Seasonal Effects:
The Netherlands versus the United States

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Abstract

In this paper we analyze seasonal patterns on the stock markets for the U.S. and the Netherlands in the time period between 1993 and 2013. The anomalies that are investigated are the day-of-the-week effect, turn-of-the-month effect and the January effect. These effects are analyzed with the daily returns and the models that have been used are the OLS regression and the GARCH model. In the results we found only evidence for the existence of the turn-of-the-month effect in both countries.

Key words: *day-of-the-week, January, turn-of-the-month, OLS, GARCH*

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1. Introduction

The famous efficient market hypothesis (EMH) was introduced by Fama (1965) a few decades ago and he stated that in an efficient market stock prices incorporate all possible information, which means that when the markets are efficient the stock prices follow a random walk. This random walk hypothesis states that it is not possible to predict future prices based on past prices, so stock price changes are not predictable. According to Fama (1965) all the information that is taken into account in past prices are also reflected into current stock prices. Subsequent with the efficient market hypothesis all investors have the same information and therefore they cannot achieve an abnormal return. The only way to receive higher returns is to take more risk.

Over the years researchers tried to find evidence against the efficient market hypothesis. Cross (1973) found as first statistical evidence for the existence of calendar anomalies on the stock markets. It is called an anomaly when it is not in line with the current theory, the Capital Asset Pricing Model (Sharpe, 1964). This model describes the relationship between risk and expected return and it is used in the pricing of risky securities. The general idea is that investors are being compensated for the time value of money and the risk they take.[1]

The evidence on calendar or seasonal patterns in stock returns that has been found over the years is quite interesting (Sar, 2003).[2] In the USA and other markets the stock returns reach abnormal high levels at certain moments in time. Examples of these moments are the beginning of the week, turn of the month, holidays and in January (see e.g. Berument and Kiymaz (2001), Gultekin and Gultekin (1983), Agrawal and Tandon (1994) for an overview). The reasons behind the anomalies are important to understand in order to rationalize observed patterns and make predictions concerning market outcomes.

The January effect can be explained by various reasons. First there is the tax explanation, this which means that investors sell their stocks at the end of the year and benefit from the tax and then repurchase the stocks in the new year to achieve abnormal returns (Chen and Singal, 2004). Second the window dressing is also an explanation for the January effect, where investors sell stocks at the end of the year to present a more acceptable portfolio to their fund holders. For the Day-of-the-week effect reasons can be settlement procedures, meaning that when buying stocks on Friday and due to the delay of the extra waiting days for the seller because of the weekend, he will demand a higher price for the stocks. Other possible reasons are whether individual or institutional investors trade and due to short selling. The turn-of-the-month effect can be explained by the preferred habitat hypothesis, which means that people often receive standardization incomes like wages, dividends and interest at the end of the month and invest this money directly (Ogden, 1987).

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[1] The formula for CAPM is as follows: $R_a = r_f + \beta_a (r_m - r_f)$, where r_f is the risk-free rate, β_a is the risk measure and $(r_m - r_f)$ is the market premium.
[2] Terms calendar effects and seasonalities can be used interchangeably.

In this paper the January effect, day-of-the-week effect and the turn-of-the-month effect will be researched for the Netherlands and the United States. To investigate these effects the data set used consists out of daily returns from the S&P 500 Composite Total Return Index[3] and the Total Market Nederlands Return Index[4] for the period from 1993 until 2013 which are obtained through DataStream.[5] Next to examining the calendar effects there will also be a simultaneous approach with a GARCH model to capture the volatility changes over time.

For the research of this paper the following research question will be used; Do seasonal anomalies exist in the United States and the Netherlands and what are the differences? So first the existence will be investigated and then possible differences will be explained.

The organization of this paper is as follows. Section 2 describes earlier papers regarding seasonal effects. In section 3 the data and methodology will be explained for all the three effects with their descriptive statistics. Section 4 focuses on the results for the effects including the GARCH model. In Section 5 there will be some limitations and extensions for the research. Section 6 provides some concluding remarks.

[3] S&P 500 consists of 500 of the largest firms on the New York Stock Exchange.
[4] Consists out of 118 largest firms in the Netherlands.
[5] See Appendix A.

2. Theoretical Framework

2.1 January Effect

The January effect has been one of the most intriguing issues in financial economics since 1976 (Gu, 2003). Rozeff and Kinney (1976) proved that returns of common stocks in January are significantly larger than those in other months and especially for smaller firms and those with low share prices and who underperformed in the past.

2.1.1 Tax-loss Selling Hypothesis

According to Wachtel (1942) and Ritter (1988) it is possible to explain the effect by the tax-loss selling hypothesis. With tax-loss selling investors sell the losing stocks in their portfolio at the end of the year so they can gain a benefit from tax. Investors repurchase the stocks in the new year and therefore creating abnormal returns in January. Chen and Singal (2004) identified the tax-loss selling as the most likely explanation for the January effect. However, other papers have noted that for many foreign countries the tax year for individuals is not the same as the calendar year (Brown, Keim, Kleidon and Marsh, 1983).

When testing for year-end tax effects a measure of potential tax-loss selling (PTS) is needed to classify securities. To measure the PTS, it means that the difference between the price of a stock at the end of a year and its maximum price during previous year needs to be calculated which would be classified by Internal Revenue Service as short-term[6]. Tax selling measure is computed by dividing the security's price on the second to the last trading day of the year by the maximum price (Reinganum, 1982).

2.1.2. Window Dressing

Another explanation for the January effect could be the window dressing hypothesis (Haugen and Lakonishok, 1987). The window dressing suggests that investors sell certain stocks at the end of the year to present more acceptable portfolio of stocks to fund holders in the end of the year reports (Moller and Zilca, 2008). Investors repurchase the stocks in the new year and therefore create abnormal returns in January.

Another problem for the existence of the January effect is the fact that investors have the knowledge of the effect and can take advantage of the anomaly (Mehdian and Perry, 2002). This means that investors would buy less and sell more in January to take the opportunity of profit, and this activity would diminish the anomaly. To understand the pattern from the January effect it is important to study the daily pattern of returns because of the findings that around 50% of the effect is concentrating in the first few days of this month (Keim, 1983).

[6] Gain or loss is considered as short-term if position was closed within six months.

2.1.3 Method

You can analyze the January effect when using monthly data and next to this it is also possible to check how daily patterns develop over time. It is preferred to use the daily analysis because these returns may give a better understanding of the evolution of the effect. To use this method it is needed to study the daily cumulative abnormal returns to each size decile across the year in all different temporal sub-periods. First the data has to be divided into two sub-periods and thereafter the cumulative abnormal returns are generated for this periods and then compared (Moller and Zilca, 2008).

Agrawal and Tandon tested in their paper for seasonality among eighteen countries, and together with the US stock market they represent 95 per cent of the world's exchange-traded equity, and one of the tested seasonalities was the January effect.[7] They used mean monthly returns and performed a non-parametric Kruskal-Wallis test and found abnormal high returns for all countries.

To estimate the relation between the January effect and possible explanatory variables it is possible to use the January effect of the combination of all the indices as a dependent variable. To capture the market's exposure to macroeconomic factors the real GDP growth and inflation are useful variables. To relate the size of January effect to annual performance of the index the annual return of the year will be used. Finally, the connection between January effect and volatility can be indicated by the standard deviation and variance of daily returns (Gu, 2003).

In the paper from Mehdian and Perry (2001) they show a January effect for the period from 1964 to 1990 on the U.S. Market. However they found that the effect is not stable during the whole period. By using a Chow-test they found a break in the researched period, which was in 1987, and after this year the effect did not exist anymore. A Chow test examines whether parameters of one group of the data are equal to those of other groups.[8] The break can be explained by the financial crisis in 1987.

[7] Ten European countries (Belgium, Denmark, France, Germany, Italy, Luxembourg, Netherlands, Sweden, Switzerland and UK), three Asian countries (Hong Kong, Japan and Singapore), two Latin American countries (Brazil and Mexico), Canada, Australia and New Zealand.

[8] Explanation comes from www.stata.com/support/faqs/statistics/chow-tests

2.2 Day-of-the-Week Effect

The day-of-the-week effect is one of the most widely documented seasonal anomalies, according to which stock returns are significantly higher on certain days of the week compared to others. Cross (1973) studied the returns on the S&P 500 over the period of 1953 and 1970, and his results showed that the mean return on Friday is higher than the mean return on Monday. Several studies tried to explain the Monday effect, with the hypothesis that the returns on Monday should be higher than on other weekdays returns (French, 1980).

The day-of-the-week effect is also called the weekend effect or the Monday effect. Possible explanations for the weekend effect have been investigated, for example: measurement errors, delay between trading and settlement in stocks and concentration of certain investment decisions (Charles, 2010). These studies measure Monday return between the closing price on Friday and the closing price on Monday (Berument and Kiymaz, 2001). However, all these explanations are not able to explain the day-of-the-week anomaly. According to Kohers et al. (2004) the day of the week effect may have disappeared in recent years through the progress of the market efficiency over time. Conversely, Cho et al. (2007) show in their paper a test of the day of the week effect in daily stock index returns based on the stochastic dominance restriction. Their finding is that there is strong evidence of a Monday effect in many datasets under the stronger criterion. In consequence of this finding the discussion concerning the existence of seasonal patterns remains open. In the next coming paragraphs the weekend effect is explained in parts.

2.2.1 Measurement Errors

The most common used explanation for the day-of-the-week effect is that it arises due to misapplication of statistical methods. According to Sullivan, Timmermann and White (2001) seasonal effects are the consequence of data mining. In the paper from Connolly (1989) he tests for robustness to check whether the day-of-the-week effect exists. When testing with a normal OLS regression he found that there was an effect in 28 of the 32 cases. With the increase of the sample size, the F-statistic has a tendency to reject the null hypothesis of equality unless the significance level is adjusted downwards, and they name this the Lindley Paradox. When Connolly (1989) adjusted for his sample size with help of the Bayesian statistical tool, he only found evidence in 4 out of the 32 cases. In the research paper from Chang, Pinegar and Ravichandran (1993) they investigate 23 markets on the day-of-the-week effect. They found evidence with the normal regression for 13 markets and when they corrected in the same manner as Connolly (1989) did the total of significant markets declined to only 9 markets.

2.2.2 Settlement Procedures

Lakonishok and Levi (1982) tried to argue that the expected stock returns as measured should depend on the day of the week. They argue that the expected returns should be lower on Monday than would be implied simply by a trading time or calendar time model and the returns should be higher on Fridays. Their argument is based on the delay between trading and settlement in stocks and in clearing checks. In the United States it is practice that the settlement of stocks take place five business days after trading, so the weekend days do not count. When a stock is purchased on Friday, there are ten days between purchasing and payment (two weekend days, five settlement days, another two weekend days and one clearing day). So buyers should prepare to pay more when they buy stocks on a Friday. The sellers of stock should demand a higher price for the stocks sold on Friday due to the extra days of delay before being paid. So the expected return should be higher on Friday then on other days of the week. Similarly, the equilibrium expected rate of return on Monday should be lower by two days of interest than the return expected from either a trading day or calendar time view (Lakonishok and Levi, 1982).

Coutts and Hayes (1999) did a study for the London Stock Exchange market (LSE), which has accounts which starts on a Monday and are two weeks long. Payment for shares bought during an account is not due until the second Monday following the end of the account. If the purchase of the shares is delayed from the last Friday of an account to the following Monday, the purchaser has an extra eleven days of interest free credit between purchase and payment. Therefore there will be ceteris paribus a higher return on a Monday that is the first day of an account (Coutts and Hayes, 1999).

Settlement procedures are different in each country, though in many countries the settlement takes place either periodically or after a fixed number of days after the purchase or sale of stocks. The account periods are either weekly or monthly, so the period starts either on the first day of the week and ends on the last day of the week or starts at the first day of the month and ends on the last day of the month. As explained by Coutts and Hayes (1999) the weekly based account periods can have a positive influence on the Monday return but is not able to explain the abnormally low returns on Monday. As explained by Lakonishok and Levi (1982) the extra days of interest have a relatively small impact and do not explain the Monday effect, however the delay of settlement explains about seventeen percent of the weekend effect. So the settlement delay does not adequately explain the total day of the week effect.

2.2.3 Individual Investors

According to Lakonishok and Maberly (1990) the low Monday return is due to the fact that individual investors are left on their own when making sell decisions, and therefore there is a tendency in making these decisions over the weekend. Financial analysts produce more buy than sell recommendations. A study by Groth, Lewellen, Schlarbaum and Lease (1979), which is based on 6000 recommendations, showed one sell recommendation for six buy recommendations[9].

