

**UNIVERSITY OF VAASA**  
**FACULTY OF BUSINESS STUDIES**  
**DEPARTMENT OF ACCOUNTING AND FINANCE**

Yekaterina Kopteva

**CALENDAR EFFECTS IN THE WORLD STOCK MARKETS:  
EVIDENCE FROM THIRTY-ONE COUNTRIES**

Master's Thesis in  
Accounting and Finance

Finance

**VAASA 2011**

<b>TABLE OF CONTENTS</b>	<b>page</b>
<b>LIST OF TABLES</b> .....	3
<b>ABSTRACT</b> .....	5
<b>1. INTRODUCTION</b> .....	7
1.1. Purpose of the research.....	9
1.2. Structure of the research.....	10
<b>2. THEORETICAL BACKGROUND</b> .....	11
2.1. Efficient Market Hypothesis.....	11
2.2. Random Walk Hypothesis.....	14
2.3. Calendar effects.....	17
<b>3. LITERATURE REVIEW</b> .....	20
3.1. January/Turn-of-the-year effect.....	23
3.2. Turn-of-the-month effect.....	27
3.3. Day-of-the-week effect.....	29
3.3.1. Monday effect.....	33
<b>4. DATA AND METHODOLOGY</b> .....	37
4.1. Data.....	37
4.2. Methodology.....	39
4.3. Hypotheses .....	41
<b>5. EMPIRICAL RESULTS</b> .....	43
<b>6. SUMMARY AND CONCLUSIONS</b> .....	50
<b>REFERENCES</b> .....	52



**LIST OF TABLES**

<b>Table 1.</b> Previous empirical findings in the field.....	20
<b>Table 2.</b> Countries, stock exchanges and stock market indices.....	37
<b>Table 3.</b> Results of GARCH (1,1) estimation of DOW, TOM, TOY effects. ....	44
<b>Table 4.</b> Results of GARCH (1,1) estimation of DOW, TOM effects.....	47



---

**UNIVERSITY OF VAASA****Faculty of Business Studies****Author:**

Yekaterina Kopteva

**Topic of the Thesis:**Calendar Effects in the World Stock Markets:  
Evidence from Thirty-One Countries**Name of the Supervisor:**

Professor Janne Äijö

**Degree:**Master of Science in Economics and Business  
Administration**Department:**

Department of Accounting and Finance

**Major subject:**

Accounting and Finance

**Line:**

Finance

**Year of Entering the University:**

2009

**Year of Completing the Thesis:**

2011

**Pages: 61**

---

**ABSTRACT**

Capital market efficiency has been a popular topic for teaching and empirical research since Fama (1965, 1970) described the theoretical analysis of market efficiency (Efficient Market Hypothesis). More recently, however researchers have demonstrated market inefficiency by identifying systematic variations in stock returns. Among the most important systematic variations or anomalies are calendar effects. The existence of calendar or time anomalies is a contradiction to the weak form of the Efficient Market Hypothesis and suggests market inefficiency.

The present paper adopts and carefully applies a procedure which examines three main calendar effects in thirty-one developed and developing countries: the January/turn-of-the-year effect, the turn-of-the-month-effect and the day-of-the-week effect. The anomalies are tested with GARCH (1,1) model using the methodology proposed by Szakmary and Kiefer (2004). The research shows that the turn-of-the-year effect is not found in observed countries, except one, which means that the effect has totally disappeared during the recent years in these countries (consistent with Giovanis (2009) for some of the examined countries). The turn-of-the-month and the day-of-the-week anomalies still exist in the majority of the analyzed stock markets. In all countries where it is found, the returns during the turn of the month are significantly positive at 1% level. The day-of-the-week effect provides some variations across countries. Results of this study suggest that the disappearance of calendar effects with time leads to the increase in market efficiency.

---

**KEYWORDS:** Calendar effects, anomalies, market efficiency, random walk, GARCH



## 1. INTRODUCTION

Capital market efficiency has been a popular topic for teaching and empirical research since Fama (1965, 1970) described the theoretical analysis of market efficiency (Efficient Market Hypothesis). Subsequent to the Fama studies a great deal of research was devoted to investigating the randomness of stock price movements for the purpose of demonstrating the efficiency of capital markets. More recently, however researchers have demonstrated market inefficiency by identifying systematic variations in stock returns. Some of the most important systematic variations, or anomalies as they are referred to are Value Line's investment recommendations, the small firm effect and extra-ordinary returns related to the time or the calendar effect (Boudreaux 1995: 15).

The existence of calendar or time anomalies is a contradiction to the weak form of the Efficient Market Hypothesis (EMH). The weak form of the EMH states that the market is efficient in past price and volume information and stock movements cannot be predicted using this historic information. This form infers that stock returns are time invariant, that is, there is no identifiable short-term time based pattern. The existence of seasonality or monthly effects in domestic and international markets suggests market inefficiency, in that investors should be able to earn abnormal rates of return incommensurate with the degree of risk (Francis 1993).

The evidence on calendar or seasonal patterns in stock returns that has accumulated over years is overwhelming. Stock market returns appear to reach abnormal levels recurrently at particular moments of time, such as the beginning of the week, the month and the year. The early literature has documented such calendar effects as January effect (Tinic and West 1984; Thaler 1987a; Haugen and Lakonishok 1987), intra-month and turn-of-the-month effects (Rozeff and Kinney 1976; Lakonishok and Smidt 1988), day-of-the-week effect (Cross 1973; Gibbons and Hess 1981; Keim and Stambaugh 1984), and holiday effects (Fields 1934; Ariel 1990). And the issue of the calendar effects is still a matter of interest of the modern researchers.



The present research focuses on three calendar effects mentioned below, which are discussed in further chapters in details. January/turn-of-the-year effect is presented by several studies that show unusually large positive rate of returns for stocks during the first few trading days of the year. Average daily stock returns around the turn of the month are different from the average daily returns for the rest of the month – stocks historically show higher returns around the turn of the month. The presence of the day-of-the-week effect is well-documented in stock markets throughout the world. The stock returns are found to be different for all weekdays. For example, Monday is the day of the week that averages a negative rate of return.

Szakmary and Kiefer (2004) show that various anomalies including turn-of-the-year effect and weekend effect seem to have disappeared, or at least substantially weakened, since they were first documented. It implies that as research findings increase, market becomes more efficient as rational traders take advantages of anomalous behavior. In contrast, if those still exist both statistically and economically, there must be some other factors that are effective. If anomalous return behavior is not definitive enough for an efficient trader to make profits in trading on it, then it is not economically significant. This definition of market efficiency directly reflects the practical relevance of academic research into return behavior. It also highlights the importance of transaction costs and other market microstructure issues for defining market efficiency.

Some of the calendar effects have been justified by theories relating to institutional arrangements in the markets. For example, the January effect has been linked to year-end tax-loss selling pressure that could suppress stock prices in December, only for them to bounce back in early January (Keim 1983; Reinganum 1983; Gultekin and Gultekin 1983). Explanations offered for the strong Monday effect in stock returns data include delays between trading and settlements in stocks (Lakonishok and Levi 1982), measurement error (Keim and Stambaugh 1984), institutional factors (Flannery and Protopapadakis 1988), and trading patterns (Lakonishok and Maberly 1990). However these factors appear to explain only a small portion of the Monday effect.

Most of the empirical studies showed that many market anomalies occur because of the lack of rational traders, whose investment decisions are influenced by either simplified evaluation methods or factors unrelated to the investment itself. Understanding the causes of calendar effects is important for rationalizing observed patterns and for making predictions about market outcomes, including the rate of stock price adjustment to changes in the determining factors and the permanence of systematic deviations from rationality (Van der Sar 2003: 271). At a practical level, investors can build trading strategies based on consistent seasonality or, at least, they can determine favorable market entry and exit moments.

### 1.1. Purpose of the research

Calendar effects occur when there is a meaningful temporal change. This may occur on a daily, weekly, monthly or even yearly basis. Anomalies indicate either market inefficiency or inadequacies in the underlying asset pricing model. After they are documented in the academic literature, anomalies often seem to disappear, reverse or attenuate. The goal of the present research is to test if calendar effects exist in stock markets of countries from different parts of the world.

The study investigates the existence of calendar effects in both developed and developing countries around the world, 31 in total. The variety of countries makes this study of particular interest for the global investor. The analyzed effects are January/turn-of-the-year effect, turn-of-the-month effect and day-of-the-week effect. The paper extends the previous research in this field for some countries during more recent years. The impact of the calendar effects towards the world economies is aimed to be discussed in the end of the study.

The presence of anomalies in the stock market reflects a level of market inefficiency, suggesting an opportunity for investors to make abnormal gains through various trading and investment strategies. But this research is aimed only to discover the existence of

calendar effects in particular countries and can be used later for further research and development of various investment and trading strategies.

## 1.2. Structure of the research

The present research is organized as follows. The first chapter acquaints with the topic and its main aspects in general. Also it defines the problem and its importance to the world of finance, suggests the possible ways in which it can be utilized and used, and benefits from its exploitation. The second chapter introduces the theoretical background of the subject, starting with the Efficient Market Hypothesis, Random Walk Hypothesis and proceeding to calendar effects. Previous studies in this field are presented in the literature review of chapter three. Subchapters describe separately each calendar effect, the reasons and explanations of their occurrence and existence. Chapter four provides the data collection procedure and the chosen methodology. Empirical results obtained after the conducted tests are presented in the tables and discussed in the fifth chapter in details. Brief summary of the study and conclusions are reported in chapter six, providing the ideas for further empirical research and some discussions about the issue of interest.

## 2. THEORETICAL BACKGROUND

### 2.1. Efficient Market Hypothesis

Investigating financial market efficiency, it is defined that market is efficient in different meanings. First of all, market can be operationally efficient, which means that trading is carried out quickly, reliably, and at minimum cost. Secondly, market is allocationally efficient. In this case funds being allocated are going to their most productive use. Finally, market is informationally efficient in the sense that prices were based on the best information available. It is important to note that in order for a market to be allocationally efficient, it must be also informationally efficient because allocation decisions are made in response to prices (Howells & Bain 2005).

An issue that is the subject of intense debate among academics and financial professionals is the Efficient Market Hypothesis (EMH) (Samuelson 1965; Fama 1970; Jensen 1978). The Efficient Market Hypothesis states that at any given time, security prices fully reflect all available information. The implications of the efficient market hypothesis are truly profound. Most individuals that buy and sell securities (stocks in particular), do so under the assumption that the securities they are buying are worth more than the price that they are paying, while securities that they are selling are worth less than the selling price. But if markets are efficient and current prices fully reflect all information, then buying and selling securities in an attempt to outperform the market will effectively be a game of chance rather than skill.

There are three forms of the EMH which are distinguished by the degree of information reflected in security prices:

1. Weak form – prices reflect the information contained in the record of past prices;
2. Semi-strong form – prices reflect not just past prices, but all publicly available information;
3. Strong form – prices reflect all information, both public and private.

Weak form of efficiency assumes that future prices cannot be predicted by analyzing prices from the past. Excess returns cannot be earned in the long run by using investment strategies based on historical stock prices or other historical data. Technical analysis techniques will not be able to consistently produce excess returns, though some forms of fundamental analysis may still provide excess returns. Stock prices exhibit no serial dependencies, meaning that there are no “patterns” in asset prices. This implies that future price movements are determined entirely by information not contained in the price series. Hence, prices must follow a random walk. This form of EMH does not require that prices remain at or near equilibrium, but only that market participants are not able to earn profit systematically from market inefficiencies. To test the weak form of the hypothesis it is necessary to measure the profitability of some of the trading rules used by those investors who claim to find patterns in security prices (Brealey and Meyers 2003: 351). The present paper is aimed to check the existence of the market inefficiency in its weak sense by testing for calendar anomalies in the stock market returns.

Semi-strong form of efficiency implies that share prices adjust to publicly available new information very rapidly and in unbiased fashion, so that no excess returns can be earned by trading on that information. Semi-strong form of efficiency claims that neither fundamental analysis nor technical analysis techniques will be able to reliably produce excess returns. To analyze the semi-strong form of the Efficient Market Hypothesis, researchers measure how rapidly security prices respond to different types of news, such as earnings or dividend announcements, news of a takeover, or macroeconomic information (Brealey and Meyers 2003: 351).

