Stock Market Seasonality: Day of the Week Effect and January Effect

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Abstract

This master's thesis uses a dummy variable approach and an extended dummy variable approach to test for the existence of calendar effects in the rates of return of common stocks. It applies the extended dummy variable approach based on a factor model to returns of 30 stocks traded at the German Stock Exchange and the dummy variable approach to returns of 28 world indices. Furthermore, it investigates time persistence and evolution of these calendar effects. Finally, it simulates two portfolio strategies based on the Monday effect and the September effect. By estimating a rolling dummy variable regression this thesis provides evidence confirming that the day of the week effect started disappearing in the second half of 1990s. The simulated portfolios are able to outperform the buy and hold strategy in all the eight indices considered. This means existence of unexploited profit opportunities, which seriously undermines the efficient market hypothesis.

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1. Introduction

In recent years, there has been a proliferation of empirical studies indicating that the distribution of stock returns varies by day of the week and month of the year. The most notable effects are a negative return for Monday and a positive return for January. These calendar anomalies are empirical results that are inconsistent with maintained theories of asset-pricing behavior. They indicate either market inefficiency or inadequacies in the underlying asset-pricing models. Particularly, they cast doubt on the widely accepted efficient market hypothesis. These anomalies include the January effect and the day of the week effect.

This study undertakes a further investigation of the day of the week effect and the January effect. The purpose of this thesis is to investigate these effects on major world stock markets by using index data as well as returns of individual stocks.

The research question that should be answered is: “Is there still seasonality at world stock exchanges?” The research objectives of this thesis are:

- to reinvestigate the day of the week effect by using an extended dummy variable approach for stocks of the German Stock Exchange;
- to explore international presence of the day of the week effect and the January effect by using a simple dummy variable approach;
- to investigate time persistence of the day of the week effect in relation to the efficient market hypothesis;
- to examine a market timing strategy based on the seasonality.

The first section of this thesis presents a brief literature review describing the efficient market hypothesis and calendar effects. The second part considers a methodology used in this thesis. The third part of this thesis presents the empirical results and the last section includes conclusion that summarizes results and also comprises possible theoretical consequences of the calendar effects.

2. Literature Review

2.1. Efficient market hypothesis

The father of the efficient market hypothesis Eugene Fama (1970) first defined the term efficient market in his groundbreaking study as “a market in which prices always fully reflect available information” (p. 384). The efficient market hypothesis predicts that security prices follow a random walk and it should be impossible to predict future returns based on publicly available information. This means that an efficient market is one where all unexploited profit opportunities are eliminated by arbitrage.

Sharpe et al. (1999), summarizes the efficient market concept stating that the efficient market is a market in which

> *“the security’s price will be a good estimate of its investment value, where the investment value is the present value of the security’s future prospects, as estimated by well-informed and skilful analysts who use the information that is currently at hand”* (Sharpe et al., 1999, p. 93).

The logical consequence of this definition means that “Market is efficient with respect to a particular set of information if it is impossible to make abnormal profits (other than by chance) by using this set of information to formulate buying and selling decisions.” (Sharpe et al., 1999, p. 93). Sharpe et al. (1999) distinguishes three forms of efficiency based on a set of information that is available to investors. Table 1 provides these three forms of efficiency.

Table 1.

Form of efficiency	Set of Information Reflected in Security Prices
Weak	Previous prices of securities
Semistrong	All publicly available information
Strong	All information, both public and private

(Sharpe et al., 1999, p. 93)

Fama (1970) provides exact formulation of the good estimate of the investment value:

> “ $\mathrm{E}(p_{j,t+1}|\Phi_t) = [1+\mathrm{E}(r_{j,t+1}|\Phi_t)]p_{jt}$ *where E is expected value operator;* p_{jt} *is a price of security j at time t;* $p_{j,t+1}$ *is its price at t+1 (with reinvestment of any intermediate cash income form the security);* $r_{j,t+1}$ *is one period-period percentage return* $(p_{j,t+1} - p_{j,t})/p_{j,t}$ *;* Φ_t *is a general symbol for whatever set of information is assumed to be "fully reflected" in the price at t.“* (Fama, 1970, p. 384).

This expression states that the expected price of j-th security in time t+1 equals the expected rate of future return conditional on the set of information available at time t multiplied by the price of j-th security at time t. Furthermore, Fama (1970) suggests to measure undervaluation or overvaluation of security as $x_{j,t+1} = p_{j,t+1} - \mathrm{E}(p_{j,t+1}|\Phi_t)$. Consequently $\mathrm{E}(x_{j,t+1}|\Phi_t) = 0$, this means that any expected undervaluation or overvaluation is equal to zero. In other words, in average share prices are valued correctly. Strategies based on the information set Φ_t cannot achieve higher expected returns than are equilibrium expected returns. There is no known strategy, which could continually outperform stock market averages, and all excess returns achieved by investors are only by chance.

2.2. Random walk hypothesis

The random walk hypothesis is closely connected with the efficient market hypothesis. This hypothesis states that stocks move randomly, because the stock markets are efficient. Thus, the random walk hypothesis is a direct consequence of the efficient market hypothesis. The random walk hypothesis was introduced by Kendall (1953) and it was later confirmed by Fama (1965). The term ‘random walk’ was further popularized by the 1973 book, A Random Walk Down Wall Street (Malkiel, 1973).

Walter Enders (2004) defines random walk as a cumulative sum of a white noise process. Whereas white noise is a sequence of random variables $\{\varepsilon_t\}$ such that $E(\varepsilon_t) = E(\varepsilon_{t-1}) = ... = 0$; $E({\varepsilon_t}^2) = E({\varepsilon^2}_{t-1}) = ... = \sigma^2$ and $E(\varepsilon_t \varepsilon_{t-s}) = E(\varepsilon_{t-j}\varepsilon_{t-j-s}) = 0$ for all *j* and *s*, consequently the random walk is defined as $p_t = \sum_{i=1}^{t} \varepsilon_i$, where $p_t = \ln P_t$. However, it is generally accepted that stock market returns do not have a zero mean and are heteroskedastic. Therefore, the time path of stock prices is more appropriately specified by a random walk plus drift model, where $\{\varepsilon_t\}$ is heteroskedastic $E({\varepsilon_t}^2) = \sigma_t^2$. This model can be defined as $p_t = a \cdot t + \sum_{i=1}^{t} \varepsilon_i$ or after taking first differences $\Delta p_t = a + \varepsilon_t$.

Under the random walk hypothesis, there is no seasonality in stock prices, because the stock prices are completely random. Let us have a model treating any kind of seasonality by using dummy variables $R_{it} = \alpha_i + \delta_{1i} D_{1t} + \delta_{2i} D_{2t} + ... + \delta_{ki} D_{kt} + \varepsilon_{it}$. If the random walk hypothesis holds, any such model must have all the parameters referring to the seasonality equal to zero. The only non-zero parameter should be the constant term, which is the drift.

2.3. Calendar effects

Since the efficient market hypothesis was introduced, a great deal of research was devoted to investigating the efficiency of capital markets. Since then, all kinds of calendar anomalies in stock market returns have been documented extensively in the finance literature. The most common calendar anomalies are the January effect and the day of the week effect. Showing that market returns follow a seasonal pattern violates the assumption of weak market efficiency in that by observing the past development of returns market participants can lead to extraordinary profits. The calendar effects should be short lasting, as market participants can learn from past experience. Hence, if a calendar effect exists, trading based on exploiting a calendar pattern of returns should yield extraordinary profits at least for a short time. Yet, such trading strategies affect the market in that further profits should not be possible: the calendar effect should disappear.

2.3.1. The day of the week effect

Despite the efficient market hypothesis and its consequences, there is a large body of literature on the day of the week effect of stock returns. This effect refers to a phenomenon that the average return on Monday is significantly lower than the average return for the other days. Most studies dealing with this anomaly use a simple dummy variable approach based on a linear regression with 5 dummy variables referring to the days of the week. French (1980) first observes negative average daily share returns for Monday in the period 1953-1977 on the New York Stock Exchange. Then, Gibbson and Hess (1981) provide further evidence of negative return for Monday. Similarly, Kato (1990) provides evidence of the day of the week effect from the Tokyo Stock Exchange from the period 1974-1987. He concludes that "low Tuesday and high Wednesday returns are observed for the close-to-close returns." (Kato, 1990, p. 1041). Wang, Li and Erickson (1997) confirm the day of the week effect in the period 1962-1993 by using three indices from the New York Stock Exchange, American Stock Exchange and NASDAQ. They observe the Monday effect in the 1962-1993 periods. Lakonishok and Smidt (1988) explore 90 years of the Dow Jones Industrial Average Index in the period 1897-1986. They observe persistent seasonality in Dow Jones Industrial Average Index returns confirming the-day-of-the-week effect with Monday's average returns -0.14%. Similarly, Keim and Stambaugh (1983) identify the Monday effect in S&P Composite Index returns form 1928 to 1982. Dubois and Louvry (1995) provide probably the most comprehensive study confirming the day-of-the-week effect. They examined eleven indexes form nine countries in the period 1969-1992. They conclude, "We find negative returns on Monday, which are compensated by abnormal positive returns on Wednesday." (Dubios and Louvry, 1995, p. 19). Similarly, Condoyanni et al. (1987) used seven indices from seven countries; Dow Jones Industrial Average Index, Australian Stock Exchange's All Ordinaries Share Price Index, Toronto Composite Index, Paris CAC Industrial, F.T. All-Share (United Kingdom), Tokyo New Stock Exchange Index and the Straits Times Index (Singapore) in the period January 1969 to December 1984. They observed, "negative mean weekend returns do appear to be the norm rather than the exception in a range of capital markets around the world" (p. 174). Most recently, Gardeazabal and Regulez (2004) reach a similar conclusion. They suggest using the so called "Extended Dummy Variable Approach" (EDVA) derived from the Fama-French three-factor model (Fama and French, 1993). Gardeazabal and Regulez (2004) used the data from the Spanish stock market. Their data set ranges from 1998 to 2000. They conclude that by using the EDVA approach they had found even stronger seasonal effects than by using the simple DVA.

2.3.2. The January effect

One of the most puzzling empirical findings is that the sample distributions of monthly stock returns vary by the month of the year. The January effect refers to the significantly higher average share market returns in January when compared with other months. The literature on monthly effects, generally, confirmed higher returns in January. Rozeff and Kinney (1976) first observed that the average return of an equal-weighted index of the New York Stock Exchange in January is statistically significantly higher than the average return for the other months in the period 1904-1974. Haugen and Jorion (1996) provide evidence confirming the persistent existence of the January effect. They conclude that the January effect still exists despite the fact that it was well known for reasonably long time and therefore should have disappeared. Furthermore, they point out that the January effect is stronger in case of small firms than in case of well-established companies with high capitalization. They conclude, “the January effect is still going strong 17 years after its discovery” (Haugen and Jorion, 1996, p. 27). International evidence of the January effect is provided by Kato and Schallheim (1985).

