31, 2009	Jun. 1, 2009 to Dec. 31, 2013
Business Cycle Stage	N/A	Expansion (51 months)	Contraction (8 months)	Expansion (73 months)	Contraction (18 months)	Expansion (54 months)

Table 3.2: Monthly Series sub-periods

Monthly anomalies	Full Period	First sub-period	Second sub-period	Third sub-Period
Dates	Jan. 1, 1996 to Dec. 31, 2013	Jan. 1, 1996 to Feb. 28, 2001	Mar. 1, 2001 to Nov. 30, 2007	Dec. 1, 2007 to Dec. 31, 2013
Business Cycle Stage	N/A	Expansion (51 months)	Contraction (8 months) and Expansion (73 months)	Contraction (18 months) and Expansion (54 months)

Given that the purpose of the investigation is to detect anomalies in the returns, the PRSI index prices are transformed to produce a time series of daily continuously compounded returns, using the following equation:

$$\mathbf{R_t = \ln (P_t/P_{t-1}) *100} \qquad \textbf{Equation 3.1}$$

R_t represents the PRSI index continuously compounded return at time period t, and P_t and P_{t-1} denotes the PRSI index price at time t and $t-1$, respectively. Nonetheless, in the case of a day following a non-trading day, the return is calculated using the closing price of the latest trading day[2]. The natural log of returns is the dependent variable.

3.2 Time Series

A time series is data collected over a period of time on one or more variables, associated with a certain frequency of collection or observation (Brooks, 2008). Many financial data are considered to be time series, like the stock returns[3] that were used in this investigation. The focus of linear time series analysis is the correlation between the variable of interest and its past values, to describe the economic environment under which the asset price is determined (Tsay, 2005). To test for calendar anomalies, the more common approach has been to use linear econometric models like the OLS, as a standard methodology. However, many researchers argue that financial time series exhibits certain characteristics the OLS model fails to consider. Tsay (2005) explains that what differentiate financial time series analysis from other time series is that the latest contain an element of uncertainty, which is the volatility. As a result the autoregressive conditional heteroskedasticity (ARCH) model and it variations were developed.

3.2.1 Low R-squared

R-squared is the coefficient of determination, which is the square correlation between the observed values and the predicted ones. This measure is used to determine the proportion of the variation explained by the model and lies between the of 0-1 interval (Kennedy, 2003). In most

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[2] Eg., Lim et al., 2010.

[3] Financial studies, including calendar anomalies investigation have a preference for returns over prices. Specifically for continuously compounded returns, because returns are scale-free and easier to handle than price series because if needed for multi period returns, is simply the sum of the continuously compounded one-period returns involved (Tsay, 2005).

fields of study, in order for the data gathered by a model to be suitable, the R-squared must be relatively high (over .70). Nonetheless, financial data can exhibit low R-squares, even outside the interval, due to high variance in the disturbance terms, sensitivity to the range of variation of the independent and dependent variables, and when running a regression without an intercept (Kennedy, 2003). Furthermore, low adjusted R-square is common in models which use dummy variables alone as explanatory variables because dummies simply capture the step changes in mean of the dependent variable and do not capture the variation of the daily series (Drauper & Paudyal, 2002). Likewise, low R-squared are expected because "changes in stock prices are likely to be difficult to explain, if the efficient market hypothesis is approximately correct" (Tong & Wei, 2009). As Kennedy (2003) stated, "econometricians are interested in obtaining "good" parameters estimates where "good" is not defined in terms of R^2."

3.2.2 Stationarity

In time series analysis is very important for the series to be stationary. A stationary time series is one whose statistical properties such as mean, variance and autocorrelation are constant over time (Brooks, 2008). Stationarity is necessary because if not, a series can strongly influence its behavior and properties, can lead to spurious regressions, and the standard assumptions for asymptotic analysis will not be valid (Brooks, 2008). However, finance literature often assumes that return series are weakly stationary (Tsay, 2005).

3.2.2.1 Stationarity Test

The Augmented Dickey-Fuller (ADF) unit root test was used to evaluate stationarity of the data. Its purpose is to include enough lagged dependent variables to correct the residuals of serial correlation and moving average errors (Mahadeva & Robison, 2004). The null hypothesis (H_0) for the ADF test, establishes there is a unit root problem, which means that the variable behavior is non-stationary. The alternate hypothesis (H_A) is that the variable does not have a unit root problem or a stationary behavior. Conclusions regarding the variable stationarity are drawn by comparing the ADF statistic with the critical value and if the ADF statistic is lower than the critical value at 5% level of significance, the null hypothesis of a unit root is rejected.

3.3 Multiple Regression

Early researchers used the regression analysis to model seasonality in stock exchanges, like Aggarwal and Rivoli (1989), Connolly (1989), French (1980), Jaffe and Westerfield (1985), Reinganum (1983), Ritter (1988), Rogalski (1989) and many others until this date. Therefore, this investigation will employ this classical method as a standard methodology.

Specifically, the purpose of a regression is to describe and evaluate the relationship between a given variable and one or more other variables (Brooks, 2008). Therefore, a regression try to explain movements in a particular variable, called dependent variable (y), based upon the movements in one or more other variables, called independent variables (x). When the effects of several independent variables are tested together on the dependent variable, the model is known as multiple regression. This model is employed in this investigation and can be described by the following equation,

$$\boldsymbol{Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + .. \beta_t X_t + \varepsilon} \qquad \textbf{Equation 3.2}$$

Where,

Y= dependent variable

X_i= independent variables

β_0= the intercept or constant term

β_t= slope or coefficient

ε = regression residual.

Therefore, β_0 gives us the value of y when x is 0, β_1 thru $\beta_{t,}$ lets us know how much y change with respect a change in x and,ε term accounts for all the variation that the other terms cannot explain. Nonetheless, the appropriate values of β_0 and β_i, must be the ones that minimize collectively the distances from the data points to the fitted line (Brooks, 2008). The most common method for this is the ordinary least squares (OLS), which minimizes the sum of squared distances. In this study, there is a conditional mean equation for each anomaly investigated as described in section 3.3.1 through section 3.3.4.

3.3.1 Day-of-the-week effect

To detect the day-of-the-week effect, the classic OLS regression includes five dummy variables as independent variables (e.g., Chen et al., 2001; Jaffe & Westerfield, 1985; Sannassee et al., 2011; Smirlock & Starks, 1986; Swami, 2011), as follows:

$$\boldsymbol{R_t = \beta_1 D_1 + \beta_2 D_2 + \beta_3 D_3 + \beta_4 D_4 + \beta_5 D_5 + \varepsilon_t} \qquad \textbf{Equation 3.3}$$

Where, R_t is the index return on period t, while the five days of the week are represented by the dummy variables, in which D_1 equals to Monday, D_2 equals to Tuesday, and so on. In addition, D_1 equals1 if the return on day t is on Monday and 0 otherwise, and this is the same for the remaining four days. Furthermore, $\boldsymbol{\varepsilon_t}$ is the error term and the coefficients to be estimated are β_1 through β_5, representing the expected returns of the corresponding day-of-the-week .

3.3.2 Monday Effect

On the other hand, the classic OLS regression to test the Monday effect differs from the previously discussed, in that the equation includes a constant term and four dummy variables as independent variables instead of five (e.g., Aggarwal & Rivoli, 1989; Connolly, 1989; Drauper

& Paudyal, 2002; French, 1980; Georgantopoulos et al, 2011; Lim, Mun & Dollery, 2010; Rafique & Shah, 2012). Therefore, the following equation was used:

$$\boldsymbol{R_t = \beta_0 + \beta_2 D_2 + \beta_3 D_3 + \beta_4 D_4 + \beta_5 D_5 + \varepsilon_t} \qquad \textbf{Equation 3.4}$$

Where, R_t is the index return on period *t*, and employed dummy variables: D_2 represent Tuesday, D_3 represent Wednesday, D_4 represent Thursday and D_5 represent Friday. The constant $\boldsymbol{\beta_0}$**,** captures the Monday mean return, whileβ_2 through $\beta_{5,}$ are coefficients which represent the mean excess daily return with respect the Monday return. Finally, $\boldsymbol{\varepsilon_t}$is the error term.

3.3.3 Month-of-the-year effect

In order to use the OLS specification for testing month-of-the-year effect, the equation included 12 dummy variables (e.g., Asteriou & Kavetsos, 2006; Marrett & Worhington, 2011; Swami, 2012) as follows:

$$\boldsymbol{R_t = \beta_1 M_1 + \beta_2 M_2 + \beta_3 M_3 \ldots + \beta_{12} M_{12} + \varepsilon_t} \qquad \textbf{(Equation 3.5)}$$

Where, R_t is the index return on month *t*, while the twelve months of the year are represented by 12 dummy variables, in which M_1 equals January, M_2 equals February, and so forth. In addition, M_1 equals 1 if month *t* is January and 0 otherwise, and this is the same for the remaining eleven months. Furthermore, ε_t is the error term and the coefficients to be estimated are β_1 through β_{12}, representing the expected returns of the corresponding month in the year and the *t*-tests for those coefficients inform if they are different from 0.

3.3.4 January effect

In order to test the January effect, the month-of-the-year OLS regression needed to be modified by adding a constant and eliminating one of the dummy variables, corresponding to the month of January (e.g.,Aggarwal and Rivoli, 1989; Asteriou & Kavetsos, 2006; Georgantopoulos et al, 2011; Mylonakis & Tserkezos, 2008; Stancu and and Geambasu, 2012). Therefore, the following equation was used:

$$\boldsymbol{R_t = \beta_0 + \beta_2 M_2 + \beta_3 M_3 \ldots + \beta_{12} M_{12} + \varepsilon_t} \qquad \textbf{(Equation 3.6)}$$

Where, R_t is the index return on month *t*, and again the dummy variables are employed. M_2 equals February, M_3 equals March, M_4 equals April, and so forth, except that the dummy variable for January is missing, because the constant captures its mean return. β_2 through β_{12}, are coefficients which represent the mean excess monthly return on the January return. The *t*-tests of the β_i coefficients inform if they are statistical significant from January mean return. Finally, $\boldsymbol{\varepsilon_t}$ is the error term.

3.3.5 Assumptions of OLS model

The regression model needs to satisfy the following assumptions to be validly estimated. These assumptions were verified either by visual examination of data (using a chart or a plot), or by formal statistical tests as explained below.

3.3.5.1 Linearity

The first assumption of the classical linear regression model is that the model parameters are linear. This means that the relationship between dependent and independent variables can be represented by a straight line, otherwise the results are unreliable. To confirm linearity, a scatter plot with Regression Standardized Residual values on one axis, and the dependent variable on the other axis should be done. The points should be symmetrically distributed around a diagonal line in the plot. In addition, the software Statistical Package for the Social Sciences (SPSS) provides the lack of fit test, which provide information to determine whether the pattern between the variables is linear. The null hypothesis for this test is that a linear model is appropriate and a failure to reject the null hypothesis satisfies the assumption of linearity (Rodriguez-Ayala, 2012).

3.3.5.2 Normality

The second assumption of the classical linear regression model is that the residuals have a normal distribution. The first way to test this assumption is by examining the kurtosis and skewness of the data. Skewness determines if the distribution is symmetric about its mean value and kurtosis measures how fat the tails of the distribution are (Brooks, 2008). Hence, to validly understand that a distribution is normal, should have skewness of 0 and with a coefficient of kurtosis of 3 (Connolly, 1989).

Also, the Jarque-Bera (JB) test examine whether the distribution of the residuals is normal. It explores if the coefficient of skewness and the coefficient of excess kurtosis are jointly zero (Brooks, 2008). The null hypothesis for this assumption is that the data is normally distributed. We will reject the null hypothesis if the calculated p-value is lower than the significance level of 5%.

3.3.5.3 Homoscedasticity

The third assumption implies that the variance of errors is equal or constant throughout the model, known as homoscedasticity. The violation of this assumption is known as heteroskedasticity, which may lead to overestimating the goodness of fit of the model. To test the compliance with this assumption, the Heteroskedasticity White test was used. The test is computed by an OLS regression to obtain the residuals. Then estimate an auxiliary regression, which is the square residuals on a constant, their explanatory variables and their cross product (Brooks, 2008).

The econometric software, EViews 7 reports three statistics: (a) the F-statistic, a redundant variable test for the joint significance of all cross products, excluding the constant, (b) the Obs*R-squared statistic, which is the White's test statistic, computed as the number of observations times the centered from the test regression, and it has a Chi-Square distribution, and (c) the LM statistic, the sum of squares from the auxiliary regression divided by $2\hat{\sigma}^4$ (EViews, 2009). The null hypothesis for this test is that there is homoscedasticity, meaning, that the variance of errors are constant. When p-values of the test statistic are lower than the significance level of 5%, the null hypothesis is rejected (Brooks, 2008).

3.3.5.4 Independence

The fourth assumption is that the covariance between the error terms over time is zero (Brooks, 2008). Therefore, the errors are not related with one another. If this fails to be truth, autocorrelation is present.

To test autocorrelation we use the Breusch-Godfrey Lagrange Multiplier test, which allows the examination between the errors and several of it lagged values at the same time, and is a more general test for autocorrelation up to the r^{th} order (Brooks, 2008). The test is executed by obtaining the OLS residuals and running another regression on all of the regressors from the previous OLS regression plus the lagged values. Then, obtain the Obs*R-squared statistic which is the Breusch-Godfrey LM test statistic, “computed as the number of observations, times the (uncentered) R-squared from the test regression” (EViews, 2009). Consequently, if the X^2 test statistic is greater than the critical value, the null hypothesis of no autocorrelation is rejected (Brooks, 2008).

3.4 Nonparametric test

Researchers used alternate methods to the usual parametric tests, when financial data are likely to violate the OLS regression model assumptions because it may invalidate the statistical inferences of the model (e.g., Hamid & Tej, 2012; Hui, 2005, Lim et al., 2010; Mylonakis & Tserkezos, 2008; Rozeff & Kinney, 1976). Therefore, researchers implement nonparametric test that does not make distributional assumptions. Indeed, "nonparametric tests have been demonstrated to be almost as powerful as a parametric test in detecting differences between samples" (Lim et al., 2010).

3.4.1 Kruskal–Wallis Test

The Kruskal–Wallis test, a non-parametric test, examines differences between two or more groups, based on the ranks of the sample observations (Lim et al., 2010). It requires that the random variables be continuous and measurable on an ordinal scale (Rozeff & Kinney, 1976). As an example, the smallest value gets a rank of 1, the next smallest gets a rank of 2, and so on, and tied observations get average ranks. Then, the sum of the ranks is calculated for each group, to subsequently calculate the statistic test as follows:

$$KW = \frac{12}{n(n+1)} \sum_{i=1}^{k} \frac{R_i^2}{n_i} - 3(n+1)$$ **Equation 3.7**

Where k is the number of trading days' return, n is the total number of sample observations, n_i is the sample size in *i* trading days and R_i is the rank sum of the *i* trading day. For large sample sizes, the test statistics KW will follow the chi-square distribution with (k – 1) degrees of freedom (Lim et al., 2010). The null hypothesis is that no difference exists in the returns across the groups and its rejection may indicate that differences or anomalies may be present in the groups, but this information does not indicate which groups mean returns are different.

3.4.2 Wilcoxon Rank Sum Test

The Wilcoxon rank sum test examines the pairs of groups which are significantly different by the comparison of the central locations of two independent random samples (Lim et al., 2010). By this, the Wilcoxon rank sum test, may determine which groups contributed to the rejection of the null hypothesis of the KW test. Nonetheless, the null hypothesis of this test is that the central locations of the two sample distributions are the same (Lim et al., 2010), and its rejection may indicate that differences or anomalies may be present in the pair of groups.

As described by Lim et al. (2010), the Wilcoxon rank sum test, consist of a mean and variance, as shown in Equations 3.8 and 3.9.

$$E(T) = \mu_T = \frac{n_1(n_1+n_2+1)}{2}$$ **Equation 3.8**

$$Var(T) = \sigma_T^2 = \frac{n_1 n_2(n_1+n_2+1)}{2}$$ **Equation 3.9**

Where $n_1$the number of observations from the first sample, n_2 is the number of observations from the second sample and T denotes the sum of ranks of the observations of the first sample. The distribution is approximated by the normal distribution as the number of samples observation increases.

3.5 Modeling Volatility

Most of the empirical work regarding time series analysis uses statistical procedures that model the conditional mean. One example of this is that many researchers employ the OLS approach as a standard methodology to detect calendar anomalies in the stocks returns. This is the case for the pioneering's investigations regarding this subject, as seen in Aggarwal and Rivoli (1989), Connolly (1989), French (1980), Jaffe and Westerfield (1985), Reinganum (1983), Ritter (1988), Rogalski (1989) and many others investigations. Nonetheless, OLS requires compliance with the following assumptions: homoscedasticity or constant variance, no serial correlation, normality and linearity, all described in detail in section 3.3.5.