During weekends individual investors have more time to understand the information and therefore the propensity to transact is relatively high on Monday. Sell transactions tend to increase more than buy transactions, and the reason for this might be that an investor decide to wait for the sell transaction to be executed before he or she participates in a buy transaction. The conjecture is that on average individuals are selling more and buying less on Monday (Lakonishok and Maberly, 1990). Another reason is in line with the 'parking the proceeds' hypothesis by Ritter (1988). This means that it is common for individuals who sold their stocks to wait a few days before reinvesting the proceeds. So for the day of the week effect it could be the case that the propensity on Monday by individuals to sell is higher than the propensity to buy.

2.2.4 Institutional Investors

Day-of-the-week patterns in returns and volumes are more pronounced in securities in which institutional investors play a big role. According to Sias and Starks (1995) institutional investors are primarily responsible for the day-of-the-week effect because of four related factors. Firstly, they avoid Monday trading because they use this time for strategic planning (Osborne, 1962). Secondly, the fact that they are responsible for the day-of-the-week pattern is in line with the microstructure model of Foster and Viswanathan (1990). They suggested that the effect is the result of interaction between informed traders, liquidity traders and market makers. Especially on Monday they have more information because private information comes throughout all week only public information comes only at week days. Thirdly, like individual investors the institutional rely also on some brokerage recommendations, however they also use brokerage firm research. Fourthly, extant work has shown that the effect is related to autocorrelation in portfolio returns (Abraham and Ikenberry, 1994). Previous study from Sias and Starks (1994) has shown that substantially stronger serial correlation in portfolios dominated by institutional investors. When day of the week return patterns are a manifestation of autocorrelation in portfolio returns, then these results proposes that the pattern is more likely to be attributable to institutional investors.

[9] The reason why there are less sell than buy recommendation is the fact that buy recommendations are in general more cost efficient because every investor can respond to this recommendation. Another reason is because analysts want to have a working relationship with the company they follow and therefore a buy recommendation is more popular for the firm.

2.2.5 Short Sellers

Chen and Singal (2003) argued that short sellers affect stock prices in a systematic and significant manner. They contend that short sellers contribute to the weekend effect, due to the fact that they are not able to trade during weekends they close their positions on Fridays and get new short positions on Mondays. Short sellers are averse to holding positions over non-market hours and that is why they would like to close their positions at the end of the day and reopen them the next day. However, due to the transaction costs it will be too expensive to close every day and reopen the next day so the weekend is a natural breakpoint. Therefore stock prices will rise on Fridays when short sellers cover their positions and fall on Mondays when they reopen positions.

2.2.6 Behavioral Impact

According to Rystrom and Benson (1989) the day-of-the-week effect can be explained by the 'blue Monday' psychological effect. People are more optimistic at Friday evening due to the fact that the weekend is beginning and on Monday morning they are less in the mood. These mood swings can lead to misvaluations because fundamental analysts can view a stock less fortunate at the beginning of the week. If a significant proportion of the investors are less optimistic on Mondays they sell their stocks on this day and the opposite will occur at Fridays. Pettengill (1994) performed his research on this 'blue Monday' hypothesis. He tested this with an experiment among two different groups. The first group were students and the second were four different civic groups. They had to allocate their wealth among different market securities, which were from risky to risk averse, during different rounds. The experiment was conducted on Monday and Friday to test for the effect. He found that both groups invested more on Friday in risky assets, so he founds evidence for the 'blue Monday' hypothesis. Only note is that with experiments the results are subject to the sample bias and other biases.

2.2.7 Other Markets

The day-of-the-week pattern exists not only in the U.S. market and the U.K. market, but also in other markets. Jaffe and Westerfield (1985) show in their paper the weekend effect in four developed markets, Australia, Canada, Japan and the U.K. Their results show the existence of the weekend effect in all four countries. Next to this fact they also found the lowest mean return for the Japanese and Australian stock market on Tuesday. In line with this findings, the paper from Solnik and Bousquet (1990) showed strong negative returns for Paris Bourse on Tuesday. Barone (1990) stated the same results for the Italian Stock Market with the largest decline in the first two days and especially Tuesday.

Decision makers do not need to know only the returns, but also its volatility. When there are variations in the volatility of stock returns in the day-of-the-week patterns and whether a high return is corresponding with a low return on a given day, investors use this knowledge to adjust their portfolio by taking this effect in account (Charles, 2010). When volatility is expected to increase it is possible for investors who dislike risk that they adjust their portfolios by reducing their investments in that certain assets (Engle, 1993).

When finding patterns in volatility it can be useful for instance by predicting volatility to value assets, especially stock index options. To study time series behavior in terms of volatility it is possible to use various GARCH models. Berument and Kiymaz (2001) use the GARCH specification by allowing the constant term to vary for each day of the week. With this model they show that for the S&P 500 index in both, the volatility and the returns, the day of the week effect is present. However, there does not seem to be a way to model conditional heteroscedasticity. In some models they allow the volatility to react asymmetrically to positive and negative changes in returns (Hansen and Lunde, 2005).

Fluctuation of asset prices is caused by two sides. First one is the fact that volatility is caused by the arrival of public information and the second one is the arrival of private information to volatility (Berument and Kiymaz, 2003). According to French and Roll (1986) asset prices are more volatile during trading hours than nontrading hours and variances for days following an exchange holiday are larger than for other days. Public information arrives during normal business hours and informed traders are likely to trade when exchanges are open. Harvey and Huang (1991) showed in their paper that they observe higher volatility during the first few trading hours on Thursdays and Fridays, as interpretation for the results they show that more public information arrives on Thursdays and Fridays.

2.3 Turn-of-the-Month Effect

Seasonal fluctuations in production and sales are a familiar fact in the market. Seasonality refers to regular and repetitive fluctuation in a time series which occurs periodically over a time of less than a year. Stock returns follow systematic patterns at certain times of a day, week or month. For monthly patterns this means that certain months provide better returns to others. Researchers have also reported half-month effects in their literature, and various studies showed that daily stock returns in the first half of the month are relatively higher than in the last half of the month (Kuria and Riro, 2013). Ariel (1987) set up a study for the US market from 1963 to 1981 to show this effectHe showed that the variation between high and low return days of the month induced by the monthly effect is of about the same order of magnitude as the variation between high and low return days of the week reflected in the weekend effect. Ariel (1987) tried to explain the monthly effect with the possibility that it is related to the January effect and small firm effects on stock returns, however none could explain the empirical regularity. He based his findings using the CRSP index to show a positive effect in the first half of the month starting from the last days of the previous month.[10] In the first half of the month he found a positive return of 0.826% and in the second half the return was -0.182%.

Lakonishok and Smidt (1988) studied 90 years of daily data on the Dow Jones Industrial Average. They did not base their research on the returns in the first half of the month, but on the last day of the previous month and the first three days of the month. They found a cumulative rate of increase over the four days around the turn of the month of 0.473% and for an average four-day period the cumulative rate of increase was 0.0612%. They found a frequency of positive rates of return around the turn of the month around 56% in comparison with 52% on a regular day of the month.

Agrawal and Tandon (1994) did research on eighteen countries and the existence of the turn-of-the-month effect. The daily stock indices for twelve of the eighteen countries were obtained from the London Financial Times for the period 1971 to 1987. The indices for the other six countries were directly obtained from their stock exchanges or banks. They looked at the rates of returns over eight days around the turn of each month (days -4 to +4). They found returns to be large and significantly positive for ten countries on the last trading day (-1) of the month. They also found cumulative returns on the four days around the turn of the month (-1 to +3) to be higher than an average four days in the month. In six countries over 70% of the average return of the month is concentrated in five days or less around the turn of the month. These results are in line with the findings of Lakonishok and Smidt (1988) for U.S. data.

[10] First half of month: first through fifteen calendar days of the month, if it is a trading day, or if not, through the next trading day. Last half of the month are remaining days.

2.3.1 Preferred Habitat Hypothesis

A possible explanation for the turn of the month effect is the fact that a standardization in the payment system in the U.S. causes a regularity in stock return and this effect is related to monetary policy. According to Ogden (1987) who argues that the end of each calendar month is a preferred habitat because the turn of each calendar month is a typical payoff date for accrued real wages, dividends, interest, principal payments and other liabilities. [11] When employees receive their money they either invest it in stocks or they have automatic transfers to institutional funds. These funds have higher liquidity around the end of the month, so this could lead to higher returns when investing.

Penman's (1987) findings suggest that the effect can partly be explained by a tendency of firms to announce good news during the first half of the month and bad news during the second half. Institutional investors try to clear their portfolio by selling the losers and buy stocks which performed well during last month. With this manner they can show better results to the management and their possible investors. This method is called window dressing and is also a possible explanation for the January effect.

In the paper from Sar (2003) they find evidence for persistently anomalous returns around the turn of the month over a five day period from -1 to +4. The returns during these days increased to about five times as high as a regular day, however their significant effect is less extreme than the effect measured by Agrawal and Tandon (1994).

[11] According to Moody's Manuals approximately 70% of interest and principal payments on corporate debt are payable on either the first or the last business day of the calendar month.

3. Data & Methodology

To do research whether the earlier mentioned effects are present in both countries, first the hypothesis need to be stated and tested. In the first paragraph the data set will be tested on normality, stationarity, heteroscedasticity, outliers and autocorrelation. In the second paragraph the descriptive statistics will be mentioned and in the last paragraph the methodology will be explained regarding the existence of the effect.

3.1 Data

To investigate the existence of calendar anomalies the closing values of the stock market are needed. For the U.S. market the data are obtained through Datastream, therefore daily returns are used for the S&P 500 Composite total return index (RI).[12] Another important notice to pick the right returns is the fact that dividend play a role. If companies pay dividend, stock prices will decrease and to correct for this in the index dividends are assumed to be reinvested. For the Dutch market the closing values of the indices on each day of the week are obtained from Datastream. The index used is the Total Market Netherlands Return Index (TOTMKNL (RI)), again with daily returns. The returns are total closing values of all indices in the Netherlands. As mentioned earlier it is important to notice that when stock markets are closed the returns are zero percent, this has a negative influence on the mean returns. Therefore days when the stock market were closed are filtered out and weekends are filtered out automatically.

To investigate the day-of-the-week, January and turn-of-the-month effect in the U.S. and Dutch stock markets, first I start with an ordinary least square regression on the first differences of the natural logarithm of daily returns with the following formula:

$$R_t = \ln\left(\frac{P_t}{P_{t-1}}\right) \tag{1}$$

The values P_t and P_{t-1} are for each index for the period t and t-1.

3.1.1. Normality

The daily returns are tested on normality because awareness of being normally distributed is important for your further research. The Jarque-Bera is a goodness-of-fit test of a sample have the skewness and kurtosis matching a normal distribution. If the null hypothesis can be rejected this means that the distribution from which the data came is non-normal (Jarque and Bera, 1987).

[12] The return index represents the theoretical aggregate growth in value of the constituents of the index. The index constituents are deemed to return an aggregate daily dividend which is included as an incremental amount to the daily change in price index.