In strong form of efficiency share prices reflect all information, public and private, and no one can earn excess returns. If there are legal barriers for private information to become public, as with insider trading laws, strong form efficiency is impossible, except the cases where the laws are universally ignored. Tests of the strong form of the hypothesis examine the recommendations of professional security analysts and have looked for mutual funds or pension funds that could predictably outperform the market (Brealey and Meyers 2003: 354). Some researchers have found a slight persistent

outperformance, but just as many have concluded that professionally managed funds fail to recoup the costs of management. A study by Carhart (1997) examines the average return on nearly 1,500 U.S. mutual funds during the period of 1962–1992. In some years the mutual funds beat the market, but more often it is on the contrary. Carhart (1997) compared in his research each fund with a benchmark portfolio of similar securities. The conclusion was that the funds earned a lower return than the benchmark portfolios after expenses and roughly matched the benchmarks before expenses.

The EMH is one of the results of the equilibrium in a market with rational traders that cannot achieve returns in excess of average market returns on a risk-adjusted basis. The Efficient Markets Hypothesis can be summarized as follows:

- all investors are fully informed and they can interpret in a right way public and private news;
- people are rational, and they can maximize their utility function based on the financial earnings/gain;
- all the trader's decisions are independent;
- all investment decisions lead to prices equilibrium.

The summary of the Efficient Market Hypotheses takes into account that the current prices of assets:

- are the best estimation of their value;
- are a result of all available information;
- change immediately when new information is released.

The main or the fundamental idea of the EMH is that if markets are efficient then it is impossible for investors to exploit information in order to earn excess returns over a sustained period of time (Howells & Bain 2005: 543). But this appeared to be highly controversial and often disputed. “The efficient markets theory reached the height of its dominance in academic circles around the 1970s. ... Faith in this theory was eroded by a succession of discoveries of anomalies, many in the 1980s...” (Shiller 2003: 83). Scores of studies that document long-term historical anomalies in the stock market seem to contradict with the Efficient Market Hypothesis (Keim 1987; Lakonishok and Smidt

1988; Barone 1990). While the existence of anomalies is generally well accepted, the question of whether investors can exploit them to earn superior returns in the future is subject to debate. Investors evaluating anomalies should keep in mind that although they have existed historically, there is no guarantee they will persist in the future. If they do persist, transactions and hidden costs may prevent outperformance in the future. Investors should also consider tax effects in their taxable portfolios when evaluating stock strategies.

Researchers that discover anomalies or styles that produce superior returns have two choices: (1) go public and seek recognition for discovering the technique; or (2) use the technique to earn excess returns. It is common to develop and use strategies that attempt to exploit anomalies and this in turn causes the anomaly to disappear. Further, even anomalies that do persist may take decades to pay off. Investors evaluating historical data should also consider the potential pitfalls of “data mining”. When searching large amounts of data, correlations between variables may occur randomly and therefore may have no predictive value. Some researchers believe that the weekday effect and other seasonals arise from data mining. For instance, Sullivan, Timmermann and White (2001) suggest an application of a new bootstrap procedure which fails to identify calendar effects. However, those calendar effects which have existed over the longest time frames and have been confirmed to exist in international markets and out of sample periods are particularly persuasive.

## 2.2. Random Walk Hypothesis

One hypothesis that links to the EMH is that the past prices are not correlated with the future ones, therefore they cannot be used to predict future prices or to understand the best moment to enter/start to operate in the market. EMH suggests that the presence of many traders in the markets that operate in different moment of time should guarantee that the market prices have a random walk near its equilibrium value.

In 1953 Maurice Kendall, a British statistician, presents a study on the behavior of stock and commodity prices. Kendall (1953) expects to find regular price cycles, but to his surprise they do not seem to exist and the researcher discovers that prices of stocks and commodities follow a random walk. When Maurice Kendall suggested that stock prices follow a random walk, he was implying that the price changes are independent of one another and have the same probability distribution, but that over a period of time, prices maintain an upward trend.

At first, Kendall's (1953) results strongly surprised and disturbed financial economists, because these results appeared to confirm the irrationality of the market. However, later it soon became apparent that random price movements indicate a well-functioning or efficient market, not an irrational one. This was proved by the Efficient Market Hypothesis, and in particular, the weak form.

Random walk hypothesis implies that the past movement or direction of the price of a stock or overall market cannot be used to predict its future movement. In other words, random walk states that stocks take a random and unpredictable path. The chance of a stock's future price going up is the same as it going down. Consequently, trading rules and security selection procedures long advocated by "technical" analysts or "chartists", which are based solely on past price movements, are not useful for the investor to increase his returns (Jensen 1967). Technical analysts argue that models and theories presented by academicians are not really captured by these statistical tests. Alexander (1961; 1964) and Fama and Blume (1966) examine the returns earned by various "filter" rules for selecting securities which are supposed to capture the essence of many technical theories. The evidence indicates these trading rules are not able to consistently earn returns superior to those of a simple buy and hold policy. So, the results of these studies support the random walk hypothesis.

Random walk hypothesis becomes popular in 1973 when Burton Malkiel writes a book "A Random Walk Down Wall Street", which is now regarded as an investment classic. Malkiel (1973), a follower of random walk, believes it is impossible to outperform the market without assuming additional risk. Researcher claims that both technical analysis



and fundamental analysis are largely a waste of time and are still unproven in outperforming the markets. Malkiel (1973) constantly states that a long-term buy-and-hold strategy is the best and that individuals should not attempt to time the markets. Attempts based on technical, fundamental, or any other analysis are futile. He supports this with statistics showing that most mutual funds fail to beat benchmark averages like the S&P 500.

However, each hypothesis has a contradiction. Levy (1967) tests a number of trading rules based on technical theories. Some of his results appeared to be inconsistent with the theory of random walk. In his article Levy (1967) introduces interesting results concerning the returns earned by several mechanical stock market trading rules in the five-year period from October 1960 to October 1965. He calculates the returns earned by a number of variations of his trading rules and finds these returns generally higher than the returns earned on a “random selection policy.” On the basis of these results Levy (1967) states that for his sample period of 1960 – 1965 the usage of the technical stock analysis could have produced much more profitability with much lower risk than the principle of randomness. Therefore, in his conclusion the researcher confutes the random walk hypothesis.

The professional stock market analysts and the academic statisticians hold a contradictory view on the price behavior in speculative markets. The professional analysts believe that there exists certain trend generating facts, knowable today, which guides a speculator to earn profit, provided he is able to read them correctly and timely. These facts are believed to generate trends rather than instantaneous jumps because most of the traders in the speculative markets have imperfect knowledge of these facts, and the future trend of prices will result from a gradual spread of awareness of these facts throughout the market. Those who gain the information earlier than others have an opportunity to earn profit. Two main schools of professional analysts, the “fundamentalists” and the “technicians”, agree on this basic assumption. The only difference lies in the methodology to gain information earlier than others. The “fundamentalists” seek early knowledge by studying the external factors that cause the

price changes. The technical analysts study price movements of the immediate past for predictive indication of the price movements in the near future (Alexander 1961).

Some studies present evidence against the random walk hypothesis, showing that stock returns contain predictable elements. Much of this work is centered on the world's largest stock markets as the United States, developed economies of Europe and Asia (Poterba and Summers 1988; Fama and French 1988; Lo and MacKinlay 1988). Researchers observe that stock prices do not follow a random walk and thus, reject the random walk model.

Discovery of calendar effects also rejects the random walk hypothesis like it is discussed in the previous subchapter about EMH. However, failure of the random walk does not necessarily confer predictability.

### 2.3. Calendar effects

Calendar effects are anomalies in stock market returns that relate to the calendar, when stock market returns reach abnormal levels comparing to other periods of the day, week, month and year. Presence of such anomalies in any stock market contradicts with the concept of market efficiency as these anomalies give the opportunity to stock market participants to earn profit by observing these patterns.

Sullivan et al. (2001) conduct the research to discover the fact whether calendar effects imply notions of market inefficiency or appear in a result of a data-snooping. On a basis of the types of calendar rules that have been studied previously by other researchers, authors construct a universe of calendar trading rules using permutational arguments that do not bias in favor of, or against, particular calendar effects. The universe contains nearly 9,500 different calendar effects and the best calendar rule is evaluated in the context of this set. Sullivan et al. (2001) use 100 years of daily data and the new bootstrap procedure which allows to measure distortions in statistical inference induced by data-snooping. They have shown that in the context of the full universe, or a

restricted version, of calendar rules which could be considered by investors and academics, the strength of the evidence on calendar effects looks much weaker. They use Reality-Check P-values that adjust for effects of data-snooping and observe that no calendar rule is capable of outperforming the benchmark market index. This appears to be true in all of the individual sample of periods, in the out-of-sample experiment with the DJIA and S&P 500 Futures data, and in the full sample using a century of data. They suggest that the single most significant calendar anomaly – the Monday effect – has indeed been identified in empirical literature.

What causes the regular unusual behavior of stock market returns? Thaler (1987b) lists a number of institutional and behavioral reasons for calendar effects:

1. movements in prices can be related to customs which influence the flow of funds in and out of the market. E.g. individuals and firms make regular payments to pension and mutual funds at the end of calendar month or year;
2. “window dressing” hypothesis, when the investment managers try to clean their portfolios to get rid of embarrassing holdings before reporting dates, which coincide with the actual year-end or month-end dates;
3. influence of the systematic arrival of good and bad news, which is mostly refers to the weekend effect, because usually the announcement of bad news is postponed until after the close of trading on Friday.

A number of alternative explanations exist for the occurrence of calendar effects. Van der Sar (2003) distinguishes four categories. The first relies on data problems and spurious results. Especially the bid-ask bias has been mentioned as a driving force of differences between returns in the time series. The second category relies on difficult to observe intertemporal changes in risk. That is, the patterns do exist but are not anomalous. The third category relies on strategic behavior of market participants in anticipation to regulations and legislation. Trading frictions, both real and informational, and other market imperfections such as taxes, settlement procedures and trade gaps as well as the concentration of various kinds of payments to investors at particular moments of time, may distort the optimal functioning of the stock market as an allocation mechanism of capital in comparison to a perfect market. This fact,

however, does not imply that stock pricing is irrational. What counts is whether, as a consequence, arbitrage opportunities have been created. The fourth category relies on behavioral considerations. Investor irrationality such as a slow response to information may be due to, e.g., effects of framing, the use of heuristics and agency problems. At present none of these explanations, that is including the risk-based stories, is completely satisfactory. That is why calendar effects are often called anomalies.

### 3. LITERATURE REVIEW

Research is a sequential process through which new studies are built on evidence from earlier papers (Sullivan et al. 2001: 32). That is why it is important to make the deep and broad analysis of the previous literature in the investigated field. The deeper and broader the analysis, the richer and the more significant the research will be. The present Chapter attempts to cover all the main and best-known studies on calendar effects in the existing literature.

The table below presents the most interesting previous empirical findings in the field which are discussed more in details in the subchapters following afterwards.

**Table 1.** Previous empirical findings in the field.

<b>Authors</b>	<b>Country, Period</b>	<b>Empirical Findings</b>
<i>Panel A: January/Turn-of-the-year effect</i>		
Wachtel (1942)	US: 1927-1942	Significant seasonal effect. First explanations of the January effect by the tax-loss selling hypothesis.
Rozeff & Kinney (1976)	US: 1904-1974	Average return of an equal-weighted index of NYSE in January is significantly higher than the average return for other months, with exception of 1929 – 1940 period.
Gultekin and Gultekin (1983)	18 countries: 1959-1979	Provide evidence in support of the January effect. Monthly returns are not equal for 12 countries from a total of 17 only at the 10% level.
Choudhry (2001)	Germany & UK: 1870-1913; US: 1871-1913	Non-tax factors may be responsible for the January effect.
Szakmary & Kiefer (2004)	US: June 1982 – May 2002	Evidence of a traditional turn-of-the-year effect, in both cash and futures, is confined to the pre-1993 period. Post-1993, there are no abnormal returns during the turn of the year window as a whole. Returns in this period remain high on the last trading day of December, but are negative.