However, financial time series often violated several of these assumptions, especially when it comes to the variance. As stated by Brooks (2008), "in the context of financial series it is unlikely that the variance of the errors will be constant over time". Financial time series usually exhibits the following characteristics: leptokursis or distribution with fat tails and excess peakedness in the mean, volatility clustering or bunches of periods of high variance and bunches of periods of low variance, and leverage meaning the tendency for volatility to rise more following a large price fall than following a price rise of the same magnitude (Brooks, 2008). Therefore, as stated by Sannassee et al. (2011), a rational financial decision maker must take into account not only returns but also the variance of returns.

In addition to the violation of the homoscedasticity assumption, failure to comply with normality and autocorrelation assumptions as well, arise problems with finding consistent estimates of the standard errors (Connolly, 1989). Although, many researchers try to address this issue by the estimation of robust standard errors, is reasonable to model the volatility to obtain more efficient estimators in the presence of heteroskedasticity in the residuals, because the standard errors and confidence intervals estimated by conventional procedures may be too narrow, giving a false sense of precision (Engle, 2001).

3.5.1 Generalized Autoregressive Conditional Heteroskedasticity (GARCH)

The generalized autoregressive conditional heteroskedasticity (GARCH), introduced by Bollerslev (1986), is an approach designed for modeling the conditional mean or volatility using historical data. This model was employed in many researches, such as Abdalla (2012), Al-Jafari (2012); Connolly (1989), Georgantopoulos et al. (2011), Kamath and Liu (2011), Nazari and Farzanegan, (2011); Sannassee et al. (2011), Yakob and Delpachitra (2005) and many others. It is useful because it "can incorporate autocorrelated returns, time-varying return volatility and the fat-tail error distribution parsimoniously (Connolly, 1989)". Moreover, "offers considerable flexibility in robust modelling stock returns" and "captures the stylized properties of the returns:

the return distribution is unimodal, symmetric and leptokurtic but returns are not independent (Connolly, 1989)”.

The GARCH model comes from the autoregressive conditional heteroskedasticity (ARCH) family, introduced by Engle (1982), which models the variance of the dependent variable as a function of the past variables of the dependent variable and independent variables (EViews, 2009). However, the ARCH model presents some limitations; the number of lags required to fulfill its function may be very large (Brooks, 2008), and assigns equal weights across all observations. The following is the conditional variance equation, h, for the ARCH process:

$$h_t^2 = \alpha_0 + \sum_{i=1}^{q} \alpha_1 \varepsilon_{t-1}^2 \qquad \textbf{Equation 3.10}$$

where, α_0 and α_1 are non-negative parameters, and ε_t^2 is the square error from the mean equation.

To address the difficulties of the ARCH model Bollerslev (1986) developed the GARCH model, approach that assigns weights that get progressively smaller but never reaching 0, to the past squared residuals. To estimate this model, specifications for the conditional mean and conditional variance equation are need, as follows:

a. Conditional Mean:

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + .. \beta_t X_t + \varepsilon$$

Is the same equation as equation 3.2, used to estimate the multiple regression in section 3.3, which is written as a function of independent variables with an error term.

b. Conditional Variance:

$$h_t^2 = \alpha_0 + \sum_{i=1}^{q} \alpha_1 \varepsilon_{t-1}^2 + \sum_{j=1}^{q} \beta_1 h_{j-1}^2 \qquad \textbf{Equation 3.11}$$

Is a function of three terms: (1) the mean of yesterday's forecast, α_0 or constant term; (2) the lag of the squared residuals obtained from the mean equation, ε^2_{t-1}, or the ARCH terms; (3) the GARCH term, h^2_{j-1}, measuring the impact of last period's forecast variance. Moreover, the parameters coefficients ($\alpha_1 i$'s and $\beta_1 j$'s) are restricted to be non-negative to ensure positive values for the conditional variance or $h^2_{j-1} \geq 0$ (Sannassee et al., 2011). Also, requires that $\alpha_1 + \beta_1 < 1$, in order to satisfy the non-explosiveness of the conditional variances (Sannassee et al., 2011).

The most commonly employed GARCH model is the GARCH (1,1), but higher orders of ARCH and GARCH terms can be included to accurately forecast volatility, resulting in a GARCH (p,q) model. The p or first term in parenthesis is the number of ARCH terms, which is how many autoregressive or previous day residuals lags appear in the equation. On the other hand, q or the second term in parenthesis is the number of GARCH terms, or the predicted variance or moving average lags included in the variable. Therefore, the model forecasts the variance of date *t* return as a weighted average of a constant, yesterday's forecast, and yesterday's squared error (Engle, 2001). Nonetheless, the GARCH (1,1) process often fits better the return series than higher orders of GARCH (p,q) (Corhay et al.,1995).

3.5.1.1 Day-of-the-week

The GARCH model for the day-of-the-week effect, was estimated using the condition mean equation, as in section 3.3.1 (e.g., Sannassee et al., 2011 and Yakob et al., 2005), which is written as a function of independent variables with an error term. For this case, the independent variables were the five days of the week, represented by five dummy variables. Moreover, the conditional variance was given employing the same equation as Equation 3.11.

3.5.1.2 Monday effect

For the Monday effect, the GARCH model was specified using the condition mean equation, as in section 3.3.2 (e.g., Connolly, 1989 and Georgantopoulos et al, 2011), which is written as a function of independent variables with an error term. For this case, the independent variables were the constant term representing Monday and four dummy variables representing the other four days of the week. Moreover, the conditional variance was given employing the same equation as Equation 3.11.

3.5.1.3 Month-of-the-year

The GARCH model for the month-of-the-year effect, was estimated using the condition mean equation, as in section 3.3.3 (see Sannassee et al., 2011 and Yakob et al., 2005), which is written as a function of independent variables with an error term. For this case, the independent variables were the 12 months of the year, represented by 12 dummy variables. Moreover, the conditional variance was given employing the same equation as Equation 3.11.

3.5.1.4 January Effect

For the January effect, the GARCH model was specified using the condition mean equation, as in section 3.3.4, which is written as a function of independent variables with an error term. For this case, the independent variables were the constant term representing January and 11 dummy variables representing the other 11 months of the year, as in Georgantopoulos et al. (2011). Moreover, the conditional variance was given employing the same equation as equation 3.11.

3.5.2 Autoregressive conditional heteroskedasticity Lagrange Multiplier (ARCH LM) test

To check specification adequacy of the estimated model, several standard tests were applied. For instance, to detect autoregressive conditional heteroskedasticity (ARCH) in the residuals of PRSI returns or if the magnitude of the residuals is related to the magnitude of recent residuals (EViews, 2009), the ARCH (LM) test was used. This test examines if the variance equation was correctly specified, before and after estimating the GARCH model. It estimates an auxiliary test regression to test the null hypothesis of no ARCH effects up to an order q in the standardized residuals. If the Obs*R-squared, Engle's LM test statistic, is significant $\alpha \leq 0.05$, results in the rejection of the null hypothesis.

3.5.3 Serial Correlation

Another characteristic of times series regressions is that the residuals are serial correlated with their own lagged values (EViews, 2009), which violates the OLS assumption that the disturbances should not be correlated. To detect serial correlation in the residuals and whether the mean equation was correctly specified, the correlogram Q-statistic was used. This test displays the autocorrelation and partial autocorrelation of the standardized residuals and computes the Ljung- Box Q-statistic at any specified number of lags. If no serial correlation is present in the residuals, the autocorrelations and partial autocorrelations should be near cero and the Q-statistic should be non-significant, i.e. $\alpha \geq 0.05$.

3.6 Summary

This chapter describes the data and the different estimation models that were used to examine whether the day-of-the-week effect, Monday effect, month-of-the-year and January effect exist in the PRSI. This included: the OLS model, the nonparametric Kruskal-Wallis test and GARCH model. The assumptions regarding each model were discussed along with their different standard specification tests.

Chapter 4: Results and Analysis

4.1 Introduction

This chapter presents the results from the parametric and non-parametric models, to determine whether calendar anomalies exist in the Puerto Rico Stock Index (PRSI). First, descriptive statistics for the data used in the regression models are presented. Then, the analysis and tests done on the data, as explained on the previous chapter. Finally, the interpretations of the models results are included.

4.2 Descriptive Statistics

For this study, a total of 4697 daily observations consisting of daily closing prices of the PRSI transformed into returns, were analyzed. This data included 17 years of returns, from January 1996 to December 2013. The investigation examined the full sample and several sub-periods, in which the data was segregated based on the phases of the US business cycle, to test daily and monthly anomalies. As explained in section 3.2, five sub-periods were used for the daily anomalies, while only three sub-periods for the monthly anomalies. Summary statistics for daily and monthly PRSI returns, for the whole and split sample, are reported in the following section. The green color in some values in the descriptive statistics tables for the full sample and sub-periods, represent the highest value for that particular statistic and the red color the lowest value for that particular statistic.

4.2.1 Descriptive Statistics for Daily Series

Table 4.1 presents the statistics of daily series for the full sample. The mean return was negative in general, as well as for Monday and Thursday, when each day was analyzed individually. Friday had the largest positive mean return while Monday had the lowest return.

This is consistent with the typical Monday-Friday day-of-the-week effect literature, where Monday generally has negative average returns while Friday generally has the highest average return in comparison with the other days of the week (Smirlock & Starks, 1986; Kamath & Liu, 2011). However, the maximum return was achieved on Monday while the minimum was achieved on Thursday, whereas the highest standard deviation happened on Monday. Additionally, the median return in general was zero, as it was for Monday and Thursday. The largest positive median return was achieved on Wednesday and there are no negative median returns.

Table 4.1 Descriptive Statistics for Daily Series: Full period (01/01/96-12/31/13)

	All Days	Monday	Tuesday	Wednesday	Thursday	Friday
Mean	-0.004229	**-0.111623**	0.062889	0.030196	-0.066291	**0.063728**
Median	0.000000	**0.000000**	0.014823	**0.075089**	**0.000000**	0.043008
Maximum	25.35906	**25.35906**	22.15519	22.45409	19.86752	20.30198
Minimum	-32.10606	-20.55326	-26.84852	-11.53849	**-32.10606**	-29.32368
Std. Dev.	2.421794	**2.59973**	2.512656	2.05311	2.539342	2.363835
Observations	4697	940	940	939	939	939

Table 4.2 shows the descriptive statistics for the returns of the first sub-period. This period runs from January 1, 1996 to February 28, 2001. The mean return was positive in general, except for Thursday in which was negative. The positive mean returns can be expected due to the fact that this period corresponds to an expansion phase of the US business cycle.

On the other hand, Wednesday had the largest positive mean return. Wednesday's effect had manifested in different stock exchanges, as evidenced by Derbali and Khadraoui, (2011) for the Moroccan Stock Exchange of Casablanca, and by Kamath and Liu (2011) for the Chilean

Stock Market. The maximum return was achieved on Friday, while Monday had the minimum but had highest standard deviation. Moreover, the median return in general was positive, as well as for Tuesday, Wednesday and Friday, while Monday had zero return and Thursday stayed negative. Once again, the positive median returns can be expected due to the fact that this period corresponds to an expansion phase of the US business cycle. The largest positive median return was achieved on Wednesday while the lowest and only negative median return was achieved on Thursday.

Table 4.2 Descriptive Statistics for Daily Series: First sub-period (01/01/96-02/28/01)

	All Days	**Monday**	**Tuesday**	**Wednesday**	**Thursday**	**Friday**
Mean	0.067990	0.015988	0.130747	**0.148397**	**-0.063170**	0.107648
Median	0.025469	0.000000	0.104277	**0.164605**	**-0.013008**	0.047937
Maximum	9.009915	5.777156	7.166294	5.129422	4.657082	**9.009915**
Minimum	-7.959698	**-7.959698**	-4.726867	-5.608743	-5.986619	-6.780323
Std. Dev.	1.334920	1.374398	1.312654	1.273818	1.190393	**1.501111**
Observations	1348	270	270	270	269	269

Regarding the second sub-period, descriptive statistics are shown in Table 4.3. This period runs from March 1, 2001 to October 31, 2001 and covers a contraction phase of the US business cycle. The mean return is positive in general, as well for each individual day, except for Monday which is negative. This is consistent with the Monday effect literature, in which Monday generally has the lowest average returns in comparison with the other days of the week (French, 1980; Keim & Stambaugh, 1984; Smirlock & Starks, 1986). Nonetheless, Tuesday has the largest positive mean return, the maximum return on Friday as the highest standard deviation, whereas the minimum was achieved on Monday.

Similarly, the median return in general is positive, as well as for Tuesday, Wednesday and Thursday, while Friday has zero return and Monday stays negative. The largest positive median return was achieved on Thursday, whereas the lowest was achieved on Monday. Therefore, this statement of a negative median return for Monday, suggest once again a Monday effect.

Table 4.3 Descriptive Statistics for Daily Series: Second sub-period (03/01/01-10/31/01)

	All Days	**Monday**	**Tuesday**	**Wednesday**	**Thursday**	**Friday**
Mean	0.059982	**-0.154659**	**0.177393**	0.174083	0.041425	0.061668
Median	0.103728	**-0.029769**	0.104033	0.163261	**0.167996**	0.000000
Maximum	4.538918	4.252477	2.610914	2.410981	2.788976	**4.538918**
Minimum	-6.019191	**-6.019191**	-2.302116	-1.623148	-4.57232	-4.950765
Std. Dev.	1.438443	1.747555	1.097633	0.997788	1.384786	**1.828027**
Observations	175	35	35	35	35	35

Table 4.4 presents the statistics for the returns of the third sub-period. This period runs from November 1, 2001 to November 30, 2007 and covers an expansion phase of the US business cycle. The mean return was negative in general, as well for each day individually except for Friday in which was positive. This means that Friday had the largest positive mean return. This is consistent with the Friday day-of-the-week effect literature, in which Friday generally has the highest average return in comparison with the other days of the week, as evidenced by Smirlock and Starks (1986), and by Kamath and Liu (2011).

On the other hand, the lowest mean return was achieved on Thursday, whereas the highest standard deviation happened on Thursday. In addition, the maximum return was achieved on Thursday while Wednesday had the minimum. Conversely, the median return in general was zero, as well as for Monday, Tuesday and Wednesday, while Thursday had a negative return and Friday remains positive, again consistent with the Friday day-of-the-week effect theory, as mentioned above.

Table 4.4 Descriptive Statistics for Daily Series: Third sub-period (11/01/01-11/30/07)

	All Days	Monday	Tuesday	Wednesday	Thursday	Friday
Mean	-0.037732	-0.075518	-0.026542	-0.038442	**-0.103298**	**0.055058**
Median	0.000000	0.000000	0.000000	0.000000	**-0.013639**	**0.054744**
Maximum	7.958158	3.699562	5.35748	6.443879	**7.958158**	4.707014
Minimum	-7.061887	-5.049987	-5.926015	**-7.061887**	-6.134242	-5.460044
Std. Dev.	1.286927	1.054072	1.370779	**1.382898**	1.33112	1.269924
Observations	1587	317	317	317	318	318

Descriptive statistics of the fourth sub-period are shown in Table 4.5. This period runs from December 3, 2007 to May 29, 2009. All mean returns were negative in general, except for Tuesday and Friday. In addition, Tuesday had the largest positive mean return and Monday had the lowest negative mean return, suggesting a Monday effect, (see French, 1980; Keim & Stambaugh, 1984; Smirlock & Starks, 1986). Nonetheless, Thursday had the highest standard deviation and both the maximum and the minimum return. Additionally, is important to note that this period exhibited the highest standard deviation values, when compared with the other sub-periods.

Similarly, the median return for the period was negative, as well for all the days of the week. However, the largest median return was achieved on Thursday, although negative and the lowest, once again achieved on Monday. The mean and median returns can be expected to be negative, because this period corresponds to a contraction or downward phase of the US business cycle, specifically the one that covers the 2008 credit crisis, though is curious that the only two periods that covers a contraction phase, seem to have negative means and median returns on Monday.

Table 4.5 Descriptive Statistics for Daily Series: Fourth sub-period (12/01/07-05/31/09)

	All Days	**Monday**	**Tuesday**	**Wednesday**	**Thursday**	**Friday**
Mean	-0.22706	**-1.093785**	**0.402797**	-0.375453	-0.080787	0.011926
Median	-0.358776	**-0.691373**	-0.211378	-0.462411	**-0.101009**	-0.677655
Maximum	19.71302	16.43578	12.04362	12.05161	**19.71302**	13.01519
Minimum	-32.10606	-18.94604	-11.39571	-11.53849	**-32.10606**	-7.882247
Std. Dev.	4.924518	5.155216	5.085336	4.256922	**6.002111**	3.829605
Observations	390	78	78	78	78	78

Lastly, Table 4.6 contains the statistics of daily series for fifth sub-period. This period runs from June 1, 2009 to December 31, 2013 and covers an expansion phase of the US business cycle. The mean return was positive in general, as well for each day individually except for Tuesday and Thursday, which had negative returns. Wednesday had the largest positive mean return and Thursday the lowest. The maximum return was achieved on Monday as the highest standard deviation, whereas the minimum return was achieved on Friday.