Figure 1: Output Dutch daily returns (TOTMKNL)

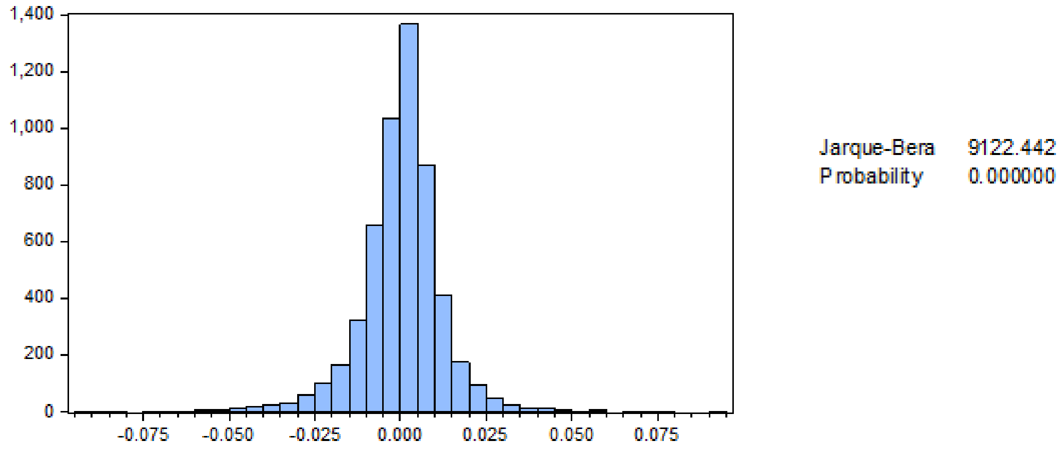
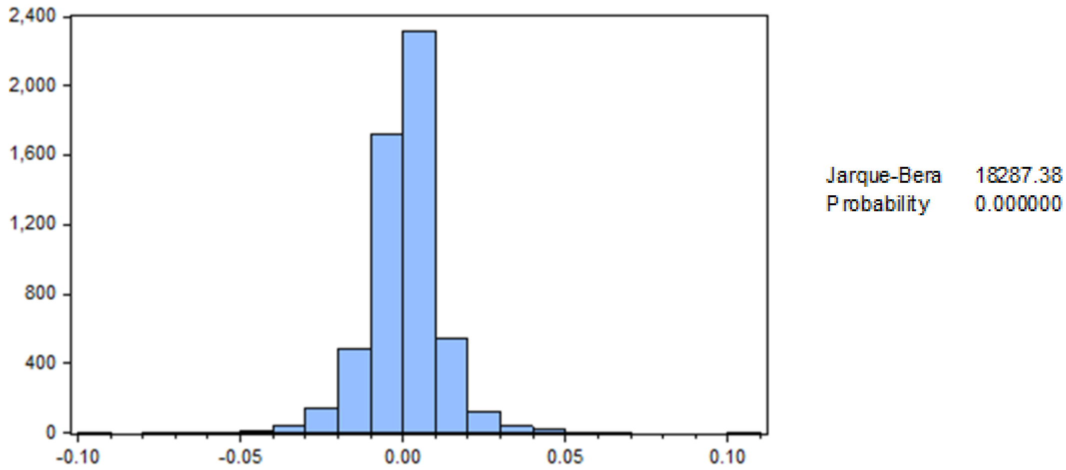


Figure 2: Output U.S. daily returns (S&P 500 Comp)



The null hypothesis for the Jarque-Bera test is that the distribution of the sample is normally distributed. As can be seen in figure 1 and 2 the null hypothesis can be rejected for the Dutch and the US data using a p-value of five percent. This means that the distribution for the daily returns are non-normal. Also the ‘Kurtosis-value’ for both indices is quite high, which means that this high value portrays a chart with fat tails and a low even distribution. This results confirms the outcome of the Jarque-Bera test that the sample is not normal distributed.

3.1.2 Stationarity

When testing for seasonal patterns we have to deal with a time series dataset, this data needs to be stationary otherwise we get a spurious regression. To test the daily returns for non-stationarity the following regression is used:

$$\Delta Z_t = \alpha_0 + \theta z_{t-1} + \alpha_1 \Delta z_{t-1} + \alpha_2 \Delta z_{t-1} + \alpha_3 \Delta z_{t-1} + \alpha_p \Delta z_{t-p} + \varepsilon_t \qquad (2)$$

Where Δ stands for the first-difference operator and (p) is determined by minimizing the Schwartz Bayesian information criterion. This is the augmented Dickey-Fuller test with the null hypothesis that the data has a unit root, the results are as follows:

Table 1: Augmented Dickey-Fuller test

	t-statistic	MacKinnon
Netherlands	-71.27	-3.4314 *
U.S.	-77.47	-3.4314 *

*statistically distinct from 0 at the 1 percent level.

As can be seen in table 1 the daily returns for the Netherlands and the United States give a test statistic of -71.27 respectively -77.47. These values leads to rejection of the null hypothesis due to the corresponding MacKinnon (1991) values, so this means that both data series are stationary.

3.1.3 Heteroscedasticity

When using Ordinary Least Square (OLS) regression one assumption is homoscedasticity. This means that the variance of the residuals have to be constant among all observations. When this is not the case there is heteroscedasticity and this can lead to wrong coefficients and in consequence of this it can happen that t- and p-values give a distorted picture. To test for heteroscedasticity in the U.S. and Dutch dataset the White-test can be used and the results are as follows:

Table 2: Heteroscedasticity test: White

	Obs*R-squared	Probability
Netherlands	22.02	0.107
U.S.	21.07	0.135

In table 1 ‘Obs*R-squared’ is the Chi-squared and this is the White test statistic. As can be seen from the p-values for all indices the null hypothesis of homoscedasticity cannot be rejected with a p-value of 5 percent for the total regression. This means that there is no heteroscedasticity, therefore there will be no correction with the White-correction in further research. However, when checking per explanatory variable for which the hypothesis holds the following results comes out:

Table 3: Heteroscedasticity test: White per effect

	Obs*R-squared	Probability	
Netherlands			
Turn-of-the-month	4.44	0.035	*
January	1.33	0.249	
Day-of-the-week	9.92	0.042	*
U.S.			
Turn-of-the-month	0.05	0.822	
January	1.02	0.313	
Day-of-the-week	6.89	0.142	

*statistically distinct from 0 at the 5 percent level.

As can be seen for the U.S. the null hypothesis of homoscedasticity still cannot be rejected. Conversely, for the Netherlands the turn-of-the-month and the day-of-the-week effect is significant different, so this means that for the total regression the data are not heteroscedastic fully driven by the January variable.

3.1.4 Outliers

Datasets can be negatively influenced by outliers, so they need to be excluded. Instead of deleting outliers it is also possible to winsorize the outliers. This technique keeps the value of the observation significant high or low, however it makes sure that the observations do not wrongly influence the conclusions. All observations which are three times the standard deviation above or beneath the average return will be replaced by this limit value.

3.1.5 Autocorrelation

According the OLS method there is no cohesion between residuals and thus no correlation between consecutive values in the same series of numbers. To test for correlation the daily returns are subjected to a Lagrange- Multiplier test.

Table 4 Breusch-Godfrey Serial Correlation Lagrange- Multiplier Test

	F-statistic	Probability	
Netherlands	4.63	0.0000	*
U.S.	3.59	0.0001	*

*statistically distinct from 0 at the 5 percent level.

When the F-statistic significant differs from zero there is autocorrelation. As can be seen in table 4 the hypothesis for no autocorrelation can be rejected. This means that there is autocorrelation between the daily returns at the U.S. and the Netherlands. This needs to be corrected to keep the standard errors efficient and this will be done by a Newey-West correction.[13]

[13] Estimator which is used to try to overcome correlation and heteroscedasticity in error terms of models

3.1.6 ARCH / GARCH

According to Apolinario, Santana and Sales (2006) an autoregressive conditional heteroscedasticity process (ARCH) model is used to correct for variability in the variance from residuals, for financial date there is volatility clustering. This means that in time series of stock prices it is observed that the variance of daily returns can be high one month and low the next. Today's volatility is correlated with the volatility in the next coming period and therefore an ARCH model can account for this. It is highly unlikely that in financial markets the variance of residuals are constant over time. Therefore ARCH assumes that the variance of residuals are not constant, which is heteroscedasticity. Engle (1982) proposed the following model to capture serial correlation in volatility:

$$\sigma^2 = \omega + \alpha(L)\varepsilon_t^2 \tag{3}$$

Where α(L) is the polynomial lag operator and $(\varepsilon_t) \sim N(0, \sigma_t^2)$ is the innovation in the asset return. However, when the polynomial presents a high order there may arise computational problems. To overcome such computation, Bollerslev (1986) introduced the generalized ARCH model (GARCH):

$$\sigma_t^2 = \omega + \beta(L)\sigma_{t-1}^2 + \alpha(L)\varepsilon_t^2 \tag{4}$$

This standard GARCH is characterized by the reaction of volatility in positive and negative shocks in symmetric way, these shocks are upward and downward price movements. However, in reality the negative shocks cause greater pikes in the volatility than the positive due to the fact that when prices go down the debt to equity ratio from a company rises. In consequence of this effect, shareholders believe their future cash flow which depends on the residual value after paying debt is more risky; this is called the leverage effect[14].

For any GARCH model the orders needs to be chosen, this is done through the Schwarz Bayesian Information Criteria (Schwarz, 1978). This is based on the following formula:

$$SIC = 1 + \ln(2\pi) + \ln\left(\frac{ESS}{T}\right) + \frac{k}{T}(\ln T) \tag{5}$$

Where T stands for the sample size, k the number of estimated parameters is and ESS is the sum of squared residuals in the regression. It penalizes more for degrees of freedom than the Aikake Information Criteria (AIC). The model with the smallest criterion value for each GARCH specification is used.

[14] See Brooks, C. (2008), Introductory Econometrics for Finance, p. 404.

With this model the variance can be dependent upon previous lags. The distribution of this model and the model that will be used in this paper are as follows:

$$\sigma_t^2 = \alpha_{tu}\sigma_{t-1}^2 + \alpha_{we}\sigma_{t-1}^2 + \alpha_{th}\sigma_{t-1}^2 + \alpha_f\sigma_{t-1}^2 + \alpha_{jan}\sigma_{t-1}^2 + \alpha_{turn}\sigma_{t-1}^2 + \varepsilon_t \qquad (6)$$

The advantage of using the GARCH model is the fact that besides it examines the arrival of private information, it takes account of tails heavier than normal distribution which is typical for daily return data (Sar, 2003).

When dummy variables were insignificant in the OLS model and appear significant in the GARCH model, this means that there is an effect which is tested. In the chapter results the outcomes from the GARCH models are shown.

3.1.7 Robustness Test

With an econometric model it is the aim to test hypothesis and predictions that come from theories. The output from the regression is robust to changes in the model if the interpretation from the researcher regarding the hypothesis does not change, and this interpretation depends on the research question (Plümper and Neumayer, 2012). Statistical inferences are based only in part upon observations, and this base is formed by assumptions about the underlying situation. These are explicit or implicit assumptions about randomness and independence regarding distributional models. These assumptions are not supposed to be precisely true; they are mathematically convenient rationalizations of a knowledge or belief. The robustness test signifies insensitivity to small deviations from the assumptions (Huber, 2011). So it is resistant to errors and tests your data without being affected by outliers. To make sure if the outcome of the tests stay the same there will be a robustness test being performed for the regression. The robustness test that will be used is the M-estimation (Huber, 1973) which addresses dependent variable outliers where the value of the dependent variable differs markedly from the regression model norm (large residuals).

3.2 Descriptive Statistics

Table 5: Descriptive statistics US and Netherlands.*

	Mean	Median	Maximum	Minimum	Std. Dev.
U.S.	0.034	0.036	10.958	-9.460	1.173
Netherlands	0.033	0.066	9.323	-9.199	1.238

Table 6: Daily returns U.S. and the Netherlands.*

U.S.	Monday	Tuesday	Wednesday	Thursday	Friday
Mean	0.030	0.035	0.036	0.026	0.016
Median	0.059	0.076	0.078	0.074	0.090
Std. Dev.	1.312	1.142	1.142	1.210	1.069
Maximum	10.958	5.578	5.575	6.704	6.154
Minimum	-9.347	-9.460	-9.460	-7.921	-6.004

NL	Monday	Tuesday	Wednesday	Thursday	Friday
Mean	0.073	0.033	0.013	0.004	0.040
Median	0.010	0.052	0.048	0.069	0.059
Std. Dev.	1.412	1.159	1.194	1.236	1.164
Maximum	9.323	5.949	7.013	7.015	7.432
Minimum	-9.199	-5.487	-8.068	-6.479	-8.055

Table 7: Mean percentage rates of returns per month U.S. and the Netherlands.*

	J	F	M	A	M	J	J	A	S	O	N	D
U.S.	0.027	-0.013	0.061	0.098	0.029	-0.010	0.017	-0.008	0.010	0.074	0.078	0.081
Netherlands	0.024	0.049	0.054	0.090	0.011	-0.006	0.065	-0.023	-0.093	0.065	0.053	0.141

Table 8: Mean percentage rates of returns around the turn-of-the-month. Days +1 and -1 denote, respectively, the first and the last trading days of a month in each country.*

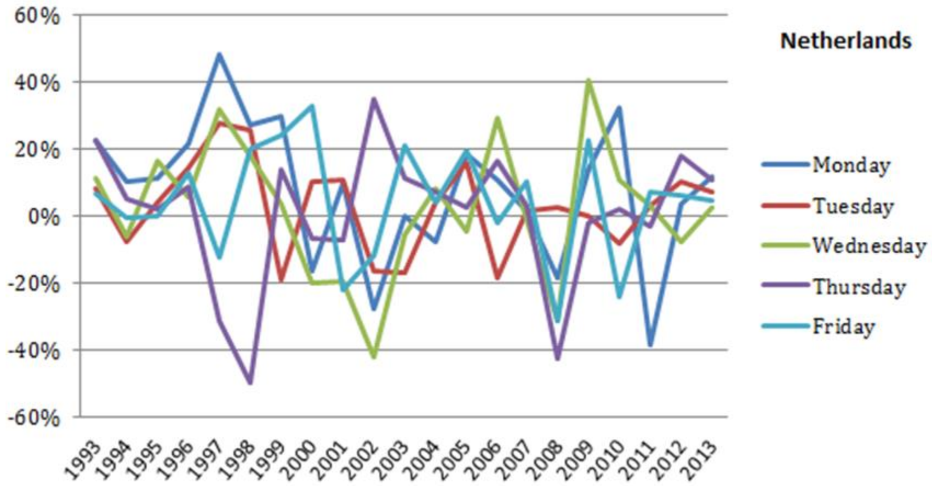
	-1	+1	+2	+3
U.S.	-0.030	0.216	0.037	0.157
Netherlands	0.114	0.223	0.115	0.076