**Table 1.** *(continued)*

Chen & Singal (2004)	US: 1993-1999	Evidence in favor of the tax-loss selling hypothesis and little or no evidence for the other hypothesis.
Kim (2006)	US: 1972-2003	Constructs a common risk factor related to information uncertainty caused by earnings volatility and claims to have found an improvement in explaining the abnormal returns in January. Systematic pattern in the residual returns across firm size disappears.
Haug & Hirschey (2006)	US: 1802-2004	Abnormally high rates of return on small-capitalization stocks during January. January effect in small-cap stock returns is remarkably consistent over time.
Cooper, McConnell & Ovtchinnikov (2006)	US: 1940-2003	January returns have predictive power for market returns over the next 11 months. The “other January effect” persists among both large and small capitalization stocks and among both value and growth stocks.
Moosa (2007)	US: 1970-2005	Presence of a significant January effect except in the most recent period, 1990-2005, when a strong negative July effect surfaced.
<i>Panel B: Turn-of-the-month effect</i>		
Ariel (1987)	US: 1963-1981	Changes in stock prices during turn of the month are found positive. Significant differences between the first and the second half of the month stock average returns: average returns of the last half of month are not different from zero, while in the first half are statistically significant.
Lakonishok & Smidt (1988)	US: 1897-1986	“Window dressing” hypothesis may be a reason of the turn-of-the-month effect.
Ogden (1990)	US: 1969-1986	Turn-of-the-month effect is likely to be influenced by the level of liquid profits.
Chris & Ziemba (1996)	US: 1928-1993	The total return of the S&P 500 over this sixty-five-year period is received mostly during the turn of the month. Investors making regular purchases may benefit by scheduling to make those purchases prior to the turn of the month.

**Table 1.** (continued)

Nikkinen, Sahlström & Äijö (2007)	US: 1995-2003	It can not be exactly proved that macroeconomic news announcements can influence higher realized returns, although the empirical results provide strong support in favor of macroeconomic news announcements.
McConnell and Xu (2008)	US: 1926-2005	Turn-of-the-month effect is pronounced over the recent two decades.
Wiley & Zumpano (2009)	US: 1980-2004	No sufficient proof that institutional investment impacts returns during the turn-of-the-month, suggesting that this calendar effect is not caused exclusively by institutional investors.
<i>Panel C: Day-of-the-week effect</i>		
Smirlock & Starks (1986)	US: 1963-1983	Evidence of nonstationarities in the Monday effect.
Condoyanni, O'Hanlon & Ward (1987)	France: 1969-1984	Significant negative returns on Tuesdays and significant positive returns on Thursdays.
Solnik & Bousquet (1990)	France: 1978-1987	Strong and persistent negative mean returns on Tuesdays.
Solnik (1990)	France: 1978-1989	Significantly negative Tuesday returns.
Chang, Pinegar & Ravichandran (1993)	US: 30.12.1985- 30.04.1992	Monday's mean returns are different from mean returns observed during the week. The effects are statistically significant in not more than two weeks of the month.
Dubois & Louvet (1996)	Nine countries: 1969-1992	Negative returns on Mondays and Tuesdays, positive returns on Wednesdays.
Wang, Li & Erickson (1997)	US: 3.07.1962- 31.12.1993	Correlation between the Friday return and the Monday return, and the expiration date of stock options cannot justify the Monday effect.
Brusa, Liu & Schulman (2000)	US: 1990-1994	Reverse weekend effect: Monday returns are significantly positive and they are higher than the returns of the other days of the week. Large firms are subjected to traditional weekend effects whereas small firms are exposed to the reverse weekend effects.

**Table 1.** *(continued)*

Keef, Khaled & Zui (2009)	Fifty countries: 1994-2006	In terms of information the poor countries are less efficient than rich countries. Monday effect weakening over time stands for a market efficiency increase.
---------------------------	-------------------------------	---

### 3.1. January/Turn-of-the-year effect

The January Effect is a calendar-related anomaly in the financial market when stock market returns in January are higher than in other 11 months of the year. This creates an opportunity for investors to buy stocks for lower prices before January and sell them after their value increases. January has historically been the best month to be invested in stocks. Therefore, the main characteristics of the January Effect are an increase in buying securities before the end of the year for a lower price, and selling them in January to generate profit from the price differences. Advocates of the turn-of-the-year effect (Keim 1983; Gultekin and Gultekin 1983) claim that small capitalization stocks tend to heavily outperform large cap stocks on the last trading day of December and the first five trading days in January.

The January effect is first mentioned by Wachtel (1942). He finds a significant seasonal effect using data of the Dow Jones Industrial Average from 1927 to 1942. Also, he was the first to explain January effect with the tax-loss selling hypothesis. He states that downward pressure on stock prices might be induced at year end by investors selling the losing stocks with the intention to realize capital losses against their taxable incomes. The abnormally high January return is the effect from the stock price rebounding to its equilibrium level when the selling pressure stops at the beginning of the year.

A more formal investigation is due to Rozeff and Kinney (1976), who sometimes are considered to be the first to introduce the January effect to the world of finance. The paper presents evidence on the existence of seasonality in monthly rates of return on the New York Stock Exchange from 1904–1974. Researchers observe that the average



return of an equal-weighted index of the NYSE in January is statistically significantly higher than the average return for the other months, with the exception of the 1929 – 1940 period. Dispersion measures reveal no consistent seasonal patterns and the characteristic exponent seems invariant among months (Rozeff and Kinney 1976). They also explore possible implications of the observed seasonality for the capital asset pricing model.

Thaler (1987a) examines the behavior of security prices in January. He finds that stock prices tend to increase in January, particularly the prices of small firms and firms whose stock price has declined substantially over the past few years. Also he claims that risky stocks earn most of their risk premiums in January.

Later, Gultekin and Gultekin (1983) provide evidence in support of the January effect for the U.S. and other 17 industrialized countries for the period 1959-1979. The return data are based on the value-weighted indexes of month-end closing prices without dividend yields. They compute first 12 monthly autocorrelations, and find that they are mostly not significant except for Australia, Denmark, and Norway. They use the Kruskal-Wallis test for the 17 countries, and find that the monthly returns are not equal for 12 countries from a total of 17 only at the 10% level. The monthly returns are equal for Australia, France, Italy, Singapore, and the US. Except for Australia, the monthly returns appear to be higher at the beginning of the tax year. In Australia, the tax year starts in July, and in the UK, it starts in April.

Haugen and Jorion (1996) note that the January effect is, perhaps the best-known example of anomalous behavior in security markets throughout the world. They provide results confirming the persistent existence of the January effect. Authors prove that the January effect still exists despite the fact that it was well known for reasonably long time and therefore should have disappeared. In their study Haugen and Jorion (1996) find that the January effect is stronger in case of small firms than in case of well-established companies with high capitalization. Haugen and Jorion (1996) conclude that the January effect still persists to be strong 17 years after publication by Rozeff and Kinney (1976).

Stocks in general and small stocks in particular have historically generated abnormally high returns during the month of January. The most common theory explaining this phenomenon is that individual investors, who are income tax-sensitive and who disproportionately hold small stocks, sell stocks for tax reasons at year end (such as to claim a capital loss) and reinvest after the first month of the year. Small firms pay higher mean returns than large ones at the beginning of the year. Chen and Singal (2004) present a comprehensive study of several explanations and find evidence in favor of the tax-loss selling hypothesis and little or no evidence for the other hypothesis. Choudhry (2001), using pre-World war data, shows that non-tax factors may be responsible for the January effect. In contrast, Kim (2006) constructs a common risk factor related to information uncertainty caused by earnings volatility and claims to have found an improvement in explaining the abnormal returns in January. Although most researchers support the tax-loss selling hypothesis, the discussion remains open.

Theoretically an anomaly should disappear as traders attempt to take advantage of it in advance. The January effect initially persisted long since it was discovered, but as documented by several researchers, it has diminished, disappeared or even reversed over time. Szakmary & Kiefer (2004) examine the returns, relative to the S&P 500, on cash indices and futures tracking smaller stocks around the turn of the year for the period of June 1982 – May 2002. The main focus of the study is the evolution of the turn-of-the-year effect through time: in particular, whether the effect diminishes or takes place earlier subsequent to the introduction of the S&P Midcap and Russell 2000 futures in 1993. In their research Szakmary & Kiefer (2004) also control for volatility clustering, return autocorrelation in small stock indices, and other calendar effects with the help of GARCH (1,1) model. The results suggest that a traditional turn of the year effect exists in both cash and futures during the pre-1993 period. After 1993 there are no abnormal returns during the turn of the year window as a whole. Authors note that returns in this period remain high on the last trading day of December, but they are negative across the first five trading days of January. In addition, post-1993, significant abnormal returns are observed prior to the traditional turn of the year, i.e., in the pre-Christmas and post-Christmas windows. Szakmary & Kiefer (2004) suppose that market

participants may be eliminating the turn of the year effect with the help of two new futures contracts that fit well for this purpose.

Moosa (2007) investigates the January effect in U.S. stock prices using monthly average data on the Dow Jones Industrial Average over the period 1970-2005. To estimate the seasonality he applies a dummy variable model using OLS and rolling regressions. The results of the study suggest the presence of a significant January effect except in the most recent period, 1990-2005, when a strong negative July effect appears. The study confirms this finding by using a more sophisticated structural time series model with an autoregressive structure. Moosa (2007) provides the following explanations for the disappearing January effect: (1) changes in accounting standards that do not make now a significant distinction between realized and unrealized capital gains and losses as in the past; (2) changes in the tax treatment of realized and unrealized gains/losses; and (3) lower marginal tax rates, which dampens the incentive to engage in tax motivated trading. Also, the researcher suggests that the possible explanation for the July effect is the selling pressure related to the summer holiday season in the northern hemisphere. Individual investors sell stocks to finance their vacations, and fund managers try to reduce their market risk because they cannot control their portfolios during their holidays.

The January effect has also become important because it can be used as a predictor of the returns over the following 11 months, which is called the “other January effect” by Cooper et al. (2006). They show that January returns have predictive power for market returns over the next 11 months of the year even after controlling for macroeconomic business cycles variables, the Presidential Cycle and investor sentiment. They also find that the “other January effect” persists among both large and small capitalization stocks and among both value and growth stocks.

While some researchers claim that the effect diminishes and disappears, other continue to prove its existence by strong evidence and profound research. Haug and Hirschey (2006) analyze broad samples of value-weighted and equal-weighted returns of U.S. equities. The study shows that there is little evidence of a January effect for large-

capitalization stocks during 1802-2004. In contrast, abnormally high rates of return on small-capitalization stocks continue to be observed during the month of January. Researchers conclude that the January effect in small-cap stock returns is remarkably consistent over time and continues to present a serious challenge to the efficient market hypothesis even after a generation of intensive study.

### 3.2. Turn-of-the-month effect

The tendency of stock returns to increase during the last few days and the first few days of each month is called a turn-of-the-month effect. Ariel (1987) is the first to identify the turn-of-the-month effect in US stock prices at the beginning of one month and the end of the other month. He uses daily data for Center for Research in Security Prices (CRSP) value-weighted and equally-weighted stock index returns from 1963 through 1981 and studies this anomaly by considering last day of one month and the first three days of upcoming month. Changes in stock prices in these days are found positive. There are significant differences between the first and second half of the month stock average returns, where the average returns of the last-half of month are not different from zero, while in the first half are statistically significant.

Some researchers have posited that the turn-of-the-month effect could be the result of systematic trading patterns by large institutional investors. Lakonishok and Smidt (1988) suggest that pension fund managers and other institutional investors might be selling off stocks that underperform and purchasing those that have recently performed well in an effort to avoid a negative bias in the estimated rates of return (“window dressing” hypothesis).

The other hypothesis which is referred to as the “preferred habitat” hypothesis is based on the idea that the end of each calendar month is a typical payoff date for the compensation of most employees in the USA. There are many employees with automatic contribution plans, where some portion of their monthly paycheck goes directly into their investment accounts providing institutional investors with excess

liquid profits to invest. If institutional investors quickly invest these liquid profits, it is likely to take place near the turn-of-the-month. In fact, Ogden (1990) provides evidence that the turn-of-the-month effect is likely to be influenced by the level of liquid profits. However, Ogden's work did not attempt to distinguish between the impacts of institutional and individual investors.

However, some researchers believe there is little evidence to support the hypothesis that the turn-of-the-month effect is caused by institutional investment. For example, Wiley and Zumpano (2009) argue that the impact of institutional investment may not be as large as some researchers have suspected. Their study provides an empirical test that measures the impact of the level of institutional investment on the turn-of-the-month effect using stock returns from a sample of 238 real estate investment trusts (REITs) over the period 1980 to 2004. They find that a significant change in the turn-of-the-month effect occurred following the Omnibus Reconciliation Act of 1993 which relaxed the requirements on the level of institutional investment in REITs. The evidence shows that the dramatic rise in institutional holdings can account for a good part of this change. However, the authors claim that there is no sufficient proof that institutional investment impacts returns on the day when the turn-of-the-month effect is most pronounced, suggesting that this calendar effect is not caused exclusively by institutional investors in the market (Wiley & Zumpano 2009: 180).