3. Methodology

3.1. Dummy variable approach

The so called "Dummy Variable Approach" to the stock market seasonality is based on estimating a simple regression model, where each individual dummy variable accounts for the excess return for the particular day. This model can be written in the following way: $R_{it} = \alpha_i + \delta_{1i} D_{1t} + \delta_{2i} D_{2t} + \delta_{3i} D_{3t} + \delta_{4i} D_{4t} + \delta_{5i} D_{5t} + v_{it}$, where R_{it} is the return of index (or security) *i* in period *t*, v_{it} is a zero-mean disturbance, D_{1t} is a dummy variable for Monday (i.e., D_{1t} = 1 if observation *t* falls on a Monday and *0* otherwise), D_{2t} is a dummy variable for Tuesday, etc. However, it is not possible to estimate this equation in the above form, because it contains all the dummy variables and the constant term. Therefore, there is a problem of a perfect mulitcolinearity. In order to cope with this problem, vast majority of authors uses elimination of the constant term or one of the dummy variables from this regression equation. Nonetheless, proceeding in this way solves the perfect multicolinearity, but leaves the parameters of the model unidentified. Gardeazabal and Regulez (2003) suggest imposing a restriction on the parameters of the model to tackle this problem. They state that this way we can solve both the exact multicolinearity problem and the problem of identification of the parameters. According to Gardeazabal and Regulez (2003), if α_i is the mean return, it must hold that $\delta_{1i} \frac{1}{T} \sum_{t=1}^{T} D_{1t} + \delta_{2i} \frac{1}{T} \sum_{t=1}^{T} D_{2t} + \delta_{3i} \frac{1}{T} \sum_{t=1}^{T} D_{3t} + \delta_{4i} \frac{1}{T} \sum_{t=1}^{T} D_{4t} + \delta_{5i} \frac{1}{T} \sum_{t=1}^{T} D_{5t} = 0$. Gardeazabal and Regulez (2003) further assume that the proportion of the returns for the individual days equal 1/5, which means $E(D_{1t}) = E(D_{2t}) = E(D_{3t}) = E(D_{4t}) = E(D_{5t}) = 1/5$. This implies that $\delta_{1i} + \delta_{2i} + \delta_{3i} + \delta_{4i} + \delta_{5i} = 0$. Gardeazabal and Regulez (2003, p. 226) state that, "This restriction says that the coefficients of the dummy variables add up to zero and can be interpreted as a normalizing restriction." By imposing this restriction we can solve both the exact multicolinearity and identification problems. If we solve for the dummy variable referring to Thursday δ_{4i}, we get $\delta_{4i} = -(\delta_{1i} + \delta_{2i} + \delta_{3i} + \delta_{5i})$. By substituting this result into the regression equation we will get $R_{it} = \alpha_i + \delta_{1i} \tilde{D}_{1t} + \delta_{2i} \tilde{D}_{2t} + \delta_{3i} \tilde{D}_{3t} + \delta_{5i} \tilde{D}_{5t} + v_{it}$, where $\tilde{D}_{kt} = D_{kt} - D_{4t}$. Now, as Gardeazabal and Regulez (2003) state, all the dummy variables are expressed as deviations with respect to the omitted dummy D_{4t} and each slope coefficient δ_{ki} measures the deviation with respect to the overall mean α_i. A consistent estimate of δ_{4i} can be recovered from the estimates of the other coefficients in the following way $\delta_{4i} = -(\delta_{1i} + \delta_{2i} + \delta_{3i} + \delta_{5i})$. (Gardeazabal and Regulez, 2003). The standard error of the coefficient can be obtained as $\sqrt{1'\hat{\Sigma}1}$ where 1 refers to a 4×1 vector of ones and $\hat{\Sigma}$ is a heteroskedasticity-consistent estimator of the covariance matrix provided by White (1980). The statistical inference can be conducted by using the t-test on each parameter.

The model is analogous in case of the January effect. In this case the basic regression equation can be defined as

$$R_{it} = \alpha_i + \delta_{1i} D_{1t} + \delta_{2i} D_{2t} + \delta_{3i} D_{3t} + \delta_{4i} D_{4t} + \delta_{5i} D_{5t} + \delta_{6i} D_{6t} + \delta_{7i} D_{7t} + \delta_{8i} D_{8t} + \delta_{9i} D_{9t} +$$
$$+ \delta_{10i} D_{10t} + \delta_{11i} D_{11t} + \delta_{12i} D_{12t} + v_{it}$$

where R_{it} is the return of index (or security) *i* in period *t*, v_{it} is a zero-mean disturbance, D_{1t} is a dummy variable for January (i.e., $D_{1t} = 1$ if observation *t* falls on a January and *0* otherwise), D_{2t} is a dummy variable for February, etc. We assume that $E(D_{1t}) = E(D_{2t}) = E(D_{3t}) = E(D_{4t}) = E(D_{5t}) = E(D_{6t}) = E(D_{7t}) = E(D_{8t}) = E(D_{9t}) = E(D_{10t}) = = E(D_{11t}) = E(D_{12t}) = 1/12$
and we restrict the parameters such that

$\delta_{1i} + \delta_{2i} + \delta_{3i} + \delta_{4i} + \delta_{5i} + \delta_{6i} + \delta_{7i} + \delta_{8i} + \delta_{9i} + \delta_{10i} + \delta_{11i} + \delta_{12i} = 0$. If we solve for the dummy variable referring to August δ_{8i}, we get

$\delta_{8i} = -(\delta_{1i} + \delta_{2i} + \delta_{3i} + \delta_{4i} + \delta_{5i} + \delta_{6i} + \delta_{7i} + \delta_{9i} + \delta_{10i} + \delta_{11i} + \delta_{12i})$. By substituting this result into the regression equation we will get

$$R_{it} = \alpha_i + \delta_{1i}\tilde{D}_{1t} + \delta_{2i}\tilde{D}_{2t} + \delta_{3i}\tilde{D}_{3t} + \delta_{4i}\tilde{D}_{4t} + \delta_{5i}\tilde{D}_{5t} + \delta_{6i}\tilde{D}_{6t} + \delta_{7i}\tilde{D}_{7t} + \delta_{9i}\tilde{D}_{9t} + \\ + \delta_{10i}\tilde{D}_{10t} + \delta_{11i}\tilde{D}_{11t} + \delta_{12i}\tilde{D}_{12t} + v_{it}$$

where $\tilde{D}_{kt} = D_{kt} - D_{8t}$.

A consistent estimate of the δ_{8i} can be computed from the estimates of the other coefficients by using the following expression

$\delta_{8i} = -(\delta_{1i} + \delta_{2i} + \delta_{3i} + \delta_{4i} + \delta_{5i} + \delta_{6i} + \delta_{7i} + \delta_{9i} + \delta_{10i} + \delta_{11i} + \delta_{12i})$. Similarly as for the day of the week effect, the standard error of the coefficient can be obtained as $\sqrt{1'\hat{\Sigma}1}$ where 1 refers to a 12×1 vector of ones and $\hat{\Sigma}$ is a White's heteroskedasticity-consistent estimator of the covariance matrix (White, 1980).

3.2. Extended dummy variable approach

According to Gardeazabal and Regulez (2004), the dummy variable approach to seasonality leaves too much variability of stock returns unexplained. They state that the portion of unexplained variability increases with sample frequency and inference on daily seasonality usually leads to weak or null evidence of seasonality. They propose the so called 'Extended Dummy Variable Approach' which leaves a lower fraction of stock returns variability unexplained. In general, their model can be defined in the following way: $R_{it} = \alpha_i + \delta_{1i}D_{1t} + \delta_{2i}D_{2t} + \delta_{3i}D_{3t} + \delta_{4i}D_{4t} + \delta_{5i}D_{5t} + \sum_{j=1}^{J}\beta_{ji}h_{jt} + u_{it}$, where h_{jt} is the *j*-th factor is orthogonal on the daily dummies. This approach is derived from the Fama-French three-factor model (Fama and French, 1993). The three factors that Fama and French (1993) used are: the excess return on the market portfolio, R_{EMRt}, the return on a portfolio of small firms minus the return on a portfolio of large firms, R_{SMBt}, and the return on a portfolio of high book-to-market firms minus the return on a portfolio of low book-to-market firms, R_{HMLt}. Taking into account only these three factors, the above mentioned equation can be written as: $R_{it} = \alpha_i + \delta_{1i}D_{1t} + \delta_{2i}D_{2t} + \delta_{3i}D_{3t} + \delta_{4i}D_{4t} + \delta_{5i}D_{5t} + \beta_{EMR_i}\hat{h}_{EMR_t} + \beta_{SMB_i}\hat{h}_{SMB_t} + \beta_{HML_i}\hat{h}_{HML_t} + u_{it}$,
where $\hat{h}_{EMR_t}, \hat{h}_{SMB_t}, \hat{h}_{HML_t}$ are defined as

$$\mathrm{R}_{\mathrm{EMR}\,it} = \alpha_i + \delta_{1i}D_{1t} + \delta_{2i}D_{2t} + \delta_{3i}D_{3t} + \delta_{4i}D_{4t} + \delta_{5i}D_{5t} + \hat{h}_{EMR_t} \,,$$
$$\mathrm{R}_{\mathrm{SMB}\,it} = \alpha_i + \delta_{1i}D_{1t} + \delta_{2i}D_{2t} + \delta_{3i}D_{3t} + \delta_{4i}D_{4t} + \delta_{5i}D_{5t} + \hat{h}_{SMB_t} \,,$$
$$\mathrm{R}_{\mathrm{HML}\,it} = \alpha_i + \delta_{1i}D_{1t} + \delta_{2i}D_{2t} + \delta_{3i}D_{3t} + \delta_{4i}D_{4t} + \delta_{5i}D_{5t} + \hat{h}_{HML_t} \,.$$

Gardeazabal and Regulez (2004) state that the model based on the dummy variable approach is "misspecified in the sense that it leaves the risk factors out of the regression equation" (p. 226). However, the OLS estimator of the parameters is consistent, because "the omitted factors are orthogonal to the daily seasonals" (p. 226). Furthermore, Gardeazabal and Regulez (2004) point out that the unexplained part of stock returns volatility is lower in case of the extended dummy variable approach, because it holds that $\sigma_{vi}^2 - \sigma_{ui}^2 = \sum_{j=1}^{J} \beta_{ji}^2 \sigma_j^2 > 0$, where $\sigma_{vi}^2 = E(v_{it}^2)$ and $\sigma_{ui}^2 = E(u_{it}^2)$.

3.3. Heteroskedasticity

It is generally accepted that variance of stock market returns is not constant. Therefore, it is necessary to use some heteroskedasticity robust method. White (1980) provides a heteroskedasticity-consistent estimator of the covariance matrix. This estimator is defined in the following way:

$\hat{\Sigma} = \frac{1}{n}(\frac{1}{n}X'X)^{-1}(\frac{1}{n}\sum_{t=1}^{T} e_t^{\,2} x_t x_t')(\frac{1}{n}X'X)^{-1} = (X'X)^{-1}(\sum_{t=1}^{T} e_t^{\,2} x_t x_t')(X'X)^{-1}$, where e_t refers to residuals from an OLS regression (Greene, 2002, p.199). In case of all the regressions estimated in this thesis, the statistical inference is based on this White heteroskedasticity-consistent estimator (White, 1980).

3.4. Data set

The data set used for the extended dummy variable approach estimations includes daily market returns of 30 German companies traded at the German Stock Exchange and daily returns of the Deutscher Aktien Index (DAX), Small-cap Deutscher Aktien Index (SDAX) and Dividend Deutscher Aktien Index index (DivDAX). The data set ranges from 1.1.2006 to 31.12.2008.

The data used for the dummy variable approach includes daily returns of the following 28 indexes: Financial Times Index 100, Standard & Poor's 500 Index, Standard & Poor's Mid Cap Index, Standard & Poor's Small Cap Index, Russel 3000 Index, NASDAQ Cmposite Idex, Deutscher Aktien Index, Mid-cap Deutscher Aktien Index, Small-cap Deutscher Aktien Index, Technology Deutscher Aktien Index (TecDAX), Swiss Market Index (SMI), IPC Mexico Index, Bovespa Index, Kuala Lumpur Stock Exchange Index (KLSE), Jakarta Composite Index (JKSE), Australia All Ordinaries Index (AORD), Bombay Stock Exchange 30 Index (BSE 30), Hang Seng Index (HSI), Shanghai Composite Index (SSE), Austrian Trade Index (ATX), Amsterdam Exchange Index (AEX), Belgium Exchange Index (BEL), Streits Times Index (STI), Euronext BEL 20 Index (BEL 20), Tel Aviv TA-100 Iindex (TA 100), Taiwan Weighted Index (TSEC), Soul Composite Index (KOSPI), NIKKIE 225, CAC 40 Index (CAC). The data range depends on availability of the data for a certain index. The longest data span is for the Standard & Poor's 500 Index and it ranges from 1.2.1955 to 8.5.2009, the shortest data range is for BOVESPA index and it is from 1.1.1997 to 8.5.2009.

All the market data was downloaded from the Yahoo Deutschland Finanzen (2008) and from the Yahoo Finance (2009). For more details, please see the reference list.

The Euro OverNight Index Average rate was used as a risk free rate of interest. The Eonia is the effective overnight reference rate for the Euro. It is computed as “a weighted average of all overnight unsecured lending transactions undertaken in the interbank market, initiated within the Euro zone by the contributing banks.” (Euribor FBE, 2000). The time series of the Eonia was downloaded from the Euribor FBE (2000). For more details, please see the reference list.