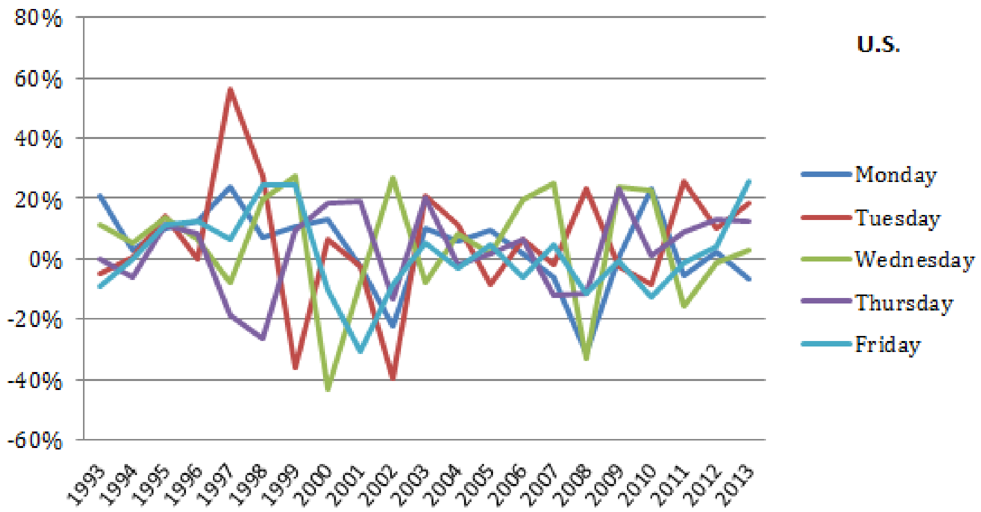
*Returns are defined as $R_t = \ln(P_t/P_{t-1}) * 100\%$.

Table 5 shows descriptive statistics for the daily returns of the stock markets for both countries. Both countries seem to behave in the same way when looking at the mean, standard deviation, minimum and maximum of the daily returns. It seems that both are not extremely volatile markets and this is interesting to take into account because you would expect the calendar anomalies to be more present in volatile markets. We can see if that is true in a later stage of the research.

Table 6 shows the pattern of the daily returns divided per day of the week. What can be noticed for the Netherlands is the higher mean return for Mondays in comparison to the other days, for the United States all the average daily returns are quite the same. In table 7 the mean returns are divided by months and what can be noticed is that the mean returns in both the United States and the Netherlands are highest in April and December. Possible explanation for the higher December return can be found in the fact that investors want to reach desired cash positions at the end of the year, but this will be explained later. When looking at table 8 the returns are divided by the end of the month and the beginning of the month. Most obvious notice from this table is the higher return on day +1 in both countries. Explanation for this higher return is the liquidity hypothesis, however this will be explained later in this paper.

Figure 3: Average return for the Netherlands and U.S. from the close of the previous trading day to the close of the day indicated*





*Returns are defined as $R_t = \ln(P_t/P_{t-1}) * 100\%$

In figure 3 the annual mean returns over the past 20 years are shown for both U.S. and Dutch stock market. The patterns for both countries are similar for each day with a few discrepancies. Interesting to see is that for both the Monday had the least negative average returns in total, with only five in the Netherlands and six in the United States. For the Dutch market Wednesday had with nine the most negative average returns and for the U.S. this holds for the same nine but then for the Friday.

3.3 Methodology

The daily returns for the indices seem to be in line with the trading time. Therefore, to test for all the possible effects which can occur with the trading time there can be regressions performed. In this chapter they will be described for the day-of-the-week effect, January effect and the turn-of-the-month effect.

3.1.1 Day-of-the-Week Effect

For the day-of-the-week effect there are significant differences in average daily returns across days of the week and at the beginning of the week the returns are the lowest and at the end of the week highest. Following French (1980) I will use dummy variables to test for the day-of-the-week-effect and the formula is as follows:

$$R_t = \alpha_0 + \alpha_{tu}D_{tu} + \alpha_w D_w + \alpha_{th}D_{th} + \alpha_f D_f + \varepsilon_t \tag{7}$$

The returns are regressed on four daily dummies without a Monday dummy to avoid the dummy variable trap of perfect multicollinearity when all possible dummies plus an intercept are included.[15] R_t is the dependent variable and this will be the daily return on day t and D_{tu}, D_w, D_{th} and D_f are dummy variables which take value one when it is a certain day of the week and value zero otherwise. With this regression it is possible to see if abnormal returns are realized in the U.S. stock market and the Dutch stock market in comparison with the Monday.

According to Berument and Kiymaz (2001) specifically in stock markets there can be big problems with autocorrelation, so to overcome this problem there will be one or two week lags added to the regression, the regression which comes along with this is as follows:

$$R_t = \alpha_0 + \alpha_{tu}D_{tu} + \alpha_w D_w + \alpha_{th}D_{th} + \alpha_f D_f + \alpha R_{t-5} + \alpha R_{t-10} + \varepsilon_t \tag{8}$$

The lag is given 5 because this means one week because there is no trading in weekends and 10 stands for two weeks. Over the entire sample period, the day-of-the-week effects can be caused by excessive effects during a particular sub-period. Therefore the Quandt–Andrews breakpoint test is carried out on the OLS regression. This test is looking for unknown structural breaks in the estimated parameters. The null hypothesis for this test is that there

[15] See Brooks, C. (2008), Introductory Econometrics for Finance, p. 455-456.

are no structural breaks in all variables simultaneously. Quandt–Andrews test conducts a single Chow Breakpoint test at every observation between two observations, τ_1 and τ_2.

3.1.2 January Effect

To investigate the January effect in the Dutch and U.S. stock market I will start as mentioned above with an ordinary least square regression analysis. With the January effect there has to be significant higher abnormal returns in January compared to other months. The OLS regression that will be used to test for this hypothesis is:

$$R_t = \alpha_0 + \alpha_{jan} D_{jan} + \varepsilon_t \tag{9}$$

Dj is a dummy variable which takes value 1 if it is a day in January and 0 otherwise. With this manner R_t is the dependent variable and stands for the daily returns.

In line with the method from Moller and Zilca (2008) I will use daily returns due to the fact that they give a better understanding of the evolution of the effect. In the paper from Kang and Wickremasinghe (1999) they investigate the fact whether data is adapted to outliers. They show evidence that the January effect is sensitive to outliers with a dataset concerning a few small outliers. When excluding these outliers, they found no significant evidence for the January effect anymore. In consequence of this fact I will exclude outliers. If there is no January effect in my time period from 1993 until 2013, then it is also possible according to Chen and Singal (2003) to test whether the effect has shifted to December. As well as for the day-of-the-week effect, there will be done a Quandt–Andrews test to check for breakpoints.

3.1.3 Turn-of-the-month Effect

The turn-of-the-month effect expects higher returns around the switch between the last day and the first day of the month. Based on the papers from Lakonishok and Schmidt (1988) and Agrawal and Tandon (1994) the period of the turn will be between the last day of the month (-1) and the first three days of the new month (+3). To investigate if there is a significant higher return on these days the following formula will be used:

$$R_t = \alpha_0 + \alpha_{turn} D_{turn} + \varepsilon_t \tag{10}$$

In the formula D_{turn} is the dummy variable that it will be a day in the interval between -1 until +3. For each year there will be done a regression for the period from the first of January until 31st of December. R_t is again the dependent variable and stands for the daily returns.

3.1.4 Regression Effects

To see whether the effects are visible in the countries, the formulas for all the three effects will be combined into one regression. This regression is as follows:

$$R_t = \alpha_0 + \alpha_{tu}D_{tu} + \alpha_w D_w + \alpha_{th}D_{th} + \alpha_f D_f + \alpha R_{t-5} + \alpha R_{t-10} + \alpha_{jan}D_{jan} + \alpha_{turn}D_{turn} + \varepsilon_t \quad (11)$$

As can be seen in the regression the dependent variable R_t stands for daily returns. All the dummies for the effects are included and as mentioned in earlier paragraphs and there are 10 lags included to overcome the autocorrelation problem.

4. Results

4.1 Day-of-the-Week Effect

For the day-of-the-week effect you expect differences in average returns between the trading days during the week. In this paragraph the results are shown for the U.S. and the Dutch stock market for the possible effect of different days on the returns. First the effect on the daily returns are tested with a regression without lags and thereafter the results are shown when lags are included[16], which means that the returns for trading today are correlated with trading before. These five and ten lags which are included are standing for one and two trading weeks respectively.

<u>Effects without lags</u>

In table 9 the coefficients are stated for all days of the week and their possible significant effect on the average returns compared to Monday. As can be seen the results are not significant for all days, this means that there is no evidence for the day-of-the-week effect. All the different days in the United States have no significant influence on the daily returns when there are no lags included. These findings are in line with the outcomes from the paper from Kohers et al. (2004), they found that they day of the week effect existed between 1980 and 1990, however between 1991 and 2002 this effect disappeared. Interesting to see is the movement during the week that on Tuesday the effect is the most positive and at the end of the week the effect on the daily return is slightly negative. However, all these effects are not significant so it is not possible to state that the effects have any predictive value.

For the Netherlands the same effects hold as for the United States, however all the daily effects are slightly negative. This means that you expect a lower return in the Netherlands for all days compared to Monday, however all these effects are not significant so again it is not possible to state this conclusions. The findings for the Netherlands are also the same as

[16] See table 9 column 1 for regression outcomes excluding lags and column 2 when lags are included.

in the article from Kohers et al. (2004), they found evidence for the day of the week effect between 1980 and 1990 in the Netherlands, hereafter until 2002 this significant effect disappeared.

In the last column from table 9 the header ''combined'' gives the statistics for the regression done with all the daily returns from both countries together. As can be seen the coefficients are still not significant for all the days of the week, so this means when all daily returns for the Netherlands and the United States are investigated together, the outcomes stay the same for the day-of-the-week effect.

Influence country

Table 10 shows that the influence of the country on the seasonal effects can also be observed. In table 10 the United States is the base country and the coefficients are the differences to the Netherlands. As can be seen for the day-of-the-week effect all days have a higher effect compared to Monday in the U.S. compared to the Netherlands. Nevertheless, all these effects do not have an significant impact.

<u>Effects with lags</u>

In column 2 in table 9 the coefficients are stated where 5 and 10 lags are included. The number of lags are standing for days of the week. These lags are included due to the fact that stock prices are correlated and with 10 lags the past two trading weeks is taken into account, as can be seen these lags influence the coefficients.

Following the statistics for the United States, the pattern for the week is still the same as in the analysis for the regression without lags. The effect for Tuesday is slightly positive and for Friday this effect is the opposite, however the differences between the average daily returns across the day of the weeks are not significant.

For the Netherlands the day-of-the-week effect is also not present, this follows from the insignificant coefficients per day, so it is not possible to observe differences between daily returns per day. What is surprisingly for the Netherlands is that all the days have a negative effect on the average returns compared to Monday.

As can be seen in the last column from table 9 the effects for the days stay the same when both countries are combined, so there are no differences as when analyzed separated.

Influence country

Regarding the differences between the countries the same outcomes can be observed for all days in table 10. Only when the lags are included the Friday impact becomes positive which means that for the Netherlands the returns can be higher than in the United States. However all the differences between the two countries are not significant.

When computing a robustness test, to see whether the outcomes change when they are not affected, the effects stay the same.[17] So for both countries the day-of-the-week effect is not visible. Also, the Quandt – Andrews test shows that there are no structural breakpoints in the stock returns for both countries.[18] This means that the results are the same for the entire sample period and there is no evidence that there is a period of time in the sample when the day-of-the-week effect is present.

4.2 January Effect

The most puzzling empirical finding widely documented is the variation of common stock returns by month of the year (Hawawini and Keim, 1995). Rozeff and Kiney (1976) found that January is a period of high stock returns. As can be seen in table 9 there is no significant effect visible for the month January. Tables 11 and 12 present the mean monthly returns per country which are the same as in the descriptive statistics, however now with the Newey-West t-statistics whether the returns have a significant influence on the returns. The statistics from the Quandt – Andrews test shows that that there are no structural breakpoints in the data for both countries.[19] When computing the Robustness test, the results stay the same for the January effect for both countries.[20] So even if the stock returns are resistant to errors and outliers the January effect still do not exist.