Chris and Ziemba (1996) present the theory that the turn-of-the-month effect results from cash flows at the end of the month (salaries, interest payments, etc.). They find returns for the turn of the month are significantly above average from 1928 to 1993 and that the total return of the S&P 500 over this sixty-five-year period is received mostly during the turn of the month. The study implies that investors making regular purchases may benefit by scheduling to make those purchases prior to the turn of the month.

Nikkinen, Sahlström and Äijö (2007) study the turn-of-the-month and intramonth effects with relation to the important macroeconomic news announcements. They provide a new and economically plausible explanation of these phenomena examining S&P100. Nikkinen et al. (2007) suggest that turn-of-the-month and intramonth

anomalies occur because of the clustered information, and more precisely – macroeconomic news announcements, which are published systematically at a certain time point every month. But as long as the researchers take the effect of macroeconomic news to account both turn-of-the-month and intramonth phenomena disappear. They propose a measure which uses information from option-implied volatilities to account for the changes in expected risk premium caused by news announcements. However, this measure captures the effects of news announcements only partially. So, it can not be exactly proved that macroeconomic news announcements can influence higher realized returns, although the empirical results provide strong support in favor of macroeconomic news announcements.

McConnell and Xu (2008) study CRSP daily returns for the 80-year period of 1926-2005. Specifically, they define turn-of-the-month as beginning with the last trading day of the month and ending with the third trading day of the following month. They find that the turn-of-the-month effect is pronounced over the recent two decades such that, if to combine their findings with those of Lakonishok and Smidt (1988), the result is that over the 109-year interval of 1897-2005, on average, all of the positive return to equities occur during the turn-of-the-month interval. They also infer that it is not confined to small and low-price stocks, calendar year-ends or calendar quarter-ends, to the U.S, and is not due to the buying of shares at the turn-of-the-month since trading volume is not higher and the net flows of funds to equity funds is not systematically higher. They conclude that the turn-of-the-month effect in equity returns poses a challenge to both “rational” and “behavioral” models of security pricing and it continues to be a puzzle in search of a solution.

### 3.3. Day-of-the-week effect

Some of the most unusual empirical results indicate that the distribution of common stock returns is not identical for all days of the week. The day-of-the-week phenomenon is observed in many developed and developing markets. Numerous studies observe that average stock returns are negative on Mondays and abnormally positive on Fridays in

many countries around the world. However, there are different variations in some countries. Several studies provide evidence that this effect displays different patterns from one country to another. For example, strong negative Tuesday effect was found in several countries particularly in Europe and Asia: in the French stock market (Condoynani, O'Hanlon & Ward 1987; Solnik & Bousquet 1990), Canadian market (Athanasakos & Robinson 1994), stock markets of Australia and Japan (Jaffe & Westerfield 1985; Dubois & Louvet 1996), stock markets of Japan and Korea (Kim 1988), stock markets of Australia, Hong Kong, Japan, Korea, Malaysia, New Zealand, Philippines, Singapore, Taiwan and Thailand (Ho 1990), stock markets of eighteen countries (Agrawal and Tandon 1994). It is explained that in Australia, Korea, Japan and Singapore average returns on Tuesday are negative because of time zone differences relative to the U.S. and European markets.

Condoynani et al. (1987) report significant negative returns on Tuesdays and significant positive returns on Thursdays in France for the period 1969-1984. Tuesdays' strongly negative returns may be explained by the fact that the French index is compiled before the US market opens. The authors suggested that France is not significantly affected by US returns over at least two days.

In his research Connolly (1989) analyzes the robustness of the day-of-the-week and weekend effects to alternative estimation and testing procedures. The results show that sample size can distort the interpretation of classical test statistics unless the significance level is adjusted downward. Specification tests reveal widespread departures from OLS assumptions. To test the hypothesis and reported the results he uses robust econometric methods and a GARCH model. Connolly (1989) claims that the strength of the day-of-the-week and weekend effects evidence depends on the estimation and testing method. Both effects seem to have disappeared by 1975. However, in his later paper Connolly (1991) presents a posterior odds evaluation of the day-of-the-week and weekend effect that largely reverses earlier findings. The interaction of large sample sizes and fixed significance level hypothesis testing is identified as the likely source of disagreements between p-values and posterior probabilities. Analysis with informative and relatively diffuse prior distributions

indicates this divergence does not apparently reflect special distributional assumptions. Further analysis suggests that earnings announcement behavior and a small number of outliers may be the reason of systematically negative Monday returns in the few years where posterior odds favor the weekend effect hypothesis.

Solnik and Bousquet (1990) focused on the period 1978-1987 and examined the CAC Index of Paris Bourse. Their results showed strong and persistent negative mean returns on Tuesdays. Also, they supported that the specific monthly settlement procedure of the Paris market, whereby the transactions' settlement occurs on the last day of each month (liquidation date), can explain the larger positive returns observed on Fridays, but cannot explain the negative mean returns observed on Tuesdays. Regarding the high positive returns on Fridays, since most of the liquidation dates happen to be on Thursdays, Fridays are the first day of the new period of liquidation, hence the highest returns.

Solnik (1990) wondered whether the settlement procedure could explain the pattern of daily returns observed in previous studies of the Paris Bourse. During the period 1978-1989, the hypothesis of equality among the daily returns of all the days of the week was rejected at the five percent confidence level. This rejection was mostly explained by the negative returns on Tuesdays and to some extent by a higher return on Fridays. Because the major impact of the liquidation on the daily return takes place on the next day, this phenomenon will tend to increase the mean return observed for Fridays. To adjust for this, days following the liquidation were excluded. After this, the mean return on Fridays was no longer the highest (but was high on Wednesdays) and the returns on Tuesdays stayed significantly negative. The hypothesis that all mean returns are equal for each day of the week was still rejected at the 5% confidence level.

Consistent with Connolly's (1989), (1991) evidence, Chang, Pinegar and Ravichandran (1993) find that sample size and/or error term adjustments render U.S. day-of-the-week effects statistically insignificant. They find that Monday's mean returns are different at the five percent confidence level from mean returns observed throughout the week for the period from December 30, 1985 to April 30, 1992. In contrast, day-of-the-week



effects in seven European countries and in Canada and Hong Kong are robust to individual sample size or error term adjustments, and day-of-the-week effects in five European countries survive the simultaneous imposition of both types of adjustments. In most countries where day-of-the-week effects are robust, however, the effects are statistically significant in not more than two weeks out of the month. These findings are inconsistent with explanations of the day-of-the-week effect based on institutional differences or on the arrival of new information. Thus, in the absence of other potential explanations, evidence in this study further complicates the international day-of-the-week effect puzzle.

Dubois & Louvet (1996), find negative returns on Mondays and Tuesdays and positive returns on Wednesdays for eleven indices in nine countries from 1969 to 1992. This study provides further international evidence for the presence of the day-of-the-week effect in local currency terms for a majority of stock markets in these countries. In this respect, it extends the analysis of most of the countries examined in Dubois & Louvet (1996) use the standard methodology as well as the moving average methodology and find returns to be lower at the beginning of the week (but not necessarily on Monday) for the full period. As in Chang et al. (1993), they observe the anomaly to disappear for the most recent period in the USA. However, the effect is still strong for European countries, Hong-Kong and Toronto market.

Among the well-know explanations of the day-of-the-week effect are: closed-market hypothesis (French 1980), settlement procedures (Gibbons & Hess 1981; Lakonishok & Levi 1982; Solnik & Bousquet 1990), econometric methods, risk level, ex-dividend days (Lakonishok & Smidt 1988; Phillips-Patrick & Schneweis 1988) behavior of individual investors (Lakonishok & Maberly 1990), liquidity, time-zone theory (Condoyanni et al. 1987), previous week's market performance, firm size and January effect (Rogalski 1984), nonsynchronous trading and bid-ask spreads (Gibbons & Hess 1981), etc. However, based on the existing literature, no satisfactory explanation has been received yet.

### 3.3.1. Monday effect

History recall Black Monday, on October 19, 1987 the Dow Jones Industrial Average (DJIA) lost almost 22% in a single day. The crash started in Hong Kong and spread to the west. That event marked the beginning of a global stock market decline. By the end of the month, most of the major exchanges had dropped over 20% (Browning 2007). This became the most famous example of the “day-of-the-week” effect.

Monday effect is the most well-know and the most frequently documented phenomenon from the day-of-the-week effects. Monday tends to be the worst day to be invested in stocks. The Monday effect (also known as the Weekend effect) can be described by the two following characteristics:

- on average, returns on Mondays are statistically lower than those on the other days of the week;
- the average return on Mondays is statistically less than zero.

French (1980) reports that returns on the S&P 500 tend to be negative from Friday’s close to Monday’s close and that this is not simply a result of the longer three-day period between these closing prices. Gibbons and Hess (1981) confirmed the thrust of French’s (1980) findings using the CRSP equal-weighted and value-weighted market return indices. An interesting discovery is made by Keim and Stambaugh (1984) who suggest that the Monday effect is a weekend effect and that it is closely related to the January effect: during January, Monday returns are positive, while they become negative during the remaining part of the year.

Academic researchers have spent considerable effort attempting to document and, with limited success, to explain the tendency for asset returns to be negative on Monday. Market practitioners identified the Monday effect at least as early as the 1920s, well in advance of the advent of studies manipulating electronic databases (Pettengill 2003: 3). Kelly (1930) cites a three-year statistical study that identified Mondays as the worse day to buy stocks. He ascribes the cause of the low Monday returns to, among other factors, weekend decision making processing by individual investors. One of the first studies

documenting a weekend effect is by Fields (1931) at a time when stocks traded on Saturdays. Later Fields (1934) also finds in a study that the DJIA commonly advanced the day before holidays. Several studies have shown that returns on Monday are worse than other days of the week.

Harris (1986) studies intraday trading and finds that the weekend effect tended to occur in the first 45 minutes of trading as prices fall, but on all other days prices rise during the first 45 minutes. This anomaly presents the interesting question: Could the effect be caused by the moods of market participants? People are generally in better moods on Fridays and before holidays, but are generally grumpy on Mondays (in fact, suicides are more common on Monday than on any other day). Investors should however, keep in mind that the difference is small and could be difficult to take advantage of because of trading costs.

Wang, Li and Erickson (1997) tried to document that the Monday effect occurs primarily in the last two weeks of the month because of the well known correlation between the Friday return and the Monday return. Additionally, they considered the expiration date of stock options (on the third Friday of the month) as one further cause of poor stock performance on the following Monday. However, the authors allege that both explanations cannot justify the Monday effect.

A reverse weekend effect is the object of the research of Brusa, Liu and Schulman (2000). They discover that the Monday returns are significantly positive and they are higher than the returns of the other days of the week. From their results it emerges that large firms are subjected to traditional weekend effects whereas small firms are exposed to the reverse weekend effects. They also affirm that the trading of institutional investors in stocks of large firms contributes to the existence of the reverse weekend effect. According to their studies, the Monday returns would be positively correlated to those trading activities of institutional investors, which however, would exert a negative impact on the individual investors.

The analysis of Keef, Khaled and Zui (2009) suggests that in terms of information the poor countries are less efficient than rich countries and that a Monday effect weakening over time stands for a market efficiency increase. They examine 50 countries, where the observed between-country differences are characterised by an economic factor based on four indices. The prior day effect captures the tendency for price changes to follow those on the prior day. A bad (good) day occurs when the price change on the prior day is negative (positive). A panel regression with panel corrected standard errors, is used to characterize the way that the Monday effect and the related prior day effect systematically vary between countries over the period 1994 to 2006. At the start of the data in 1994, there is a considerable prior day effect which is larger for poor countries. This difference between countries declines over time and has essentially disappeared by 2006. The bad non-Monday effect and the bad-Monday effect also decline over time. Further analysis with six leading economies provides evidence that the prior day influence on Mondays and non-Mondays dates back to at least 1973.