4. Results

4.1. Extended dummy variable approach: DAX Index

A model extended by three factors was estimated. This model is based on the same logic as the model estimated by Gardeazabal and Regulez (2003), the only difference are factors deployed. Similarly as in Gardeazabal and Regulez (2003), the first factor is the excess return on the market portfolio.

However, the second factor refers to the difference between returns of small-cap SDAX and large-cap DAX index. The third factor is the difference between returns of the DivDAX index and TecDAX index. It is generally known that firms with high book to market ratio have also high dividend yield. Therefore, we can use the DivDAX index, which is an index of companies paying high dividends. In general, the companies of the DivDAX index can be regarded as "value" companies, with low expected growth of earnings low price to earnings ratio, high book to market ratio and high dividend yield. On the other hand the TecDax index represents a portfolio of "growth" companies. This index consists of technology stocks, which means fast growing companies with very high expected growth of earnings and consequently very high price to book ratio and low book to market ratio.

Figures 1 to 5 report the results. Each figure contains the results for one explanatory variable. The horizontal line represents the 95% confidence interval. For each stock, the combination of t-statistic in absolute value and coefficient estimate is represented by a blue cross. If the cross falls above the 95% confidence interval line, it is significantly different from 0.

Fig. 1. Monday

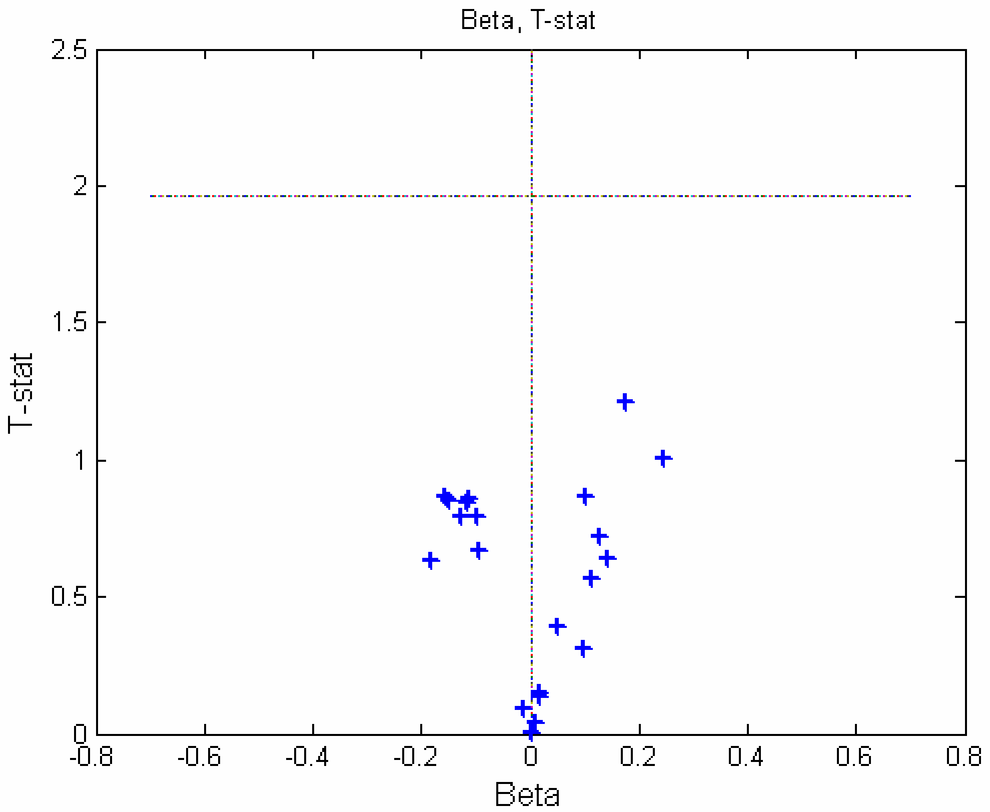


Fig. 2. Tuesday

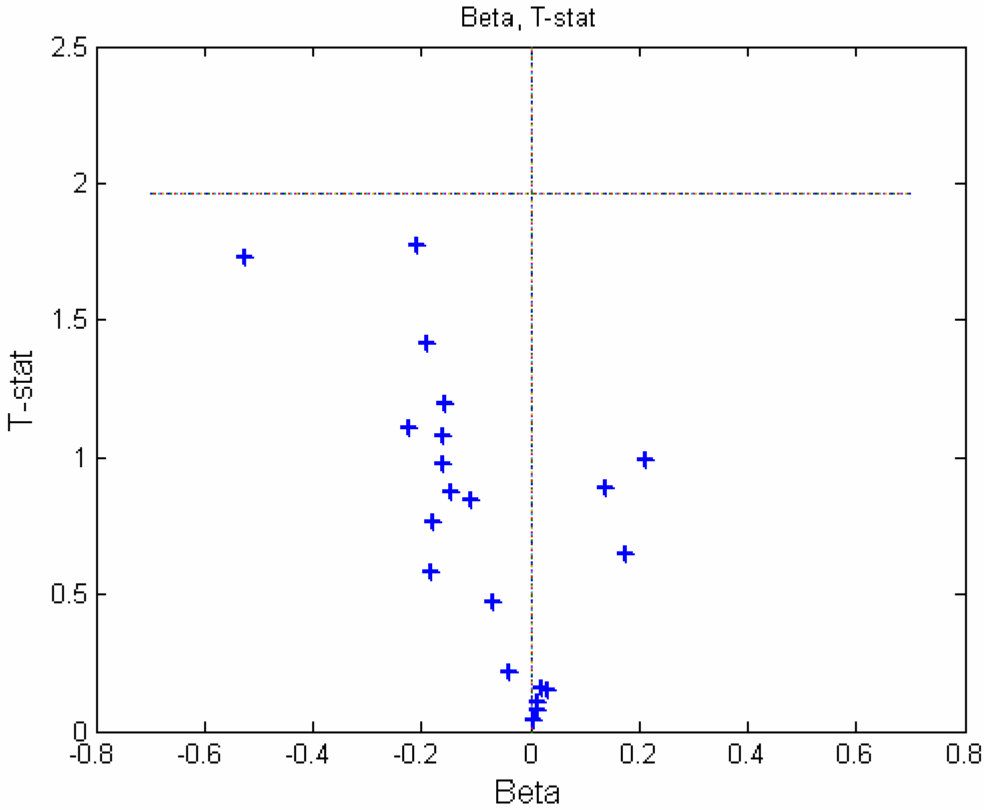


Fig. 3. Wednesday

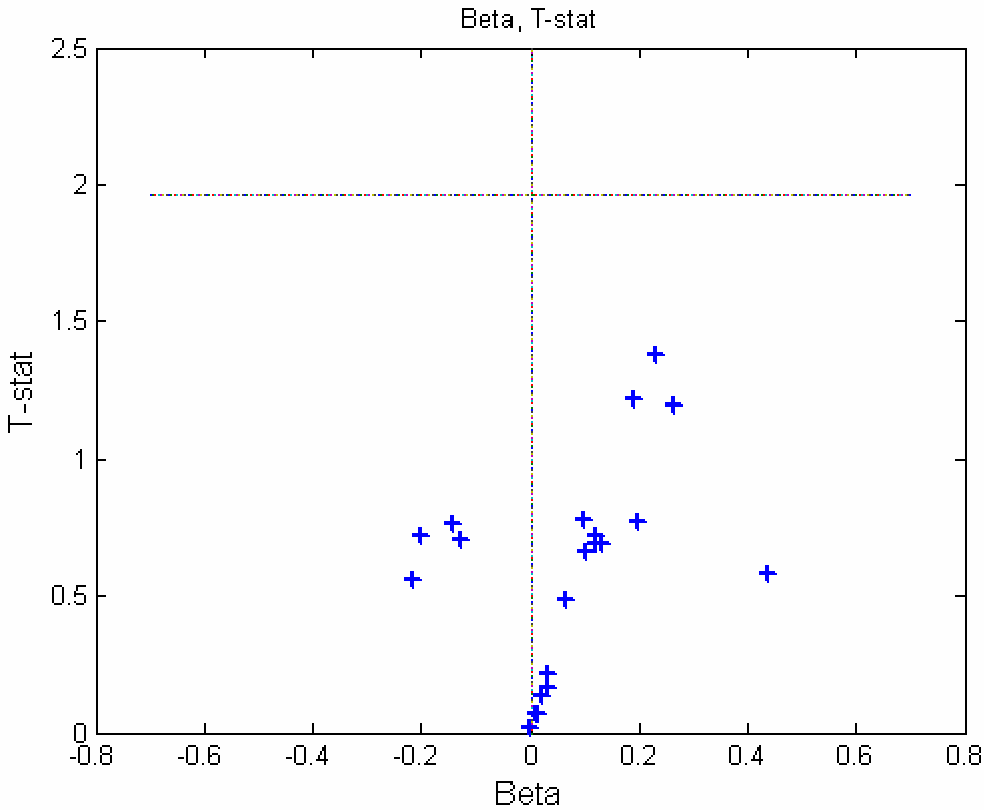


Fig. 4. Thursday

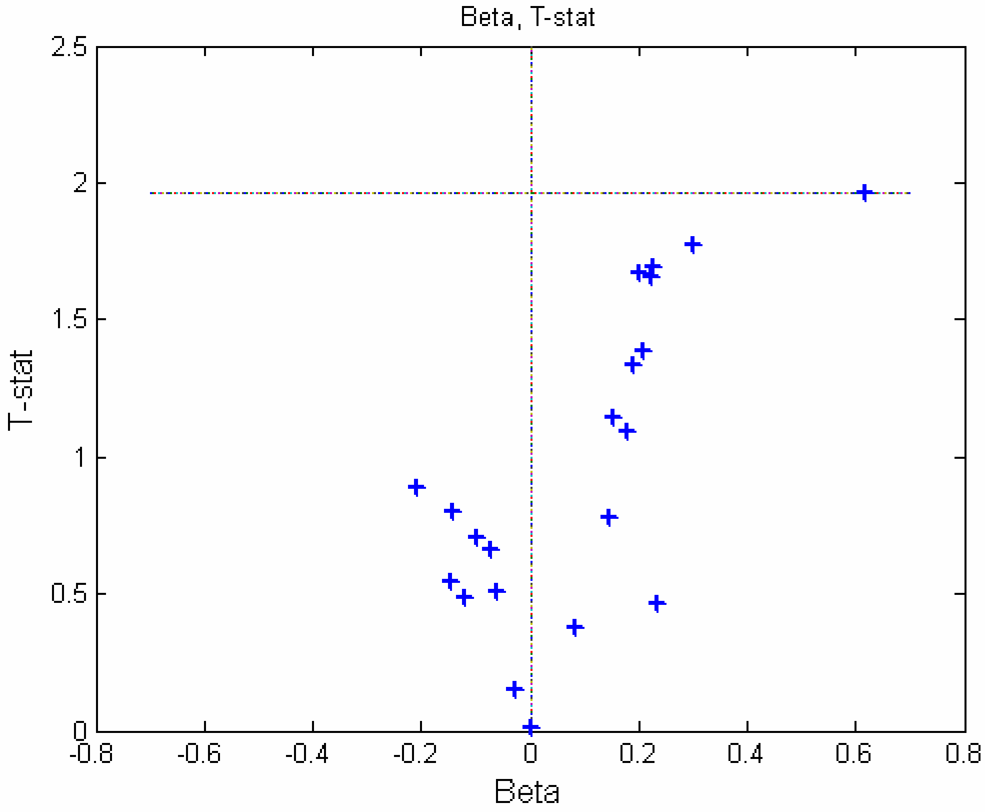
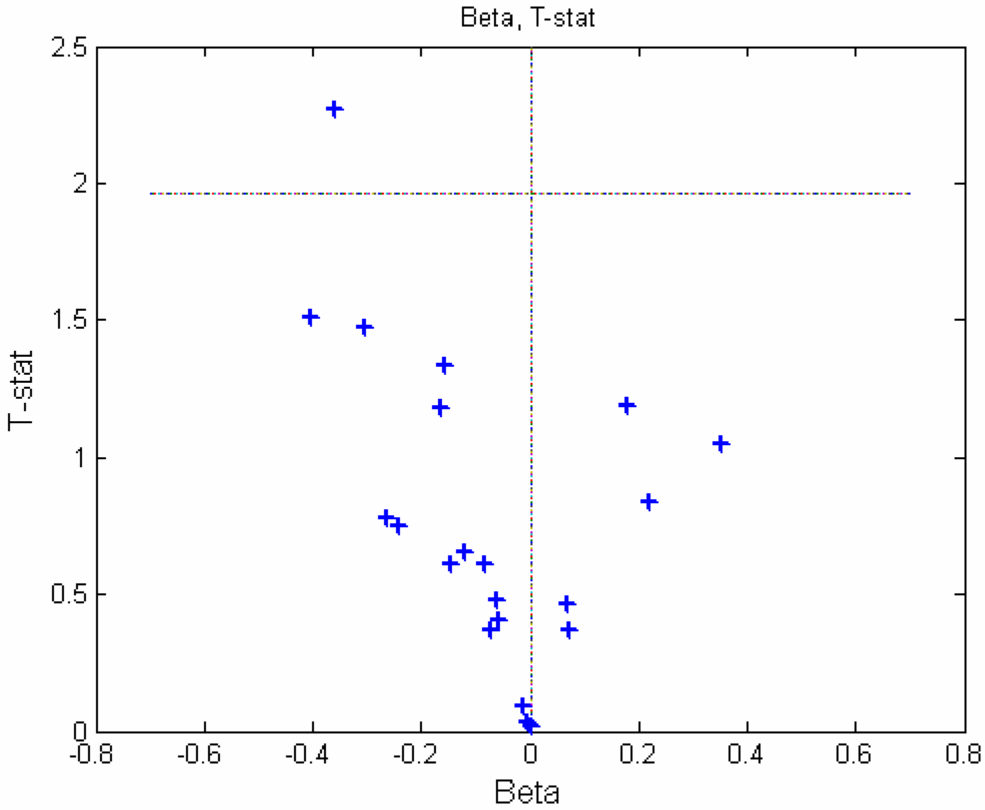


