Erasmus University Rotterdam

Erasmus School of Economics

Bachelor Thesis Financial Economics

Revisiting Calendar Anomalies in Europe

Changes over time

This paper considers the day-of-the-week effect and the month-of-the-year effect over time in Europe. These general effects have been split up into the Monday effect, the twist-on-the-Monday effect, the January effect and the Halloween effect. Using daily return data from 1990 to 2017 from the DAX, the CAC 40, the FTSE 100 and the SMI, the Monday, twist-on-the-Monday and January effect have found not to have been significantly present in the time period. The Halloween effect was significantly present in the first half of the time period, but disappeared in the second. Furthermore, t-tests testing for a difference in means of two different time periods concluded that the mean effects in the control period are significantly different from the mean effects in the test period, adding to the argument of disappearing calendar anomalies where applicable.

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Introduction

Opening

Calendar anomalies have been studied numerous times in the financial world. They are one of the greatest arguments against the existence of a perfectly efficient market, where the only way to realise a higher return is to expose yourself to a higher amount of risk.

In 1988, Lakonishok and Smidt documented and proved the existence of certain calendar anomalies over a ninety-year period. The fact that a systematically different return can be realised on certain days of the week, or in certain months of the year is in sharp contrast with the “efficient market”. The so-called Monday effect, also called Weekend effect, as described by Cross in 1973, states that Mondays show a systematically lower return on the stock market than the other days of the week. The January effect has been documented for the first time in 1976 by Rozeff and Kinney. They showed that the return on the stock market in January is significantly larger than in other months.

These specific anomalies can be placed under two larger, more generalised anomalies. Anomalies like the Monday effect can be placed under the day-of-the-week effect, which states that the day of the week has a significant and systematic influence on the stock market return. Anomalies like the January effect can be placed under the month-of-the-year effect. This effect states that, just like the days in the day-of-the-week effect, the months of the year have a significant and systematic influence on stock market returns. The day-of-the-week effect and the month-of-the-year effect are the two effects that this paper will focus on. These will then be split up more precisely in smaller effects, dependent on the results of the initial tests. The day-of-the-week effect can then be split up into the already mentioned Monday effect, but also into the twist-on-the-Monday effect found by Jaffe, Westerfield and Ma in 1989, which states that abnormally low returns occur on Mondays when the stock market has previously declined. The month-of-the-year effect can be split up into several effects. including the already mentioned January effect, the school holiday effect found by Fang, Lin and Shao (2017), or the Halloween effect as described by Bouman and Jacobsen (2002).

Aim of the research

Lakonishok, Shleifer and Vishny in 1994 state that the return patterns are not a cause of a higher exposure to risk. They provide evidence that the high returns are caused by taking advantage of suboptimal behaviour of other investors, and not because of a higher exposure to risk. This view opposes the view that a higher risk exposure is the reason for these higher return patterns, and introduces a behavioural argument for anomalies in return patterns.

In 1996, Fama and French released their paper *Multifactor explanations of asset pricing anomalies.* They explain that even though the Capital Asset Pricing Model (CAPM) cannot explain the patterns in the average returns correctly, that does not mean that they should be called anomalies. They state that in their three-factor model, almost all of these anomalies disappear. This strengthens their claim that the only way to realise a higher return is to expose yourself to more risk. This is a risk-based view on anomalies.

Although the anomalies, discussed by Lakonishok, Shleifer and Vishny and by Fama and French, are anomalies that concern trading strategies based on stocks with firm characteristics like the earnings to price ratio and the book-to-market ratio and not calendar based anomalies, tying these anomalies to one another could still provide new insights. After all, both the anomalies that are based on the calendar as the anomalies based on firm characteristics have a key similarity: they both question the precision of the CAPM. Studying the possible decline of the anomalies over time could therefore provide valuable arguments for the *risk versus behavioural argument.* Specifically, an ongoing existence of calendar anomalies could prove to be an argument for the risk based view. If behavioural argumentation caused the existence of anomalies, the simple knowledge of their existence should lead them to be arbitraged away. When this is not the case, this could mean that the anomalies are the cause of common global risk factors as described by Fama and French in 1996.

Calendar anomalies have been studied worldwide. However, the largest fraction of research originates from the United States, and uses data samples from the United States. To provide more meaningful results that add to the overall understanding and documentation of calendar anomalies, this paper will specifically focus on anomalies in Europe. The aim is to clearly state whether or not calendar anomalies show a decline over time in Europe. This leads to the main research question of this paper:

Have the day-of-the-week effect and the month-of-the-year effect decreased over time in Europe?

These two broad effects will then be split up specifically into the Monday effect, the twist-on-the-Monday, the January effect and the Halloween effect.