Some findings question the stability of the Monday effect. Using hourly return data from 1963 to 1983, Smirlock and Starks (1986) find evidence of nonstationarities in the Monday effect. In the beginning of their sample (1963 – 1968), negative returns occur in every hour of trading on Mondays, while the Friday close to Monday open return is positive. In a later part of their sample (post-1974), the negative weekend effect results in negative average returns from Friday's close to Monday's open. So, as it is concluded by Connolly (1989: 134), Monday effect is time inconsistent – appears strongly in some time periods, nonexistent in other time periods, and weak in most time periods.

What causes the Monday effect? The literature proposes a variety of explanations for occurrence of this phenomenon. Lakonishok and Maberly (1990) in their study report that investors tend to increase their trading activities, (particularly, sell orders) on Mondays. So, heavy sell orders might trigger bearish trend in the market causing negative returns. Damodaran (1989) reports that firms in general report bad news on Fridays. He claims that reporting and delay in reporting of bad news might cause the negative Monday effect. A research by Kamara (1997) shows that equity derivatives and the institutionalization of equity markets affects the Monday seasonal. However,

Keim (2008) suggests that if the pattern exists in so many different markets, it argues persuasively against many institution-specific explanations. Research has shown that the weekend effect cannot be explained by: differences in settlement periods for transactions occurring on different weekdays; measurement error in recorded prices; market maker trading activity; or systematic patterns in investor buying and selling behavior (Keim 2008).

## 4. DATA AND METHODOLOGY

### 4.1. Data

Data are obtained from Datastream which is widely recognized as the number one historical financial information provider, offering the highest quality and most comprehensive coverage in the world. It contains key data sets from both developed and emerging markets – equities, market indices, company accounts, macroeconomics, bonds, foreign exchange, interest rates, commodities and derivatives.

Data of the present study represent daily closing values of the main stock market indices of 31 developed and developing countries. Originally it was planned to take the data for the period of 30 years in order to test properly the January/turn-of-the-year effect, but as for some countries it were not available for the entire period, it was decided to take two distinct data samples consisting of different time periods. The first sample is taken for the period from January 1, 1980 to February 11, 2011 which is used to test three effects: the January effect/turn-of-the-year effect (or TOY), turn-of-the-month effect (TOM) and day-of-the-week effect (DOW) in 11 countries. The second sample is for the period from January 2, 1991 to February 11, 2011 to test two effects – TOM and DOW – in remaining 20 countries. Table 2 (Panels A and B) presents the lists of countries in alphabetical order, their stock exchanges and names of indices which were taken for the analysis.

**Table 2.** Countries, stock exchanges and stock market indices.

<i>Panel A: countries taken to test TOY, TOM &amp; DOW</i>			
	<b>Country</b>	<b>Stock Exchange</b>	<b>Stock Market Index</b>
1.	Canada	Toronto Stock Exchange	S&P/TSX Composite
2.	Germany	Frankfurt Stock Exchange	DAX 30
3.		Hong Kong Stock Exchange	Hang Seng
4.	Japan	Tokyo Stock Exchange	TOPIX

**Table 2.** (continued)

5.	Malaysia	Malaysia Stock Exchange	KLCI
6.	South Korea	Korea Stock Exchange	KOSPI
7.	Spain	Madrid Stock Exchange	IGBM
8.	Sweden	Stockholm Stock Exchange	SWSEALI
9.	Thailand	Stock Exchange of Thailand	SET Index
10.	United Kingdom	London Stock Exchange	FTSE 100
11.	United States	New York Stock Exchange	S&P500
<i>Panel B: countries taken to test TOM &amp; DOW</i>			
1.	Austria	Vienna Stock Exchange	ATX
2.	Belgium	Euronext Brussels	BEL 20
3.	Brazil	São Paulo Stock Exchange	IBOVESPA
4.	Chile	Santiago Stock Exchange	IGPA
5.	Denmark	Copenhagen Stock Exchange	OMXC20
6.	Finland	Helsinki Stock Exchange	OMXH25
7.	Greece	Athens Stock Exchange	ATHEX Composite
8.	Hungary	Budapest Stock Exchange	BUX
9.	India	Bombay Stock Exchange	BSE 100
10.	Indonesia	Indonesia Stock Exchange	JSX Composite
11.	Ireland	Irish Stock Exchange	ISEQ
12.	Israel	Tel Aviv Stock Exchange	TA-100
13.	Mexico	Mexican Stock Exchange	IPC
14.	Netherlands	Euronext Amsterdam	AEX
15.	Norway	Oslo Stock Exchange	OSEAX
16.	Pakistan	Karachi Stock Exchange	KSE 100
17.	Peru	Lima Stock Exchange	IGBVL
18.	Philippines	Philippine Stock Exchange	PSEi
19.	Switzerland	SIX Swiss Exchange	SMI
20.	Turkey	Istanbul Stock Exchange	ISE National- 100

## 4.2. Methodology

Most researchers employ the simple linear regression model (French 1980; Gibbons and Hess 1981; Jaffe and Westerfield 1985). However, as Connolly (1989, 1991) claims, several specific problems may arise while using this approach:

- a) The returns are likely to be auto correlated;
- b) The residuals are possibly non-normal;
- c) The issue of heteroskedasticity may arise;
- d) Outliers with high/low value of return may distort the overall picture.

Therefore Connolly (1989) suggests using GARCH on dummies, in order to deal with auto correlation and heteroskedasticity issues. Instead of considering heteroskedasticity as a problem to be corrected, the GARCH models treat heteroskedasticity as a variance to be modelled. As a result, not only are the deficiencies of least squares corrected, but a prediction is computed for the variance of each error term. GARCH (1,1) model is first proposed by Bollerslev (1986) and is admitted by previous studies as a well-fitting for modeling conditional volatility in financial time series (Akgiray 1989; Day and Lewis 1992; Nelson 1982; Szakmary and Kiefer 2004).

The methodology applied in the present paper is similar to that one used in the research of Szakmary and Kiefer (2004), because it tests all effects at the same time what is appropriate for this study. They claim that the method should be inclusive enough to provide robust estimates of the effects in the presence of numerous other features of index returns data that may interact with these effects. These features are:

1. volatility clustering, which has been shown to be a key element of stock return series (French, Schwert & Stambaugh 1987; Akgiray 1989);
2. previous studies find both positive autocorrelations in index returns, and positive cross-autocorrelations between large cap and small-cap portfolios (Campbell, Lo & MacKinlay 1997);
3. mean returns across trading days, even outside the 19 trading days around the turn of the year, which are one of the main focus, have been shown to vary, for



example, in the following studies: French (1980), Dyl and Maberly (1986), Kamara (1997), Lakonishok & Smidt (1988).

The following GARCH (1,1) model is used for the first data sample to test turn-of-the-year, turn-of-the-month and day-of-the-week effects:

$$(1) \quad R_t = a_1 MON + a_2 TUE + a_3 WED + a_4 THU + a_5 FRI + a_6 TOM \\ + \sum_{i=-8}^{10} b_i TD(i) + \sum_{j=1}^n \rho_j R_{t-j} + e_t \\ e_t \sim N(0, h_t^2); h_t^2 = \delta + \theta h_{t-1}^2 + \gamma e_{t-1}^2$$

where  $R_t$  is the return of the stock market index (excluding dividends) on day  $t$ ;  
 $MON$ ,  $TUE$ ,  $WED$ ,  $THU$ , and  $FRI$  are dummy variables representing days of the week;  
 $TOM$  is a dummy variable equal to 1 on the last trading day and the first three trading days of each calendar month and zero otherwise;  
 $TD(i)$  are dummy variables representing trading days  $i$  ( $-8, -7, \dots, +9, +10$ ) relative to the turn of the year, which equal 1 on trading day  $i$  and 0 otherwise;  
 $e_t$  is an error term assumed to be normally distributed with zero mean and finite variance;  
 $h_t^2$  is the conditional variance.

Model used for the second data sample to test turn-of-the-month and day-of-the-week effects is as follows:

$$(2) \quad R_t = a_1 MON + a_2 TUE + a_3 WED + a_4 THU + a_5 FRI + a_6 TOM \\ + \sum_{j=1}^n \rho_j R_{t-j} + e_t \\ e_t \sim N(0, h_t^2); h_t^2 = \delta + \theta h_{t-1}^2 + \gamma e_{t-1}^2$$

where  $R_t$  is the return of the stock market index (excluding dividends) on day  $t$ ;  
 $MON$ ,  $TUE$ ,  $WED$ ,  $THU$ , and  $FRI$  are dummy variables representing days of the week;

*TOM* is a dummy variable equal to 1 on the last trading day and the first three trading days of each calendar month and zero otherwise;

$e_t$  is an error term assumed to be normally distributed with zero mean and finite variance;

$h_t^2$  is the conditional variance.

To capture the turn-of-the-year effect, and a possible migration of the effect to earlier in December, daily returns are examined for a total of 19 trading days [ $TD(i)$ ] ranging from nine trading days prior to the turn of the year to ten trading days after. Thus, for example,  $TD(8)$  is the ninth trading day prior to the turn of the year,  $TD(0)$  is the last trading day in December,  $TD(1)$  is the first trading day in January, and  $TD(10)$  is the tenth trading day in January.

The inclusion of day of the week and turn of the month dummy variables in the models, which are estimated using all days throughout the year, allows the coefficients on the turn-of-the-year days to be interpreted as the average return over and above the conditional return given the day of the week, and given whether the trading day falls into the turn of the month period.

#### 4.3. Hypotheses

Summarizing the evidence from the previous literature, the following statements represent the most common findings:

1. Significantly positive stock returns around the turn of the year;
2. Positive stock returns around the turn of the month;
3. Significantly negative average stock returns on Mondays;
4. Strong negative Tuesday returns for some countries;
5. Significantly positive stock returns on Fridays;

In addition, each calendar effect can exist or not in particular country. Consequently, based on the previous findings the following testable hypotheses can be formulated:

Turn-of-the-year effect

$H_{1,0}$ : *The stock market returns are not significantly different from zero.*

$H_{1,1}$ : *The stock market returns are significantly different from zero.*

Turn-of-the-month effect

$H_{2,0}$ : *The stock market returns are not significantly different from zero.*

$H_{2,1}$ : *The stock market returns are significantly different from zero.*

Day-of-the-week effect

$H_{3,0}$ : *The stock market returns are not significantly different from zero.*

$H_{3,1}$ : *The stock market returns are significantly different from zero.*

If the null hypotheses appear to be true, this would mean that the market is efficient and rational traders can not take advantages from trading at specific time in calendar. And on the contrary, if the null hypotheses are rejected, this means that the market is efficient and market participants can exploit calendar anomalies to make profits.

Of course, it can happen and will be natural if calendar effects are different from country to country. But also it is logically to expect some similarities in countries from the same regions, e.g. Europe, Asia, Pacific region, South and North Americas, or countries with the same level of development, i.e. developed or emerging ones.

## 5. EMPIRICAL RESULTS

The empirical results of GARCH (1,1) estimation of calendar effects in the countries from both data samples are presented in the Table 3 and Table 4. Tables are divided into *panels A, B, and C* which present countries by regions: Europe, Asia, North and South Americas. This makes it more convenient to make a comparison of countries from the same regions.

Table 3 presents the results of testing the countries from the first data sample for the existence of turn-of-the-year, turn-of-the-month and day-of-the-week effects for the period January 1, 1980 – February 11, 2011. The significance of coefficients is taken at 1% level to pick up the most significant ones.

From the table it is seen that turn-of-the-year effect does not exist in the investigated countries, except Malaysia. The returns during the turn of the year in Malaysia are significantly positive at 1% level. The non-existence of the January/turn-of-the-year effect is consistent for the following countries with Giovanis (2009) who uses approximately the same time period: Germany, UK, South Korea, Hong Kong, Thailand, Canada and US. As said previously, several studies prove that the January/turn-of-the-year effect existed before, but has disappeared or diminished over the recent period. The present study examines the data from 1980 till 2011 without splitting the data into subperiods and the results are shown for the entire period, so they do not show the possible existence of the effect in the early years. Also, January/turn-of-the-year effect is more attributed to small-cap stocks, but the present study focuses on indices which consist of large-cap stocks.

Turn-of-the-month effect is the most observed phenomenon among investigated countries, it exists almost in all of them (except Japan, Malaysia and Thailand) with significantly positive returns at 1% level. This is consistent with Giovanis (2009) for Germany, UK, South Korea, Hong Kong, Canada and US, who found turn-of-the-month effect in most countries examined in his study.