Fig. 5. Friday



Under the assumption of no seasonality we expect not more than 5% of crosses to be above the line. Since we have 30 stocks, 5% means 2 crosses. Indeed, there is never more than 1 cross above the line. This supports evidence of no seasonality in the returns of the 30 companies of the DAX index.

4.2. International evidence of the day of the week effect and the January effect

In order to cope with the specific risk of individual stocks, in the sense of the security characteristic line (Sharpe et al., 1999), it is much better to exploit the profits of the calendar effects by trading the market portfolios represented by the whole index. This can be easily conducted even by an individual investor by trading futures contracts fixed on various indices. This way, the investor will get a sufficient financial leverage at a negligible cost and will completely eliminate the specific risk of individual stocks.

Therefore, from the practical point of view it is much more exciting to investigate the seasonal patterns of stock market indices rather than seasonal patterns of individual stocks. This can be done by using the simple dummy variable approach. The model estimated in this thesis joins both the day of the week effect and the January effect by using dummy variables for months and for days. The model has the following form:

$$R_{it} = \alpha_i + \delta_{Mi} D_{Mt} + \delta_{Ti} D_{Tt} + \delta_{Wi} D_{Wt} + \delta_{Hi} D_{Ht} + \delta_{Fi} D_{Ft} + \delta_{1i} D_{1t} + \delta_{2i} D_{2t} + \delta_{3i} D_{3t} + \delta_{4i} D_{4t} +$$
$$+ \delta_{5i} D_{5t} + \delta_{6i} D_{6t} + \delta_{7i} D_{7t} + \delta_{8i} D_{8t} + \delta_{9i} D_{9t} + \delta_{10i} D_{10t} + \delta_{11i} D_{11t} + \delta_{12i} D_{12t} + u_{it}$$

Where D_k, k = M, T, W, H, F refer to daily dummies and D_{kt}, k = 1, 2, 3, 4, 5, 6, 7, 8, 9. 10. 11. 12 refer to monthly seasonal dummies.

Tables 1 to 7 provide the results of this regression model estimated on the data of 28 world stock exchange indices.

Table 2.

Index	NASDAQ	t-statistic in absolute value	S&P 500	t-statistic in absolute value	S&P mid cap	t-statistic in absolute value	S&P small cap	t-statistic in absolute value
Data range	5.2.1971		2.1.1985		20.8.1991		15.8.1995	
constant	0.0354	2.7732	0.0315	2.6292	0.0402	2.1488	0.0318	1.3306
Monday	-0.1696	6.1475	-0.0489	1.7635	-0.0959	2.2886	-0.1269	2.4208
Tuesday	-0.0491	1.8782	0.0292	1.2157	-0.0134	0.3588	0.0310	0.6456
Wednesday	0.0810	3.2206	0.0354	1.5739	0.0563	1.5655	0.0411	0.8874
Thursday	0.0689	2.7474	-0.0216	0.9333	0.0254	0.6609	0.0074	0.1493
Friday	0.0688	2.8735	0.0059	0.2632	0.0276	0.7947	0.0473	1.0541
January	0.0956	2.1123	0.0069	0.1734	-0.0511	0.8568	-0.0696	0.8890
February	-0.0435	1.1257	-0.0595	1.6334	-0.0441	0.7806	-0.0758	1.0668
March	-0.0066	0.1619	0.0180	0.4705	0.0132	0.2026	0.0270	0.3224
April	0.0409	0.8823	0.0561	1.5020	0.0873	1.3619	0.1251	1.5620
May	0.0121	0.3194	0.0248	0.7776	0.0564	1.1134	0.0739	1.1390
June	0.0049	0.1436	-0.0060	0.1975	-0.0543	1.1074	0.0127	0.2007
July	-0.0524	1.3549	-0.0164	0.4732	-0.0563	0.9857	-0.1359	1.7909
August	-0.0228	0.6225	-0.0134	0.3752	-0.0194	0.3701	-0.0283	0.4156
September	-0.0968	2.2723	-0.0772	1.8220	-0.0689	1.0702	-0.0509	0.6284
October	-0.0255	0.4694	-0.0238	0.4039	-0.0100	0.1259	-0.0352	0.3457
November	0.0398	0.8778	0.0459	1.0380	0.0284	0.3960	0.0400	0.4452
December	0.0545	1.2635	0.0445	1.2167	0.1190	1.8234	0.1170	1.3907
critical value		1.9602		1.9602		1.9605		1.9607

Table 3.

Index	Russell 3000	t-statistic in absolute value	FTSE 100	t-statistic in absolute value	DAX	t-statistic in absolute value	MDAX	t-statistic in absolute value
Data range	10.9.1987		2.4.1984		26.11.1990		3.1.2000	
constant	0.0259	1.6171	0.0282	2.0096	0.0384	1.7855	0.0217	0.8217
Monday	-0.0432	1.1489	-0.0553	1.7505	0.0499	1.0323	-0.0340	0.5597
Tuesday	0.0310	0.9740	0.0244	0.8821	0.0287	0.6966	-0.0720	1.4027
Wednesday	0.0329	1.0889	-0.0153	0.5670	-0.0651	1.5717	-0.0375	0.7153
Thursday	-0.0244	0.7757	-0.0059	0.2166	-0.0148	0.3465	0.0165	0.3186
Friday	0.0038	0.1253	0.0520	1.8590	0.0014	0.0327	0.1270	2.7331
January	-0.0026	0.0489	-0.0099	0.2234	-0.0150	0.2114	0.0052	0.0624
February	-0.0453	0.9489	0.0075	0.1765	-0.0078	0.1182	-0.0091	0.1140
March	0.0197	0.3776	0.0040	0.0837	-0.0185	0.2529	-0.0264	0.2947
April	0.0642	1.2847	0.0772	1.9102	0.1560	2.4543	0.2390	2.9799
May	0.0623	1.4811	-0.0205	0.5105	0.0143	0.2428	0.0614	0.7913
June	-0.0346	0.8681	-0.0545	1.4701	-0.0319	0.5658	-0.0457	0.6113
July	-0.0156	0.3318	-0.0086	0.1936	-0.0127	0.1900	-0.0567	0.7131
August	-0.0566	1.2125	0.0026	0.0596	-0.1005	0.9805	0.0138	0.1554
September	-0.0547	0.9784	-0.0945	1.8400	-0.2304	2.8848	-0.2279	2.2559
October	-0.0353	0.4387	-0.0074	0.1120	0.0735	0.7657	-0.0125	0.1005
November	0.0140	0.2395	0.0110	0.2300	0.0703	0.9751	0.0025	0.0247
December	0.0846	1.7215	0.0932	2.1934	0.1028	1.4197	0.0564	0.7614
critical value		1.9604		1.9603		1.9605		1.9610

Table 4.

Index	SDAX	t-statistic in absolute value	TecDAX	t-statistic in absolute value	SMI	t-statistic in absolute value	IPC Mexico	t-statistic in absolute value
Data range	3.1.2000		24.3.2003		9.11.1990		8.11.1991	
constant	0.0016	0.0792	0.0525	1.1885	0.0364	2.0578	0.0785	3.0933
Monday	0.0340	0.7056	0.1347	1.2775	-0.0286	0.7051	-0.1581	2.9490
Tuesday	-0.0582	1.4854	0.0022	0.0265	0.0129	0.3823	0.0151	0.2906
Wednesday	-0.0534	1.3676	-0.0028	0.0317	-0.0076	0.2272	0.0413	0.8155
Thursday	-0.0292	0.7448	-0.1023	1.1645	-0.0054	0.1532	0.0586	1.1498
Friday	0.1069	2.8440	-0.0318	0.4142	0.0287	0.8248	0.0432	0.9189
January	0.0817	1.2465	0.0314	0.2032	-0.0199	0.3413	-0.0169	0.1805
February	0.0513	0.8270	-0.0001	0.0006	-0.0300	0.5957	-0.1336	1.6462
March	0.0409	0.6278	-0.0435	0.2870	0.0332	0.5322	0.1457	1.7830
April	0.1857	3.0792	0.2642	2.1299	0.0612	1.2531	-0.0027	0.0317
May	0.0405	0.6585	0.0086	0.0644	0.0360	0.7405	-0.0256	0.3443
June	-0.0523	0.8957	-0.0398	0.3142	-0.0433	0.8584	-0.0244	0.3084
July	-0.0534	0.8830	-0.0677	0.5070	-0.0320	0.5475	-0.0530	0.6780
August	-0.0178	0.3259	0.0652	0.2985	-0.0789	1.0543	-0.1250	1.7053
September	-0.2349	3.0930	-0.1000	0.7268	-0.0991	1.3982	-0.0387	0.4056
October	-0.0423	0.4176	-0.0838	0.4063	0.0607	0.7610	0.0144	0.1389
November	-0.0334	0.4580	-0.0762	0.4280	0.0521	0.9585	0.1027	1.1781
December	0.0340	0.5511	0.0417	0.3619	0.0600	1.2005	0.1570	2.1558
critical value		1.9610		1.9615		1.9605		1.9605

Table 5.

Index	Bovespa	t-statistic in absolute value	CAC 40	t-statistic in absolute value	Kuala Lumpur	t-statistic in absolute value	Jakarta Comosite	t-statistic in absolute value
Data range	27.4.1993		1.3.1990		3.12.1993		1.7.1997	
constant	0.0535	1,3061	0.0220	1.0836	0.0126	0.4899	0.0518	1.4961
Monday	-0.1650	1.8315	-0.0483	1.0599	-0.1535	2.7193	-0.1882	2.5345
Tuesday	0.0136	0.1742	0.0318	0.8191	-0.0024	0.0424	-0.0182	0.2759
Wednesday	0.0614	0.7866	-0.0232	0.5907	0.0709	1.4728	-0.0315	0.4695
Thursday	-0.0416	0.4884	0.0188	0.4619	-0.0266	0.5742	0.0875	1.2414
Friday	0.1316	1.6691	0.0209	0.5313	0.1115	2.3472	0.1504	2.1910
January	0.2220	1.4289	0.0131	0.1938	0.0449	0.4802	0.1160	0.8341
February	0.0415	0.3371	0.0190	0.3148	0.1572	1.4494	-0.0732	0.6546
March	0.0122	0.1030	0.0628	0.9483	-0.1243	1.8480	0.0255	0.2686
April	0.0635	0.4640	0.1245	2.0949	0.0487	0.7077	0.1595	1.5054
May	-0.1375	1.0488	-0.0155	0.2739	-0.0326	0.4759	0.0551	0.4553
June	-0.0516	0.3995	-0.0746	1.3461	-0.0693	1.1121	0.1165	1.1096
July	-0.0797	0.6450	-0.0342	0.5311	-0.0265	0.4229	-0.0061	0.0763
August	-0.2979	1.0627	-0.0863	1.2197	-0.1596	1.9698	-0.4962	4.1950
September	0.0620	0.4334	-0.1908	2.4544	-0.0469	0.3229	-0.1187	0.9437
October	-0.1047	0.6377	0.0848	0.9668	-0.0014	0.0204	-0.1259	0.8770
November	-0.0094	0.0738	0.0382	0.5509	0.0025	0.0308	0.1085	0.9785
December	0.2797	1.9790	0.0591	0.9370	0.2074	2.6453	0.2392	2.2730
critical value		1.9607		1.9605		1.9606		1.9608

Table 6.