For the United States the result is in contradiction with the findings from Gu (2003), who stated that the January effect is declining but is still observable at the S&P 500.[21] The reason for this declining trend is the fact that the anomaly became well known since 1980 and more experienced investors bought less and sold more stocks in January to gain profits. In the results we find that for the U.S. the mean returns in December are higher than in January. In consequence of this results it cannot be explained by the tax-loss selling at the end of the tax year (Reinganum, 1983). April and December show the highest average returns and these months are the only who are significant. When looking at the standardized coefficients for the unlagged and lagged regression in table 9 for the January effect we see the confirmation for the fact that the effect is not visible because they are not significant.

In the Netherlands the results are in line with the U.S. when looking at the January effect. This evidence is in line with the findings from Sar (2003) where he stated that in the Netherlands there is no support for the existence of the January effect between 1981 and 1999. This outcome is not surprisingly due to the fact that capital gains are not being taxed

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[17] See table 14.
[18] See Appendix B.
[19] See Appendix B
[20] See table 14
[21] Measured with power ratio, evidence that 32 of 52 years (1950-2000) is significant for January effect at S&P 500.

in the Netherlands (apart from some exceptions). The lagged and unlagged regression for the January effect confirm the non-existence of the effect.

In table 9 where the daily returns for the Netherlands and the U.S. are combined to see whether there is an significant effect for the January effect, the outcomes stay the same as when the analysis is done separated. This means that when taking all daily returns from both countries together there is no significant effect for January.

When looking at table 12 for the returns in the Netherlands we see that for the months April and December the returns are highest for the year and significant. A possible explanation can be that investors, in order to avoid price-pressure effects on less liquid stocks at the beginning of the year and to earn a premium on these stocks in January, want to reach desired positions before the end of the year and therefore transfer cash receipts directly instead of parking them until January (Sar, 2003).

When comparing the Netherlands versus the United States in table 10 the effect is slightly negative for the Netherlands. This means that the returns in the Netherlands are a fraction more negative than in the U.S. in January compared to other months of the year, however this effect is not significant so it is not possible to state that this conclusion is completely true.

A possible explanation that the January effect is not visible in the United States can be that the effect is greater for stocks in small firms and in this paper only the stocks from bigger firms are tested. This is due to the fact that individual investors hold proportionately more small firm stocks and institutional investors hold more stocks of large firms (Ritter, 1988). When individual investors realize more liquid profits at the end of the calendar year than institutional investors, the returns in January will be greater for small firm stocks than for large firm stocks (Ogden, 1990). For the Netherlands this explanation can also hold due to the fact that for this country only the biggest companies are investigated.

4.3 Turn-of-the-Month Effect

The turn-of-the-month effect denotes excessively high returns realized on five or less consecutive trading days around the turn of the month. Ariel (1987) proved that this effect existed in the U.S. between 1963 and 1981. In his research he made a comparison between the first half of the month with the last day of the last month and the second half of the month. In the paper from Lakonishok and Smidt (1988) they researched the turn-of-the-month effect by looking at the last day of the last month and the first three days of the month in the period between 1897 and 1986. They found abnormal high returns during these days and confirmed the findings from Ariel (1987). According to Agrawal and Tandon (1994) the turn-of-the-month effect is also present in many other countries and especially on the last trading day of the month.

Table 13 reports the average daily returns on the S&P 500 between 1993 and 2013 over four days around the turn of the month, days -1 to +3, the returns increase during the first three days and on the first (+1) and third (+3) trading day the effect is significant. However, the last trading day is negative and according to Ariel (1987) the returns should be positive from the last trading upon the first half of the month, so nowadays the returns only get positive from the first day of the new month. Table 9 shows that the effect is not significant for the U.S. when the lags are not included, but the effect is significant when the lags are included. So when taken into account that prices are related to earlier stock returns, the effect is visible. The robustness test result also shows that the significant effect stays for the United States.[22]

In table 13 the average daily returns for the Netherlands are posted, from day -1 to +3. Returns are large and significantly positive (relative to an average day) for the first trading day (+1) of the month. Agrawal and Tandon (1994) found that the returns in the Netherlands are positive and significant for the trading days -1, +1 and +2.[23] So the effect is less extreme nowadays. This result is in line with the findings from Sar (2003), he found also a significant effect but this effect was also less extreme than the results from Agrawal and Tandon (1994). As can be seen in table 9 the turn-of-the-month effect is visible for the Netherlands, either when excluding respectively including the lags. The outcome from the robustness test shows that the outcomes stay the same[24].

When looking at the combined column in table 9 the result for the turn-of-the-month effect is significant either when including respectively excluding lags. In table 10 the comparison between the two countries is measured for the turn-of-the-month effect. As can be seen the differences are not significant. However, the turn-of-the-month effect is the only effect from the ones measured that is positive in the Netherlands. This means that the returns in the Netherlands are higher during the turn-of-the-month compared to normal days in the month versus the United States. Only note is that the effect is not significant, so it is not possible to state that this effect can be reported.

Ogden (1990) argues a good explanation for the turn-of-the-month effect, according to his paper the effect is caused by liquidity hypothesis. This hypothesis states that flows of investment funds increase during the turn of the month because of the bulk of expected monthly cash income for representative investors is received at this period. Due to the fact that investor's liquid profit position generally will be the greatest during the turn of each calendar month, his demand for stocks will be the greatest during this time period. According to Ritter (1988) and Ziemba (1989), they suggest that investors often reinvest their liquid profits quickly.

[22] See table 14.
[23] Research was in time period 1971 – 1987.
[24] See table 14.

Table 9: Seasonal effects per country and combined, in column 1 the effects are shown with lags included and in column 2 when lags are excluded and in last columns the countries are combined.

	U.S.[a]		NL[a]		Combined[a]	
	(1)	(2)	(1)	(2)	(1)	(2)
Tuesday	0.005	0.006	-0.017	-0.015	-0.011	-0.006
	(0.304)	(0.318)	(-1.016)	(-.958)	(0.587)	(0.466)
Wednesday	0.002	0.001	-0.020	-0.016	-0.009	-0.007
	(0.107)	(0.083)	(-1.184)	(-1.053)	(0.423)	(-0.547)
Thursday	-0.002	-0.004	-0.022	-0.022	-0.015	-0.13
	(-0.227)	(-0.230)	(-1.461)	(-1.417)	(0.218)	(-1.090)
Friday	-0.010	-0.010	-0.013	-0.001	-0.011	-0.004
	(-0.544)	(-0.553)	(-0.745)	(-0.065)	(0.351)	(-0.370)
January	-0.003	-0.003	-0.003	-0.003	-0.003	-0.003
	(-0.190)	(-0.221)	(-0.240)	(-0.217)	(-0.305)	(-0.287)
Turn of the	0.027	0.028 *	0.039 *	0.026 *	0.033 **	0.026 *
month	(1.928)	(2.035)	(2.902)	(2.157)	(3.439)	(2.696)

Table 10: US compared to the Netherlands and their influence on effects.[a]

	U.S. compared to NL	
	(1)	(2)
Tuesday	-0.017	-0.012
	(-0.939)	(-0.655)
Wednesday	-0.017	-0.014
	(-0.920)	(-0.778)
Thursday	-0.016	-0.015
	(-0.882)	(-0.842)
Friday	-0.003	0.001
	(-0.882)	(0.058)
January	-0.001	-0.001
	(-0.149)	(-0.082)
Turn of the	0.011	0.013
month	(0.726)	(0.890)

Table 11: Mean monthly percentage returns with Newey-West t-statistics in parentheses for the U.S.[b]

J	F	M	A	M	J	J	A	S	O	N	D
0.027	-0.013	0.061	0.098	0.029	-0.010	0.017	-0.008	0.010	0.074	0.078	0.081
(0.605)	(-0.288)	(1.314)	(2.554) *	(0.771)	(-0.237)	(0.338)	(-0.177)	(0.204)	(1.285)	(1.543)	(2.399) *

Table 12: Mean monthly percentage returns with Newey-West t-statistics in parentheses for the Netherlands.[b]

J	F	M	A	M	J	J	A	S	O	N	D
0.024	0.049	0.054	0.090	0.011	-0.006	0.065	-0.023	-0.093	0.065	0.053	0.141
(0.474)	(0.931)	(1.046)	(2.041) *	(0.258)	(-0.122)	(1.102)	(-0.418)	(-1.406)	(1.074)	(0.944)	(3.268) *

Table 13: Mean percentage rates of returns around the turn-of-the-month. Days +1 and -1 denote, respectively, the first and the last trading days of a month in each country. [b]

	-1	+1	+2	+3
U.S.	-0.030	0.216**	0.037	0.157 *
Netherlands	0.114	0.223**	0.115	0.076

Table 14: Outcomes Robustness Test M-estimation

	Z-statistic	Probability
Netherlands		
Tuesday	1.124	0.261
Wednesday	1.184	0.236
Thursday	1.384	0.167
Friday	*1.572*	*0.116*
January	-0.156	0.876
Turn-of-the-month	3.856	0.000 **
U.S.		
Tuesday	0.866	0.386
Wednesday	1.448	0.148
Thursday	1.745	0.081
Friday	1.339	0.181
January	1.086	0.277
Turn-of-the-month	2.844	0.005 **

Explanatory notes:

[a] Regression standardized coefficients with the t-statistics in parentheses.

[b] Returns are defined as $R_t = \ln(P_t/P_{t-1}) * 100\%$.

** and * denote statistical significance at the 1 percent and 5 percent levels, respectively, in two-tailed tests. Tests are based on Newey-West t-statistics for the difference of the mean from zero.

4.4 GARCH Models

When looking at table 15 the outcomes for the GARCH models are presented for both countries. The ARCH parameter, also named the lagged squared residual, gives a significant high output in the two investigated markets. This has as a consequence that there is autocorrelation in the squared residuals for the S&P 500 and the TOTMKNL, so this means that there is an ARCH effect.

Table 15: Estimation results of calendar effects in daily returns for the S&P 500 and the TOTMKNL with the variance specified related to an ARCH/GARCH structure.

	Netherlands			United States		
Variable	**Coefficient**	**Std. Error**	**p-value**	**Coefficient**	**Std. Error**	**p-value**
Equation for the mean						
Dummy Tuesday	0.002	0.026	0.945	-0.034	0.038	0.365
Dummy Wednesday	0.035	0.025	0.162	0.007	0.034	0.846
Dummy Thursday	0.040	0.025	0.118	-0.035	0.034	0.301
Dummy Friday	0.030	0.026	0.239	-0.036	0.033	0.273
Dummy January	0.052	0.036	0.152	0.003	0.034	0.925
Dummy turn-of-the-month	0.156	0.027	0.000	0.065	0.027	0.017
Variance equation						
Constant	0.009	0.002	0.000	0.009	0.002	0.001
ARCH (1)	0.079	0.008	0.000	0.064	0.007	0.000
GARCH (1)	0.914	0.008	0.000	0.928	0.007	0.000

* All coefficients estimates other than the one corresponding with ARCH(1) and GARCH(1) are in percentage points, and the standard errors are heteroskedasticity consistent (Bollerslev-Wooldridge).

The lagged conditional variance, also named as the GARCH, is significant in both countries. So this means that there is a positive relation between the volatility and the stock returns. What follows from the table is also that for the Netherlands Friday is the most volatile day and for the U.S. this is Monday.

When analyzing the data for the Netherlands we see that still all the dummy variables cannot be rejected for the day-of-the-week and the January effect. Only the dummy for turn-of-the-month is still significant.

For the U.S. we see that the turn-of-the-month effect is still significant which is in line with the OLS outcome. All the other dummies are still not significant in the GARCH model. The possibility that the day-of-the-week effect occurred due to measurement errors is not the case for this paper. Besides the fact that there is no evidence for this effect, the outcome from the GARCH model is that the effect after adjustment is not visible.

5. Limitations and Extensions

In this paper there has been done research to the existence of seasonal anomalies in stock markets in the Netherlands and the United States for the period 1983 until 2013. We found evidence that the only existing anomaly nowadays is the turn-of-the-month effect in both countries. When comparing the two countries there are no significant differences between the two regarding the seasonal anomalies. To limit the research only the three largest anomalies are investigated. A possibility is to test whether it is possible to obtain abnormal returns during other time periods, for example trading in the morning compared to the afternoon.

Also it is a possibility to research possible explanations for anomalies. With the knowledge from the existence of the turn-of-the-month effect it will be interesting to test in future research what the reasons are for this anomaly. It is possible to test whether this effect is caused by the liquidity hypothesis by doing an experiment in real life or by doing an analysis with more variables that can explain this anomaly.

It is hard to trade on the results from this study for individual investors to obtain high returns at the end of a month due to the fact that they deal have to deal with transaction costs. With this costs it can be not profitable anymore to trade during the end of a month. For institutional investors it can be profitable, however it is not entirely sure that this theoretical profit can also be made in practice.