Structure

This paper consists of the following parts:

- Theoretical Framework:
  In this part of the research, certain core principles will be discussed. These core principles are vital in understanding the rest of the paper. Some of the core principles that will be discussed are the Capital Asset Pricing Model (CAPM) and the Efficient Market Hypothesis (EMH). A clear understanding of these principles will help improve the understanding of the calendar anomalies.

- Literature Review:
  The literature review will help create a broad image about the extensive research that was already executed regarding calendar anomalies. Some researchers found a disappearance of calendar anomalies, while others found they persisted over time. The different opinions and results regarding these matters will be mentioned and discussed to create a clear path for this paper.

- Data and Methodology:
  This section covers the used data in this paper, as well as the methods used. A clear description of the data will be given, followed by an explanation and justification on the research methods.

- Results:
  In this section the empirical results of the tests are provided and discussed. Clear interpretations of the results will be given to provide a coherent image of the persistence of calendar anomalies over time.

- Conclusion:
  The last section of this paper will provide and overall conclusion, as well as an answer to the main research question. This is also the section where the implications of the found results are given, and where recommendations on how to continue in this field of research are mentioned.

Theoretical Framework

Efficient Market Hypothesis

One of the most important principles to consider is the principle of the efficient market. This hypothesis states that it is impossible to beat the market, because the current share price incorporates all known and relevant information. Therefore, the only reason share prices fluctuate is the release of new, previously unknown information. This information ranges from financial data concerning the companies, as well as future expectations. Considering that all information is incorporated in the share prices, the only way to obtain a higher return is to expose themselves to more risk (Fama, 1970).

Fama considers three forms of market efficiency. Each of these forms is related to a different assemblage of information in the market.

1. Weak form of the EMH
   This form of the efficient market holds if the current share prices incorporate all the information held by historical share prices. This would mean that predicting the future share price through the historical share price is meaningless, since all information regarding historical share prices is already incorporated in the share price. An implication of this efficient market form is that studying historical share prices to determine a trading strategy is useless.

2. Semi-strong form of the EMH
   The semi-strong form of the EMH holds when the current share price correctly incorporates all publicly known information. Furthermore, a semi-strong efficient market will directly and correctly react to the release of new public information. This means that there will not be cases of over- or underreaction to the release of public information. An implication of this efficient market form is that studying financial statements is useless when determining a trading strategy.

3. Strong form of the EMH
   This form of the efficient market holds when the current share price correctly incorporates all current information. This means that private information, for example inside knowledge of board members, is also perfectly incorporated into the share prices. This form implies that it is impossible to systematically obtain abnormal returns, even when having access to private, inside information.

The Capital Asset Pricing Model

The Capital Asset Pricing Model (CAPM) is a financial model that shows the relation between exposed risk and expected return. Litner describes this model in 1965, after Sharpe introduced it in 1964. The CAPM described by Sharpe and Litner is actually a modernisation of the Modern Portfolio Theory (MPT) by Markowitz (1952). They state that there are two types of risk a stock can be exposed to: systematic risk, and unsystematic risk. Systematic risk concerns all stocks, and cover events like changes in the expected inflation and changes in the exchange rate. Unsystematic risk is firm specific. Even though all stocks are exposed to a degree of systematic risk and a degree of unsystematic risk, in the CAPM you are only compensated for systematic risk in the form of a higher expected return. The reason for this is that unsystematic risk can be diversified away completely in a portfolio, and therefore does not warrant compensation. The other factor that is being compensated for in a portfolio is the time factor. Postponing consumption results in a utility loss, therefore a consumption is warranted in the form of a risk-free rate. This leads to the following formula:

$$E(r_i) = R_f + \beta_i\left[E(R_m) - R_f\right]$$

Where:

$E(r_i)$	= the expected return on financial instrument i
R_f	= the risk-free rate
$Beta$	= the measure of systematic risk of financial instrument i
$E(R_m)$	= the expected return on the market portfolio that contains all assets
$E(R_m) - R_f$	= the market risk premium

The coefficient *Beta* determines the amount if systematic risk the financial instrument is exposed to. This is what decides what share of the market risk premium is allocated to the financial instrument. This formula shows a linear relation between the level of systematic risk and the expected return. This linear relation is called the Security Market Line (SML). This line shows that a higher exposure to risk leads to a higher expected return.

Calendar Anomalies in relation to the EMH and the CAPM

The reason calendar anomalies are a widely researched topic is that they are exceptions to the EMH and the CAPM. When positive abnormal returns can be systematically obtained on a Friday, this must be caused by an increased exposure to risk on a Friday according to the CAPM. If no increased risk is found on Friday's, the only possible explanation left is that the market does not behave in an efficient way, thus questioning the EMH. There are more anomalies that question the EMH and the CAPM. When these anomalies specifically revolve around the calendar cycle, they are labelled as calendar anomalies.