Index	Australia All Ordinaries	t-statistic in absolute value	BSE 30	t-statistic in absolute value	HSI	t-statistic in absolute value	Shanghai Composite	t-statistic in absolute value
Data range	3.8.1984		1.7.1997		2.1.1987		4.1.2000	
constant	0.0331	2.6811	0.0485	1.4760	0.0517	2.1313	0.0369	1.0901
Monday	-0.0055	0.2080	0.0614	0.8447	-0.1178	1.9412	0.1023	1.3152
Tuesday	-0.0465	1.6726	-0.0102	0.1670	0.0191	0.4388	-0.0295	0.4594
Wednesday	0.0247	1.0526	0.0612	0.9870	0.0837	1.7869	0.0811	1.1996
Thursday	0.0171	0.7262	-0.0354	0.5721	-0.0762	1.7044	-0.1403	2.1537
Friday	0.0101	0.4336	-0.0771	1.1246	0.0913	2.0964	-0.0135	0.2186
January	0.0028	0.0685	-0.0567	0.4984	-0.0693	0.8003	0.0019	0.0157
February	-0.0280	0.7783	0.0146	0.1463	0.1355	1.7724	0.1793	1.4210
March	0.0272	0.7212	-0.0774	0.6433	-0.0989	1.4138	0.0289	0.2860
April	0.1036	2.6649	-0.0006	0.0047	0.0726	1.0396	0.1465	1.3080
May	0.0131	0.4005	-0.0751	0.5922	0.0335	0.4866	0.0055	0.0557
June	-0.0461	1.4518	-0.0290	0.2539	-0.0502	0.6393	-0.1589	1.1579
July	0.0419	1.2312	0.0331	0.3322	0.0692	1.2348	-0.0376	0.3645
August	0.0059	0.1646	0.0361	0.4301	-0.1050	1.4675	-0.0248	0.2428
September	-0.0395	1.0431	-0.0272	0.2770	-0.0467	0.6434	-0.0651	0.5641
October	-0.0963	1.3965	-0.1566	1.1914	-0.0329	0.2477	-0.2048	1.8141
November	-0.0470	1.0208	0.1396	1.3731	0.0064	0.0847	0.0342	0.2963
December	0.0622	1.7520	0.1992	2.3110	0.0858	1.1246	0.0948	1.0319
critical value		1.9603		1.9608		1.9604		1.9610

Table 7.

Index	Straits Times	t-statistic in absolute value	AEX	t-statistic in absolute value	BEL 20	t-statistic in absolute value	TA 100	t-statistic in absolute value
Data range	4.1.1988		12.10.1992		9.4.1991		1.7.1997	
constant	0.0272	1.4975	0.0277	1.2477	0.0195	1.1484	0.0535	1.4954
Monday	-0.1082	2.5156	0.0557	1.0862	-0.0268	0.7048	0.1782	2.3082
Tuesday	-0.0357	1.0649	0.0144	0.3452	0.0003	0.0102	-0.0381	0.7017
Wednesday	0.0505	1.4366	-0.0595	1.3988	0.0034	0.1057	-0.1084	1.9671
Thursday	0.0184	0.5188	-0.0390	0.8824	-0.0003	0.0078	-0.0371	0.6699
Friday	0.0751	2.2113	0.0285	0.6525	0.0232	0.6853	0.0054	0.0540
January	0.0226	0.2810	-0.0289	0.4078	0.0131	0.2361	-0.1324	1.1981
February	0.0315	0.4931	-0.0016	0.0255	-0.0358	0.7266	0.0849	0.9719
March	-0.0214	0.4021	-0.0239	0.3008	-0.0113	0.1653	-0.0333	0.3224
April	0.1152	1.9361	0.1406	2.1292	0.1297	2.6411	0.2155	1.7823
May	-0.0333	0.6417	-0.0036	0.0616	-0.0128	0.2774	0.1757	1.6860
June	-0.0245	0.4843	-0.0221	0.3616	-0.0355	0.7777	-0.1049	1.2108
July	0.0019	0.0419	-0.0079	0.1062	-0.0067	0.1194	-0.0455	0.5074
August	-0.1582	2.6013	-0.0268	0.3757	-0.0429	0.7871	-0.1549	1.7186
September	-0.1108	1.9121	-0.2341	2.5875	-0.1221	1.8082	-0.1418	1.4968
October	0.0035	0.0450	0.0385	0.3897	0.0024	0.0327	-0.1538	1.0571
November	0.0650	1.0843	0.0765	1.0548	0.0057	0.1087	0.1635	1.4998
December	0.1086	2.0977	0.0931	1.4308	0.1162	2.4184	0.1269	1.2304
critical value		1.9604		1.9605		1.9605		1.9609

Table 8.

Index	ATX	t-statistic in absolute value	TSEC	t-statistic in absolute value	Kospi	t-statistic in absolute value	Nikkei 225	t-statistic in absolute value
Data range	11.11.1992		2.7.1997		1.7.1997		4.1.1984	
constant	0.0342	1.6604	0.0060	0.1930	0.0437	1.0794	0.0089	0.4749
Monday	0.0033	0.0729	-0.1225	1.7089	-0.0262	0.2821	-0.0832	2.0579
Tuesday	0.0156	0.3749	-0.0851	1.4339	-0.0530	0.7334	0.0133	0.3574
Wednesday	0.0111	0.2851	0.0772	1.3255	0.0572	0.7316	0.0359	1.0037
Thursday	-0.0577	1.4616	0.0142	0.2300	0.0315	0.3847	0.0572	1.5411
Friday	0.0277	0.6766	0.1162	2.0013	-0.0094	0.1212	-0.0233	0.6500
January	0.0422	0.6363	0.1438	1.2875	0.1821	1.2034	0.0310	0.4676
February	0.0486	0.7605	0.1451	1.2766	-0.0868	0.6977	0.0064	0.1270
March	0.0209	0.3286	0.1139	1.2019	0.0060	0.0548	0.0625	1.0037
April	0.1272	2.2371	-0.0355	0.3809	0.0838	0.6474	0.0730	1.2281
May	0.0204	0.3172	-0.0000	0.0004	-0.0736	0.5630	0.0285	0.5429
June	-0.0055	0.0970	-0.0382	0.3981	0.0050	0.0355	-0.0307	0.6189
July	-0.0234	0.4019	-0.0776	0.7816	0.0010	0.0084	-0.0357	0.6821
August	-0.0716	1.2101	-0.0248	0.2632	-0.0695	0.6559	-0.0177	0.3063
September	-0.2058	2.7999	-0.3100	2.9273	-0.2164	1.6109	-0.1112	1.7397
October	-0.0579	0.5654	-0.0768	0.6239	-0.1259	0.7824	-0.0557	0.6372
November	-0.0232	0.3053	0.0439	0.4032	0.2123	1.5470	0.0171	0.2485
December	0.1282	1.9795	0.1161	1.2134	0.0818	0.5279	0.0323	0.5413
Critical value		1.9605		1.9608		1.9608		1.9603

Table 9 summarizes the results by providing the number of cases out of 28 in which the parameters were statistically significant. It is apparent from this table that the most significant day of the week effect was Monday, which exactly confirms existing literature. However, only 1 index out of 28 achieved statistically significant excess returns in January. The January effect was overtaken by April, December, September and August. It should be pointed out that parameters for April and December were positive and parameters for August and September were negative.

Table 9.

	Number of Statistically Significant Cases
Monday	9
Tuesday	0
Wednesday	2
Thursday	2
Friday	8
January	1
February	0
March	0
April	10
May	0
June	0
July	0
August	3
September	7
October	0
November	0
December	8

4.3. Time persistence of the day of the week effect

This thesis also examines time persistence of the Monday effect of 7 out of 28 indices. According to the efficient market hypothesis, once discovered this effect should disappear in a very short time. The reason why the Monday has been chosen is that this effect was the most significant. The other day's effects were also considered. However, their evolution through time is very similar to the Monday effect. Therefore, their time paths are not reported. The time path of the Monday effect is computed by estimating a rolling regression. The regression equation is estimated on the first 1250 trading days, which approximately represents a 5 years period, and then this regression equation is reestimated by moving towards the end of the time series by 5 trading days. The 7 figures bellow provide the time path of the t-statistics of the Monday effect for Financial Times Index 100, Australia All Ordinaries Index, Hang Seng Index, Straits Times Index, Nikkei 225, NASDAQ Composite Index, and Standard & Poor's 500 Index.