6. Conclusion

In this paper various seasonal patterns are measured from daily returns for the Netherlands and the United States. The results show that there is no existence of the day-of-the-week effect, meaning that all separate days do not have significantly higher returns compared to Monday. These results stay the same when testing with and without lags included. When looking at the results for the United States we found that at the beginning of the week the average returns were slightly positive and became negative at the end of the week. For the Netherlands all days of the week had slightly negative returns. When comparing the U.S. with the Netherlands, the Netherlands had all days of the week a negative relation in relation to the United States, except for Fridays. When comparing the United States with the Netherlands the impact of the country is not significant, only outcome that can be observed is that in the U.S. all days have a positive return compared to the Netherlands. However, all these results were not significant so it is impossible to draw this conclusion.

For the January effect there is also no evidence for the existence of this anomaly. In earlier papers was stated that this effect was already declining over the years. For this research the effect did not exist anymore, reasons for this can be that the effect do not hold for the larger firms. In this paper only the biggest companies in the U.S. have been tested and according to

Ogden (1990) the returns for small firm stocks have been higher than for large firm stocks. In the Netherlands the effect is not present what can be driven by the fact that capital gains are not being taxed. What was surprisingly in the two countries was that the average return in April and December is significantly higher. For December this can be explained by the fact that people want to reach desired liquid positions at the beginning of the year and therefore transfer cash receipts directly instead of parking them until January. When comparing the Netherlands with the United States for the January effect, the only observed outcome is that the Netherlands have just like with the days of the week a negative relation to the returns. This result is not significant, so it not possible to conclude that this effect is true.

The turn-of-the-month effect was the only effect which existed in both countries during the investigated time period, this effect can be explained by the liquidity hypothesis. This means that investment funds have an increased flow at the end of the month because most individual investors receive their monthly cash income at this period. With the improvement of the liquidity position the investors demands more stocks during this time period. According to Ritter (1988) and Ziemba (1989) investors often reinvest their liquid profits quickly. If the Netherlands and the U.S. are compared regarding the turn-of-the-month effect wat can be noticed is that for this effect the Netherlands have a positive relation to the daily returns. So the average daily returns can be higher at the turn of the month in the Netherlands in comparison with the United States. However, this conclusion is not significant so it is again not possible to state that this is true.

All the seasonal effects have also been tested in the GARCH model. The results show that there is a significant ARCH and GARCH effect. This means that there is autocorrelation between the squared residuals respectively a positive relation between the volatility and the stock returns. The outcomes from the GARCH model show that the turn-of-the-month effect is still visible for both the United States and the Netherlands. Only effect what changed in comparison with the OLS regression is the influence from the Wednesday in the United States, which is now significant and positive. A possible explanation for this change is that when volatility is not taken into account the day-of-the-week effects are neglected for the market. The results from this paper are in line with the paper from Marquering et al (2006), who stated that the turn-of-the-month effect is the only still current anomaly.

7. References

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8. Appendix

A. List TOTMKNL

			Netherlands	Euro	Equity
UNILEVER CERTS.	H:UNIL	42Y	Netherlands	Euro	Equity
HEINEKEN	H:HB	42Y	Netherlands	Euro	Equity
ASML HOLDING	H:ASML	20Y	Netherlands	Euro	Equity
PHILIPS ELTN.KONINKLIJKE	H:PHIL	42Y	Netherlands	Euro	Equity
ALTICE	H:ATC	1Y	Netherlands	Euro	Equity
UNIBAIL-RODAMCO	H:UBL	41Y	France	Euro	Equity
AHOLD KON.	H:AH	42Y	Netherlands	Euro	Equity
KPN KON	H:KPN	21Y	Netherlands	Euro	Equity
AKZO NOBEL	H:AKZO	42Y	Netherlands	Euro	Equity
HEINEKEN HLDG.	H:HBA	42Y	Netherlands	Euro	Equity
AEGON	H:AGN	42Y	Netherlands	Euro	Equity
ARCELORMITTAL	H:MT	18Y	Netherlands	Euro	Equity
RELX	H:REN	38Y	Netherlands	Euro	Equity
RANDSTAD HOLDING	H:RAND	25Y	Netherlands	Euro	Equity
DSM KONINKLIJKE	H:DSM	26Y	Netherlands	Euro	Equity
HAL TRUST	H:HAT	42Y	Netherlands	Euro	Equity
WOLTERS KLUWER	H:WSG	42Y	Netherlands	Euro	Equity
NN GROUP	H:NN	1Y	Netherlands	Euro	Equity
GEMALTO	H:GTO	11Y	Netherlands	Euro	Equity
OCI	H:OCIO	2Y	Netherlands	Euro	Equity
PERSHING SQUARE HDG.	H:PSH	<1Y	Netherlands	United	Closed-End Fund
VOPAK	H:VPK	15Y	Netherlands	Euro	Equity
BOSKALIS WESTMINSTER	H:BOSK	42Y	Netherlands	Euro	Equity
GRANDVISION	H:GVNV	<1Y	Netherlands	Euro	Equity
AALBERTS INDUSTRIES	H:ALBI	28Y	Netherlands	Euro	Equity
ASM INTERNATIONAL	H:ASIN	18Y	Netherlands	Euro	Equity
DELTA LLOYD GROUP	H:DL	5Y	Netherlands	Euro	Equity
TNT EXPRESS	H:TNTE	4Y	Netherlands	Euro	Equity
APERAM	H:APAM	4Y	Netherlands	Euro	Equity
CORBION	H:CRBN	42Y	Netherlands	Euro	Equity
POSTNL	H:PNL	17Y	Netherlands	Euro	Equity
ROBECO	H:ROBA	42Y	Netherlands	Euro	Closed-End Fund
RORENTO DH	H:ROR	41Y	Netherlands	Euro	Closed-End Fund
SBM OFFSHORE	H:SBMO	42Y	Netherlands	Euro	Equity
WERELDHAVE	H:WH	42Y	Netherlands	Euro	Equity
AP ALTERNAT ASSETS	H:APAA	8Y	United Kingdom	United	Closed-End Fund
ARCADIS	H:HDJ	19Y	Netherlands	Euro	Equity
EUROCOMMERCIAL	H:SIPF	23Y	Netherlands	Euro	Equity
FUGRO	H:FUG	23Y	Netherlands	Euro	Equity
GALAPAGOS	B:GLPG	10Y	Belgium	Euro	Equity
IMCD GROUP	H:IMCD	1Y	Netherlands	Euro	Equity
ROLINCO	H:RLC	42Y	Netherlands	Euro	Closed-End Fund
TEN CATE	H:NTC	42Y	Netherlands	Euro	Equity
TOM TOM	H:TOM	10Y	Netherlands	Euro	Equity
VAN LANSCHOT	H:VANL	16Y	Netherlands	Euro	Equity
WESSANEN	H:BOWE	42Y	Netherlands	Euro	Equity
BAM GROEP KON.	H:BAM	42Y	Netherlands	Euro	Equity
BE SEMICONDUCTOR	H:BESI	19Y	Netherlands	Euro	Equity
BINCKBANK	H:BINC	30Y	Netherlands	Euro	Equity
BRUNEL INTL.	H:BRU	18Y	Netherlands	Euro	Equity
HUNTER DOUGLAS	H:HD@A	42Y	Netherlands	Euro	Equity
MOTA ENGIL AFRICA	H:MEAF	<1Y	Portugal	Euro	Equity
ORDINA	H:ORB	28Y	Netherlands	Euro	Equity
REFRESCO GERBER	H:RFRG	<1Y	Netherlands	Euro	Equity
ROYAL IMTECH	H:IM	42Y	Netherlands	Euro	Equity
SLIGRO FOOD GROUP	H:SGRB	25Y	Netherlands	Euro	Equity
TETRAGON FINANCIAL	H:TEFG	8Y	United Kingdom	United	Closed-End Fund
TKH GROUP	H:TKF	42Y	Netherlands	Euro	Equity
AFC AJAX	H:AFC	17Y	Netherlands	Euro	Equity

AMER HYPOBANK	H:TNLA	16Y	Netherlands	Euro	Equity
AMG	H:AMG	8Y	Netherlands	Euro	Equity
AMSTERDAM	H:ARBR	42Y	Netherlands	Euro	Equity
AND INTL.PUBLISHERS	H:AND	18Y	Netherlands	Euro	Equity
BALLAST NEDAM	H:BALL	21Y	Netherlands	Euro	Equity
BATENBURG TECHNIEK	H:BAT	42Y	Netherlands	Euro	Equity
BETER BED HOLDING	H:BET	18Y	Netherlands	Euro	Equity
BEVER HOLDING	H:BEV	32Y	Netherlands	Euro	Equity
BOUSSARD GAVAUDAN E	H:BOG	8Y	United	Euro	Closed-End Fund
BRILL (KON.)	H:BRL	18Y	Netherlands	Euro	Equity
CTAC NM	H:CTAC	17Y	Netherlands	Euro	Equity
DICO INTL.	H:DICO	28Y	Netherlands	Euro	Equity
DOCDATA	H:DOC	18Y	Netherlands	Euro	Equity
DPA GROUP	H:DPAF	16Y	Netherlands	Euro	Equity
ESPERITE	H:ESP	5Y	Netherlands	Euro	Equity
EUROCASTLE INV.	H:ECT	9Y	United	Euro	Equity
EUROPEAN ASSET TRUST	H:EURA	30Y	Netherlands	Euro	Closed-End Fund
GRONTMIJ	H:GRON	33Y	Netherlands	Euro	Equity
GROOTHANDELSGEB.	H:GROT	30Y	Netherlands	Euro	Equity
HEIJMANS	H:HEI	21Y	Netherlands	Euro	Equity
HOLLAND COLOURS	H:HCA	25Y	Netherlands	Euro	Equity
HYDRATEC INDUSTRIES	H:HYDR	17Y	Netherlands	Euro	Equity
ICT AUTOMATISERING	H:ICTA	18Y	Netherlands	Euro	Equity
INVERKO	H:INVR	15Y	Netherlands	Euro	Equity
KARDAN N V	H:KARD	12Y	Netherlands	Euro	Equity
KAS BANK	H:KAS	28Y	Netherlands	Euro	Equity
KENDRION	H:SCHV	42Y	Netherlands	Euro	Equity
KIADIS	H:KDS	<1Y	Netherlands	Euro	Equity
LAVIDE HOLDING	H:LVID	16Y	Netherlands	Euro	Equity
LUCASBOLS	H:BOLS	<1Y	Netherlands	Euro	Equity
MACINTOSH RETAIL	H:MAC	42Y	Netherlands	Euro	Equity
MTY HOLDINGS	H:MTY	33Y	Netherlands	Euro	Equity
NB PRIVATE EQUITY PTNS.	H:NBPE	8Y	Channel	United	Equity
NEDAP	H:NDAP	42Y	Netherlands	Euro	Equity
NEDSENSE ENTERPRISES	H:NEDE	16Y	Netherlands	Euro	Equity
NEW SOURCES ENERGY	H:NSE	28Y	Netherlands	Euro	Equity
NEWAYS ELEC.INTL.	H:NEW	28Y	Netherlands	Euro	Equity
NOVISOURCE	H:1NON	42Y	Netherlands	Euro	Equity
NSI	H:NSI	17Y	Netherlands	Euro	Equity
ORANJEWOUD 'A'	H:MUL	29Y	Netherlands	Euro	Equity
PC EMERG EUR REIT	H:MER	11Y	Netherlands	Euro	Equity
PHARMING GROUP	H:PHAR	16Y	Netherlands	Euro	Equity
PORCELEYNE FLES	H:PORF	42Y	Netherlands	Euro	Equity
PROBIODRUG	H:PBD	<1Y	Germany	Euro	Equity
ROODMICROTEC	H:ROD	28Y	Netherlands	Euro	Equity
ROTO SMEETS	H:ROTO	42Y	Netherlands	Euro	Equity
ROYALREESINK	H:RE	42Y	Netherlands	Euro	Equity
SNOWWORLD	H:SNOW	22Y	Netherlands	Euro	Equity
STERN GROEP	H:AIR	42Y	Netherlands	Euro	Equity
TELEGRAAF MEDIA GROEP	H:TMG	42Y	Netherlands	Euro	Equity
TIE KINETIX	H:TIE	15Y	Netherlands	Euro	Equity
VALUE8	H:VALU	29Y	Netherlands	Euro	Equity
HUNTER DOUGLAS PREF.	H:HUNT	29Y	Netherlands	Euro	Preference Share
ROLINCO 6.5% CUM.PF.	H:ROLC	24Y	Netherlands	Euro	Preference Share
VALUE8 PREFERENCE	H:PREV	3Y	Netherlands	Euro	Equity
USG PEOPLE	H:USG	42Y	Netherlands	Euro	Equity
VASTNED RETAIL	H:VAST	27Y	Netherlands	Euro	Equity
ACCELL GROUP	H:ACCE	16Y	Netherlands	Euro	Equity