On the other hand, the median return in general was zero, as well as for Monday, but for the rest of the days showed a positive return. The lowest median return was achieved on Monday, and the highest was achieved on Wednesday, as with the highest positive mean return. This could signal a Wednesday's effect (Derbali & Khadraoui, 2011; Kamath & Liu, 2011).

Table 4.6 Descriptive Statistics for Daily Series: Fifth sub-period (06/01/09-12/31/13)

	All Days	Monday	Tuesday	Wednesday	Thursday	Friday
Mean	0.022074	0.022603	-0.022014	**0.098122**	**-0.031609**	0.043038
Median	0.000000	**0.000000**	0.000425	**0.117540**	0.058518	0.081381
Maximum	25.35906	**25.35906**	22.15519	22.45409	19.86752	20.30198
Minimum	-29.32368	-20.55326	-26.84852	-7.217459	-22.0718	**-29.32368**
Std. Dev.	3.257617	**3.688977**	3.441667	2.468917	3.086101	3.480084
Observations	1197	240	240	240	239	239

4.2.2 Descriptive Statistics for Monthly Series

The descriptive statistics for the monthly series of the full period are shown on Table 4.7. The months of January, March, April, July, September, November and December had a positive mean return, but in general and for the rest of the months the return were negative. March had the largest positive mean return, as well as the highest standard deviation, whereas June presented the lowest return. The maximum return was achieved on July and the minimum on January. The median return in general was zero, as well as for January, February, May, July, September and November while only June had a negative return and the rest of the months stayed positive. The largest positive median return was achieved on December. However, both the lowest mean and median return manifested on June, signaling a possible negative June effect.

Table 4.7 Descriptive Statistics for Monthly Series: Full Period (01/01/96-12/31/13)

	All Months	January	February	March	April	May	June	July	August	September	October	November	December
Mean	-0.00423	0.002117	-0.11841	**0.108357**	0.042848	-0.06911	**-0.14567**	0.074069	-0.05646	0.107464	-0.10418	0.015532	0.083872
Median	0.000000	0.000000	0.000000	0.014323	0.015323	0.000000	**-0.10887**	0.000000	0.026182	0.000000	0.031833	0.000000	**0.055961**
Maximum	25.35906	12.69229	6.710657	23.25825	22.15519	9.218907	4.22435	**25.35906**	9.314327	19.71302	13.01519	5.940118	25.17829
Minimum	-32.1061	**-32.1061**	-23.1197	-22.4479	-26.8485	-11.4695	-6.89263	-9.11572	-10.6714	-11.24166	-10.9782	-11.53849	-29.32368
Std. Dev.	2.421794	2.556701	2.093496	**3.635301**	2.990913	1.728596	1.665732	2.34144	2.033008	2.391027	2.208578	1.934883	2.731071
Observations	4697	399	364	397	387	399	384	400	398	385	400	385	399

Table 4.8 Descriptive Statistics for Monthly Series: First sub-period (01/01/96-02/28/01)

	All Months	January	February	March	April	May	June	July	August	September	October	November	December
Mean	0.06799	-0.028758	0.072707	0.093931	0.074007	0.060975	-0.053195	0.141074	**-0.188363**	**0.375748**	0.020485	0.08025	0.184236
Median	0.025469	0.000000	0.040115	**0.215201**	0.045055	0.043833	**-0.129512**	0.025701	-0.121685	0.110906	0.092368	0.000000	0.099612
Maximum	9.009915	4.377079	5.129422	4.657082	3.570451	2.173169	2.81283	3.682101	2.512666	**9.009915**	5.777156	5.096937	4.659707
Minimum	-7.959698	-6.780323	-4.402911	-3.370457	-3.861619	-2.837629	-6.295862	-2.681835	**-7.959698**	-3.75602	-5.986619	-4.726867	-2.923969
Std. Dev.	1.33492	1.37031	1.350965	1.170923	1.20616	0.953457	1.233473	1.071099	1.352057	**1.872377**	1.585947	1.362905	1.244479
Observations	1348	133	122	110	108	110	107	112	109	108	111	106	112

Table 4.8 provides the statistics of the first sub-period. This period runs from January 1, 1996 to February 28, 2001 and covers an expansion phase of the US business cycle. The mean return was positive in general, as well for each month individually except for January, June and August which were negative returns. September had the largest positive mean return, highest standard deviation and the maximum return, but the lowest mean and minimum return were achieved on August. The median return in general was positive, as well for the rest of the months individually except for June and August that remained negative while January and November had a zero return. The largest positive median return was achieved on March. Nonetheless, did not present any signs of a consistent effect for this period.

On the other hand, statistics for the second sub-period of the monthly series are shown in Table 4.9. This period runs from March 01, 2001 to November 30, 2007 and displayed a negative mean return in general, as well for each month individually except for May, June, September, November and December which were positive returns. May had the largest positive mean return and April the lowest. The maximum return was achieved on August with the highest standard deviation, while the minimum return was achieved on March. Moreover, the months of June, August, October, November and December had a positive median return, but March and April presented a negative return while the rest of the months and the general median showed zero return. The largest positive median return was achieved on August and in April the lowest, as happened with the lowest mean return, indicating a possibly negative April effect for this particular period.

Table 4.9 Descriptive Statistics for Monthly Series: Second sub-period (03/01/01-11/30/07)

	All Months	January	February	March	April	May	June	July	August	September	October	November	December
Mean	-0.02803	-0.024257	-0.013676	-0.089382	**-0.109740**	**0.047339**	0.039466	-0.043181	-0.031161	0.007877	-0.148159	0.03381	0.005947
Median	0.000000	0.000000	0.000000	-0.030626	**-0.008475**	0.000000	0.008703	0.000000	**0.144177**	0.000000	0.002195	0.008839	0.062013
Maximum	7.958158	2.719934	2.842538	3.889493	3.733014	3.081553	2.962287	4.993223	**7.958158**	6.443879	4.420739	4.707014	2.198338
Minimum	-7.06189	-2.949475	-2.860855	**-7.061887**	-5.960738	-3.219433	-5.926015	-4.024198	-6.019191	-4.57232	-5.966199	-6.134242	-2.631489
Std. Dev.	1.30265	0.935977	0.976261	1.366151	1.228391	1.023502	1.168238	1.356514	**1.606121**	1.593199	1.514601	1.573622	0.836497
Observations	1762	134	120	155	149	157	149	154	157	148	156	151	132

Table 4.10 Descriptive Statistics for Monthly Series: Third sub-period (12/01/07-12/31/13)

	All Months	January	February	March	April	May	June	July	August	September	October	November	December
Mean	-0.03915	0.059998	-0.412549	**0.352573**	0.191851	-0.316007	**-0.438477**	0.152814	0.02238	-0.00289	-0.156649	-0.059625	0.077713
Median	0.000000	0.067956	0.000000	0.088800	**0.337038**	-0.267109	**-0.427281**	-0.199139	-0.082348	0.000000	0.040528	0.000000	0.017304
Maximum	25.35906	12.69229	6.710657	23.25825	22.15519	9.218907	4.22435	**25.35906**	9.314327	19.71302	13.01519	5.940118	25.17829
Minimum	-32.10606	**-32.10606**	-23.1197	-22.44786	-26.84852	-11.46949	-6.892631	-9.115724	-10.6714	-11.24166	-10.97824	-11.53849	-29.32368
Std. Dev.	3.736588	4.13196	3.201687	**6.042143**	4.876408	2.642426	2.318087	3.65332	2.815144	3.349758	3.15221	2.61719	4.189562
Observations	1587	132	122	132	130	132	128	134	132	129	133	128	155

Finally, Table 4.10 presents the statistics of the third and last sub-period for the month-of-the-year anomaly. This period runs from December 3, 2007 to December 31, 2013, and exhibited a negative mean return in general, as well for the majority of the months except for January, March, April, July, August and December. March had the largest positive mean return, and the highest standard deviation, whereas June had the lowest mean return. The maximum return was achieved on July and the minimum on January. Moreover, May, June, July and August displayed a negative median return, but the rest of the months had zero or positive median returns. The largest positive median return was reached on April and the lowest on June. However, both the lowest mean and median return manifested on June, signaling a possible negative June effect for this period and the same was found when the full sample was analyzed.

4.3 Stationarity Test

Given that many financial time series exhibit non-stationary behavior is important to determine whether the behavior of the returns series used in this research were stationary or not. Stationarity is when statistical properties in a series, such as mean, variance and autocorrelation are constant over time (Brooks, 2008). If the condition of stationarity is not met, a series can strongly influence its behavior and properties, can lead to spurious regressions, and the standard assumptions for asymptotic analysis will not be valid (Brooks, 2008). To test for stationarity the Augmented Dickey Fuller test was used.

Tables 4.11 and 4.12, show the results at level and with the first difference, for the daily and monthly series, respectively. The t-statistic was compared to the critical value, and in all cases the statistic was lower than 5% level of significance, leading to the rejection of the null hypothesis of a unit root. Therefore, the results showed that PRSI returns are stationary in the full sample and sub-periods for both series.

Table 4.11 Summary of Unit Root Tests for Daily Series

	ADF at level			ADF 1st difference		
	t-statistic	**Critical Value at 5% level**	**Ho decision**	**t-statistic**	**Critical Value at 5% level**	**Ho decision**
Full Period (01/01/96-12/31/13)	-31.56730	-3.431561	R-S	-29.46584	-3.431565	R-S
First sub-period (01/01/96-02/28/01)	-37.59479	-3.434994	R-S	-19.37368	-3.435038	R-S
Second sub-period (03/01/01-10/31/01)	-10.15089	-3.468295	R-S	-9.476693	-3.469933	R-S
Third sub-period (11/01/01-11/30/07)	-36.96761	-3.434268	R-S	-20.80440	-3.434299	R-S
Fourth sub-period (12/01/07-05/31/09)	-24.49771	-3.446949	R-S	-12.21873	-3.447304	R-S
Fifth sub-period (06/01/09-12/31/13)	-16.93721	-3.435622	R-S	-18.63613	-3.435663	R-S

Note:
1. R-S: Reject Null: variable is stationary
2. NR-NS: Do not reject Null: variable is non-stationary.

Table 4.12 Summary of Unit Root Tests for Monthly Series

	ADF at level			ADF 1st difference		
	t-statistic	**Critical Value at 5% level**	**Ho decision**	**t-statistic**	**Critical Value at 5% level**	**Ho decision**
Full Period (01/01/96-12/31/13)	-31.56730	-3.431561	R-S	-29.46584	-3.431565	R-S
First sub-period (01/01/96-02/28/01)	-37.59479	-3.434994	R-S	-19.37368	-3.435038	R-S
Second sub- Period (03/01/01-11/30/07)	-38.92185	-3.433861	R-S	-22.00511	-3.433886	R-S
Third sub- Period (12/01/07-12/31/13)	-49.15598	-3.434268	R-S	-18.24617	-3.434309	R-S

Note:
1. R-S: Reject Null: variable is stationary
2. NR-NS: Do not reject Null: variable is non-stationary.

4.4 Multiple Regression Results

This section presents the results of the multiple regression analysis using the OLS procedure, for testing for specific calendar anomalies in the PRSI index. The day-of-the-week effect, Monday effect, month-of-the-year and January effect, were the anomalies analyzed in this research.

Nonetheless, Heteroskedasticity and Autocorrelation Consistent Covariance (HAC) or Newey-West estimator was employed in the OLS regression[4]. This procedure provided by EViews is commonly used "under the assumption of heteroskedasticity and autocorrelation" (EViews, 2009), traits that usually characterizes financial time series. This approach generates robust coefficients standard errors of an equation under heteroskedasticity and autocorrelation conditions, but do not change their point estimates (EViews, 2009).

4.4.1 Day-of-the-week effect

Since little is known regarding calendar anomalies in the PRSI, this investigation starts analyzing the day-of-the-week effect with a regression model. This model includes 5 dummy variables representing each day in the week without a constant term, allowing the detection of an irregularity without focusing in a certain day (e.g., Chen et al., 2001; Jaffe & Westerfield, 1985; Sannassee et al., 2011; Smirlock & Starks, 1986; Swami, 2011). The regressions results of whether the day-of-the-week effect is present in the return of the daily series, for the full period and sub-periods, are shown in Table 4.13. The coefficients for the full sample attempts to identify which days, if any, might have a mean different from 0. In addition, the sign of the coefficient would suggest if the returns are higher or lower than 0 for that particular day. In

[4] This procedure has been used in many investigations, such as Asteriou and Kavetsos (2006), Georgantopoulos et al. (2011), Lim et al. (2010) and Marrett and Worthington (2011).

other words, if the average expected return for a particular day is more positive or negative than the average.

According to the model, there is no indication of the day-of-the-week effect in the PRSI because no statistical significant coefficients were found in the full period. However, in the first sub-period a significant positive estimated coefficient for Wednesday (0.148397 at 10 % level of significance) was found, suggesting that the returns on Wednesday were statistically higher than the others days of the week for that period. Wednesday's effect had been known to exist in different stock exchanges, as evidenced by Derbali and Khadraoui, (2011) for the Moroccan Stock Exchange of Casablanca, and by Kamath and Liu (2011) for the Chilean Stock Market. Moreover, a significant negative Monday effect (-1.093785 at 10 % level of significance) was found in the fourth sub-period, suggesting that Monday returns were statistically lower than the others days of the week for the period. This last finding is what is generally observed when the DOW anomaly is examined (French, 1980; Keim & Stambaugh, 1984; Smirlock & Starks, 1986), and in this research, was only shown in a contraction phase period, particularly the period in which the credit crisis of 2008 unfolded. Nonetheless, both of the effects found in their respective sub-periods were isolated and not as strong; giving their significance was at the 10% level.

Table 4.13 OLS for the DOW effect

Variable	Full Period (Jan 1996- Dec 2013)	Sub-period 1 (Jan 1996- Feb 2001)	Sub-period 2 (Mar 2001- Oct 2001)	Sub-period 3 (Nov 2001- Nov 2007)	Sub-period 4 (Dec 2007 - May 2009)	Sub-period 5 (Jun 2009 - Dec 2013)
Monday	-0.111623 (0.078407)	0.015988 (0.083684)	-0.154659 (0.295391)	-0.075518 (0.058546)	**-1.093785*** (0.563791)	0.022603 (0.226329)
Tuesday	0.062889 (0.073344)	0.130747 (0.080973)	0.174083 (0.168657)	-0.026542 (0.076388)	0.402797 (0.570635)	-0.022014 (0.196956)
Wednesday	0.030196 (0.068937)	**0.148397*** (0.076984)	0.177393 (0.185534)	-0.038442 (0.077962)	-0.375453 (0.493825)	0.098533 (0.159668)
Thursday	-0.066291 (0.084794)	-0.06317 (0.074183)	0.041425 (0.234072)	-0.103298 (0.074509)	-0.080787 (0.68937)	-0.031609 (0.200679)
Friday	0.063728 (0.076426)	0.107648 (0.092752)	0.061668 (0.308993)	0.055058 (0.068264)	0.011926 (0.427801)	0.043038 (0.226211)
# observations	4697	1348	175	1587	390	1197
R squared[5]	0.000877	0.003579	0.007118	0.00175	0.010323	0.000209

Note:
Standard errors are shown in parentheses.
***, **, * denotes significance at the 1%, 5% level and 10%, respectively.

4.4.2 Monday effect

Financial literature often points out that Monday generally generates lower returns than the remaining days in the week (Aggarwal & Rivoli, 1989; Connolly, 1989; French, 1980). To determine whether this anomaly is or was present in the return of the daily series, a regression including a constant term, representing the average daily return for Monday and 4 dummy variables representing the remaining days in the week was estimated. Table 4.14 presents the results of the regression for the Monday effect for the full period and sub-periods. The

[5] All periods exhibited very low R-squares, like Asteriou and Kavetsos (2006) and French (1980), although in most researches this statistic is not included. This is common in models which use dummy variables alone as explanatory variables because dummies simply capture the step changes in mean of the dependent variable and do not capture the variation of daily returns (Drauper & Paudyal, 2002). However, even with low R-squares, individual coefficients significantly different from zero can be useful (Holden, Thompson & Ruangrit, 2004) and conclusions can be drawn (Kennedy, 2003).

coefficients for the general model attempts to identify which variables, if any, might have a mean excess the mean daily return of the Monday. In addition, the sign of the coefficient would suggest if the returns are higher or lower than the mean of Monday returns.

According to the analysis, the Monday effect does not exist in the PRSI, except in the fourth sub-period in which the constant had a significant negative coefficient (-1.093785) at the 10% level, suggesting that the returns on Monday are statistically lower than the others days of the week. This result is consistent with the DOW examination for the same period in section 4.4.2 and with previous studies regarding the Monday effect (French, 1980; Keim & Stambaugh, 1984; Smirlock & Starks, 1986), although in this case was isolated and weak due to only 10% significance. Moreover, this negative Monday effect may be linked to an event or circumstance that prompted the contraction phase experienced in the fourth sub-period, like the financial crisis of 2008.