Fig. 6. FTSE 100

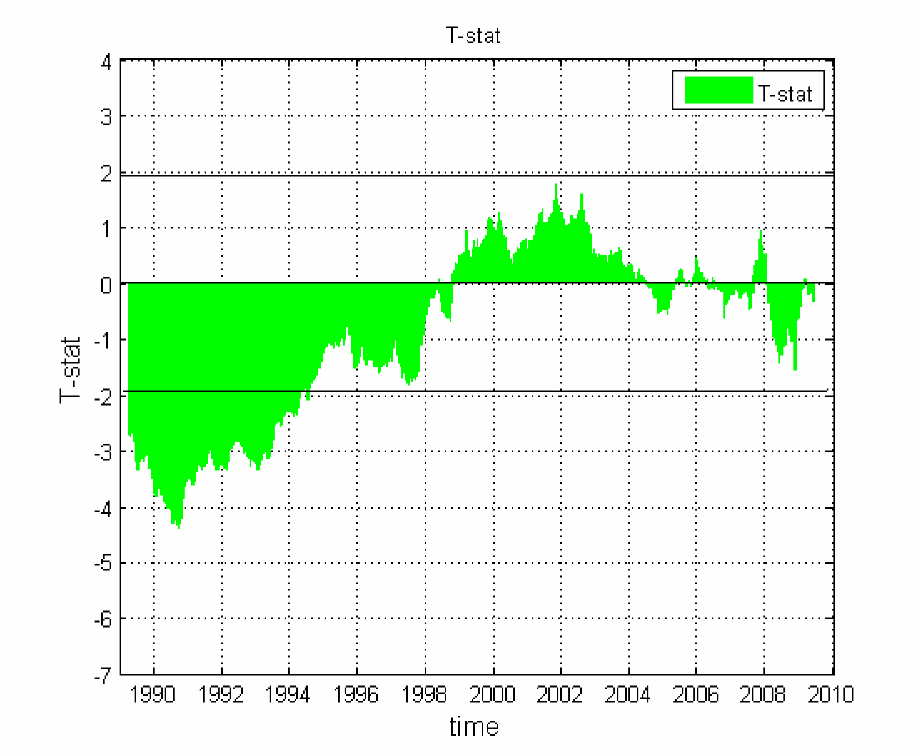


Fig. 7. Australia All Ordinaries

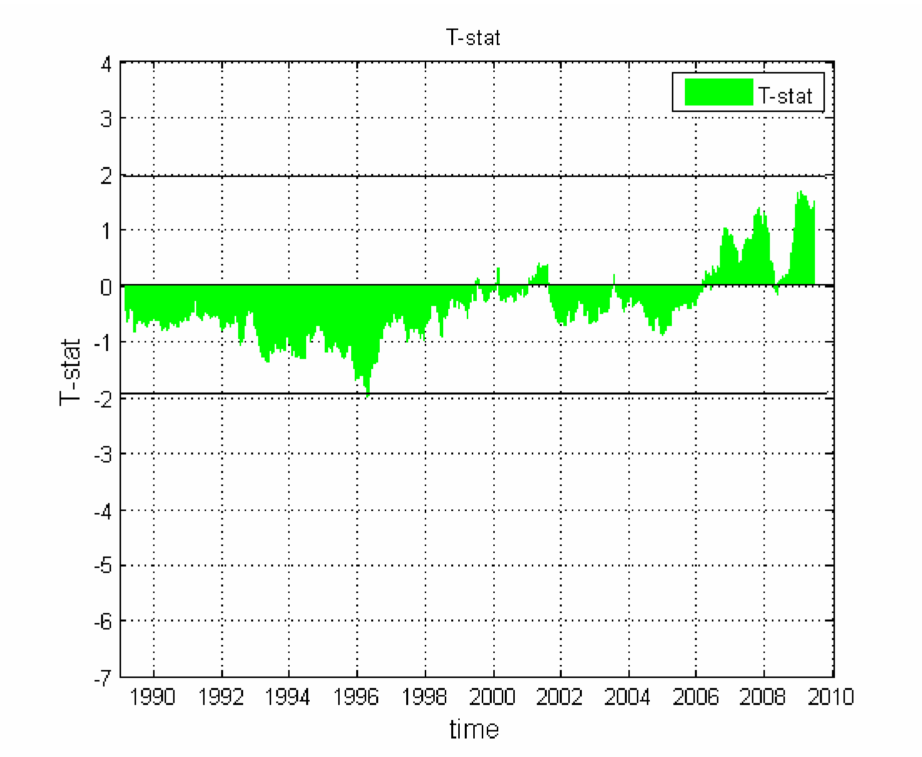


Fig. 8. Hang Seng Index

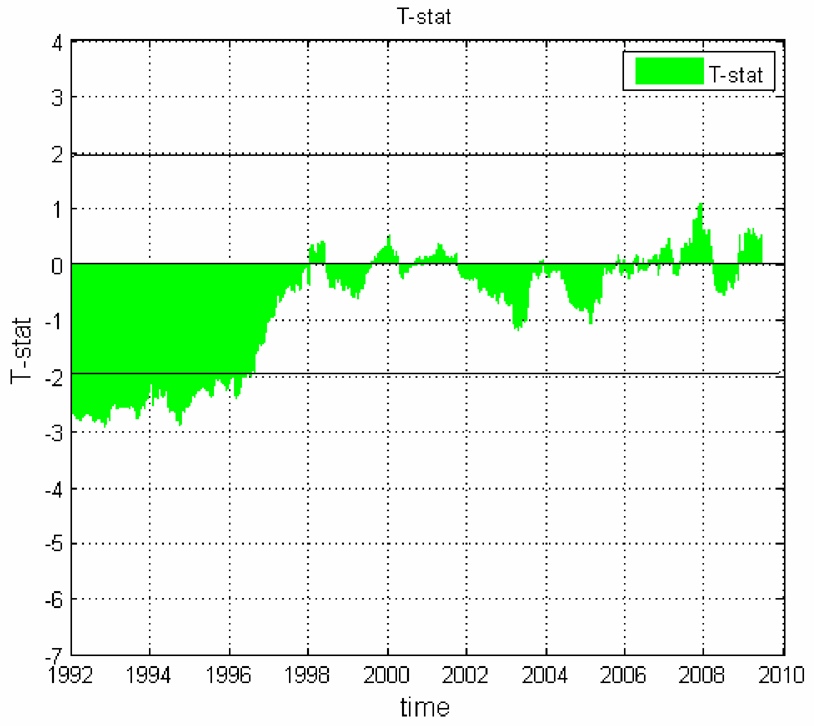


Fig. 9. Straits Times Index

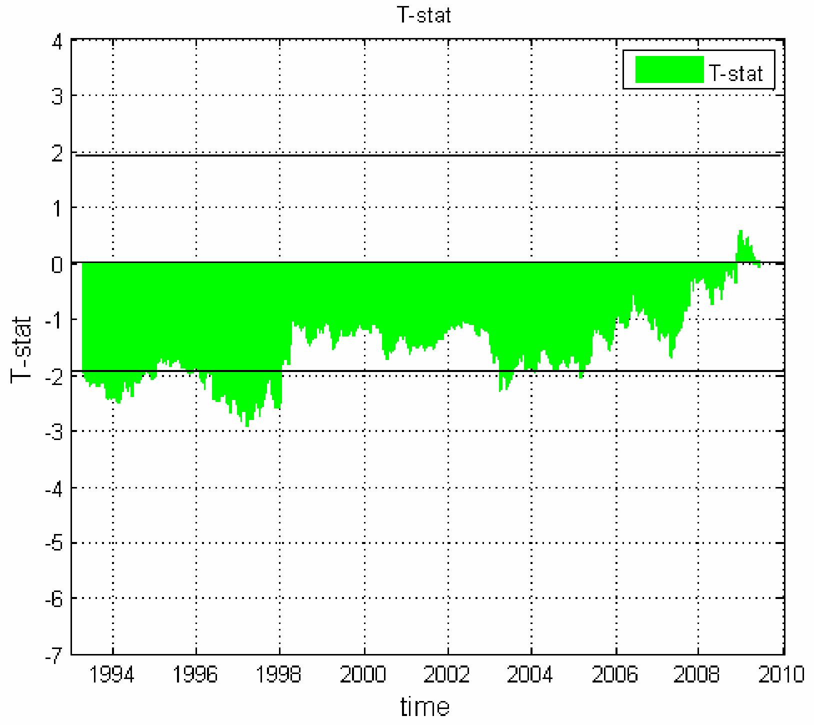


Fig. 10. Nikkei 225

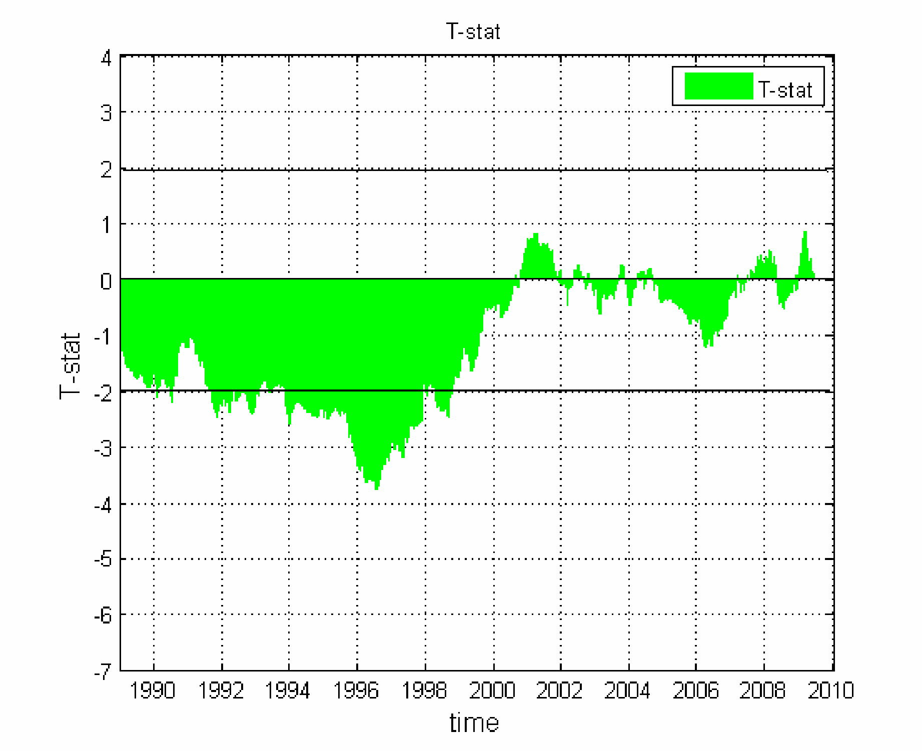


Fig. 11. NASDAQ Composite Index

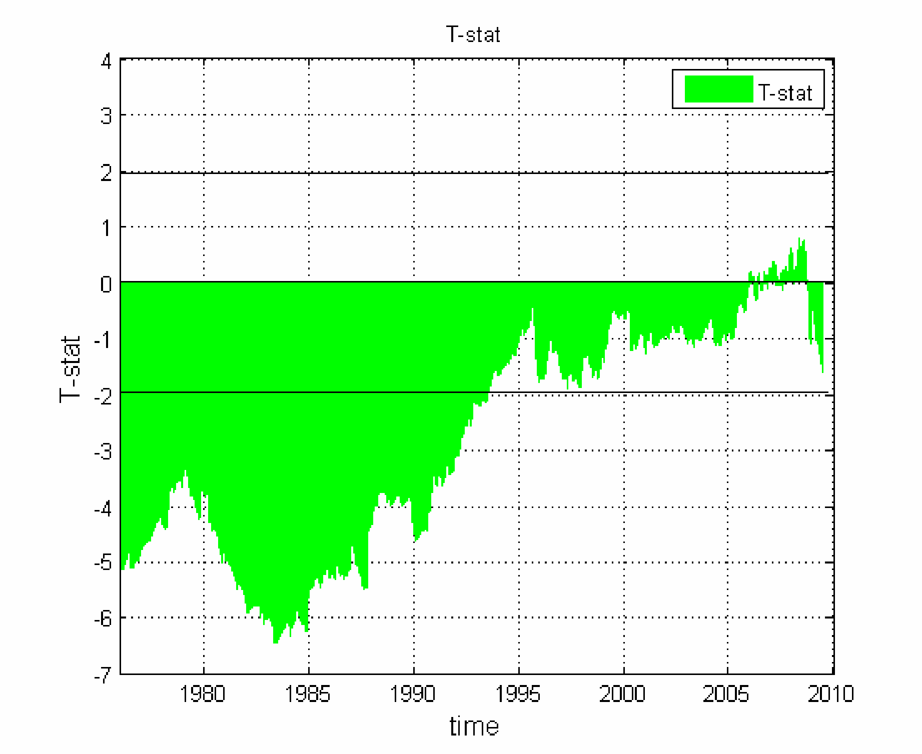
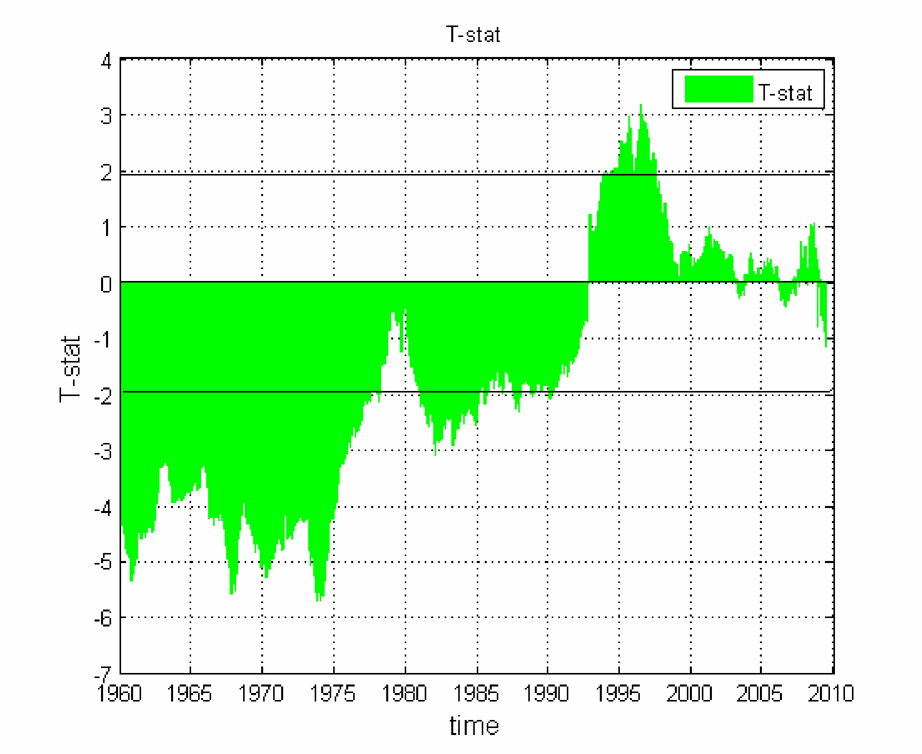


Fig. 12. Standard & Poor's 500 Index



It is apparent from the 7 figures above that the day of the week effect has very similar patter for all the indices examined. It occurred in the 1960s, which can be seen on the last figure, and it was very strong and stable till the second half of the 1990s. Probably the longest time persistence of this effect is in case of the Straits Times Index and Nikkei 225, where it stayed significant till 1998. Furthermore, we can observe that this effect disappeared first from the S&P 500 index.