S&P 500 Composite Index

Company	Industry	Company	Industry
3M Company	Industrial Conglomerates	Johnson & Johnson	Health Care Equipment & Services
Abbott Laboratories	Health Care Equipment & Services	Johnson Controls	Auto Parts & Equipment
AbbVie	Pharmaceuticals	Joy Global Inc.	Industrial Machinery
Accenture plc	IT Consulting & Other Services	JPMorgan Chase & Co.	Banks
ACE Limited	Property & Casualty Insurance	Juniper Networks	Networking Equipment
Adobe Systems Inc	Application Software	Kansas City Southern	Railroads
ADT Corp	Diversified Commercial Services	Kellogg Co.	Packaged Foods & Meats
Advance Auto Parts	Automotive Retail	KeyCorp	Banks
AES Corp	Independent Power Producers & Energy Traders	Keurig Green Mountain	Packaged Foods & Meats
Aetna Inc	Managed Health Care	Kimberly-Clark	Household Products
AFLAC Inc	Life & Health Insurance	Kimco Realty	REITs
Affiliated Managers Group Inc	Asset Management & Custody Banks	Kinder Morgan	Oil & Gas Refining & Marketing & Transportation
Agilent Technologies Inc	Health Care Equipment & Services	KLA-Tencor Corp.	Semiconductor Equipment
AGL Resources Inc.	Gas Utilities	Kohl's Corp.	General Merchandise Stores
Air Products & Chemicals Inc	Industrial Gases	Kraft Heinz Co	Packaged Foods & Meats
Airgas Inc	Industrial Gases	Kroger Co.	Food Retail
Akamai Technologies Inc	Internet Software & Services	L Brands Inc.	Apparel Retail
Alcoa Inc	Aluminum	L-3 Communications Holdings	Industrial Conglomerates
Allergan plc	Pharmaceuticals	Laboratory Corp. of America Holding	Health Care Facilities
Alexion Pharmaceuticals	Biotechnology	Lam Research	Semiconductor Equipment
Allegion	Building Products	Legg Mason	Asset Management & Custody Banks
Alliance Data Systems	Data Processing & Outsourced Services	Leggett & Platt	Industrial Conglomerates
Allstate Corp	Property & Casualty Insurance	Lennar Corp.	Homebuilding
Altera Corp	Semiconductors	Level 3 Communications	Alternative Carriers
Altria Group Inc	Tobacco	Leucadia National Corp.	Multi-Sector Holdings
Amazon.com Inc	Internet Retail	Lilly (Eli) & Co.	Pharmaceuticals
Ameren Corp	MultiUtilities	Lincoln National	Multi-line Insurance
American Airlines Group	Airlines	Linear Technology Corp.	Semiconductors
American Electric Power	Electric Utilities	Lockheed Martin Corp.	Aerospace & Defense
American Express Co	Consumer Finance	Loews Corp.	Multi-Sector Holdings
American International Group, Inc.	Property & Casualty Insurance	Lowe's Cos.	Home Improvement Retail
American Tower Corp A	Specialized REITs	LyondellBasell	Diversified Chemicals
Ameriprise Financial	Diversified Financial Services	M&T Bank Corp.	Banks
AmerisourceBergen Corp	Health Care Distribution & Services	Macerich	Retail REITs
Ametek	Electrical Components & Equipment	Macy's Inc.	Department Stores
Amgen Inc	Biotechnology	Mallinckrodt Plc	Pharmaceuticals
Amphenol Corp A	Electrical Components & Equipment	Marathon Oil Corp.	Oil & Gas Exploration & Production
Anadarko Petroleum Corp	Oil & Gas Exploration & Production	Marathon Petroleum	Oil & Gas Refining & Marketing & Transportation
Analog Devices, Inc.	Semiconductors	Marriott Int'l.	Hotels, Resorts & Cruise Lines
Aon plc	Insurance Brokers	Marsh & McLennan	Insurance Brokers
Apache Corporation	Oil & Gas Exploration & Production	Martin Marietta Materials	Construction Materials
Apartment Investment & Mgmt	REITs	Masco Corp.	Building Products
Apple Inc.	Computer Hardware	Mastercard Inc.	Internet Software & Services
Applied Materials Inc	Semiconductor Equipment	Mattel Inc.	Leisure Products
Archer-Daniels-Midland Co	Agricultural Products	McCormick & Co.	Packaged Foods & Meats
Assurant Inc	Multi-line Insurance	McDonald's Corp.	Restaurants
AT&T Inc	Integrated Telecommunications Services	McGraw Hill Financial	Diversified Financial Services
Autodesk Inc	Application Software	McKesson Corp.	Health Care Distributors & Services
Automatic Data Processing	Internet Software & Services	Mead Johnson	Packaged Foods & Meats
AutoNation Inc	Specialty Stores	Westrock Co	Paper Packaging
AutoZone Inc	Specialty Stores	Medtronic plc	Health Care Equipment & Services
Avago Technologies	Semiconductors	Merck & Co.	Pharmaceuticals
AvalonBay Communities, Inc.	Residential REITs	MetLife Inc.	Life & Health Insurance
Avery Dennison Corp	Paper Packaging	Michael Kors Holdings	Apparel, Accessories & Luxury Goods
Baker Hughes Inc	Oil & Gas Equipment & Services	Microchip Technology	Semiconductors
Ball Corp	Metal & Glass Containers	Micron Technology	Semiconductors
Bank of America Corp	Banks	Microsoft Corp.	Systems Software
The Bank of New York Mellon Corp.	Banks	Mohawk Industries	Home Furnishings
Bard (C.R.) Inc.	Health Care Equipment & Services	Molson Coors Brewing Company	Brewers
Baxalta	Biotechnology	Mondelez International	Packaged Foods & Meats
Baxter International Inc.	Health Care Equipment & Services	Monsanto Co.	Fertilizers & Agricultural Chemicals
BB&T Corporation	Banks	Monster Beverage	Soft Drinks
Becton Dickinson	Health Care Equipment & Services	Moody's Corp	Diversified Financial Services
Bed Bath & Beyond	Specialty Stores	Morgan Stanley	Investment Banking & Brokerage
Berkshire Hathaway	Multi-Sector Holdings	The Mosaic Company	Fertilizers & Agricultural Chemicals
Best Buy Co. Inc.	Computer & Electronics Retail	Motorola Solutions Inc.	Telecommunications Equipment
BIOGEN IDEC Inc.	Biotechnology	Murphy Oil	Integrated Oil & Gas
BlackRock	Asset Management & Custody Banks	Mylan N.V.	Pharmaceuticals
Block H&R	Consumer Finance	NASDAQ OMX Group	Diversified Financial Services

Boeing Company	Aerospace & Defense	National Oilwell Varco Inc.	Oil & Gas Equipment & Services
BorgWarner	Auto Parts & Equipment	Navient	Consumer Finance
Boston Properties	REITs	NetApp	Internet Software & Services
Boston Scientific	Health Care Equipment & Services	Netflix Inc.	Internet Software & Services
Bristol-Myers Squibb	Health Care Distributors & Services	Newell Rubbermaid Co.	Housewares & Specialties
Broadcom Corporation	Semiconductors	Newfield Exploration Co	Oil & Gas Exploration & Production
Brown-Forman Corporation	Distillers & Vintners	Newmont Mining Corp. (Hldg. Co.)	Gold
C. H. Robinson Worldwide	Air Freight & Logistics	News Corp.	Publishing
CA, Inc.	Systems Software	NextEra Energy	MultiUtilities
Cablevision Systems Corp.	Broadcasting & Cable TV	Nielsen Holdings	Research & Consulting Services
Cabot Oil & Gas	Oil & Gas Exploration & Production	Nike	Apparel, Accessories & Luxury Goods
Cameron International Corp.	Oil & Gas Equipment & Services	NiSource Inc.	MultiUtilities
Campbell Soup	Packaged Foods & Meats	Noble Energy Inc	Oil & Gas Exploration & Production
Capital One Financial	Consumer Finance	Nordstrom	Department Stores
Cardinal Health Inc.	Health Care Distributors & Services	Norfolk Southern Corp.	Railroads
Henry Schein	Health Care Distributors	Northern Trust Corp.	Asset Management & Custody Banks
Carmax Inc	Specialty Stores	Northrop Grumman Corp.	Aerospace & Defense
Carnival Corp.	Hotels, Resorts & Cruise Lines	NRG Energy	Independent Power Producers & Energy Traders
Caterpillar Inc.	Construction & Farm Machinery & Heavy Trucks	Nucor Corp.	Steel
CBRE Group	Real Estate Services	Nvidia Corporation	Semiconductors
CBS Corp.	Broadcasting & Cable TV	O'Reilly Automotive	Specialty Stores
Celgene Corp.	Biotechnology	Occidental Petroleum	Oil & Gas Exploration & Production
CenterPoint Energy	MultiUtilities	Omnicom Group	Advertising
CenturyLink Inc	Integrated Telecommunications Services	ONEOK	Oil & Gas Exploration & Production
Cerner	Health Care Distributors & Services	Oracle Corp.	Application Software
CF Industries Holdings Inc	Fertilizers & Agricultural Chemicals	Owens-Illinois Inc	Metal & Glass Containers
Charles Schwab Corporation	Investment Banking & Brokerage	PACCAR Inc.	Construction & Farm Machinery & Heavy Trucks
Chesapeake Energy	Integrated Oil & Gas	Pall Corp.	Industrial Conglomerates
Chevron Corp.	Integrated Oil & Gas	Parker-Hannifin	Industrial Conglomerates
Chipotle Mexican Grill	Restaurants	Patterson Companies	Health Care Supplies
Chubb Corp.	Property & Casualty Insurance	Paychex Inc.	Internet Software & Services
CIGNA Corp.	Managed Health Care	PayPal	Data Processing & Outsourced Services Oil
Cimarex Energy	Oil & Gas Exploration & Production	Pentair Ltd.	Industrial Conglomerates
Cincinnati Financial	Property & Casualty Insurance	People's United Financial	Thrifts & Mortgage Finance
Cintas Corporation	Diversified Support Services	Pepco Holdings Inc.	Electric Utilities
Cisco Systems	Networking Equipment	PepsiCo Inc.	Soft Drinks
Citigroup Inc.	Banks	PerkinElmer	Health Care Equipment & Services
Citrix Systems	Internet Software & Services	Perrigo	Pharmaceuticals
The Clorox Company	Household Products	Pfizer Inc.	Pharmaceuticals
CME Group Inc.	Diversified Financial Services	PG&E Corp.	MultiUtilities
CMS Energy	MultiUtilities	Philip Morris International	Tobacco
Coach Inc.	Apparel, Accessories & Luxury Goods	Phillips 66	Oil & Gas Refining & Marketing & Transportation
The Coca Cola Company	Soft Drinks	Pinnacle West Capital	MultiUtilities
Coca-Cola Enterprises	Soft Drinks	Pioneer Natural Resources	Oil & Gas Exploration & Production
Cognizant Technology Solutions	IT Consulting & Services	Pitney-Bowes	Office Services & Supplies
Colgate-Palmolive	Household Products	Plum Creek Timber Co.	REITs
Columbia Pipeline Group Inc	Oil & Gas Storage & Transportation	PNC Financial Services	Banks
Comcast Corp.	Broadcasting & Cable TV	Polo Ralph Lauren Corp.	Apparel, Accessories & Luxury Goods
Comerica Inc.	Banks	PPG Industries	Diversified Chemicals
Computer Sciences Corp.	IT Consulting & Services	PPL Corp.	Electric Utilities
ConAgra Foods Inc.	Packaged Foods & Meats	Praxair Inc.	Industrial Gases
ConocoPhillips	Oil & Gas Exploration & Production	Precision Castparts	Industrial Conglomerates
CONSOL Energy Inc.	Coal & Consumable Fuels	Priceline.com Inc	Hotels, Resorts & Cruise Lines
Consolidated Edison	Electric Utilities	Principal Financial Group	Diversified Financial Services
Constellation Brands	Distillers & Vintners	Procter & Gamble	Personal Products
Corning Inc.	Construction & Engineering	Progressive Corp.	Property & Casualty Insurance
Costco Co.	Hypermarkets & Super Centers	Prologis	Diversified Financial Services
Crown Castle International Corp.	REITs	Prudential Financial	Diversified Financial Services
CSX Corp.	Railroads	Public Serv. Enterprise Inc.	Electric Utilities
Cummins Inc.	Industrial Machinery	Public Storage	REITs
CVS Caremark Corp.	Drug Retail	Pulte Homes Inc.	Homebuilding
D. R. Horton	Homebuilding	PVH Corp.	Apparel, Accessories & Luxury Goods
Danaher Corp.	Industrial Machinery	Qorvo	Semiconductors
Darden Restaurants	Restaurants	Quanta Services Inc.	Industrial Conglomerates
DaVita Inc.	Health Care Facilities	QUALCOMM Inc.	Semiconductors
Deere & Co.	Construction & Farm Machinery & Heavy Trucks	Quest Diagnostics	Health Care Facilities
Delphi Automotive	Auto Parts & Equipment	Range Resources Corp.	Oil & Gas Exploration & Production
Delta Air Lines	Airlines	Raytheon Co.	Aerospace & Defense
Dentsply International	Health Care Supplies	Realty Income Corporation	Office REITs
Devon Energy Corp.	Oil & Gas Exploration & Production	Red Hat Inc.	Systems Software