**Table 3.** Results of GARCH (1,1) estimation of DOW, TOM, TOY effects.

<i>Panel A: Europe</i>												
	<i>Germany</i>			<i>Spain</i>			<i>Sweden</i>			<i>United Kingdom</i>		
	<i>Estimate</i>	<i>z-stat</i>	<i>p-value</i>	<i>Estimate</i>	<i>z-stat</i>	<i>p-value</i>	<i>Estimate</i>	<i>z-stat</i>	<i>p-value</i>	<i>Estimate</i>	<i>z-stat</i>	<i>p-value</i>
<i>MON</i>	-0.008	-0.784	0.433	0.025	2.565	0.010	0.016	1.122	0.262	-0.007	-0.861	0.389
<i>TUE</i>	-0.007	-0.599	0.549	0.003	0.290	0.772	-0.001	-0.087	0.931	0.009	1.091	0.275
<i>WED</i>	0.030*	2.943	0.003	0.004	0.460	0.645	0.002	0.127	0.899	0.030*	3.890	0.000
<i>THU</i>	0.022	1.904	0.057	0.025	2.504	0.012	0.035	2.479	0.013	0.013	1.492	0.136
<i>FRI</i>	0.030*	2.934	0.003	0.033*	3.508	0.001	0.044*	3.022	0.003	0.028*	3.386	0.001
<i>TOM</i>	0.074*	6.221	0.000	0.043*	3.838	0.000	0.119*	8.451	0.000	0.045*	4.748	0.000
<i>TOY</i>	0.023	1.310	0.190	0.037	2.300	0.022	0.024	1.037	0.300	0.018	1.322	0.186
$\delta$	0.006*	13.354	0.000	0.004*	19.359	0.000	0.076*	18.004	0.000	0.003*	9.434	0.000
$\theta$	0.880*	184.27	0.000	0.884*	204.11	0.000	0.638*	32.449	0.000	0.887*	159.41	0.000
$\gamma$	0.106*	27.923	0.000	0.010*	23.872	0.000	0.128*	14.774	0.000	0.097*	20.434	0.000

  

<i>Panel B: Asia</i>												
	<i>Japan</i>			<i>Malaysia</i>			<i>South Korea</i>			<i>Thailand</i>		
	<i>Estimate</i>	<i>z-stat</i>	<i>p-value</i>	<i>Estimate</i>	<i>z-stat</i>	<i>p-value</i>	<i>Estimate</i>	<i>z-stat</i>	<i>p-value</i>	<i>Estimate</i>	<i>z-stat</i>	<i>p-value</i>
<i>MON</i>	0.027*	3.748	0.000	-0.029*	-3.191	0.001	0.020	1.876	0.061	-0.026*	-3.155	0.002
<i>TUE</i>	-0.016	-1.772	0.076	0.004	0.364	0.716	-0.019	-1.195	0.232	0.002	0.201	0.840
<i>WED</i>	0.043*	5.065	0.000	0.021	2.203	0.028	0.028	1.981	0.048	0.016	1.984	0.047
<i>THU</i>	0.025*	2.990	0.003	0.037*	3.764	0.000	0.032*	2.639	0.004	0.014	1.711	0.087
<i>FRI</i>	0.020	2.373	0.018	0.051*	5.208	0.000	0.048*	2.925	0.007	0.050*	5.270	0.000
<i>TOM</i>	0.020	1.842	0.066	0.012	1.104	0.270	0.050*	3.219	0.001	-0.015	-1.638	0.101
<i>TOY</i>	0.028	2.010	0.045	0.064*	3.251	0.001	0.044	2.095	0.053	0.018	0.972	0.331
$\delta$	0.002*	8.788	0.000	0.005*	20.787	0.000	0.007*	16.633	0.000	0.001*	10.756	0.000
$\theta$	0.883*	246.43	0.000	0.867*	249.34	0.000	0.899*	256.94	0.000	0.883*	268.70	0.000
$\gamma$	0.123*	35.775	0.000	0.127*	27.765	0.000	0.088*	24.855	0.000	0.136*	27.937	0.000

  

<i>Hong Kong</i>			
	<i>Estimate</i>	<i>z-stat</i>	<i>p-value</i>
<i>MON</i>	-0.001	-0.109	0.913
<i>TUE</i>	0.018	1.312	0.190
<i>WED</i>	0.045*	3.399	0.001
<i>THU</i>	0.035*	2.625	0.009
<i>FRI</i>	0.051*	3.779	0.000
<i>TOM</i>	0.065*	3.970	0.000
<i>TOY</i>	0.048	1.919	0.055
$\delta$	0.010*	15.472	0.000
$\theta$	0.867*	205.76	0.000
$\gamma$	0.122*	37.401	0.000

\*denotes the significance at 1% level

**Table 3.** (continued)

<i>Panel C: North America</i>						
	<i>Canada</i>			<i>United States</i>		
	<i>Estimate</i>	<i>z-stat</i>	<i>p-value</i>	<i>Estimate</i>	<i>z-stat</i>	<i>p-value</i>
<i>MON</i>	-0.013	-1.769	0.077	0.015	1.586	0.113
<i>TUE</i>	0.003	0.455	0.649	0.014	1.620	0.105
<i>WED</i>	0.024*	3.299	0.001	0.036*	3.710	0.000
<i>THU</i>	0.015	2.225	0.026	0.013	1.445	0.149
<i>FRI</i>	0.023*	3.105	0.002	0.011	1.316	0.188
<i>TOM</i>	0.044*	4.921	0.000	0.027*	2.668	0.008
<i>TOY</i>	0.025	1.887	0.059	0.008	0.564	0.573
$\delta$	0.002*	13.644	0.000	0.002*	11.252	0.000
$\theta$	0.887*	275.81	0.000	0.920*	363.72	0.000
$\gamma$	0.102*	34.739	0.000	0.071*	44.348	0.000

\* denotes the significance at 1% level

The day-of-the-week anomaly has variations from country to country. Like the turn-of-the-month effect, the day-of-the-week anomaly exists in all investigated stock market indexes and the returns are significantly positive almost in all cases. The exceptions are Thailand and Malaysia with “traditional” weekend effect when the returns are significantly negative on Mondays and significantly positive on Fridays, and in addition, Malaysia has significantly positive Thursday returns (consistent with Giovanis (2009) for Thailand, and with Chan, Khanthavit and Thomas (1996) – for Malaysia).

The US stock market index S&P 500 shows significantly positive returns on Wednesdays, which is consistent with Cho, Linton and Whang (2007). In their study Cho et al. (2007) examine the Monday effect in US using S&P 500 approximately during the same period and report that this effect in S&P 500 has weakened post 1987. From the results of their study it can be seen that returns on Wednesdays are significantly positive. Kamara (1997) reports that the weekend effect, while still exists, has diminished significantly since the introduction of the S&P 500 futures contract in 1982. He claims that the Monday effect is not statistically significant in the DJIA and S&P 500 indices that are dominated by large and mature firms.

In Germany, United Kingdom and Canada the returns on Wednesdays and Fridays are significantly higher than on other weekdays. Interestingly, Wednesday returns are approximately equal to Friday returns. In Spain and Sweden the day of significantly positive returns is only Friday, while for Japan these days are Monday, Wednesday and Thursday, for Korea – Thursday and Friday, and for Hong Kong – Wednesday, Thursday and Friday. So, the null hypothesis appears to be valid for the turn-of-the-year effect (except Malaysia) and is rejected for the turn-of-the-month effect for most of the countries and for the day-of-the-week – for all countries.

Table 4 presents the results of testing the countries from the second data sample for the existence of turn-of-the-month and day-of-the-week effects for the period 1991 – 2011. As in the previous table, here turn-of-the-month effect also exists almost in all countries, except Indonesia and Pakistan, and the returns are significantly positive at 1% level. For Brazil, Mexico, Netherlands, Norway and Turkey these findings are consistent with Giovanis (2009).

Unlike the first data sample, day-of-the-week effect is found not in all countries, but it also presents different variations among countries. There is no effect in Austria, Belgium, Denmark, India and Israel. The “traditional” weekend effect is found in Greece: it has negative Monday and positive Friday returns, and in addition, negative Tuesday returns. Chile has significantly negative returns on Mondays, and significantly positive returns on all other weekdays, except Tuesday, with the largest return on Friday equal to 0.053 percent. This can be also considered as a “traditional” weekend effect. Other countries present various combinations of the day-of-the-week effect.

The fact, that the weekend effect is not found in most countries as it was expected, has a reasonable explanation. Brusa, Liu and Schulman (2003) noted that all studies using pre-1987 data (e.g. Keim 1987) document the weekend effect and studies using post-1988 data (Kamara 1997; Steeley 2001) tend to document the effect diminishing or disappearing. An interesting suggestion is proposed by Keef et al. (2009). They claim that Monday effect weakening over time stands for a market efficiency increase.

**Table 4.** Results of GARCH (1,1) estimation of DOW, TOM effects.

<i>Panel A: Europe</i>												
	<i>Austria</i>			<i>Belgium</i>			<i>Denmark</i>			<i>Finland</i>		
	<i>Estimate</i>	<i>z-stat</i>	<i>p-value</i>	<i>Estimate</i>	<i>z-stat</i>	<i>p-value</i>	<i>Estimate</i>	<i>z-stat</i>	<i>p-value</i>	<i>Estimate</i>	<i>z-stat</i>	<i>p-value</i>
<i>MON</i>	0.014	1.130	0.259	0.008	0.704	0.482	0.003	0.244	0.807	0.017	1.018	0.309
<i>TUE</i>	0.018	1.341	0.180	0.006	0.508	0.611	0.020	1.527	0.127	0.009	0.559	0.576
<i>WED</i>	0.015	1.152	0.249	0.007	0.663	0.507	0.022	1.782	0.075	0.019	1.217	0.224
<i>THU</i>	0.017	1.243	0.214	0.015	1.430	0.153	0.011	0.862	0.389	0.041*	2.655	0.008
<i>FRI</i>	0.013	0.975	0.329	0.014	1.322	0.186	0.012	0.819	0.413	0.050*	2.968	0.003
<i>TOM</i>	0.067*	4.404	0.000	0.079*	6.153	0.000	0.074*	5.039	0.000	0.068*	3.399	0.001
$\delta$	0.008*	11.468	0.000	0.005*	15.971	0.000	0.006*	14.867	0.000	0.005*	7.327	0.000
$\theta$	0.864*	122.82	0.000	0.855*	116.37	0.000	0.891*	154.80	0.000	0.913*	201.05	0.000
$\gamma$	0.109*	18.885	0.000	0.119*	17.899	0.000	0.085*	16.613	0.000	0.078*	18.945	0.000

  

	<i>Greece</i>			<i>Hungary</i>			<i>Ireland</i>			<i>Netherlands</i>		
	<i>Estimate</i>	<i>z-stat</i>	<i>p-value</i>	<i>Estimate</i>	<i>z-stat</i>	<i>p-value</i>	<i>Estimate</i>	<i>z-stat</i>	<i>p-value</i>	<i>Estimate</i>	<i>z-stat</i>	<i>p-value</i>
<i>MON</i>	-0.046*	-3.113	0.002	0.041*	2.661	0.008	-0.015	-1.260	0.208	0.032*	2.610	0.009
<i>TUE</i>	-0.049*	-3.144	0.002	0.002	0.115	0.908	0.011	0.962	0.336	0.013	0.999	0.318
<i>WED</i>	0.003	0.208	0.835	0.010	0.670	0.503	0.019	1.786	0.074	0.005	0.406	0.685
<i>THU</i>	0.019	1.281	0.200	0.005	0.311	0.756	0.035*	3.072	0.002	0.015	1.257	0.209
<i>FRI</i>	0.051*	2.739	0.006	0.023	1.270	0.204	0.026	2.117	0.034	0.010	0.796	0.426
<i>TOM</i>	0.010*	5.183	0.000	0.067*	3.221	0.001	0.055*	4.068	0.000	0.060*	4.331	0.000
$\delta$	0.011*	11.439	0.000	0.017*	16.911	0.000	0.003*	9.177	0.000	0.003*	10.611	0.000
$\theta$	0.841*	128.83	0.000	0.823*	169.7	0.000	0.913*	183.27	0.000	0.896*	157.38	0.000
$\gamma$	0.146*	20.370	0.000	0.151*	36.210	0.000	0.078*	16.606	0.000	0.093*	16.920	0.000

  