4.4. Simulated portfolio strategies

The calendar effects should also be considered in terms of their exploitability. In other words, it has to be assessed if it was possible to achieve profits that would be able to outperform the buy and hold strategy. This thesis aims to consider this issue by focusing on the negative September effect and Monday effect only. The same 7 indices out of 28 were considered. Financial Times Index 100, Australia All Ordinaries Index, Hang Seng Index, Straits Times Index, Nikkei 225, NASDAQ Composite Index, and Standard & Poor's 500 Index. Figures 13 to 19 graphically compare performance of 3 market timing strategies by plotting their time path and a relative performance of a strategy based on Monday effect and a strategy based on September effect with respect to the buy and hold strategy. The blue line represents the buy and hold strategy. The red line marks a market timing strategy based on selling the index on Friday at a closing price and buying again on Monday at a closing price. The green line corresponds to a market timing strategy based on selling the index in August at a closing price and buying again in September at a closing price.

Fig. 13. FTSE 100

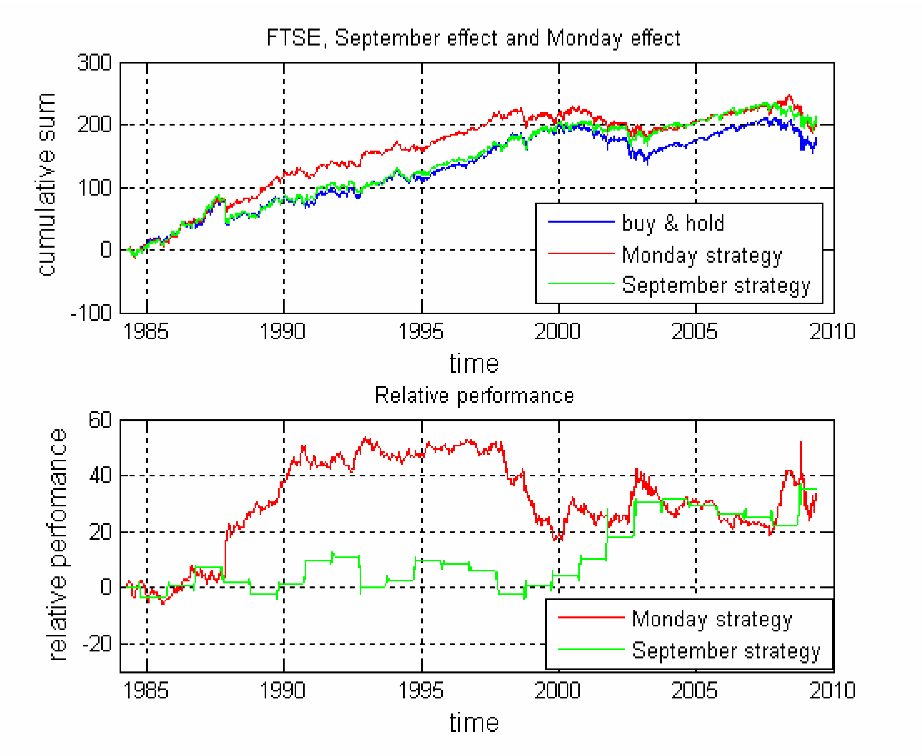


Fig. 14. Australia all Ordinaries

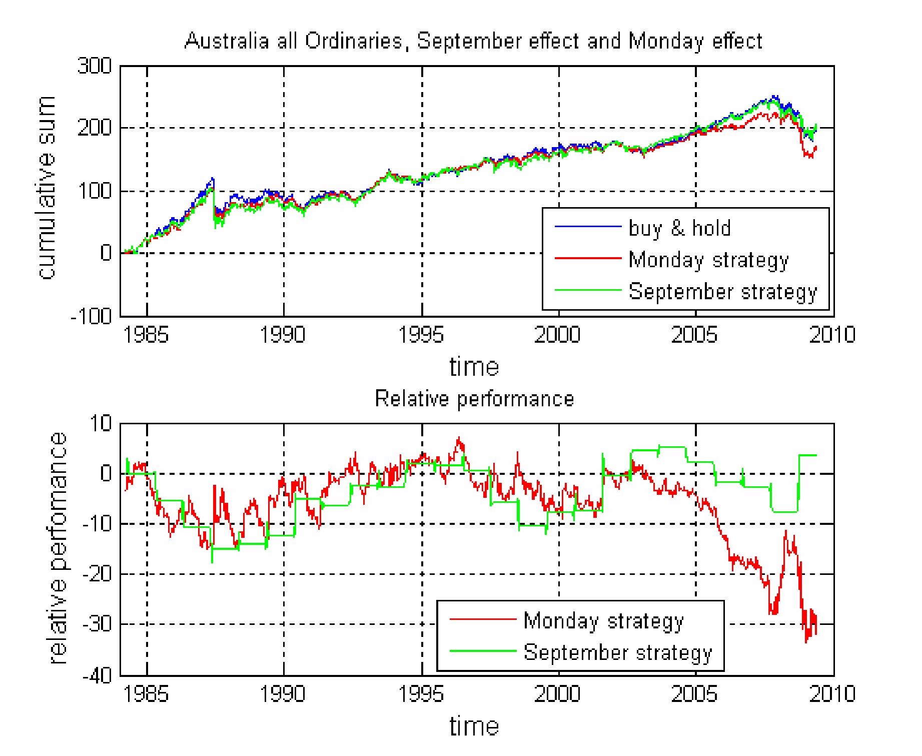


Fig. 15. Hang Seng Index

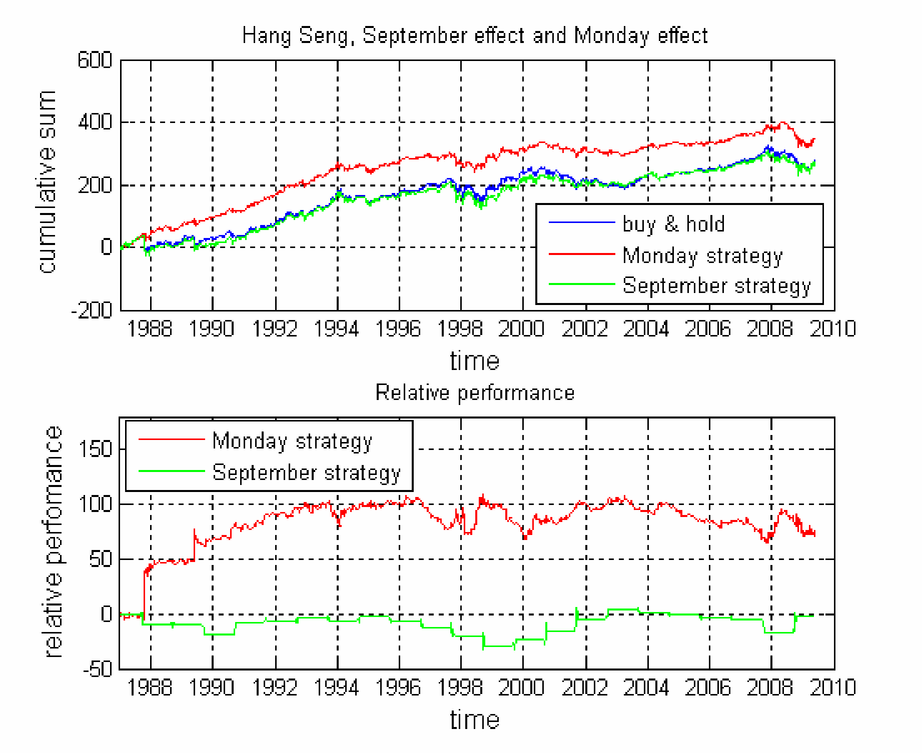


Fig. 16. Straits Times Index

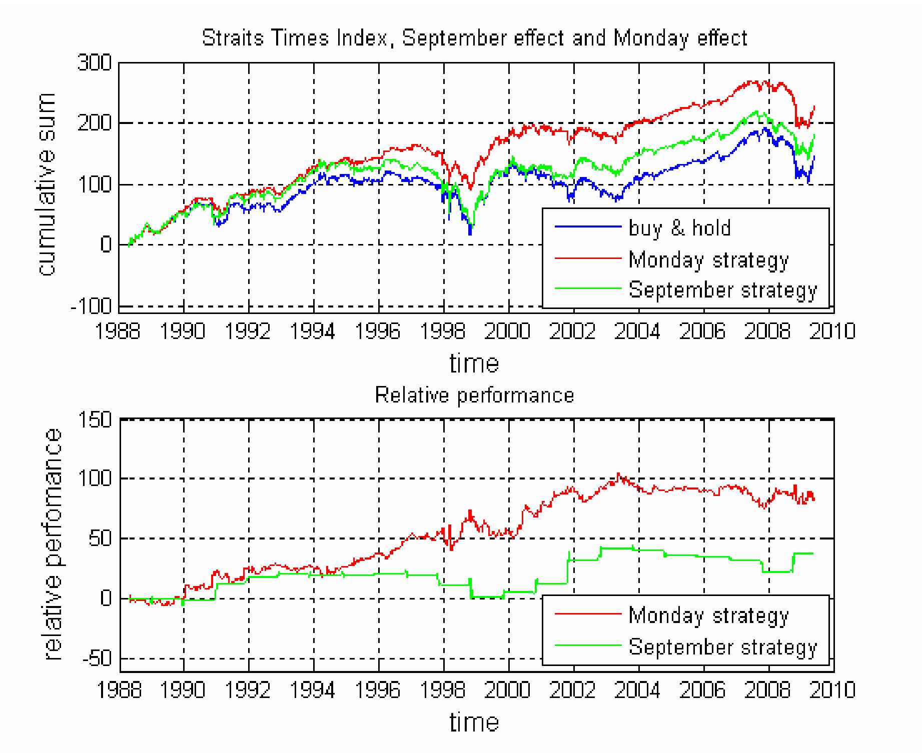


Fig. 17. Nikkei 225

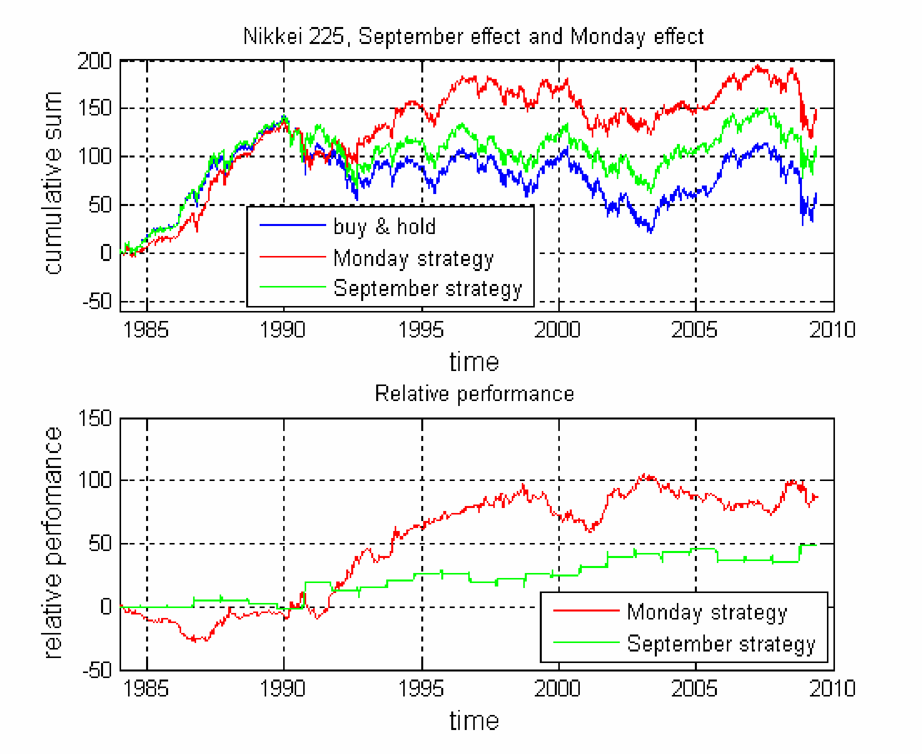


Fig. 18. NASDAQ Composite Index

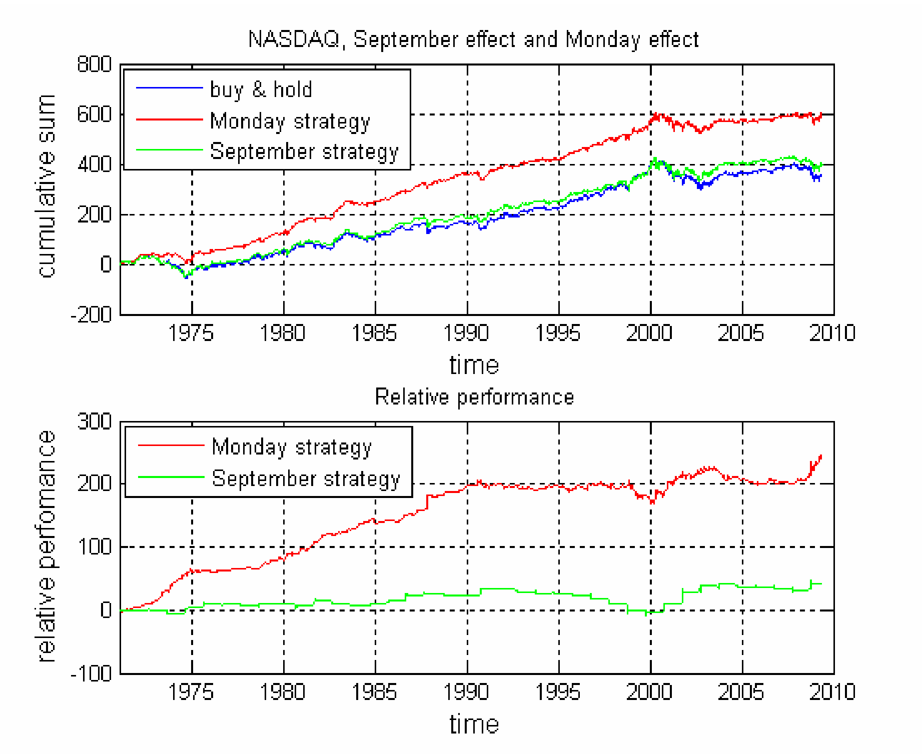
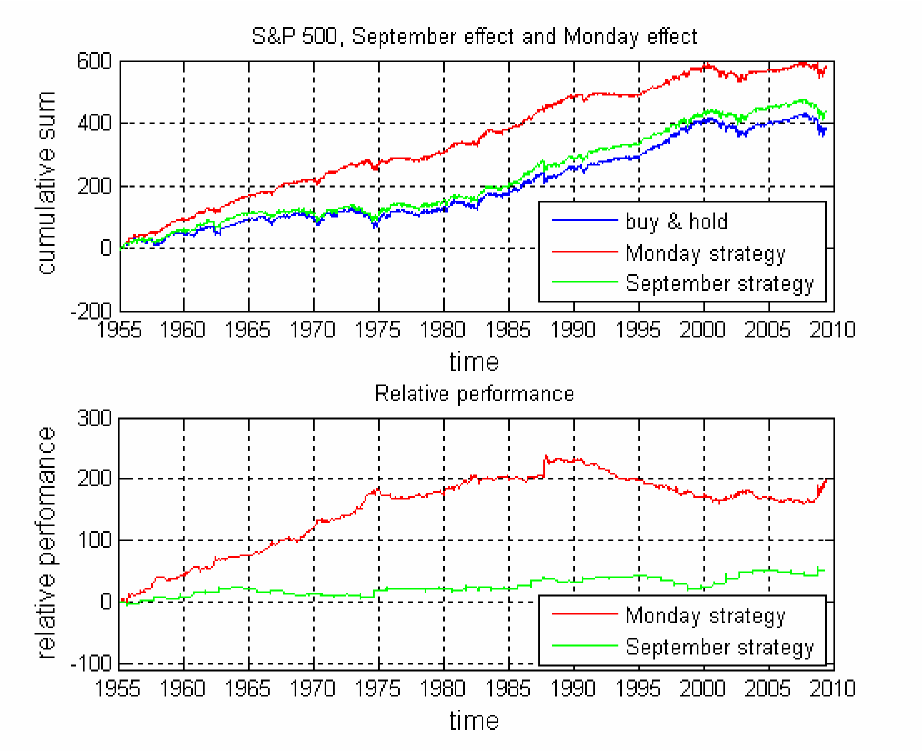


Fig. 19. Standard & Poor's 500 Index



In case of the FTSE 100, Straits Times, Nikkei 225, NASDAQ and S&P 500, which means 5 indices out of 8, the buy and hold strategy was the worst performing strategy. The buy and hold strategy is not the best strategy in any of the considered indices.

If we had used the strategy based on short selling of the portfolio every September in case of the FTSE 100, we would have moderated the crash that followed the DotCom bubble. Moreover, the standard deviation of returns would have been lower than in case of the buy and hold strategy, which implies higher returns at a lower risk.

It might be appropriate to mention that if we had used the strategy based on the Monday effect for the Nikkei 225, we would have not suffered a loss connected with the so called "Lost decade" on the Japan Stock Exchange.

The most pronounced is the day of the week effect in case of the S&P 500 and NASDAQ Composite. If we had allowed short selling, we would have outperformed the buy and hold strategy by almost 400%, which means twice as big performance as is achieved by the buy and hold. The September effect would have led to a remarkable outperformance of 100%.

The strategies based on calendar effects did not perform very well on the Australian stock market. In this case, the additional profits achieved by these strategies would not be probably high enough to cover transaction costs.

Table 10 further summarizes the results by providing the mean daily return, its standard deviation, and a ratio of these two variables. This is in fact the reward-to-variability ratio (Sharpe, 1966) or the Sharpe ratio with a constant risk free rate (Sharpe, 1994). It is apparent from this table that the buy and hold strategy preformed always worst. The best strategy in terms of mean return was the strategy based on the Monday effect. The best performing strategy in terms of the standard deviation of returns was also the strategy based on the Monday effect. This implies that a risk averse investor would prefer this strategy. It should be pointed out that this strategy was the best in all the 7 cases out of 7 in terms of the standard deviation of returns. This probably means that Monday returns are very volatile. If we assume a constant rate of substitution between risk and return, we can conclude that the best performing strategy was the strategy based on the ration between the mean return and standard deviation of returns, which was again the strategy based on the Monday effect. On base of this ex post observation, it can be concluded that this strategy is superior both in terms of risk and return. It can provide a higher return with a lower risk than the buy and hold strategy.

Table 10.

Index	Strategy	Mean Return %	Standard Deviation of Returns	Ratio of the mean return and its standard deviation
Australia All Ordinaries	Buy and Hold	0.0322	0.9898	0.0325
	Long Positions Monday	0.0271	0.8789	0.0309
	Long Positions September	0.0327	0.9537	0.0343
FTSE 100	Buy and Hold	0.0283	1.1232	0.0252
	Long Positions Monday	0.0335	0.9833	0.0341
	Long Positions September	0.0339	1.0629	0.0319
Hang Seng	Buy and Hold	0.0506	1.7901	0.0283
	Long Positions Monday	0.0635	1.4607	0.0435
	Long Positions September	0.0502	1.7293	0.0290
NASDAQ Composite	Buy and Hold	0.0375	1.2597	0.0298
	Long Positions Monday	0.0627	1.1104	0.0565
	Long Positions September	0.0418	1.2099	0.0345
Nikkei 225	Buy and Hold	0.0100	1.4709	0.0068