Diamond Offshore Drilling	Oil & Gas Drilling	Regeneron	Biotechnology
Discover Financial Services	Consumer Finance	Regions Financial Corp.	Diversified Financial Services
Discovery Communications-A	Broadcasting & Cable TV	Republic Services Inc	Industrial Conglomerates
Discovery Communications-C	Broadcasting & Cable TV	Reynolds American Inc.	Tobacco
Dollar General	General Merchandise Stores	Robert Half International	Human Resource & Employment Services
Dollar Tree	General Merchandise Stores	Rockwell Automation Inc.	Industrial Conglomerates
Dominion Resources	Electric Utilities	Rockwell Collins	Industrial Conglomerates
Dover Corp.	Industrial Machinery	Roper Industries	Industrial Conglomerates
Dow Chemical	Diversified Chemicals	Ross Stores	Apparel Retail
Dr Pepper Snapple Group	Soft Drinks	Royal Caribbean Cruises Ltd	Hotel, Resorts and Cruise Lines
DTE Energy Co.	MultiUtilities	Ryder System	Industrial Conglomerates
Du Pont (E.I.)	Diversified Chemicals	Salesforce.com	Internet Software & Services
Duke Energy	Electric Utilities	SanDisk Corporation	Computer Storage & Peripherals
Dun & Bradstreet	Data Processing Services	SCANA Corp	MultiUtilities
E*Trade	Investment Banking & Brokerage	Schlumberger Ltd.	Oil & Gas Equipment & Services
Eastman Chemical	Diversified Chemicals	Scripps Networks Interactive Inc.	Broadcasting & Cable TV
Eaton Corporation	Industrial Conglomerates	Seagate Technology	Computer Storage & Peripherals
eBay Inc.	Internet Software & Services	Sealed Air Corp.(New)	Paper Packaging
Ecolab Inc.	Specialty Chemicals	Sempra Energy	MultiUtilities
Edison Int'l	Electric Utilities	Sherwin-Williams	Specialty Chemicals
Edwards Lifesciences	Health Care Equipment & Services	Sigma-Aldrich	Diversified Chemicals
Electronic Arts	Home Entertainment Software	Signet Jewelers	Specialty Stores
EMC Corp.	IT Consulting & Services	Simon Property Group Inc	REITs
Emerson Electric Company	Industrial Conglomerates	Skyworks Solutions	Semiconductors
Endo International	Pharmaceuticals	SL Green Realty	Office REITs
Ensco plc	Oil & Gas Drilling	Smucker (J.M.)	Packaged Foods & Meats
Entergy Corp.	Electric Utilities	Snap-On Inc.	Household Appliances
EOG Resources	Oil & Gas Exploration & Production	Southern Co.	Electric Utilities
EQT Corporation	Oil & Gas Exploration & Production	Southwest Airlines	Airlines
Equifax Inc.	Diversified Financial Services	Southwestern Energy	Oil & Gas Exploration & Production
Equinix	Internet Software & Services	Spectra Energy Corp.	Oil & Gas Refining & Marketing & Transportation
Equity Residential	REITs	St Jude Medical	Health Care Equipment & Services
Essex Property Trust Inc	Residential REITs	Stanley Black & Decker	Household Appliances
Estee Lauder Cos.	Personal Products	Staples Inc.	Specialty Stores
Eversource Energy	MultiUtilities	Starbucks Corp.	Restaurants
Exelon Corp.	MultiUtilities	Starwood Hotels & Resorts	Hotels, Resorts & Cruise Lines
Expedia Inc.	Hotels, Resorts & Cruise Lines	State Street Corp.	Diversified Financial Services
Expeditors Int'l	Air Freight & Logistics	Stericycle Inc	Industrial Conglomerates
Express Scripts	Health Care Distributors & Services	Stryker Corp.	Health Care Equipment & Services
Exxon Mobil Corp.	Integrated Oil & Gas	SunTrust Banks	Banks
F5 Networks	Networking Equipment	Symantec Corp.	Application Software
Facebook	Internet Software & Services	Sysco Corp.	Food Distributors
Fastenal Co	Building Products	T. Rowe Price Group	Diversified Financial Services
FedEx Corporation	Air Freight & Logistics	Target Corp.	General Merchandise Stores
Fidelity National Information Services	Internet Software & Services	TE Connectivity Ltd.	Electronic Equipment & Instruments
Fifth Third Bancorp	Banks	TECO Energy	Electric Utilities
First Solar Inc	Semiconductors	Tegna	Publishing
FirstEnergy Corp	Electric Utilities	Tenet Healthcare Corp.	Health Care Facilities
Fiserv Inc	Internet Software & Services	Teradata Corp.	Application Software
FLIR Systems	Aerospace & Defense	Tesoro Petroleum Co.	Oil & Gas Refining & Marketing & Transportation
Flowserve Corporation	Industrial Machinery	Texas Instruments	Semiconductors
Fluor Corp.	Diversified Commercial Services	Textron Inc.	Industrial Conglomerates
FMC Corporation	Diversified Chemicals	The Hershey Company	Packaged Foods & Meats
FMC Technologies Inc.	Oil & Gas Equipment & Services	The Travelers Companies Inc.	Property & Casualty Insurance
Ford Motor	Automobile Manufacturers	Thermo Fisher Scientific	Health Care Equipment & Services
Fossil, Inc.	Apparel, Accessories & Luxury Goods	Tiffany & Co.	Apparel, Accessories & Luxury Goods
Franklin Resources	Asset Management & Custody Banks	Time Warner Inc.	Broadcasting & Cable TV
Freeport-McMoran Cp & Gld	Diversified Metals & Mining	Time Warner Cable Inc.	Broadcasting & Cable TV
Frontier Communications	Integrated Telecommunications Services	TJX Companies Inc.	Apparel Retail
GameStop Corp.	Computer & Electronics Retail	Torchmark Corp.	Life & Health Insurance
Gap (The)	Apparel Retail	Total System Services	Internet Software & Services
Garmin Ltd.	Consumer Electronics	Tractor Supply Company	Specialty Retail
General Dynamics	Aerospace & Defense	Transocean	Oil & Gas Drilling
General Electric	Industrial Conglomerates	TripAdvisor	Internet Retail
General Growth Properties Inc.	REITs	Twenty-First Century Fox	Publishing
General Mills	Packaged Foods & Meats	Tyson Foods	Packaged Foods & Meats
General Motors	Automobile Manufacturers	Tyco International	Industrial Conglomerates
Genuine Parts	Specialty Stores	U.S. Bancorp	Banks
Genworth Financial Inc.	Life & Health Insurance	Under Armour	Apparel, Accessories & Luxury Goods
Gilead Sciences	Biotechnology	Union Pacific	Railroads

Goldman Sachs Group	Investment Banking & Brokerage	United Health Group Inc.	Managed Health Care
Goodyear Tire & Rubber	Tires & Rubber	United Parcel Service	Air Freight & Logistics
Google Inc Class A	Internet Software & Services	United Rentals, Inc.	Trading Companies & Distributors
Google Inc Class C	Internet Software & Services	United Technologies	Industrial Conglomerates
Grainger (W.W.) Inc.	Industrial Materials	Universal Health Services, Inc.	Health Care Facilities
Halliburton Co.	Oil & Gas Equipment & Services	Unum Group	Diversified Financial Services
Hanesbrands Inc	Apparel, Accessories & Luxury Goods	Urban Outfitters	Apparel Retail
Harley-Davidson	Motorcycle Manufacturers	V.F. Corp.	Apparel, Accessories & Luxury Goods
Harman Int'l Industries	Consumer Electronics	Valero Energy	Oil & Gas Refining & Marketing & Transportation
Harris Corporation	Telecommunications Equipment	Varian Medical Systems	Health Care Equipment & Services
Hartford Financial Svc.Gp.	Property & Casualty Insurance	Ventas Inc	Diversified Financial Services
Hasbro Inc.	Leisure Products	Verisign Inc.	Internet Software & Services
HCA Holdings	Health Care Facilities	Verizon Communications	Integrated Telecommunications Services
HCP Inc.	REITs	Vertex Pharmaceuticals Inc	Biotechnology
Health Care REIT, Inc.	REITs	Viacom Inc.	Broadcasting & Cable TV
Helmerich & Payne	Oil & Gas Drilling	Visa Inc.	Internet Software & Services
Hess Corporation	Integrated Oil & Gas	Vornado Realty Trust	REITs
Hewlett-Packard	Computer Hardware	Vulcan Materials	Construction Materials
Home Depot	Home Improvement Retail	Wal-Mart Stores	Hypermarkets & Super Centers
Honeywell Int'l Inc.	Industrial Conglomerates	Walgreens Boots Alliance	Drug Retail
Hormel Foods Corp.	Packaged Foods & Meats	The Walt Disney Company	Broadcasting & Cable TV
Hospira Inc.	Health Care Equipment & Services	Waste Management Inc.	Environmental Services
Host Hotels & Resorts	REITs	Waters Corporation	Health Care Distributors & Services
Hudson City Bancorp	Thrifts & Mortgage Finance	Anthem Inc.	Managed Health Care
Humana Inc.	Managed Health Care	Wells Fargo	Banks
Huntington Bancshares	Banks	Western Digital	Computer Storage & Peripherals
Illinois Tool Works	Industrial Machinery	Western Union Co	Internet Software & Services
Ingersoll-Rand PLC	Industrial Conglomerates	Weyerhaeuser Corp.	REITs
Intel Corp.	Semiconductors	Whirlpool Corp.	Household Appliances
Intercontinental Exchange	Diversified Financial Services	Whole Foods Market	Food Retail
International Bus. Machines	IT Consulting & Services	Williams Cos.	Oil & Gas Exploration & Production
International Paper	Paper Products	Wisconsin Energy Corporation	Electric Utilities
Interpublic Group	Advertising	Wyndham Worldwide	Hotels, Resorts & Cruise Lines
Intl Flavors & Fragrances	Specialty Chemicals	Wynn Resorts Ltd	Casinos & Gaming
Intuit Inc.	Internet Software & Services	Xcel Energy Inc	MultiUtilities
Intuitive Surgical Inc.	Health Care Equipment & Services	Xerox Corp.	IT Consulting & Services
Invesco Ltd.	Asset Management & Custody Banks	Xilinx Inc	Semiconductors
Iron Mountain Incorporated	Data Processing Services	XL Capital	Property & Casualty Insurance
Jacobs Engineering Group	Industrial Conglomerates	Xylem Inc.	Industrial Conglomerates
J. B. Hunt Transport Services	Trucking	Yahoo Inc.	Internet Software & Services
Zions Bancorp	Banks	Yum! Brands Inc	Restaurants
Zoetis	Pharmaceuticals	Zimmer Biomet Holdings	Health Care Equipment & Services

B. Quandt – Andrews test:

The Netherlands

Quandt-Andrews unknown breakpoint test
Null Hypothesis: No breakpoints within 5% trimmed data

Equation Sample: 1/01/1993 12/31/2013
Test Sample: 1/20/1994 12/13/2012
Number of breaks compared: 4931

Statistic	Value	Prob.
Maximum LR F-statistic (11/06/1998)	2.732505	0.4134
Exp LR F-statistic	0.387519	0.8601
Ave LR F-statistic	0.703239	0.7505

Note: probabilities calculated using Hansen's (1997) method

United States:

Quandt-Andrews unknown breakpoint test
Null Hypothesis: No breakpoints within 5% trimmed data
Varying regressors: All equation variables
Equation Sample: 1/01/1993 12/31/2013
Test Sample: 1/20/1994 12/13/2012
Number of breaks compared: 4931

Statistic	Value	Prob.
Maximum LR F-statistic (1/27/1999)	2.533017	0.5038
Maximum Wald F-statistic (1/27/1999)	10.13207	0.5038
Exp LR F-statistic	0.359826	0.8979
Exp Wald F-statistic	2.035604	0.6732
Ave LR F-statistic	0.641950	0.8206
Ave Wald F-statistic	2.567798	0.8206

Note: probabilities calculated using Hansen's (1997) method