Table 4.14 OLS for the Monday effect

Variable	Full Period (Jan 1996-Dec 2013)	Sub-period 1 (Jan 1996-Feb 2001)	Sub-period 2 (Mar 2001-Oct 2001)	Sub-period 3 (Nov 2001-Nov 2007)	Sub-period 4 (Dec 2007 - May 2009)	Sub-period 5 (Jun 2009 - Dec 2013)
Constant	-0.111623 (0.078407)	0.015988 (0.083684)	-0.154659 (0.295391)	-0.075518 (0.058546)	**-1.093785*** (0.563791)	0.022603 (0.226329)
Tuesday	0.174512 (0.116172)	0.114759 (0.121156)	0.328741 (0.353424)	0.048976 (0.09479)	1.496581 (0.92671)	-0.044617 (0.335072)
Wednesday	0.141819 (0.100239)	0.132409 (0.108206)	0.332052 (0.379757)	0.037076 (0.0978)	0.718331 (0.746414)	0.07593 (0.263693)
Thursday	0.045332 (0.12165)	-0.079158 (0.107284)	0.196084 (0.405688)	-0.02778 (0.096257)	1.012997 (0.933117)	-0.054212 (0.322081)
Friday	0.175351 (0.115738)	0.09166 (0.125119)	0.216326 (0.409144)	0.130576 (0.089428)	1.105711 (0.743242)	0.020435 (0.347618)
# observations	4697	1348	175	1587	390	1197
R squared[6]	0.000877	0.003579	0.007118	0.00175	0.010323	0.000209

Note:
Standard errors are shown in parentheses.
***, **, * denotes significance at the 1%, 5% level and 10%, respectively.

4.4.3 Month-of-the-year effect

To analyze whether the month-of-the-year was present in the PRSI index, a regression model including 12 dummy variables representing each month in the year without a constant term was used (e.g., Asteriou & Kavetsos, 2006; Marrett & Worhington, 2011; Swami, 2012). This allows the detection of any irregularity without focusing in a specific month. The results for the monthly return series for the full period and sub-periods are shown in Table 4.15. The

[6] All periods exhibited very low R-squares like Asteriou and Kavetsos (2006) and French (1980), although in most researches this statistic is not included. This is common in models which use dummy variables alone as explanatory variables because dummies simply capture the step changes in mean of the dependent variable and do not capture the variation of daily returns (Drauper & Paudyal, 2002). However, even with low R-squares, individual coefficients significantly different from zero can be useful (Holden et al., 2004) and conclusions can be drawn (Kennedy, 2003).

coefficients for the general model attempts to identify which variables, if any, might have a mean different from 0.

Consequently, when analyzing the full sample, no indication of a monthly effect appeared to exist in the PRSI index because no significant estimated coefficients were found in the full sample period. However, in the first sub-period seemed to be a significant and positive estimated coefficient for September (0.375748 at 10% of significance), suggesting that the returns on September are statistically higher than the others months of the year (Nazari & Farzanegan, 2011). Conversely, in the third sub-period there was a significant and negative estimated coefficient for June (-0.438477 at 5% of significance), suggesting that the returns on this month were statistically lower than the others months of the year. This last finding can be associated with the fact that this period, comprehends 18 months of a contraction phase of the US business cycle that contains the credit crisis of 2008. Furthermore, the sub-periods supports the findings of Álvarez and Rodríguez (2006), which suggested that PRSI display some degree of predictability.

Table 4.15 OLS for the MOY effect

Variable	Full Period (Jan 1996-Dec 2013)	Sub-period 1 (Jan 1996-Feb 2001)	Sub-period 2 (Mar 2001-Nov 2007)	Sub-period 3 (Dec 2007-Dec 2013)
January	0.002117 (0.121205)	-0.028758 (0.113067)	-0.024257 (0.077904)	0.059998 (0.32573)
February	-0.118412 (0.126747)	0.072707 (0.133942)	-0.013676 (0.088101)	-0.412549 (0.338817)
March	0.108357 (0.115453)	0.093931 (0.145448)	-0.089382 (0.139974)	0.352573 (0.32573)
April	0.042848 (0.129829)	0.074007 (0.13497)	-0.10974 (0.112241)	0.191851 (0.328226)
May	-0.069106 (0.079869)	0.060975 (0.077461)	0.047339 (0.083551)	-0.316007 (0.32573)
June	-0.145668 (0.098349)	-0.053195 (0.109669)	0.039466 (0.117735)	**-0.438477**** (0.330781)
July	0.074069 (0.112304)	0.141074 (0.100995)	-0.043181 (0.133825)	0.152814 (0.32329)
August	-0.056456 (0.091721)	-0.188363 (0.164423)	-0.031161 (0.094534)	0.02238 (0.32573)
September	0.107464 (0.1148)	**0.375748*** (0.202214)	0.007877 (0.141288)	-0.00289 (0.329496)
October	-0.104183 (0.107859)	0.020485 (0.181993)	-0.148159 (0.134047)	-0.156649 (0.324503)
November	0.015532 (0.101986)	0.08025 (0.155481)	0.03381 (0.134289)	-0.059625 (0.330781)
December	0.083872 (0.07782)	0.184236 (0.128288)	0.005947 (0.056054)	0.077713 (0.17842)
# observations	4697	1348	1762	1587
R squared[7]	0.001292	0.009446	0.002136	0.003868

Note:
Standard errors are shown in parentheses.
***, **, * denotes significance at the 1%, 5% level and 10%, respectively.

[7] All periods exhibited very low R-squares like Asteriou and Kavetsos (2006) and French (1980), although in most researches this statistic is not included. This is common in models which use dummy variables alone as explanatory variables because dummies simply capture the step changes in mean of the dependent variable and do not capture the variation of daily returns (Drauper & Paudyal, 2002). However, even with low R-squares, individual coefficients significantly different from zero can be useful (Holden et al., 2004) and conclusions can be drawn (Kennedy, 2003). .

4.4.4 January effect

Financial literature frequently remarks that January generally generates higher returns than the remaining months in the year. Still to this date, there are no consensus for a reason that explains this anomaly, but according to Rafique and Shah (2012), the most accepted justifications are the window dressing hypothesis (i.e., institutional investors sell of underperforming stocks in December, "dress up" their portfolios before the disclosure dates), the tax-loss selling hypothesis (i.e., institutional investors sell of underperforming stocks in December to reduce tax liabilities), and the risk shifting hypothesis (i.e., institutional investors buy on January small risky stocks to increase expected returns).

For this reason, this research used the January effect regression model to determine whether this anomaly was present in the return of the monthly series, for the full period and sub-periods. This model includes a constant term, representing the average daily return for January and only 11 dummy variables representing the remaining months in the year (e.g., Aggarwal and Rivoli, 1989; Asteriou & Kavetsos, 2006; Georgantopoulos et al, 2011; Mylonakis & Tserkezos, 2008; Stancu & Geambasu, 2012). Table 4.16 presents the results for the January effect. In this model, the coefficient of the constant term represented the average daily return for January. The rest of the coefficients attempt to identify which variables, if any, might have a mean excess the mean return of January. In addition, the sign of the coefficient would suggest if the returns are higher or lower than the mean of January returns.

The results showed that the January effect does not exist in the PRSI because no significant estimated coefficients were found in the full period sample. However, the only period that revealed an anomalous behavior was the first sub-period, with a significant and positive estimated coefficient for September (0.404505 at the 10 % level), consistent with the MOY anomaly examination for the same period in Section 4.4.3, and suggesting that returns on September are statistically higher than January returns for this period (Nazari & Farzanegan, 2011). This supports the findings of Álvarez and Rodríguez (2006) that suggested that PRSI display some degree of predictability, although weakly, given is only 10% significant.

Table 4.16 OLS for the January effect

Variable	Full Period (Jan 1996-Dec 2013)	Sub-period 1 Jan 1996-Feb 2001)	Sub-period 2 (Mar 2001-Nov 2007)	Sub-period 3 (Dec 2007-Dec 2013)
Constant	0.002117 (0.121205)	-0.028758 (0.113067)	-0.024257 (0.077904)	0.059998 (0.327265)
February	-0.120528 (0.175434)	0.101465 (0.180223)	0.010581 (0.11612)	-0.472547 (0.46482)
March	0.106241 (0.167393)	0.122689 (0.184226)	-0.065125 (0.160193)	0.292575 (0.431304)
April	0.040731 (0.177613)	0.102764 (0.176071)	-0.085482 (0.1366280	0.131853 (0.472709)
May	-0.071223 (0.145155)	0.089732 (0.137056)	0.071596 (0.114236)	-0.376005 (0.385563)
June	-0.147784 (0.156087)	-0.024437 (0.157516)	0.063723 (0.141175)	-0.498475 (0.394841)
July	0.071952 (0.165236)	0.169832 (0.151605)	-0.018924 (0.154848)	0.092816 (0.431134)
August	-0.058573 (0.151998)	-0.159605 (0.199547)	-0.006903 (0.122498)	-0.037618 (0.394491)
September	0.105348 (0.166942)	**0.404505*** (0.231678)	0.032134 (0.161342)	-0.062888 (0.410947)
October	-0.1063 (0.162248)	0.049243 (0.214256)	-0.123902 (0.155041)	-0.216647 (0.406836)
November	0.013415 (0.158404)	0.109008 (0.192246)	0.058067 (0.15525)	-0.119623 (0.402214)
December	0.081755 (0.145346)	0.212993 (0.181122)	0.030204 (0.099661)	0.017715 (0.370381)
# observations	4697	1348	1762	1587
R squared[8]	0.001292	0.009446	0.002136	0.003868

Note:
Standard errors are shown in parentheses.
***, **, * denotes significance at the 1%, 5% level and 10%, respectively.

[8] All periods exhibited very low R-squares like Asteriou and Kavetsos (2006) and French (1980), although in most researches this statistic is not included. This is common in models which use dummy variables alone as explanatory variables because dummies simply capture the step changes in mean of the dependent variable and do not capture the variation of daily returns (Drauper & Paudyal, 2002). However, even with low R-squares, individual coefficients significantly different from zero can be useful (Holden et al., 2004) and conclusions can be drawn (Kennedy, 2003).

4.4.5 Analysis of Assumptions

The following section presents the analysis of the underlying assumptions for the multiple regression models that were explained in Chapter 3.

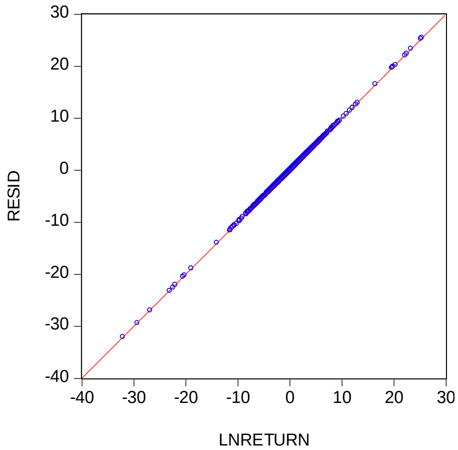
4.4.5.1 Linearity

As discussed in Chapter 3, to graphically validate if the parameters of the OLS model were linear, a scatterplot with the regression standardized residual on one axis and the dependent variable, in this case LnReturn, on the other axis, was employed. Figures 4.1 and 4.2 graphically demonstrated that the linearity assumption was met for both return series, because the points were symmetrically distributed around a diagonal line in the plot.

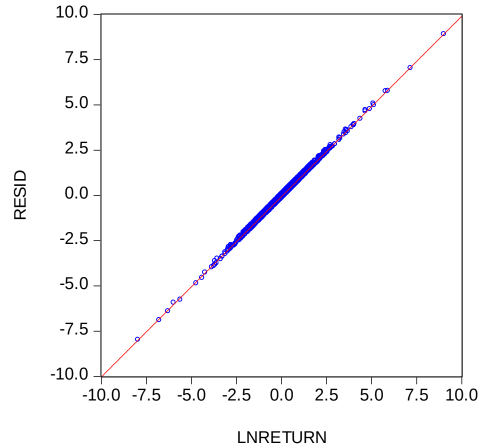
Correspondingly, the Lack of Fit test assessed statistically if the linearity assumption was met. As shown in Table 4.17, the value of the F-test statistic was greater than the significance level of 5%, meaning that the null hypothesis that a linear regression model is appropriate, was not rejected for the daily series. The same holds in the lack of fit test for the monthly series, shown in Table 4.18. Thus, the relationship between the dependent and independent variables was linear and the assumption of linearity was satisfied.

Figure 4.1 Scatterplot Dependent Variable for Daily Series

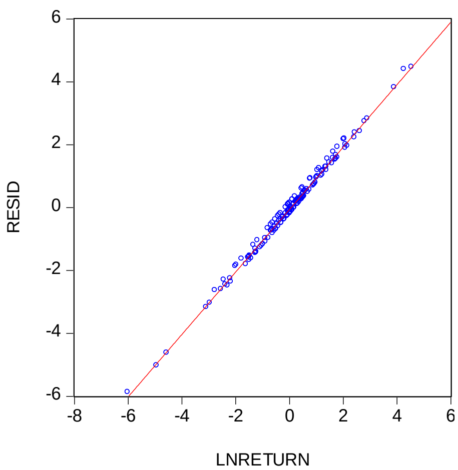
Full Period (01/01/96-12/31/13)



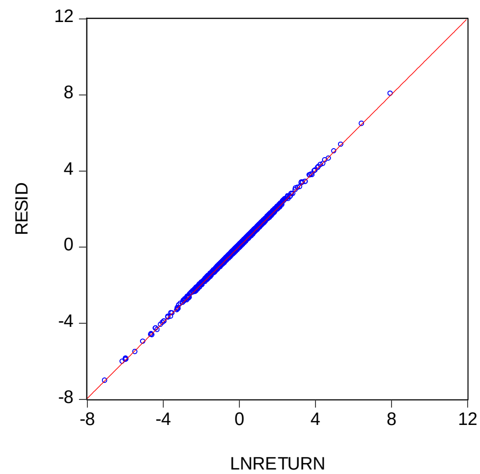
First sub-period (01/01/96-02/28/01)



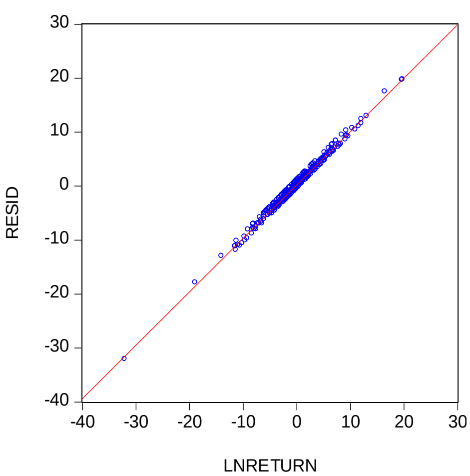
Second sub-period (03/01/01-10/31/01)



Third sub-period (11/01/01-11/30/07)



Fourth sub-period (12/01/07-05/31/09)



Fifth sub-period (06/01/09-12/31/13)

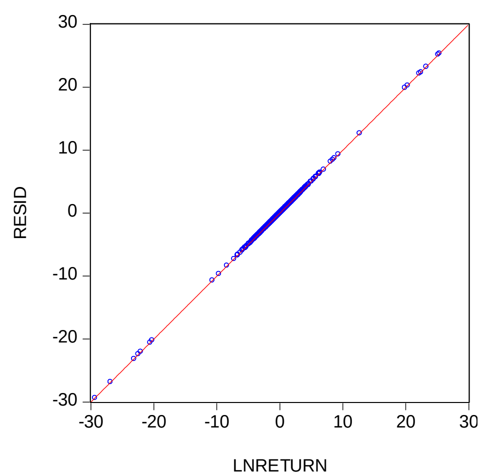
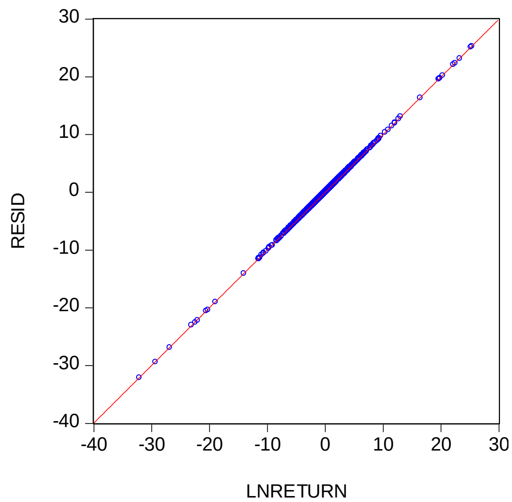
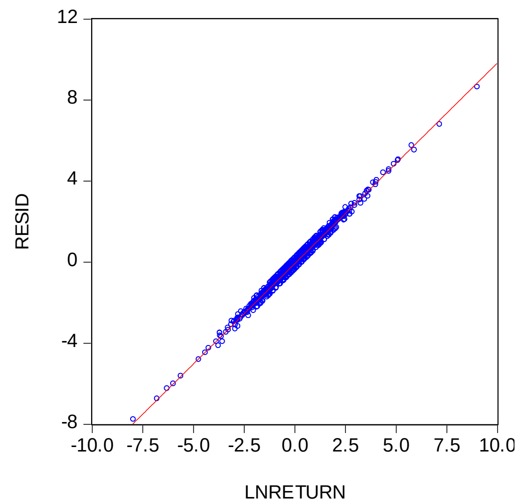