	<i>Norway</i>			<i>Switzerland</i>			<i>Turkey</i>		
	<i>Estimate</i>	<i>z-stat</i>	<i>p-value</i>	<i>Estimate</i>	<i>z-stat</i>	<i>p-value</i>	<i>Estimate</i>	<i>z-stat</i>	<i>p-value</i>
<i>MON</i>	0.010	0.773	0.439	0.025*	2.121	0.034	-0.015	-0.595	0.552
<i>TUE</i>	0.001	0.057	0.955	-0.002	-0.177	0.859	-0.008	-0.260	0.795
<i>WED</i>	0.003	0.279	0.780	0.012	0.966	0.334	0.094*	3.244	0.001
<i>THU</i>	0.067*	5.617	0.000	0.012	1.042	0.297	0.102*	3.682	0.000
<i>FRI</i>	0.061*	4.201	0.000	0.029	2.454	0.014	0.073	2.327	0.020
<i>TOM</i>	0.068*	4.515	0.000	0.071*	5.133	0.000	0.102*	3.086	0.002
$\delta$	0.010*	10.765	0.000	0.008*	15.380	0.000	0.018*	7.867	0.000
$\theta$	0.001*	112.37	0.000	0.854*	99.532	0.000	0.903*	233.85	0.000
$\gamma$	0.003*	17.360	0.000	0.112*	14.556	0.000	0.086*	21.456	0.000

\* denotes the significance at 1% level



**Table 4.** (continued)

<i>Panel B: Asia</i>												
	<i>India</i>			<i>Indonesia</i>			<i>Israel</i>			<i>Pakistan</i>		
	<i>Estimate</i>	<i>z-stat</i>	<i>p-value</i>	<i>Estimate</i>	<i>z-stat</i>	<i>p-value</i>	<i>Estimate</i>	<i>z-stat</i>	<i>p-value</i>	<i>Estimate</i>	<i>z-stat</i>	<i>p-value</i>
<i>MON</i>	0.037	2.359	0.018	-0.022	-1.637	0.102	0.039	2.180	0.029	-0.030	-2.012	0.044
<i>TUE</i>	-0.006	-0.324	0.746	-6.87E-05	-0.005	0.996	0.021	1.272	0.204	0.042	2.520	0.012
<i>WED</i>	0.020	1.195	0.232	0.045*	3.292	0.001	-0.006	-0.388	0.698	0.073*	4.324	0.000
<i>THU</i>	0.015	0.877	0.381	0.042*	3.092	0.002	0.036	2.224	0.026	0.044	2.406	0.016
<i>FRI</i>	0.041	2.499	0.013	0.071*	5.449	0.000	0.025	1.806	0.071	0.002	0.125	0.900
<i>TOM</i>	0.091*	5.164	0.000	0.021	1.304	0.192	0.093*	5.043	0.000	0.041	2.232	0.026
$\delta$	0.009*	9.703	0.000	0.003*	11.068	0.000	0.011*	10.978	0.000	0.015*	18.192	0.000
$\theta$	0.874*	165.95	0.000	0.896*	291.98	0.000	0.872*	127.70	0.000	0.824*	156.19	0.000
$\gamma$	0.116*	21.670	0.000	0.104*	25.800	0.000	0.102*	16.910	0.000	0.151*	23.028	0.000

  

<i>Philippines</i>			
	<i>Estimate</i>	<i>z-stat</i>	<i>p-value</i>
<i>MON</i>	-0.020	-1.109	0.267
<i>TUE</i>	-0.045	-2.567	0.010
<i>WED</i>	0.020	1.212	0.226
<i>THU</i>	0.055*	3.227	0.001
<i>FRI</i>	0.045	2.477	0.013
<i>TOM</i>	0.104*	5.357	0.000
$\delta$	0.021*	11.912	0.000
$\theta$	0.828*	105.33	0.000
$\gamma$	0.131*	28.983	0.000

  

<i>Panel C: South America</i>												
	<i>Brazil</i>			<i>Chile</i>			<i>Mexico</i>			<i>Peru</i>		
	<i>Estimate</i>	<i>z-stat</i>	<i>p-value</i>	<i>Estimate</i>	<i>z-stat</i>	<i>p-value</i>	<i>Estimate</i>	<i>z-stat</i>	<i>p-value</i>	<i>Estimate</i>	<i>z-stat</i>	<i>p-value</i>
<i>MON</i>	-0.003	-0.088	0.929	-0.033*	-4.131	0.000	0.008	0.488	0.625	0.037*	2.702	0.007
<i>TUE</i>	0.055	1.772	0.076	-0.003	-0.328	0.743	0.027	1.722	0.085	-0.001	-0.074	0.941
<i>WED</i>	0.127*	4.072	0.000	0.026*	3.266	0.001	0.060*	3.551	0.000	0.026	1.758	0.079
<i>THU</i>	0.066	2.323	0.020	0.043*	5.252	0.000	0.062*	3.555	0.000	0.041*	3.092	0.002
<i>FRI</i>	0.124*	3.584	0.000	0.053*	6.373	0.000	0.038	2.125	0.034	0.099*	6.819	0.000
<i>TOM</i>	0.099*	2.774	0.006	0.043*	4.131	0.000	0.098*	4.796	0.000	0.066*	3.745	0.000
$\delta$	0.040*	36.405	0.000	0.002*	8.202	0.000	0.008*	8.693	0.000	0.010*	12.825	0.000
$\theta$	0.884*	286.08	0.000	0.837*	117.16	0.000	0.886*	160.39	0.000	0.803*	138.05	0.000
$\gamma$	0.082*	25.560	0.000	0.148*	18.709	0.000	0.104*	20.753	0.000	0.179*	24.697	0.000

\* denotes the significance at 1% level

Summarizing the results from the both data samples, it is seen that the turn-of-the-year effect does not exist in stock markets from the first data sample (except Malaysia), the turn-of-the-month and the day-of-the-week effects are found in 26 countries out of 31. The day-of-the-week anomaly presents various differences across countries. “Traditional” weekend effect with negative Monday returns and positive Friday returns is found in Thailand, and with small variations in Malaysia and Greece. For Scandinavia the turn-of-the-month effect, Thursday and Friday effects are observed, except Sweden which has only Friday effect. Interestingly, negative returns on Tuesdays were not found at 1% significance level in Japan, Korea, Malaysia, Philippines, Thailand and Hong Kong as it is presented by other studies in earlier years (Jaffe & Westerfield 1985; Dubois & Louvet 1996; Kim 1988; Ho 1990). So, this means that the day-of-the-week effect is changing with time. In both data samples all GARCH parameters for all stock market indices are statistically significant.

## 6. SUMMARY AND CONCLUSIONS

The present paper adopts and carefully applies a procedure which examines the calendar effects in 31 developed and developing countries. The anomalies which are investigated are turn-of-the-year effect, turn-of-the-month effect and day-of-the-week effect. Two data samples with unequal time periods are analyzed: the first sample is from January 1, 1980 to February 11, 2011, and the second one is for the period from January 2, 1991 to February 11, 2011. The anomalies are tested with GARCH (1,1) model using the methodology proposed by Szakmary and Kiefer (2004).

The study presented adequate challenges to the author. Results appeared to be different from what was expected. The research shows that the turn-of-the-year effect is not found in observed countries except Malaysia, which means that the effect has totally disappeared during the recent years in analyzed countries. The turn-of-the-month and the day-of-the-week anomalies still exist in the majority of the analyzed stock markets. In all countries where it is found, the returns during the turn of the month are significantly positive at 1% level. The day-of-the-week effect provides some variations across countries.

The results of this study and others similar to it may be important for financial managers, financial counselors and investors interested in international diversification. Its relevance lies in the direct bearing of its results on the timing and nature of investment decisions (Boudreaux 1995: 15). Compiling together all the available results from this and other studies on the calendar effects investors and other financiers can choose their own strategy of investing and diversify their assets by allocating them to the financial markets of the countries which show the highest return during definite periods of time of the year, month and week.

The existence of predictable seasonal behavior in stock returns may lead to profitable trading strategies, and in turn, abnormal returns. Seasonality is an important factor of predictable behaviors in stock returns. Investors have long been fascinated by the possibility of finding systematic patterns in stock prices that, once detected, promise

easy profits when exploited by simple trading rules. Calendar effects have a significant economic value if it is possible for investors to use them in a trading strategy. The development of such strategies can be a matter of interest for the further research.

Summarizing the conclusions, one interesting issue comes to the mind: if in some countries there are no calendar effects, does it mean that the market is/became efficient? Keef et al. (2009) claim that the effects are likely to disappear in advanced economies. Does this mean that if the economy that achieved advanced level became efficient? The term “efficient” itself means something rational and advanced. Thus, if the economy is advanced then markets are efficient, and from this follows that investors are not able to earn excess returns in such economies. In such case the Efficient Market Hypothesis and the Random Walk Theory will become true some day. And it will not be possible for market participants to earn profit systematically from market inefficiencies. Therefore, the question arises: Is this good and for whom?

As the efficiency is the sign of advanced economy, the question can be answered: it is good for everyone – better to be advanced and efficient than not advanced and inefficient. Therefore, market inefficiency is good just for a part of people; for those, who can get more information than others and then use it, making abnormal returns. And it can be bad for the rest of the society, because this part of people can manipulate markets seeking their own goals. In order to prevent this, it is necessary to eliminate inefficiency and aspire to reach the advanced level in economies. Achieving the market efficiency can be another option for the further research.

**REFERENCES**

- Agrawal, A. & K. Tandon (1994). Anomalies or illusions? Evidence from stock markets in eighteen countries. *Journal of International Money and Finance*. 13: 1, 83-106.
- Akgiray, V. (1989). Conditional Heteroscedasticity in Time Series of Stock Returns: Evidence and Forecasts. *Journal of Business*. 62: 1, 55–80.
- Alexander, S. S. (1961). Price Movements in Speculative Markets: Trends or Random Walks. *Industrial Management Review*. 2: 2, 7-26.
- Alexander, S. S. (1964). Price Movements in Speculative Markets: Trends or Random Walks, Number 2. *Industrial Management Review*. 5, 25-46.
- Ariel, R. A. (1987). A Monthly Effect in Stock Returns. *Journal of Financial Economics*. 18: 1, 161-174.
- Ariel, R. A. (1990). High Stock Returns Before Holidays: Existence and Evidence on Possible Causes. *Journal of Finance*. 45, 1611-1626.
- Athanassakos, G. & M. J. Robinson (1994). The Day of the Week Anomaly: The Toronto Stock Exchange Experience. *Journal of Business Finance & Accounting*. 21: 6, 833-856.
- Barone, E. (1990). The Italian Stock Market: Efficiency and Calendar Anomalies. *Journal of Banking & Finance*. 14: 2-3, 483-510.
- Bollerslev, T. (1986). Generalized Autoregressive Conditional Heteroskedasticity. *Journal of Econometrics*, 31: 3, 307–328.

- Boudreaux, D. O. (1995). The monthly effect in international stock markets: evidence and implications. *Journal of Financial and Strategic Decisions*. 8: 1, 15-20.
- Brealey, R. A. & S. C. Meyers (2003). *Principles of Corporate Finance*. 7th ed. New York: McGraw-Hill Companies Inc.
- Browning, E. S. (2007-10-15). Exorcising Ghosts of Octobers Past. *The Wall Street Journal* (Dow Jones & Company): pp. C1–C2. Retrieved 2007-10-15.
- Brusa, J., P. Liu & C. Shulman (2000). The Weekend Effect, 'Reverse' Weekend Effect, and Firm Size. *Journal of Business Finance & Accounting*. 27: 5-6, 555–574.
- Brusa, J., P. Liu & C. Schulman (2003). The Weekend and “Reverse” Weekend Effect: An Analysis by Month of the Year, Week of the Month, and Industry. *Journal of Business Finance & Accounting*. 30: 5 & 6, 863-890.
- Campbell, J. Y., A. W. Lo & C. A. Mackinlay (1997). *The Econometrics of Financial Markets* (65–80). Princeton, NJ: Princeton University Press.
- Carhart, M. M. (1997). On Persistence in Mutual Fund Performance. *Journal of Finance*. 52: 1, 57–82.
- Chan, M. W. L., A. Khanthavit & H. Thomas (1996). Seasonality and Cultural Influences on Four Asian Stock Markets. *Asia Pacific Journal of Management*. 13: 2, 1-24.
- Chang, E. C., J. M. Pinegar & R. Ravichandran (1993). International evidence on the robustness of the day-of-the-week effect. *The Journal of Financial and Quantitative Analysis*. 28: 4, 497–514.
- Chen, H. & V. Singal (2004). All Things Considered, Taxes Drive the January Effect. *The Journal of Financial Research*. 27: 3, 351-372.