	Long Positions Monday	0.0240	1.2944	0.0186
	Long Positions September	0.0179	1.4102	0.0127
Straits Times	Buy and Hold	0.0269	1.3284	0.0203
	Long Positions Monday	0.0430	1.1144	0.0386
	Long Positions September	0.0340	1.2756	0.0266
SP 500	Buy and Hold	0.0284	0.9841	0.0288
	Long Positions Monday	0.0426	0.8447	0.0504
	Long Positions September	0.0322	0.9378	0.0343

However, it is necessary, to test if the differences in returns and standard deviations are statistically significant. At first, the equality of variances must be tested by a F-test, which is defined as $F = \frac{s_1^2}{s_2^2}$. H_0 states $\sigma_1^2 = \sigma_2^2$ and is rejected if $F > F(\alpha/2, n_1 - 1, n_2 - 1)$. Then if variances are unequal, equality of means can be tested by the following t-statistic

$t = \dfrac{(\bar{x}_1 - \bar{x}_2)}{\left(\dfrac{(n_1 - 1)s_1^2 + (n_2 - 1)s_2^2}{n_1 + n_2 - 2}\right)\sqrt{\dfrac{1}{n_1} + \dfrac{1}{n_2}}}$. H_0 stating $\bar{x}_1 - \bar{x}_2$ is rejected if $t > t(1 - \alpha/2, df)$,

where $df = \dfrac{\left(\dfrac{s_1^2}{n_1} + \dfrac{s_2^2}{n_2}\right)^2}{\dfrac{\left(\dfrac{s_1^2}{n_1}\right)^2}{n_1 - 1} + \dfrac{\left(\dfrac{s_2^2}{n_2}\right)^2}{n_2 - 1}}$.

Table 11 provides values of t-statistics and critical values of a relevant distribution. It is apparent from this table that variances are always statistically significantly different from the buy and hold strategy. However, mean returns are never statistically significantly different. This implies that the two strategies considered are not able to achieve statistically significantly higher mean returns. Nonetheless, they can significantly lower risk in terms of standard deviations. Particularly the strategy based on avoiding Mondays is very powerful in this sense. It has statistically significantly lower standard deviations of returns than the buy and hold strategy in all the 7 cases considered. The strategy based on avoiding September is able to beat the buy and hold strategy in 6 cases out of 7, in terms of standard deviation of returns.

Table 11.

Index	Strategy	F-statistic	critical value of F-distribution	t-statistic in absolute value	critical value of t-distribution
Australia All Ordinaries	Long Positions Monday	1.2683	1.0424	0.3050	1.9602
	Long Positions September	1.0771	1.0424	0.0288	1.9602
FTSE 100	Long Positions Monday	1,3048	1.0422	0.2774	1.9602
	Long Positions September	1.1167	1.0422	0.2884	1.9602
Hang Seng	Long Positions Monday	1,5019	1.0452	0.4157	1.9602
	Long Positions September	1.0716	1.0452	0.0120	1.9602
NASDAQ Composite	Long Positions Monday	1,2870	1.0341	1,4743	1.9601
	Long Positions September	1.0840	1.0341	0.2419	1.9601
Nikkei 225	Long Positions Monday	1,2913	1,0426	0.5642	1.9602
	Long Positions September	1.0879	1.0426	0.3061	1.9602
Straits Times	Long Positions Monday	1,4209	1.0461	0.6781	1.9602
	Long Positions September	1.0845	1.0461	0.2815	1.9602
SP 500	Long Positions Monday	1,3573	1.0285	1,2797	1.9601
	Long Positions September	1,1012	1,0285	0.3267	1.9601

5. Conclusion

This thesis has examined 30 individual stocks of the German Stock Exchange for the presence of the day of the week effect and 28 world indices for presence of the day of the week effect and the month of the year effect. No evidence of the day of the week effect has been found for stocks of the German Stock Exchange where an extended dummy variable approach was applied. The international evidence in support of the calendar effects is mixed. The day of the week effect was found in case of 12 indices out of 28 considered and the month of the year effect in case of 17 out of 28 by using a simple dummy variable approach. It has been also found that the day of the week effect became insignificant during the second half of 1990s. This was concluded by using time series of 7 indices with the longest data range.

Furthermore, four market timing strategies were simulated on the data sets of these 7 indices. These strategies were able to statistically significantly outperform the buy and hold strategy, which the efficient market hypothesis implicitly recommends, in terms of standard deviations. They were also able to outperform the buy and hold strategy in terms of the mean return. However, this outperformance was not statistically significant. Nonetheless, it still implies an unexploited profit opportunity that should have been eliminated by rational investors once it was discovered. It might be appropriate to mention that the day of the week effect was discovered in 1960 and it disappeared around 1995. In other words, it took approximately 1820 weeks or 9100 trading days to the investors to exploit this effect and to wipe it out. If we recall the formula from Fama (1970) expressing undervaluation and overvaluation of security price $\mathrm{E}(x_{j,t+1}|\Phi_t)=0$, it appears that in terms of the day of the week effect the indices were persistently, significantly overvalued for far too long time for the market to be at least weakly efficient. This seems to violate the efficient market hypothesis.

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