Figure 4.2 Scatterplot Dependent Variable for Monthly Series

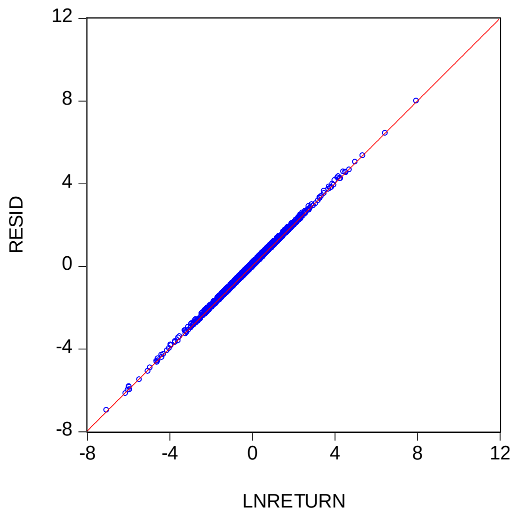
Full Period (01/01/96-12/31/13)



First sub-period (01/01/96-02/28/01)



Second sub-period (03/01/01-11/30/07)



Third sub-period (12/01/07-12/31/13)

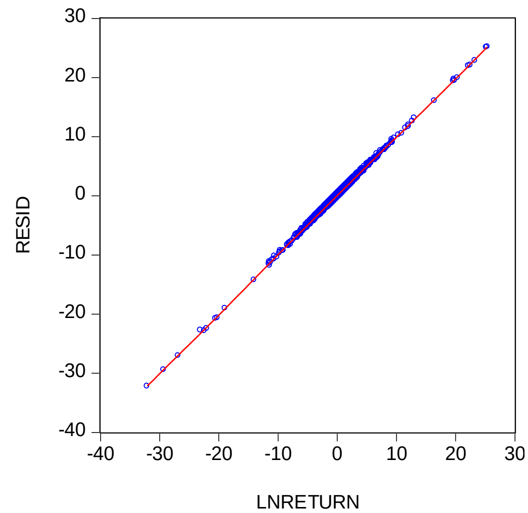


Table 4.17 Lack of Fit test for Daily Series

			Sum of Squares	Df	Mean Square	F	Sig.
LNreturn * DOW	Between Groups	(Combined)	24.142	4	6.036	**1.029**	**.391**
		Linearity	4.612	1	4.612	.786	.375
		Deviation from Linearity	19.530	3	6.510	1.110	.344
	Within Groups		27518.304	4692	5.865		
	Total		27542.446	4696			

Table 4.18 Lack of Fit test for Monthly Series

			Sum of Squares	Df	Mean Square	F	Sig.
LNreturn * MOY	Between Groups	(Combined)	35.598	11	3.236	**.551**	**.869**
		Linearity	.841	1	.841	.143	.705
		Deviation from Linearity	34.757	10	3.476	.592	.822
	Within Groups		27506.848	4685	5.871		
	Total		27542.446	4696			

4.4.5.2 Normality

To graphically verify the assumption of normality, a Normal Probability Plot was created for the full sample as well for the sub-periods. The X axis of the plot represented the observed probabilities while the Y axis denoted the predicted probabilities. If the data points fall around a diagonal line, can be interpreted as that the model follows a normal distribution. Figures 4.3 and 4.4 examined this assumption for daily and monthly series, and can be observed that the points do not follow a straight line. Therefore, the normal probability plot results do not support the normal distribution assumption.

Figure 4.3 Normal Probability Plot for Daily Series

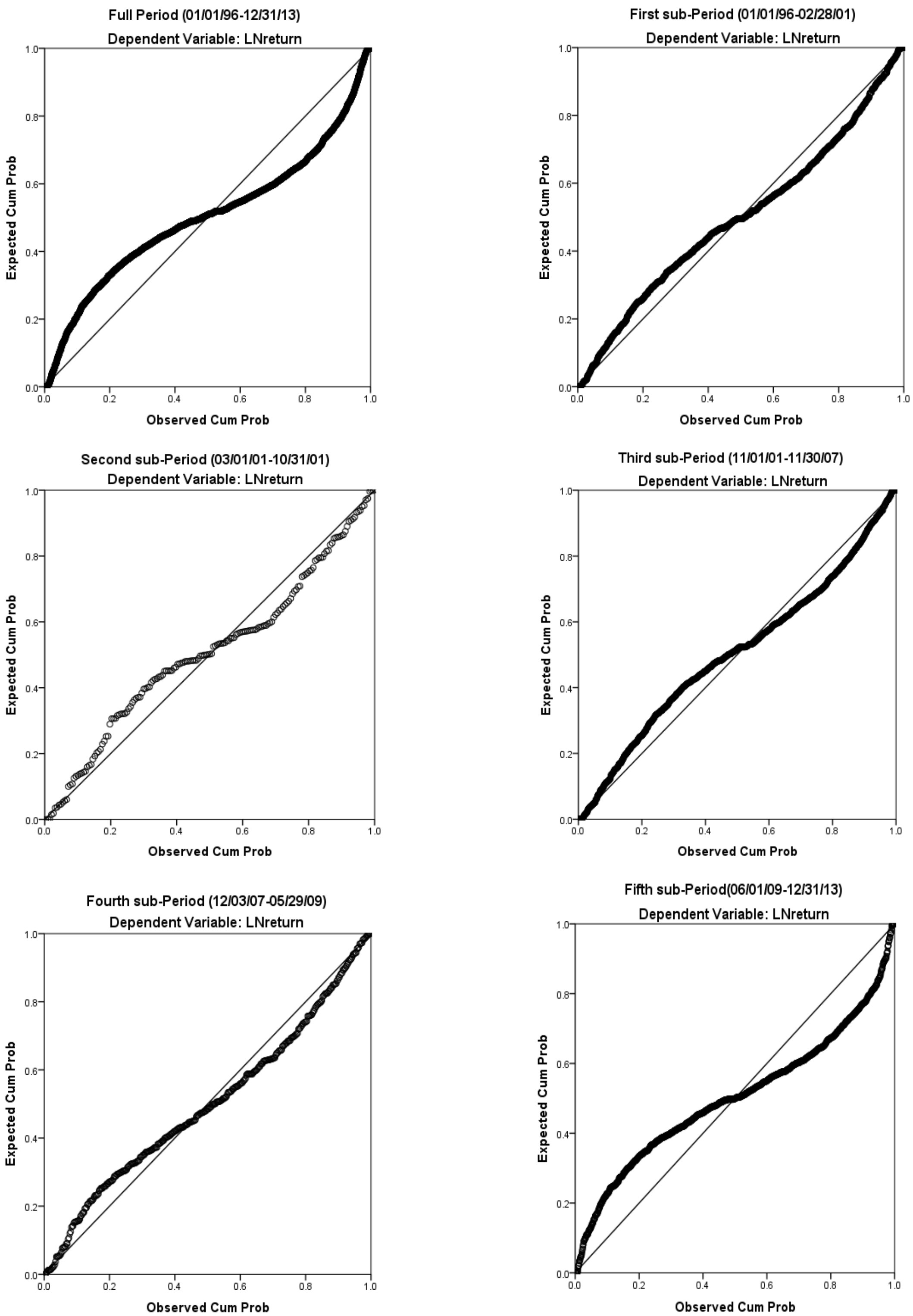
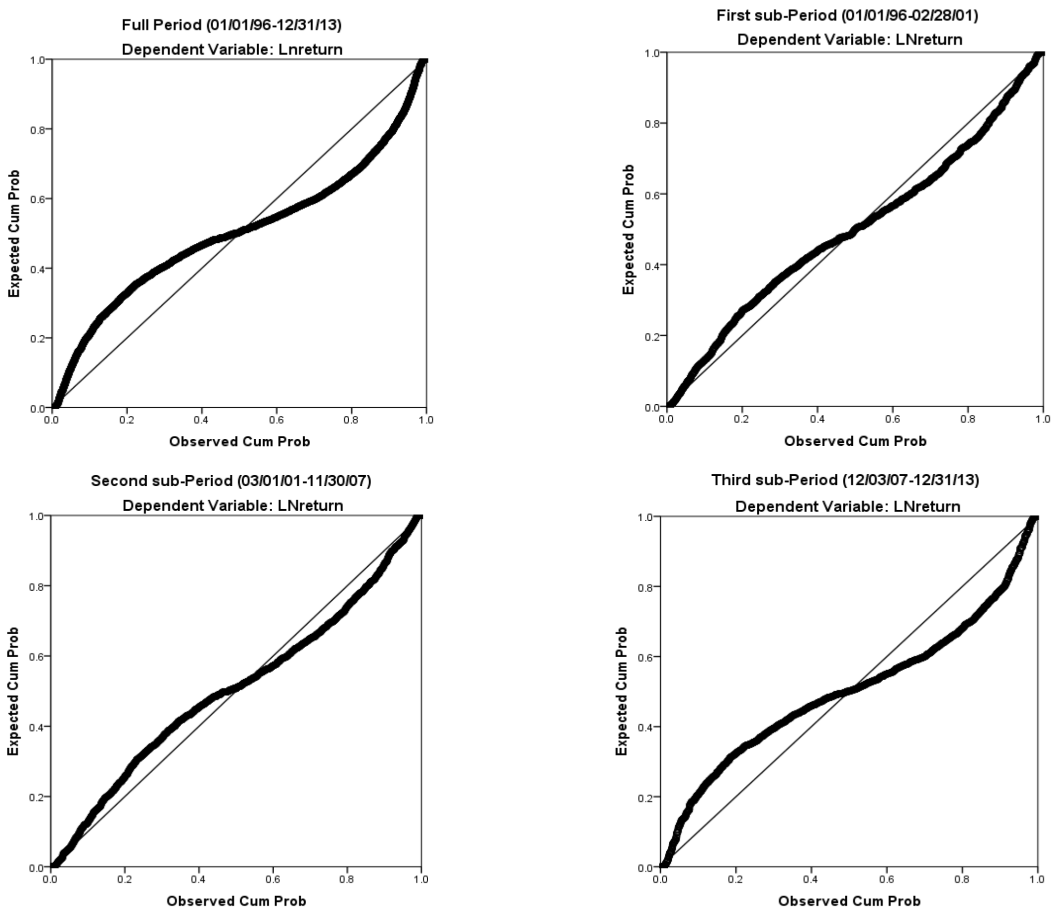


Figure 4.4 Normal Probability Plot for Monthly Series



In addition, to validate what was shown on the normal p-plots, we looked at both the skewness and kurtosis of the distribution. In all cases, the skewness statistics are near 0 but the kurtosis exceeded the accepted range of -3 and 3, as shown in Tables 4.19 and 4.20. In addition, the Jarque-Bera statistic, also rejected the null hypothesis of normality in all cases, because the calculated p-value was lower than the significance level of 5%. Therefore, it can be stated that neither the full sample nor the respective sub-periods, of both return series were normally distributed.

Table 4.19 Skewness, Kurtosis and Jarque-Bera statistic for Daily Series

	Skewness	Kurtosis	JB	Prob.	Ho decision
Full Period (01/01/96-12/31/13)	-0.5191127	40.80816	279967.6	0.00	R- Non-normal
First sub-period (01/01/96-02/28/01)	0.077357	8.300662	1579.460	0.00	R- Non-normal
Second sub- Period (03/01/01-10/31/01)	-0.452895	5.767824	61.84288	0.00	R- Non-normal
Third sub- Period (11/01/01-11/30/07)	-0.181409	7.216196	1184.163	0.00	R- Non-normal
Fourth sub- Period (12/01/07-05/31/09)	-0.365895	9.000704	593.8395	0.00	R- Non-normal
Fifth sub- Period (06/01/09-12/31/13)	-0.299780	33.07399	45127.13	0.00	R- Non-normal

Note:
1. R- Non-normal: Reject Null: Non-normal distribution.
2. NR- Normal: Do not reject Null: Normal distribution.

Table 4.20 Skewness, Kurtosis and Jarque-Bera statistic for Monthly Series

	Skewness	Kurtosis	JB	Prob.	Ho decision
Full Period (01/01/96-12/31/13)	-0.562364	40.66427	277878.9	0.00	R- Non-normal
First sub-period (01/01/96-02/28/01)	0.046075	7.892321	1344.815	0.00	R- Non-normal
Second sub- Period (03/01/01-11/30/07)	-0.208121	7.015732	1196.645	0.00	R- Non-normal
Third sub- Period (12/01/07-12/31/13)	-0.483119	21.06988	21652.92	0.00	R- Non-normal

Note:
1. R- Non-normal: Reject Null: Non-normal distribution.
2. NR- Normal: Do not reject Null: Normal distribution.

4.4.5.3 Homoscedasticity

As mentioned in Chapter 3, homogeneity is achieved when the variance of errors is equal throughout the independent variables. Table 4.21 presents the Heteroskedasticity White test results for the daily series. Because all the p-values were greater than the significance level of 5%, we failed to reject the null hypothesis of homoscedasticity for the full sample, and for all 5 sub-periods.

Table 4.21 Heteroskedasticity White test results for Daily Series

					Ho decision
Full Period (01/01/96-12/31/13)	F-statistic	0.709323	Prob. F(4,4692)	0.5855	NR-Homocedastic
	Obs*R-squared	**2.838600**	**Prob. Chi-Square(4)**	**0.5852**	
	Scaled explained SS	56.37949	Prob. Chi-Square(4)	0.0000	
First sub-Period (01/01/96-02/28/01)	F-statistic	1.149201	Prob. F(4,1343)	0.3317	NR-Homocedastic
	Obs*R-squared	**4.598179**	**Prob. Chi-Square(4)**	**0.3311**	
	Scaled explained SS	16.66059	Prob. Chi-Square(4)	0.0022	
Second sub-Period (03/01/01-10/31/01)	F-statistic	1.898071	Prob. F(4,170)	0.1130	NR-Homocedastic
	Obs*R-squared	**7.481462**	**Prob. Chi-Square(4)**	**0.1125**	
	Scaled explained SS	16.83056	Prob. Chi-Square(4)	0.0021	
Third sub-Period (11/01/01-11/30/07)	F-statistic	1.988914	Prob. F(4,1582)	0.0938	NR-Homocedastic
	Obs*R-squared	**7.940868**	**Prob. Chi-Square(4)**	**0.0938**	
	Scaled explained SS	24.52572	Prob. Chi-Square(4)	0.0001	
Fourth sub-Period (12/01/07-05/31/09)	F-statistic	1.142994	Prob. F(4,385)	0.3359	NR-Homocedastic
	Obs*R-squared	**4.577000**	**Prob. Chi-Square(4)**	**0.3335**	
	Scaled explained SS	17.84314	Prob. Chi-Square(4)	0.0013	
Fifth sub-Period (06/01/09-12/31/13)	F-statistic	0.559880	Prob. F(4,1192)	0.6918	NR-Homocedastic
	Obs*R-squared	**2.244697**	**Prob. Chi-Square(4)**	**0.6909**	
	Scaled explained SS	35.69810	Prob. Chi-Square(4)	0.0000	

Note:
1. R-Heteroskedastic: Reject Null: Heteroskedastic returns.
2. NR-Homocedastic: Do not reject Null: Homocedastic returns.

As for the monthly series, Table 4.22 shows that all p-values were lower than the significance level of 5%, rejecting the null hypothesis of homoscedasticity. Therefore, there was evidence of heteroskedasticy for the full sample and for all 5 sub-periods in the monthly series.

Table 4.22 Heteroskedasticity-White test results for Monthly Series

					Ho decision
Full Period (01/01/96-12/31/13)	F-statistic	2.499610	Prob. F(11,4685)	0.0039	R-Heteroskedastic
	Obs*R-squared	**27.40529**	**Prob. Chi-Square(11)**	**0.0040**	
	Scaled explained SS	540.7320	Prob. Chi-Square(11)	0.0000	
First sub-period (01/01/96-02/28/01)	F-statistic	2.334620	Prob. F(11,1336)	0.0076	R-Heteroskedastic
	Obs*R-squared	**25.42281**	**Prob. Chi-Square(11)**	**0.0079**	
	Scaled explained SS	86.05818	Prob. Chi-Square(11)	0.0000	
Second sub-period (03/01/01-11/30/07)	F-statistic	4.022480	Prob. F(11,1750)	0.0000	R-Heteroskedastic
	Obs*R-squared	**43.45204**	**Prob. Chi-Square(11)**	**0.0000**	
	Scaled explained SS	128.9238	Prob. Chi-Square(11)	0.0000	
Third sub-period (12/01/07-12/31/13)	F-statistic	2.683494	Prob. F(11,1575)	0.0020	R-Heteroskedastic
	Obs*R-squared	**29.19615**	**Prob. Chi-Square(11)**	**0.0021**	
	Scaled explained SS	288.5677	Prob. Chi-Square(11)	0.0000	

Note:
1. R-Heteroskedastic: Reject Null: Heteroskedastic returns.
2. NR-Homocedastic: Do not reject Null: Homocedastic returns.