- Cho, Y.-H., O. Linton, Y.-J. Whang (2007). Are There Monday Effects in Stock Returns: A Stochastic Dominance Approach. *Journal of Empirical Finance*. 14: 5, 736–755.
- Choudhry, T. (2001). Month of the Year Effect and January Effect in pre-WWI Stock Returns: Evidence from a Non-Linear GARCH Model. *International Journal of Finance and Economics*. 6: 1, 1-11.
- Chris, R. H. & W. T. Ziemba (1996). Investment Results from Exploiting Turn-of-the-Month Effects. *Journal of Portfolio Management*. 22: 3, 17-23.
- Condoyanni, L., J. O' Hanlon & C. W. R. Ward (1987). Day of the Week Effects on Stock Returns: International Evidence. *Journal of Business Finance and Accounting*. 14: 2, 159-174.
- Connolly, R. A. (1989). An Examination of the Robustness of the Weekend Effect. *The Journal of Financial and Quantitative Analysis*. 24: 2, 133-169.
- Connolly, R. A. (1991). A posterior odds analysis of the weekend effect. *Journal of Econometrics*. 49: 1-2, 51-104.
- Cooper, M. J., J. J. McConnell & A. V. Ovtchinnikov (2006). The Other January Effect. *Journal of Financial Economics*. 82: 2, 315-341.
- Cross, F. (1973). The Behavior of Stock Prices on Fridays and Mondays. *Financial Analysts Journal*. 29: 6, 67-69.
- Damodaran, A. (1989). The Weekend Effect in Information Releases: A Study of Earnings and Dividend Announcements. *The Review of Financial Studies*. 2: 4, 607-623.

- Day, T. E., & Lewis, C. M. (1992). Stock Market Volatility and the Information Content of Stock Index Options. *Journal of Econometrics*. 52: 1/2, 267–288.
- Dubois, M. & P. Louvet (1996). The Day-of-the-Week Effect: International Evidence. *Journal of Banking and Finance*. 20: 9, 1463-1484.
- Dyl, E. A. and E. D. Maberly (1986). The Weekly Pattern in Stock Index Futures: A Further note. *Journal of Finance*. 41: 5, 1149–1152.
- Fama, E. F. (1965). The Behavior of Stock Market Prices. *Journal of Business*. 38: 1, 34-105.
- Fama, E. F. (1970). Efficient Capital Markets: A Review of Theory & Empirical Work. *Journal of Finance*. 25: 2, 383-417.
- Fama, E. F. & M. Blume (1966). Filter Rules and Stock Market Trading. *Journal of Business*. 39, 226-241.
- Fama, E. F. & K. R. French (1988). Permanent and Temporary Components of Stock Prices. *Journal of Political Economy*. 96: 2, 246-73.
- Fields, M. J. (1931). Stock Prices: A Problem in Verification. *Journal of Business*. 4: 4, pp. 415-418.
- Fields, M. J. (1934). Security prices and stock exchange holidays in relation to short selling. *Journal of Business*. 7: 4, 328-338.
- Flannery, M. J. & A. A. Protopapadakis (1988). From T-Bills to Common Stocks: Investigating the Generality of Intra-Week Return Seasonality. *Journal of Finance*. 43: 2, 431-450.
- Francis, J. C. (1993). *Management of Investments*. 3 ed. New York: McGraw-Hill Inc.



- French, K. R. (1980). Stock Returns and the Weekend Effect. *Journal of Financial Economics*. 8: 1, 55-69.
- Gibbons, M. R. & P. Hess (1981). Day of the Week Effects and Asset Returns. *Journal of Business*. 54: 4, 579-596.
- Giovanis, E. (2009). Calendar Effects in Fifty-five Stock Market Indices. *Global Journal of Finance and Management*. 1: 2, 75-98.
- Gultekin, M. N. & N. B. Gultekin (1983). Stock Market Seasonality International Evidence. *Journal of Financial Economics*. 12: 4, 469-481.
- Haug, M. & M. Hirschey (2006). The January Effect. *Financial Analysts Journal*. 62: 5, 78-88.
- Haugen, R. A. & P. Jorion (1996). The January Effect: Still There after All These Years. *Financial Analysts Journal*. 52: 1, 27-31.
- Haugen, R. A. & J. Lakonishok (1987). *The Incredible January Effect: The Stock Market's Unsolved Mystery*. 1 ed. Homewood, III. : Dow Jones-Irwin.
- Harris, L. (1986). A Transaction Data Study of Weekly and Intradaily Patterns in Stock Returns. *Journal of Financial Economics*. 16: 1, 99-117.
- Ho, Y. K. (1990). Stock Return Seasonalities in Asia Pacific Markets. *Journal of International Financial Management and Accounting*. 2: 1, 47-77.
- Howells, P. & K. Bain (2005). *The Economics of Money, Banking and Finance*. 3rd ed. Harlow, England: Pearson Education Limited.

- Jaffe, J. & R. Westerfield (1985). Patterns in Japanese Common Stock Returns: Day of the Week and Turn of the Year Effects. *Journal of Financial and Quantitative Analysis*. 20: 2, 261-272.
- Jensen, M. C. (1967). Random Walks: Reality or Myth – Comment. *Financial Analysts Journal*. 23: 6, 77-85.
- Jensen, M. (1978). Some Anomalous Evidence Regarding Market Efficiency. *Journal of Financial Economics*. 6: 2/3. 95-101.
- Kamara, A. (1997). New Evidence on the Monday Seasonal in Stock Returns. *Journal of Business*. 70: 1, 63-84.
- Keef, S. P., M. Khaled & H. Zhu (2009). The dynamics of the Monday effect in international stock indices. *International Review of Financial Analysis*. 18: 3, 125-133.
- Keim, D. B. (1983). Size-Related Anomalies and Stock Return Seasonality: Further Empirical Evidence. *Journal of Financial Economics*. 12: 1, 13-32.
- Keim, D. B. (1987). Daily Returns and Size-related Premiums: One More Time. *The Journal of Portfolio Management*. 13: 2, 41-47.
- Keim, D. B. (2008). Financial Market Anomalies. In: *The New Palgrave Dictionary of Economics*. 2 ed. Eds. Steven N. Durlauf and Lawrence E. Blume. Palgrave Macmillan.
- Keim, D. B. & R. Stambaugh (1984). A Further Investigation of the Weekend Effect in Stock Returns. *Journal of Finance*. 39: 3, 819-837.
- Kendall, M. G. (1953). The Analysis of Economic Time-Series-Part I: Prices. *Journal of the Royal Statistical Society*. Series A (General). 116: 1, 11–34.

- Kim, D. (2006). On the Information Uncertainty Risk and the January Effect. *Journal of Business*. 79: 4, 2127-2162.
- Kim, S. W. (1988). Capitalizing on the Weekend Effect. *Journal of Portfolio Management*. 14: 3, 59-63.
- Lakonishok J. & M. Levi (1982). The Weekend Effects on Stock Returns. *Journal of Finance*. 37: 3, 883-889.
- Lakonishok J. & E. Maberly (1990). The Weekend Effect: Trading Patterns of Individual and Institutional Investors. *Journal of Finance*. 45: 1, 231-243.
- Lakonishok, J. & S. Smidt (1988). Are Seasonal Anomalies Real? A Ninety Year Perspective. *Review of Financial Studies*. 1: 4, 403-425.
- Levy, R. A. (1967). Random Walks: Reality or Myth. *Financial Analysts Journal*. 23: 6, 69-77.
- Lo, A. W. & A. C. MacKinlay (1988). Stock Market Prices do not Follow Random Walks: Evidence from a Simple Specification Test. *Review of Financial Studies* 1: 1, 41-66.
- Malkiel, B. G. (1973). *A Random Walk Down Wall Street*. 6th ed. New York: W.W. Norton & Company, Inc.
- McConnell, J. J. & W. Xu (2008). Equity Returns at the Turn of the Month. *Financial Analysts Journal*. 64: 2, 49-64.
- Moosa, I. A. (2007). The Vanishing January Effect. *International Research Journal of Finance and Economics*. 7, 92-103.

- Nelson, D. B. (1982). Filtering and Forecasting with Misspecified ARCH models: Getting the Right Variance with the Wrong Model. *Journal of Econometrics*. 52: 1-2, 61–90.
- Nikkinen, J., P. Sahlström & J. Äijö (2007). Turn-of-the-Month and Intramonth Effects: Explanation from the Important Macroeconomic News Announcements. *Journal of Futures Markets*. 27: 2, 105–126.
- Ogden, J. P. (1990). Turn-of-month evaluations of liquid profits and stock returns: A common explanation for the monthly and January effects. *Journal of Finance*. 45: 4, 1259–1272.
- Pettengill, G. N. (2003). A survey of the Monday effect literature. *Quarterly Journal of Business and Economics*. 42: 3/4, 3-28.
- Phillips-Patrick, F. J. & T. Schneeweis (1988). The Weekend Effect for Stock Indexes and Stock Index Futures: Dividend and Interest Rate Effects. *Journal of Futures Markets*. 8: 1, 115-121.
- Poterba, J. M. & L. H. Summers (1988). Mean-reversion in Stock Prices: Evidence and Implications. *Journal of Financial Economics*. 22: 1, 27-59.
- Reinganum, M. R. (1983). The Anomalous Stock Market Behavior of Small Firms in January – Empirical Tests for Tax-Loss Selling Effects. *Journal of Financial Economics*. 12: 1, 89-104.
- Rogalski, R. (1984). New Findings Regarding Day-of-the-Week Returns over Trading and Non-Trading Periods. *Journal of Finance*. 39: 5, 1603-1614.
- Rozeff, M. S. & W. R. Kinney, Jr. (1976). Capital Market Seasonality: The Case of Stock Returns. *Journal of Financial Economics*. 3: 4, 379–402.

- Samuelson, P. (1965). Proof that Properly Anticipated Prices Fluctuate Randomly. *Industrial Management Review*. 6: 2, 41-49.
- Shiller, R. J. (2003). From Efficient Markets Theory to Behavioral Finance. *Journal of Economic Perspectives*. 17: 1, 83–104.
- Sias, R. W. & L. T. Starks (1995). The Day-of-the-Week Anomaly: The Role of Institutional Investors. *Financial Analysts Journal*. 51: 3, 58-67.
- Smirlock, M. & L. Starks (1986). Day of the Week and Intraday Effects in Stock Returns. *Journal of Financial Economics*. 17: 1, 197–210.
- Solnik, B. & L. Bousquet (1990). Day-of-the-Week Effect on the Paris Bourse. *Journal of Banking and Finance*. 14: 2-3, 461-468.
- Sullivan, R., A. Timmermann & H. White (2001). Dangers of Data Mining: The Case of Calendar Effects in Stock Returns. *Journal of Econometrics*. 105: 1, 249-286.
- Szakmary, A. C. & D. B. Kiefer (2004). The Disappearing January/Turn of the Year Effect: Evidence from Stock Index Futures and Cash Markets. *Journal of Futures Markets*. 24: 8, 755–784.
- Thaler, R. H. (1987a). Anomalies: The January Effect. *Journal of Economic Perspectives*. 1: 1, 197-201.
- Thaler, R. H. (1987b). Anomalies: Weekend, Holiday, Turn of the Month, and Intraday Effects. *Journal of Economic Perspectives*. 1: 2, 169-178.
- Tinic, S. M. & R. R. West (1984). Risk and return: January vs. the rest of the year. *Journal of Financial Economics*. 13: 4, 561-574.
- Van der Sar, N. L. (2003). Calendar Effects on the Amsterdam Stock Exchange. *De Economist*. 151: 3, 272-292.

Wachtel, S. B. (1942). Certain Observations on Seasonal Movements in Stock Prices. *Journal of Business*. 15: 2, 184-193.

Wang K., Li Y. & Erickson J. (1997). A New Look at the Monday Effect. *The Journal of Finance*. 52: 5, 2171-2186.

Wiley, J. A. & L. V. Zumpano (2009). Institutional Investment and the Turn of the Month Effect: Evidence from REITs. *Journal of Real Estate Finance and Economics*. 39: 2, 180-201.