4.4.5.4 Independent errors

The last assumption required the residuals to be independent, otherwise autocorrelation is present. The Breusch-Godfrey tests verified the no autocorrelation assumption and generated mixed results for the daily series, as shown in Table 4.23. For the full sample period, as well as for the last three sub-periods, p-values were lower than the 5% significance level, rejecting the null hypothesis of no autocorrelation. Conversely, this was not the case for the first and second sub-periods, meaning that the null hypothesis of no autocorrelation could not be rejected.

Table 4.23 Breusch-Godfrey test results for Daily Series

	Breusch-Godfrey test				Ho decision
Full Period (01/01/96-12/31/13)	F-statistic **Obs*R-squared**	65.31789 **127.2853**	Prob. F(2,4690) **Prob. Chi-Square(2)**	0.0000 **0.0000**	R-Serial correlation
First sub-period (01/01/96-02/28/01)	F-statistic **Obs*R-squared**	0.358818 **0.720996**	Prob. F(2,1341) **Prob. Chi-Square(2)**	0.6986 **0.6973**	NR-Independent
Second sub-period (03/01/01-10/31/01)	F-statistic **Obs*R-squared**	2.208619 **4.483407**	Prob. F(2,168) **Prob. Chi-Square(2)**	0.1130 **0.1063**	NR-Independent
Third sub-period (11/01/01-11/30/07)	F-statistic **Obs*R-squared**	4.638735 **9.264176**	Prob. F(2,1580) **Prob. Chi-Square(2)**	0.0098 **0.0097**	R-Serial correlation
Fourth sub-period (12/01/07-05/31/09)	F-statistic **Obs*R-squared**	8.962424 **17.43641**	Prob. F(2,383) **Prob. Chi-Square(2)**	0.0002 **0.0002**	R-Serial correlation
Fifth sub-period (06/01/09-12/31/13)	F-statistic **Obs*R-squared**	33.10625 **63.09152**	Prob. F(2,1190) **Prob. Chi-Square(2)**	0.0000 **0.0000**	R-Serial correlation

Note:
1. R-Serial correlation: Reject Null: Autocorrelation.
2. NR-Independent: Do not reject Null: No autocorrelation.

Moreover, the Breusch-Godfrey tests generated mixed results for the monthly series as well. Table 4.24 presents that for all periods, the p-values were significant at 5 % level, except for the first sub-period. As a result, this was the only sub-period with no signs of autocorrelation, meaning that for the remaining sub-periods, the null hypothesis of no autocorrelation or serial correlation was rejected.

Table 4.24 Breusch-Godfrey test results for Monthly Series

Breusch-Godfrey test					Ho decision
Full Period (01/01/96-12/31/13)	F-statistic **Obs*R-squared**	66.65342 **130.0046**	Prob. F(2,4683) **Prob. Chi-Square(2)**	0.0000 **0.0000**	R-Serial correlation
First sub-period (01/01/96-02/28/01)	F-statistic **Obs*R-squared**	0.462294 **0.933644**	Prob. F(2,1334) **Prob. Chi-Square(2)**	0.6299 **0.6270**	NR-Independent
Second sub-period (03/01/01-11/30/07)	F-statistic **Obs*R-squared**	4.609663 **9.244409**	Prob. F(2,1748) **Prob. Chi-Square(2)**	0.0101 **0.0098**	R-Serial correlation
Third sub-period (12/01/07-12/31/13)	F-statistic **Obs*R-squared**	40.60696 **77.91404**	Prob. F(2,1573) **Prob. Chi-Square(2)**	0.0000 **0.0000**	R-Serial correlation

Note:
1. R-Serial correlation: Reject Null: Autocorrelation.
2. NR-Independent: Do not reject Null: No autocorrelation.

4.5 Nonparametric test results

This section presents the results of the nonparametric procedures, applied to the daily return series and the monthly return series of the PRSI. Since the normality assumption was violated in all cases for daily and monthly series in section 4.4.5.1, the use of nonparametric estimation was justified. The nonparametric Kruskal-Wallis (KW) test is widely used when normality assumption is violated (e.g., Hamid & Tej, 2012; Hui, 2005, Lim et al., 2010; Mylonakis & Tserkezos, 2008; Rozeff & Kinney, 1976).

4.5.1 Kruskal-Wallis Results

The KW test was used to examine the differences between the means of the days of the week and the months of the year, based on the ranks of the sample observations. Table 4.25 shows the results for the daily series and only revealed a significant X^2 value at 5% level, for the full sample. This caused the rejection of the null hypothesis of equality in the means for the full sample, indicating that there was evidence of the day-of-the-week effect. However, this result were not consistent with the OLS results.

Table 4.25 KW Test Results for Daily Series

	X^2 statistic	Ho decision
Full Period (01/01/96-12/31/13)	10.882**	Reject at the 5 percent level
First sub-period (01/01/96-02/28/01)	6.732	Accept
Second sub- Period (03/01/01-10/31/01)	1.204	Accept
Third sub- Period (11/01/01-11/30/07)	4.380	Accept
Fourth sub- Period (12/01/07-05/31/09)	4.505	Accept
Fifth sub- Period (06/01/09-12/31/13)	3.130	Accept

Then the Wilcoxon rank sum test was applied to identify those trading days that contributed to the rejection of the null hypothesis of equality of the means. Table 4.26 shows that the difference in returns was significant (at 5% significance level) when Monday was compared to Tuesday, Wednesday and Friday. The test highlighted that Monday had lower returns compared to Tuesday, Wednesday and Friday returns. Also, there was a significant negative estimated coefficient when Thursday was compared to Friday (at 10% significance level), suggesting that Thursday had lower returns compared to Friday. On the other hand, there was no indication of the day-of-the-week in the sub-periods of the daily series.

Furthermore, Table 4.27 shows that the null hypothesis of equality of the means in the monthly series was accepted, concluding that the month-of-the-year effect was not present in the full sample nor in the sub-periods.

Table 4.26 KW and Wilcoxon Rank-Sum Test Results for Daily Series

	X^2 statistics		Null hypothesis	
KW	10.882**		Rejected at 5% level.	
Wilcoxon rank sum	Tuesday	Wednesday	Thursday	Friday
Monday	**-2.203****	**-2.553****	-1.177	**-2.889****
Tuesday		-0.226	-1.007	-0.606
Wednesday			-1.314	-0.361
Thursday				**-1.675***

Note: **, and * denote significance at 5 and 10% levels, respectively.

Table 4.27 KW Test Results for Monthly Series

	X2 statistic	Ho decision
Full Period (01/01/96-12/31/13)	6.466	Accept
First sub-period (01/01/96-02/28/01)	6.085	Accept
Second sub- Period (03/01/01-11/30/07)	3.248	Accept
Third sub- Period (12/01/07-12/31/13)	9.576	Accept

4.6 Generalized Autoregressive Conditional Heteroskedasticity (GARCH) results

Since the regression results failed to comply with several of the assumptions of the OLS models as presented in section 4.4.5, the use of the GARCH model was justified. This section presents the results of the GARCH model, after testing the day-of-the-week effect, Monday effect, month-of-the-year and January effect calendar anomalies in the returns of the PRSI. Different GARCH (p,q) models were estimated using the t-distribution, due to the fatter tails (Connolly, 1979). The parameters selection of the model was determined by the Akaike information criterion (AIC), Schwarz criterion (SC) and Hannan–Quinn (HQ) information criterion, but emphasizing in the SC because impose larger penalties for additional coefficients (EViews, 2009). The model with the lowest criterions that complied with the restrictions that the conditional variance parameters coefficients are non-negative, that the sum of the coefficients are less than one[9] (i.e. $\alpha_1+\beta_1<1$) to satisfy the non-explosiveness of the conditional variances (Sannassee et al., 2011), and satisfied the serial correlation and arch effects specifications, was selected. Moreover, Autoregressive Moving Average (ARMA) process was integrated when the serial correlation condition was not satisfied. Therefore, Autoregressive (AR) and Moving Average (MA) terms were incorporated as needed.

4.6.1 GARCH results for the Day-of-the-Week effect

The conditional variance of the returns was allowed to change for each day-of-the-week by the GARCH (p,q) model. This model included 5 dummy variables representing each day in the week without a constant term, allowing the detection of an irregularity by incorporating volatility without focusing in a certain day, as in Sannassee et al. (2011) and Yakob et al. (2005). The GARCH (p,q) findings of whether the day-of-the-week effect was present in the return of the daily series for the full period and sub-periods, are reported in Table 4.28.

According to the model, the day-of-the-week effect exists in the PRSI. The results show a significant positive estimated coefficients for Wednesday (0.09204) and Friday (0.08905) at 5% level of significance in the full sample, suggesting that the returns on these days are statistically higher than the others days of the week. This means that two days manifest anomalous behavior as happened in Kamath and Liu (2011) investigation, which found a Monday-Friday effect during the first half of the study. The same is true for the first sub-period, in which significant positive estimated coefficients for Wednesday (0.164209 at 1% level of

[9] Values of the sum lower than unity imply a tendency for the volatility response to decay over time, at a slower rate the closer the sum is to unity. In contrast, values of the sum equal to (or greater) unity imply indefinite (or increasing) volatility persistence to shocks over time (Sannassee et al., 2011).

significance) and Friday (0.108517 at 10% level of significance) were detected. Conversely, for the second sub-period no anomaly persisted but for the third sub-period, a significant positive estimated coefficient for Friday (0.119027 at 5% significance) resurged. This is consistent with the Friday day-of-the-week effect literature, where Friday generally has the highest average return in comparison with the other days of the week (Smirlock & Starks, 1986; Kamath & Liu, 2011). Moreover, as in the full sample, all these significant positive coefficients in the sub-periods, suggest that the returns on these specific days are statistically higher than the others days of the week. Nevertheless, none of the effects carried on to the fourth and fifth period. Maybe the credit crisis that took place in the fourth period, and the drastic composition change of the PRSI in the fifth period, prevented the existence of significant positive effects, nor were sufficient to allow for significant negative effects. Also the changing of significant anomalous days as time goes by, represented by the 5 sub-periods, was also found in Kamath and Liu (2011) investigation.

Table 4.28 GARCH results for the DOW effect

	GARCH (P,Q)											
	MEAN EQUATION											
Variable	**Full Period (January 1996-December 2013)**		**Sub-period 1 (January 1996-February 2001)**		**Sub-period 2 (March 2001-October 2001)**		**Sub-period 3 (November 2001-November 2007)**		**Sub-period 4 (December 2007-May 2009)**		**Sub-period 5 (June 2009-December 2013)**	
	GARCH(1,2)		**GARCH(1,1)**		**GARCH(1,0)**		**GARCH(1,1)**		**GARCH(1,1)**		**GARCH(1,1)**	
	Coef.	**Std. Error**	**Coef.**	**Std. Error**	**Coef.**	**Std. Error**	**Coef.**	**Std. Error**	**Coef.**	**Std. Error**	**Coef.**	**Std. Error**
Monday	-0.00488	0.040033	0.01135	0.059339	-0.00474	0.167312	-0.00997	0.055953	-0.62614	0.387518	-0.05928	0.109719
Tuesday	0.058196	0.038285	0.084953	0.055789	0.126743	0.162977	0.056606	0.053275	0.03852	0.408615	0.037579	0.104387
Wednesday	**0.09204****	0.039668	**0.164209*****	0.057281	0.237442	0.166384	0.020497	0.055809	-0.35763	0.394882	0.08202	0.104479
Thursday	0.017312	0.03901	-0.022039	0.055847	0.17808	0.167609	-0.02089	0.055736	0.167242	0.364151	0.135939	0.102655
Friday	**0.08905****	0.039933	**0.108517***	0.056039	0.110932	0.173025	**0.119027****	0.057607	-0.61603	0.392611	0.109098	0.108054
AR(1)							0.058663**	0.023774	-0.12851***	0.048345		
AR(3)			0.102078***	0.026000								
AR(5)	0.856587***	0.045035										
MA(2)	0.020916***	0.007462										
MA(3)	0.026253***	0.007808										
MA(5)	-0.84992***	0.045768										
# observations	4692 after adjustments		1345 after adjustments		175		1587		390		1197	
R squared[10]	0.002821		0.007864		0.002314		0.004299		0.042283		-0.00061	

Note:
***, **, * denotes significance at the 1%, 5% level and 10%, respectively.

[10] All periods exhibited very low R-squares like Asteriou and Kavetsos (2006) and French (1980), although in most researches this statistic is not included. This is common in models which use dummy variables alone as explanatory variables because dummies simply capture the step changes in mean of the dependent variable and do not capture the variation of daily returns (Drauper & Paudyal, 2002). However, even with low R-squares, individual coefficients significantly different from zero can be useful (Holden et al., 2004) and conclusions can be drawn (Kennedy, 2003).

4.6.2 GARCH results for Monday effect

The conditional variance of the returns was allowed to change for the Monday effect by the GARCH (p,q) model. This model included a constant term, representing the average daily return for Monday and only 4 dummy variables representing the remaining days in the week, (e.g., Connolly, 1989 and Georgantopoulos et al, 2011). Table 4.29 presents the results for the GARCH (p,q) for the Monday effect to determine whether this anomaly was present in the return of the daily series, for the full period and sub-periods.

According to the model, the Monday effect does not exist in the PRSI. However, the model reports significant positive estimated coefficients for Wednesdays, at a 5% level of significance in the full sample (0.096925) and in the first sub-period (0.152858), stating the returns on Wednesdays are statistically higher than Monday, validating the previous DOW results in section 4.6.1 and OLS DOW examination in section 4.4.1 for the first sub-period (Derbali & Khadraoui, 2011; Kamath & Liu, 2011). Also, reports significant positive estimated coefficients for Friday, at a 10 % level of significance in the full sample (0.096925) and in the third sub-period (0.128992), stating the returns on Friday are statistically higher than Monday, again validating the previous DOW results in section 4.6.1. Nonetheless, in the fourth and fifth sub-period, no significant estimated coefficients were found, consistent with the previous DOW results in section 4.6.1.

Table 4.29 GARCH results for the Monday effect

Variable	Full Period (January 1996-December 2013)		Sub-period 1 (January 1996-February 2001)		Sub-period 2 (March 2001-October 2001)		Sub-period 3 (November 2001-November 2007)		Sub-period 4 (December 2007-May 2009)		Sub-period 5 (June 2009-December 2013)	
	GARCH (P,Q)											
	MEAN EQUATION											
	GARCH(1,2)		**GARCH(1,1)**		**GARCH(1,0)**		**GARCH(1,1)**		**GARCH(1,1)**		**GARCH(1,1)**	
	Coef.	**Std. Error**	**Coef.**	**Std. Error**	**Coef.**	**Std. Error**	**Coef.**	**Std. Error**	**Coef.**	**Std. Error**	**Coef.**	**Std. Error**
C	-0.00488	0.040033	0.011352	0.059339	-0.00474	0.167312	-0.00997	0.055953	-0.62615	0.38752	-0.05928	0.109719
Tuesday	0.063081	0.054813	0.073601	0.081245	0.131487	0.225617	0.066572	0.074678	0.66468	0.603771	0.09686	0.151455
Wednesday	**0.096925****	0.047157	**0.152858****	0.077592	0.242182	0.237264	0.030462	0.078821	0.268524	0.541641	0.141301	0.151316
Thursday	0.022197	0.046759	-0.03339	0.076936	0.182827	0.239084	-0.01093	0.07882	0.793384	0.52937	0.195221	0.149468
Friday	**0.093935***	0.055852	0.097166	0.081253	0.115672	0.241584	**0.128992***	0.077695	0.010116	0.569879	0.168379	0.153744
AR(1)							0.05866**	0.02377	-0.1285***	0.04835		
AR(3)			0.102078***	0.026000								
AR(5)	0.856587***	0.045035										
MA(2)	0.020916***	0.007462										
MA(3)	0.026253***	0.007808										
MA(5)	-0.84992***	0.045768										
# observation	4692 after adjustments		1345 after adjustments		175		1587		390		1197	
R squared[11]	0.002821		0.007864		0.002314		0.004299		0.042284		-0.0006	

Note:
***, **, * denotes significance at the 1%, 5% level and 10%, respectively.

[11]All periods exhibited very low R-squares like Asteriou and Kavetsos (2006) and French (1980), although in most researches this statistic is not included. This is common in models which use dummy variables alone as explanatory variables because dummies simply capture the step changes in mean of the dependent variable and do not capture the variation of daily returns (Drauper & Paudyal, 2002). However, even with low R-squares, individual coefficients significantly different from zero can be useful (Holden et al., 2004) and conclusions can be drawn (Kennedy, 2003).

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4.6.3 GARCH results for the Month-of-the-Year effect

The conditional variance of the returns was allowed to change for each month-of-the-year by the GARCH (p,q) model. This model included all 12 dummy variables representing each month in the year without a constant term, allowing the detection of an irregularity modeling volatility without focusing in a specific month (e.g., Sannassee et al., 2011 and Yakob et al., 2005). The GARCH (p,q) findings of whether the MOY effect was present in the returns of the monthly series for the full period and sub-periods, are reported in Table 4.30.

Therefore, the results demonstrated that the month-of-the-year effect exist in the PRSI. The full sample shows significant positive estimated coefficients for September (0.13479 at 5% level of significance) and November (0.118229 at 10% level of significance), suggesting that the returns on these days were statistically higher than the others months of the year. This means that more than one month exhibited an anomalous behavior (Mylonakis & Tserkezos, 2008; Marrett & Worthington, 2011). Thus, supporting the Álvarez and Rodríguez (2006) conclusion that suggested that PRSI display some degree of predictability.

However, in the first sub-period only a significant positive estimated coefficient for September (0.216106 at 5% level of significance) was found, confirming the MOY OLS results for this period in section 4.4.3 (Nazari & Farzanegan, 2011). There were no significant coefficients for the second sub-period, whereas for the third sub-period, revealed a significant negative coefficient for June (-0.26286 at 10% level of significance), asserting that the returns on June were statistically lower than the others months in the third period, as in the MOY OLS results in section 4.4.3. This was the only sub-period with significant negative returns. This can be associated to the fact that this period comprehends 18 months of a contraction phase, the same 18 months that conform the fourth period in the daily series, which also manifested significant negative coefficients in the month-of-the-year OLS results in section 4.4.3. Moreover, two negative events took place in this time frame; the credit crisis and the change of composition of the PRSI.

4.6.4 GARCH results for the January effect

The conditional variance of the returns was allowed to change for the January effect by the GARCH (p,q) model. This model included a constant term, representing the average daily return for January and only 11 dummy variables representing the remaining months in the year (Georgantopoulos et al., 2011). Table 4.31 presents the results for the GARCH (p,q) for the January effect to determine whether this anomaly is present in the return of the monthly series, for the full period and sub-periods.

The results showed that the January effect does not exist in the PRSI. In addition, no significant estimated coefficients were found for the first and second sub-periods. However, the third sub-period showed significant negative estimated coefficients for June (-0.44372 at 5% level of significance) and July (-0.39627 at 10% level of significance), stating that the returns on these months were statistically lower than January returns. This means that more than one month exhibited an anomalous behavior (Mylonakis & Tserkezos, 2008; Marrett & Worthington, 2011). The significant negative results for this period are similar to those found in the MOY OLS and MOY GARCH analysis, in section 4.4.3 and 4.6.3 respectively for the same time frame. This suggests that behavior may be product of the contraction phase enclosed in this sub-period and the negative events that took place in it.

Table 4.30 GARCH results for the MOY effect

				GARCH (P,Q)				
				MEAN EQUATION				
Variable	**Full Period (January 1996- December 2013)**		**Sub-period 1 (January 1996- February 2001)**		**Sub-period 2 (March 2001-November 2007)**		**Sub-period 3 (December 2007- December 2013)**	
	GARCH(1,2)		**GARCH(1,1)**		**GARCH(1,1)**		**GARCH(1,1)[12]**	
	Coefficient	**Std. Error**	**Coefficient**	**Std. Error**	**Coefficient**	**Std. Error**	**Coefficient**	**Std. Error**
January	0.032376	0.060812	0.05332	0.0809	0.006201	0.077734	0.180862	0.161002
February	0.049662	0.067314	0.121599	0.095914	0.002927	0.095626	0.031646	0.181176
March	0.040331	0.061743	0.096555	0.106092	0.03555	0.077112	0.067312	0.162406
April	0.041362	0.060644	0.045324	0.096358	-0.03268	0.086482	0.247971	0.166973
May	0.026065	0.061905	0.035233	0.094688	0.065041	0.091053	-0.17285	0.146186
June	0.00964	0.055852	-0.02225	0.089137	0.093224	0.076295	**-0.26286***	0.147342
July	0.045306	0.062318	0.078128	0.090623	0.080723	0.085928	-0.21541	0.176317
August	0.026774	0.066279	0.018489	0.100098	0.07806	0.093549	-0.1183	0.152405
September	**0.13479****	0.063259	**0.216106****	0.094261	0.088961	0.090548	0.039318	0.164495
October	0.011431	0.066814	0.04363	0.113127	-0.00804	0.091342	-0.03429	0.148174
November	**0.118229***	0.067103	0.084325	0.109238	0.098499	0.093413	0.176714	0.153679
December	0.087953	0.06357	0.14374	0.111551	0.042883	0.087681	0.131752	0.138857
AR(1)					0.052883**	0.023016		
AR(2)	0.019669***	0.007018						
AR(3)			0.10063***	0.026204				
AR(5)	0.871357***	0.040455						
MA(3)	0.024765***	0.00747						
MA(5)	-0.86475***	0.041426						
# observations	4692 after adjustments		1345 after adjustments		1762		1587	
R squared[13]	0.00224		0.01024		0.003078		0.000507	

Note:
***, **, * denotes significance at the 1%, 5% level and 10%, respectively.

[12] Do not comply with $\alpha_1+\beta_1<1$ restriction, implying indefinite volatility persistence to shocks over time (Sannassee et al., 2011)

[13] All periods exhibited very low R-squares like Asteriou and Kavetsos (2006) and French (1980), although in most researches this statistic is not included. This is common in models which use dummy variables alty as explanatory variables because dummies simply capture the step changes in mean of the dependent variable and do not capture the variation of daily returns (Drauper & Paudyal, 2002). However, even with low R-squares, individual coefficients significantly different from zero can be useful (Holden et al., 2004) and conclusions can be drawn (Kennedy, 2003).

Table 4.31 GARCH results for the January effect

MEAN EQUATION								
Variable	Full Period (January 1996-December 2013)		Sub-period 1 (January 1996-February 2001)		Sub-period 2 (March 2001-November 2007)		Sub-period 3 (December 2007-December 2013)	
	GARCH(1,2)		GARCH(1,1)		GARCH(1,1)		GARCH(1,1)[14]	
	Coefficient	**Std. Error**	**Coefficient**	**Std. Error**	**Coefficient**	**Std. Error**	**Coefficient**	**Std. Error**
C	0.032377	0.060812	0.053321	0.0809	0.006201	0.077734	0.180862	0.161002
February	0.017287	0.081018	0.068279	0.124874	-0.00327	0.122632	-0.14922	0.242628
March	0.007954	0.081111	0.043237	0.133582	0.029349	0.109396	-0.11355	0.228567
April	0.008985	0.082457	-0.008	0.125695	-0.03888	0.116332	0.067109	0.231993
May	-0.00631	0.084696	-0.01809	0.12454	0.058842	0.119681	-0.35371	0.217444
June	-0.02274	0.081108	-0.07557	0.120323	0.087023	0.108874	**-0.44372****	0.218647
July	0.012929	0.085733	0.024807	0.121624	0.074522	0.115837	**-0.39627***	0.238435
August	-0.0056	0.088582	-0.03483	0.128894	0.071859	0.121531	-0.29916	0.22181
September	0.102413	0.085942	0.162785	0.124329	0.082761	0.11931	-0.14155	0.230077
October	-0.02095	0.08744	-0.00969	0.139291	-0.01424	0.119829	-0.21516	0.218766
November	0.085852	0.086046	0.031005	0.136037	0.092297	0.121565	-0.00415	0.222645
December	0.055577	0.080624	0.090419	0.136788	0.036686	0.117133	-0.04911	0.211692
AR(1)					0.052884**	0.023016		
AR(2)	0.019669***	0.007018						
AR(3)			0.10063***	0.026204				
AR(5)	0.871357***	0.040455						
MA(3)	0.024765***	0.00747						
MA(5)	-0.86475***	0.041426						
# observations	4692 after adjustments		1345 after adjustments		1762		1587	
R squared[15]	0.00224		0.01024		0.003078		0.000507	

Note:
***, **, * denotes significance at the 1%, 5% level and 10%, respectively.

[14] Do not comply with $\alpha_1+\beta_1<1$ restriction, implying indefinite volatility persistence to shocks over time (Sannassee et al., 2011).
[15] All periods exhibited very low R-squares like Asteriou and Kavetsos (2006) and French (1980), although in most researches this statistic is not included. This is common in models which use dummy variables alone as explanatory variables because dummies simply capture the step changes in mean of the dependent variable and do not capture the variation of daily returns (Drauper & Paudyal, 2002). However, even with low R-squares, individual coefficients significantly different from zero can be useful (Holden et al., 2004) and conclusions can be drawn (Kennedy, 2003).

4.6.5 Specification test for the GARCH (p,q) model

To check the specification adequacy of the GARCH (p,q) estimated model, several standard tests were applied. In order, to detect ARCH effects in the residuals of PRSI returns, the ARCH LM test was used. In addition, to detect serial correlation in the residuals and whether the mean equation was correctly specified, the correlogram Q-statistic provided by EViews was used.

4.6.5.1 ARCH LM test results

This test examined ARCH effects in the residuals and whether the variance equation was correctly specified. The null hypothesis states that there are no ARCH effects up to an order q in the standardized residuals. The ARCH LM test results reported that in most cases for both series, the null hypothesis was not rejected because the ARCH LM statistics were larger than 0.05 ($\alpha \geq 0.05$)[16], except for the third period in the daily series and the second period in the monthly series[17]. Therefore, the GARCH (p,q) variance equation was robust.

4.6.5.2 Serial Correlation test results .

This test displays the autocorrelation and partial autocorrelation of the standardized residuals and computes the Ljung-Box Q-statistic at any specified number of lags. If no serial correlation was present in the residuals, the autocorrelations and partial autocorrelations should be near cero and the Q-statistic should be non-significant, i.e., $\alpha \geq 0.05$. The Ljung- Box Q-statistic test results reported that in all cases for the daily and monthly series, the null hypothesis was not rejected because the Q-statistic statistics, were larger than 0.05 or got to be larger than 0.05 within the firsts few lags out of 35 that were calculated[18].

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[16] ARCH LM test results are presented in Appendix A.
[17] This signals model misspecification, however higher order of the GARCH (p,q) process were estimated that corrected for arch effects and evidenced the same results, but violated the non-negative and $\alpha_1+\beta_1<1$ restrictions, for the parameters coefficients in the conditional variance. Therefore, the GARCH (1,1) was used.
[18] Correlogram Q-statistic results are presented in Appendix B.

4.7 Summary

After employing the OLS multiple regression, the KW procedure and the GARCH model, to test the anomalies analyzed in this study, the research revealed the following results:

a) Day-of-the-Week effect (DOW)

1. OLS model results- evidenced that the DOW does not exist in the PRSI returns for the full period. However, the first sub-period exhibited a weak Wednesday effect, while the fourth sub-period a weak negative Monday effect.
2. KW results- evidenced a DOW only in the full sample. The Wilcoxon test distinguished a negative Monday effect, when compared to Tuesday, Wednesday and Friday, and a negative Thursday when compared to Friday.
3. GARCH model results- evidenced that the DOW exists in the PRSI returns, displaying a Wednesday and Friday effect in the full sample. In addition, the first sub-period revealed the same anomaly but by the second sub-period none of the effects persisted, although in third sub-period the Friday effect resurged.

b) Monday effect

1. OLS model results- evidenced that the Monday effect does not exist in the PRSI returns for the full period, yet was only observed in the fourth sub-period.
2. KW and Wilcoxon test- evidenced a negative Monday, when compared to Tuesday, Wednesday and Friday, as mentioned for DOW effect.

3. GARCH model results- evidenced that the Monday effect does not exist in the PRSI returns for the full period, but reported a positive Wednesday and Friday effects with respect to Monday. Also found significant Wednesday in the first period and Friday in the third.

c) Month-of-the-Year effect (MOY)

1. OLS model results- evidenced that the MOY does not exist in the PRSI returns for the full sample, but the first sub-period revealed a weak September effect and the third sub-period a negative June effect.
2. KW test -supported that the MOY does not exist in the PRSI.
3. GARCH model results- evidenced that the MOY exists in the PRSI returns, because showed September and November effects in the full sample. Moreover, the September effect was also found in the first sub-period. Conversely, the third sub-period exhibited a negative June effect.

d) January effect

1. OLS model results -evidenced that the January effect does not exist in the PRSI returns for the full sample, yet the first sub-period showed a September effect with respect to January
2. KW test - evidenced that the January effect does not exist in the PRSI.
3. GARCH model results- evidenced that the January effect does not exist in the PRSI returns for the full sample, but revealed negative June and July effects in the last period, with respect to January.

Chapter 5: Conclusion and Recommendations

5.1 Conclusions

The main objective of this research was to empirically investigate whether calendar anomalies, such as the day-of-the-week effect, Monday effect, month-of-the-year and January effect were reflected in the returns of the Puerto Rico Stock Index (PRSI). In addition, it was expected to determine if the presence of these calendar anomalies persisted across the different US business cycles periods, from 1996 to 2013, in which the sample was divided. In order to test the mentioned anomalies, an ordinary least squares (OLS) multiple regression, a non-parametric Kruskal-Wallis (KW) procedure and the generalized autoregressive conditional heteroskedasticity (GARCH) model, were used. The findings were mixed and some are contradictory.

Nonetheless, the GARCH model was the most robust procedure to examine the calendar anomalies of this study, because accounted for the stylized facts characteristic of the financial time series. The GARCH results evidenced that the DOW exists in the PRSI returns because displayed significant Wednesday and Friday effects in the full sample, therefore more than one day manifested an anomalous behavior (Kamath & Liu, 2011). On the contrary, provided evidence that the Monday effect does not exist in the PRSI returns, but reported significant positive Wednesday and Fridays effects in the full sample, suggesting that the return on these days are statistically higher than Monday, validating the previous DOW results. As for the five periods that were analyzed for both daily anomalies, anomalous behavior was concentrated in the firsts few sub periods but was unsteady throughout the sample periods (Kamath & Liu, 2011).

On the other hand, the GARCH model found evidence that the MOY manifested in the PRSI returns, because showed significant September and November effects in the full sample, thus more than one month exhibited an anomalous behavior (Mylonakis & Tserkezos, 2008; Marrett & Worthington, 2011). Moreover, regarding the three periods that also were analyzed, revealed a significant September effect (Nazari & Farzanegan, 2011) in the first period and a significant negative June effect in the last period. Conversely, for the January effect the results showed that does not exist in the PRSI returns. As for the three periods that were analyzed, there was no indication of the January effect but revealed significant negative returns for more than one month (Mylonakis & Tserkezos, 2008; Marrett & Worthington, 2011), June and July in the third and last period, similar to those found in the MOY estimation for the same period.

Overall, the only calendar anomaly analyzed in this investigation that all procedures agreed that was not present in the PRSI, was the January effect. Moreover, consistent negative anomalies were detected in the third and last sub-period for both anomalies tested using the monthly series. Therefore, there is a possibility that they may still taking place, and perhaps triggered by the 2008 credit crisis and/or by the drastic PRSI composition change in April 30, 2010. Nonetheless, there is the chance that the effect was more related to the contraction months from January 1, 2008 to June 30, 2009 contained in the third sub-period, because there were not sufficient months for an independent analysis, than to the expansion months enclosed in the same sub-period. This would mean that the 2008 crisis unfolded this effect and if true, diminishing the likelihood of holding this negative effect, because in 2014 the US economy is on an expansion phase.

As for the daily series, no significant effect was found in the last period but consistently significant positive Wednesday and Friday effects were found in the full sample analysis for both anomalies tested using the daily series. Therefore, is more likely to have a chance of higher returns on Wednesday and Friday than any other days in the week. However is crucial to understand, that to profit from the awareness of market anomalies is difficult and limited due to transaction costs, but this does not mean that this knowledge is irrelevant, because investors can beneficiate by altering the timing of their trades (French, 1980).

5.2 Further Research

Further research could investigate other calendar anomalies not included in this study for the PRSI returns, like the turn of the month, the holiday effect, the twist of the Monday effect, etc. Moreover, another area of research would be to test if there is any interaction or correlation between the different types of calendar anomalies employed in this investigation. Also it can be further expanded by including other relevant variables to the mean and variance equations.

In addition, future research could compare the PRSI returns with the returns of other indexes for the same time period and sub-periods. Since the stocks that compose the PRSI, trade in US stock exchanges, these other indexes could be one of the major US indices; i.e., NASDAQ, Dow Jones Industrial Average (DJIA), and /or S&P 500 composites. Furthermore, it could be tested whether the stocks that comprised the PRSI, exhibit anomalous behavior when examined individually.

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Appendixes

Appendix A: ARCH LM test results

Table A. 1 ARCH LM results for DOW effect

	ARCH LM Test				Ho decision
Full Period (01/01/96-12/31/13)	F-statistic	0.01578	Prob. F(1,4689)	0.9001	NR-
	Obs*R-squared	0.01578	Prob. Chi-Square(1)	0.9000	No ARCH
First sub-period (01/01/96-02/28/01)	F-statistic	0.06421	Prob. F(1,1342)	0.8000	NR-
	Obs*R-squared	0.06431	Prob. Chi-Square(1)	0.7998	No ARCH
Second sub- Period (03/01/01-10/31/01)	F-statistic	0.31615	Prob. F(1,172)	0.5747	NR-
	Obs*R-squared	0.31924	Prob. Chi-Square(1)	0.5721	No ARCH
Third sub- Period (11/01/01-11/30/07)	F-statistic	4.33266	Prob. F(1,1584)	0.0375	R-
	Obs*R-squared	4.32629	Prob. Chi-Square(1)	0.0375	ARCH
Fourth sub- Period (12/01/07-05/31/09)	F-statistic	0.94230	Prob. F(1,387)	0.3323	NR-
	Obs*R-squared	0.94486	Prob. Chi-Square(1)	0.3310	No ARCH
Fifth sub- Period (06/01/09-12/31/13)	F-statistic	0.00905	Prob. F(1,1194)	0.9242	NR-
	Obs*R-squared	0.00906	Prob. Chi-Square(1)	0.9242	No ARCH

Note:
1. R-ARCH: Reject Null: ARCH effects.
2. NR-No ARCH: Do not reject Null: No ARCH effects.

Table A. 2 ARCH LM results for the Monday effect

	ARCH LM Test				Ho decision
Full Period (01/01/96-12/31/13)	F-statistic	0.01578	Prob. F(1,4689)	0.9000	NR-
	Obs*R-squared	0.01579	Prob. Chi-Square(1)	0.9000	No ARCH
First sub-period (01/01/96-02/28/01)	F-statistic	0.06422	Prob. F(1,1342)	0.8000	NR-
	Obs*R-squared	0.06431	Prob. Chi-Square(1)	0.7998	No ARCH
Second sub- Period (03/01/01-10/31/01)	F-statistic	0.31617	Prob. F(1,172)	0.5746	NR-
	Obs*R-squared	0.31926	Prob. Chi-Square(1)	0.5721	No ARCH
Third sub- Period (11/01/01-11/30/07)	F-statistic	4.33266	Prob. F(1,1584)	0.0375	R-
	Obs*R-squared	4.32630	Prob. Chi-Square(1)	0.0375	ARCH
Fourth sub- Period (12/01/07-05/31/09)	F-statistic	0.94232	Prob. F(1,387)	0.3323	NR-
	Obs*R-squared	0.94489	Prob. Chi-Square(1)	0.3310	No ARCH
Fifth sub- Period (06/01/09-12/31/13)	F-statistic	0.00905	Prob. F(1,1194)	0.9242	NR-
	Obs*R-squared	0.00906	Prob. Chi-Square(1)	0.9242	No ARCH

Note:
1. R-ARCH: Reject Null: ARCH effects.
2. NR-No ARCH: Do not reject Null: No ARCH effects.

Table A.3 ARCH LM results for the MOY effect

	ARCH LM Test				Ho decision
Full Period (01/01/96-12/31/13)	F-statistic Obs*R-squared	0.01811 0.01812	Prob. F(1,4689) Prob. Chi-Square(1)	0.8929 0.8929	NR- No ARCH
First sub-period (01/01/96-02/28/01)	F-statistic Obs*R-squared	0.01389 0.01391	Prob. F(1,1342) Prob. Chi-Square(1)	0.9062 0.9061	NR- No ARCH
Second sub- Period (03/01/01-11/30/07)	F-statistic Obs*R-squared	8.49452 8.46033	Prob. F(1,1759) Prob. Chi-Square(1)	0.0036 0.0036	R- ARCH
Third sub- Period (12/01/07-12/31/13)	F-statistic Obs*R-squared	0.01851 0.01853	Prob. F(1,1584) Prob. Chi-Square(1)	0.8918 0.8917	NR- No ARCH

Note:
1. R-ARCH: Reject Null: ARCH effects.
2. NR-No ARCH: Do not reject Null: No ARCH effects.

Table A. 4 ARCH LM results for the January effect

	ARCH LM Test				Ho decision
Full Period (01/01/96-12/31/13)	F-statistic Obs*R-squared	0.01811 0.01812	Prob. F(1,4689) Prob. Chi-Square(1)	0.8929 0.8929	NR- No ARCH
First sub-period (01/01/96-02/28/01)	F-statistic Obs*R-squared	0.01390 0.01392	Prob. F(1,1342) Prob. Chi-Square(1)	0.9062 0.9061	NR- No ARCH
Second sub- Period (03/01/01-11/30/07)	F-statistic Obs*R-squared	8.49153 8.46034	Prob. F(1,1759) Prob. Chi-Square(1)	0.0036 0.0036	R- ARCH
Third sub- Period (12/01/07-12/31/13)	F-statistic Obs*R-squared	0.01851 0.30185	Prob. F(1,1584) Prob. Chi-Square(1)	0.8918 0.8917	NR- No ARCH

Note:
1. R-ARCH: Reject Null: ARCH effects.
2. NR-No ARCH: Do not reject Null: No ARCH effects.

Appendix B: Correlogram Q-Statistic

Table B.1 Correlogram Q-Statistic DOW: Full period (01/01/96-12/31/13)

Included observations: 4692
Q-statistic probabilities adjusted for 4 ARMA term(s)

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
| |	| |	5	-0.008	-0.008	5.0706	0.024
| |	| |	10	0.022	0.022	8.2425	0.221
| |	| |	15	0.009	0.008	17.24	0.101
| |	| |	20	0.018	0.017	20.489	0.199
| |	| |	25	0.008	0.008	23.823	0.302
| |	| |	30	-0.004	-0.003	26.178	0.453
| |	| |	35	-0.031	-0.029	31.473	0.443

Table B.2 Correlogram Q-Statistic DOW: First sub-period (01/01/96-2/28/01)

Included observations: 1345
Q-statistic probabilities adjusted for 1 ARMA term(s)

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
| |	| |	5	0.003	0.002	9.7462	0.045
| |	| |	10	0.007	0.008	12.761	0.174
| |	| |	15	0.002	-0.007	22.224	0.074
| |	| |	20	0.015	0.013	24.791	0.168
| |	| |	25	0.016	0.01	25.746	0.366
| |	| |	30	-0.022	-0.023	27.854	0.526
| |	| |	35	-0.003	0.001	31.449	0.593

Table B.3 Correlogram Q-Statistic DOW: Second sub-period (03/01/01-10/31/01)

Included observations: 175

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
*|. |	*|. |	5	-0.188	-0.194	8.9803	0.11
.|. |	.|. |	10	0.044	0.02	11.867	0.294
*|. |	.|. |	15	-0.075	-0.062	14.327	0.501
.|. |	*|. |	20	-0.012	-0.095	21.697	0.357
*|. |	*|. |	25	-0.127	-0.122	29.147	0.258
.|* |	.|. |	30	0.088	0.035	34.215	0.272
.|. |	.|. |	35	-0.01	0.014	35.655	0.437

Table B.4 Correlogram Q-Statistic DOW: Third sub- period (11/01/01-11/30/07)

Included observations: 1587
Q-statistic probabilities adjusted for 2 ARMA term(s)

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
| |	| |	5	-0.021	-0.023	4.285	0.369
| |	| |	10	0.067	0.064	13.516	0.141
| |	| |	15	0.011	0.011	21.397	0.092
| |	| |	20	0.038	0.033	29.196	0.063
| |	| |	25	0.038	0.031	36.709	0.047
| |	| |	30	0.012	0.004	40.402	0.078
| |	| |	35	-0.03	-0.041	42.899	0.141

Table B.5 Correlogram Q-Statistic DOW: Fourth sub-period (12/01/07-05/31/09)

Included observations: 390

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
.|. |	.|. |	5	0.031	0.034	2.0964	0.718
.|. |	.|. |	10	-0.036	-0.036	4.6683	0.862
.|. |	.|. |	15	0.048	0.043	8.8977	0.838
.|. |	.|. |	20	0.044	0.029	12.374	0.869
.|. |	.|. |	25	0.02	0.012	13.88	0.949
.|. |	.|. |	30	0.015	0.021	16.623	0.968
*|. |	*|. |	35	-0.104	-0.105	24.689	0.879

Table B.6 Correlogram Q-Statistic DOW: Fifth sub-period (06/01/09-12/31/13)

Included observations: 1197

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
| |	| |	5	0.006	0.003	3.7598	0.584
| |	| |	10	0.03	0.029	5.8504	0.828
| |	| |	15	0.004	0	11.525	0.715
| |	| |	20	-0.002	-0.001	15.127	0.769
| |	| |	25	0.001	0.005	18.556	0.818
| |	| |	30	-0.006	-0.004	25.788	0.686
| |	| |	35	-0.048	-0.049	30.933	0.665

Table B.7 Correlogram Q-Statistic for Monday effect: Full Period (01/01/96-12/31/13*)*

Included observations: 4692
Q-statistic probabilities adjusted for 4 ARMA term(s)

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
| |	| |	5	-0.008	-0.008	5.0706	0.024
| |	| |	10	0.022	0.022	8.2425	0.221
| |	| |	15	0.009	0.008	17.24	0.101
| |	| |	20	0.018	0.017	20.489	0.199
| |	| |	25	0.008	0.008	23.823	0.302
| |	| |	30	-0.004	-0.003	26.178	0.453
| |	| |	35	-0.031	-0.029	31.473	0.443

Table B.8 Correlogram Q-Statistic for Monday effect: First sub-period (01/01/96-02/28/01)

Included observations: 1345
Q-statistic probabilities adjusted for 1 ARMA term(s)

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
| |	| |	5	0.003	0.002	9.7462	0.045
| |	| |	10	0.007	0.008	12.761	0.174
| |	| |	15	0.002	-0.007	22.224	0.074
| |	| |	20	0.015	0.013	24.791	0.168
| |	| |	25	0.016	0.01	25.746	0.366
| |	| |	30	-0.022	-0.023	27.854	0.526
| |	| |	35	-0.003	0.001	31.449	0.593

Table B.9 Correlogram Q-Statistic for Monday effect: Second sub-period (03/01/01-10/31/01)

Included observations: 175

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
*|. |	**|. |	5	-0.188	-0.194	8.9802	0.11
.|. |	.|. |	10	0.044	0.02	11.867	0.294
.|. |	.|. |	15	-0.075	-0.062	14.327	0.501
.|. |	*|. |	20	-0.012	-0.095	21.697	0.357
*|. |	*|. |	25	-0.127	-0.122	29.147	0.258
.|* |	.|. |	30	0.088	0.035	34.215	0.272
.|. |	.|. |	35	-0.01	0.014	35.655	0.437

Table B.10 Correlogram Q-Statistic for Monday effect: Third sub-period (11/01/01-11/30/07)

Included observations: 1587
Q-statistic probabilities adjusted for 2 ARMA term(s)

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
| |	| |	5	-0.021	-0.023	4.285	0.369
| |	| |	10	0.067	0.064	13.516	0.141
| |	| |	15	0.011	0.011	21.397	0.092
| |	| |	20	0.038	0.033	29.196	0.063
| |	| |	25	0.038	0.031	36.709	0.047
| |	| |	30	0.012	0.004	40.402	0.078
| |	| |	35	-0.03	-0.041	42.899	0.141

Table B.11 Correlogram Q-Statistic for Monday effect: Fourth sub-period (12/01/07-05/31/09)

Included observations: 390

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
.|. |	.|. |	5	0.031	0.034	2.0964	0.718
.|. |	.|. |	10	-0.036	-0.036	4.6683	0.862
.|. |	.|. |	15	0.048	0.043	8.8978	0.838
.|. |	.|. |	20	0.044	0.029	12.374	0.869
.|. |	.|. |	25	0.02	0.012	13.88	0.949
.|. |	.|. |	30	0.015	0.021	16.624	0.968
*|. |	*|. |	35	-0.104	-0.105	24.689	0.879

Table B.12 Correlogram Q-Statistic for Monday effect: Fifth sub-period (06/01/09-12/31/13)

Included observations: 1197

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
| |	| |	5	0.006	0.003	3.7598	0.584
| |	| |	10	0.03	0.029	5.8504	0.828
| |	| |	15	0.004	0	11.525	0.715
| |	| |	20	-0.002	-0.001	15.127	0.769
| |	| |	25	0.001	0.005	18.556	0.818
| |	| |	30	-0.006	-0.004	25.788	0.686
| |	| |	35	-0.048	-0.049	30.933	0.665

Table B.13 Correlogram Q-Statistic MOY: Full Period (01/01/96-12/31/13)

Included observations: 4692
Q-statistic probabilities adjusted for 4 ARMA term(s)

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
| |	| |	5	-0.009	-0.009	5.1137	0.024
| |	| |	10	0.022	0.022	8.1356	0.228
| |	| |	15	0.009	0.008	17.43	0.096
| |	| |	20	0.018	0.017	20.712	0.19
| |	| |	25	0.008	0.007	23.862	0.3
| |	| |	30	-0.005	-0.004	26.243	0.45
| |	| |	35	-0.033	-0.03	31.829	0.425

Table B.14 Correlogram Q-Statistic MOY: First sub-period (01/01/96-02/28/01)

Included observations: 1345
Q-statistic probabilities adjusted for 1 ARMA term(s)

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
| |	| |	5	0.003	0.003	9.1167	0.058
| |	| |	10	0.009	0.011	12.269	0.199
| |	| |	15	0.005	-0.004	21.548	0.088
| |	| |	20	0.019	0.018	24.522	0.177
| |	| |	25	0.02	0.013	25.552	0.376
| |	| |	30	-0.019	-0.021	27.692	0.534
| |	| |	35	0.003	0.006	31.123	0.609

Table B.15 Correlogram Q-Statistic MOY: Second sub-period (03/01/01-11/30/07)

Included observations: 1762
Q-statistic probabilities adjusted for 3 ARMA term(s)

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
| |	| |	5	-0.034	-0.035	4.0644	0.397
| |	| |	10	0.064	0.06	13.63	0.136
| |	| |	15	0.011	0.014	21.134	0.098
| |	| |	20	0.031	0.025	30.687	0.044
| |	| |	25	0.028	0.023	35.978	0.055
| |	| |	30	0.018	0.015	38.759	0.106
| |	| |	35	-0.033	-0.042	41.948	0.164

Table B.16 Correlogram Q-Statistic MOY: Third sub-period (12/01/07-12/31/13)

Included observations: 1587

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
| |	| |	5	0.016	0.015	7.8486	0.165
| |	| |	10	0.01	0.009	9.4101	0.494
| |	| |	15	0.018	0.012	15.493	0.416
| |	| |	20	0.018	0.016	18.253	0.571
| |	| |	25	0.004	0.006	19.877	0.753
| |	| |	30	0.001	0.001	25.152	0.718
| |	| |	35	-0.049	-0.049	30.295	0.695

Table B.17 Correlogram Q-Statistic for January effect: Full Period (01/01/96-12/31/13)

Included observations: 4692
Q-statistic probabilities adjusted for 4 ARMA term(s)

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
| |	| |	5	-0.009	-0.009	5.1137	0.024
| |	| |	10	0.022	0.022	8.1356	0.228
| |	| |	15	0.009	0.008	17.43	0.096
| |	| |	20	0.018	0.017	20.712	0.19
| |	| |	25	0.008	0.007	23.862	0.3
| |	| |	30	-0.005	-0.004	26.243	0.45
| |	| |	35	-0.033	-0.03	31.829	0.425

Table B.18 Correlogram Q-Statistic for January effect: First sub-period (01/01/96-02/28/01)

Included observations: 1345
Q-statistic probabilities adjusted for 1 ARMA term(s)

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
| |	| |	5	0.003	0.003	9.1167	0.058
| |	| |	10	0.009	0.011	12.269	0.199
| |	| |	15	0.005	-0.004	21.548	0.088
| |	| |	20	0.019	0.018	24.522	0.177
| |	| |	25	0.02	0.013	25.552	0.376
| |	| |	30	-0.019	-0.021	27.692	0.534
| |	| |	35	0.003	0.006	31.123	0.609

Table B.19 Correlogram Q-Statistic for January effect: Second sub-period (03/01/01-11/30/07)

Included observations: 1762
Q-statistic probabilities adjusted for 3 ARMA term(s)

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
| |	| |	5	-0.034	-0.035	4.0644	0.397
| |	| |	10	0.064	0.06	13.63	0.136
| |	| |	15	0.011	0.014	21.134	0.098
| |	| |	20	0.031	0.025	30.687	0.044
| |	| |	25	0.028	0.023	35.978	0.055
| |	| |	30	0.018	0.015	38.759	0.106
| |	| |	35	-0.033	-0.042	41.948	0.164

Table B.20 Correlogram Q-Statistic for January effect: Third sub-period (12/01/07-12/31/13)

Included observations: 1587

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
| |	| |	5	0.016	0.015	7.8486	0.165
| |	| |	10	0.01	0.009	9.4101	0.494
| |	| |	15	0.018	0.012	15.493	0.416
| |	| |	20	0.018	0.016	18.253	0.571
| |	| |	25	0.004	0.006	19.877	0.753
| |	| |	30	0.001	0.001	25.152	0.718
| |	| |	35	-0.049	-0.049	30.295	0.695