The day-of-the-week effect is often referred to as the Monday effect, as most studies show an identical result where Mondays show significantly negative returns on the stock market. However, we cannot exclude that we might find results showing a calendar effect concerning other days of the week. Therefore, the day-of-the-week effect will be split up into two separate effects; the Monday effect and the twist-on-the-Monday effect.

The month-of-the-year effect is often called the January effect. This anomaly concerns positive abnormal returns in the month January. There are many factors believed to be causing the January effect, all which will be reviewed in the Literature Review section. Similarly to the day-of-the-week effect, the month-of-the-year effect will be split up into two separate effects. The two effects that will be examined are the January effect, and the Halloween effect.

Literature review

This literature review will extensively review previous literature regarding calendar anomalies. Even though the main focus lies on the day-of-the-week effect and the month-of-the-year effect, this literature review will mainly focus on the more specified Monday effect, the twist-on-the-Monday effect, the January effect and the Halloween effect.

Monday effect

Cross (1973) first documented the Monday effect. The Monday effect known today states that Mondays show a systematically lower return than the other days of the week. Cross described this somewhat differently. He found that the S&P Composite Stock index increased on 62% of the Fridays between 1953 and 1970. An increase only occurred on 39.5% of the Mondays. The mean percentage of change was 0.12% on Fridays, while the mean percentage of change was -0.18% on Mondays.

Even though Cross did not model the Monday effect exactly as we define it today, it still opened up a large field of possible research. French (1980) used the S&P Composite portfolio from 1953 to 1977 to find a significantly negative return on Mondays in five-year subperiods, as well as in the entire period as a whole. He discussed that a possible reason for this phenomenon is the announcement of bad news by the firms in the weekend. They would do this to allow investors to have a longer period to digest the bad news and act accordingly. If they would release bad news mid-week, this might induce panic selling by investors, which is catastrophic for the stock prices. The bad news on the weekend will cause a delayed selling reaction on Mondays, explaining the significantly negative returns on Mondays. However, this chain of events would not be possible in an efficient market as described by Fama (1970). In an efficient market the stock prices would be discounted accordingly throughout time instead of suddenly on Mondays. French argues that even though the Monday effect points towards market inefficiency, a simple trading strategy that buys on Mondays in the afternoon and sells on Fridays would result in lower returns than a buy and hold strategy due to the transaction costs involved. French adds that the knowledge of the Monday effect could however still be valuable if the timing of trades by an investor is adjusted accordingly.

Ritter (1988) proposed that the January effect is caused by the behaviour of individual investors. Lakonishok and Maberly (1990) used the same hypothesis to find an explanation for the Monday effect. They tested this hypothesis by using the daily stock price data from the S&P for the New York Stock Exchange covering 1962 to 1986. Furthermore, they used the daily sales and purchase volumes of New York Stock Exchange listed common stocks by so called Merrill Lynch cash-account customers. These customers are used as a proxy to model non-institutional investors. They found that in a regular trading week including five trading days, the trading volume is the lowest on Mondays, that individual investors have the highest trading volume on Monday relative to other days of the week and that institutional investors have the lowest trading volume on Monday relative to other days of the week. Furthermore, they conclude that for individuals, the tendency to sell on Monday is higher than the tendency to buy on Monday. This sell-driven behaviour by individuals might be a partial explanation to the Monday effect. They argued that in its turn, this could lead to an increased buying volume on Fridays. The reason for this is that individual investors want to know the exact proceeds before reinvesting their money. This causes a delay in the reinvestment, leading to a higher trading volume later in the week. This could potentially explain the high returns on Fridays. Even though Lakonishok and Maberly find consistent empirical evidence, they do not claim to have found a cause-and-effect relationship between trading and price, as they believe a more powerful test could be performed if intraday trading data of all market participants were available.

Twist-on-the-Monday effect

Jaffe, Westerfield and Ma (1989) stated there is a twist on the Monday/weekend effect. They found that abnormal declines in a stock market are followed by abnormally low returns on the next Monday. A stock market that has risen in the week before Monday causes the Monday effect to disappear almost completely. They have conducted this study for stock markets in the U.S., Canada, Japan, the U.K. and Australia. Additionally, they did not observe this effect for other days of the week. Jaffe, Westerfield and Ma argued that risk is not an explanation for this phenomenon, since they found a higher standard deviation of return on Mondays after a stock market decline than on Mondays after a stock market rise. A greater standard deviation is a proxy for higher risk. Since, according to the CAPM model, stock returns are a function of exposure to risk, this would mean that the returns should be greater on Mondays after a stock market decline, however, the exact opposite pattern was found. Furthermore, the average return on Mondays after a stock market decline are found to be negative. This would mean that investors are exposed to a risk lower than zero on Mondays after a stock market decline, since returns are the compensation for risk. Naturally, negative risk is not possible, since risk cannot be lower than zero. These arguments rule out a risk based explanation for their findings. While they rule out several explanations, they are unfortunately unable to find an appropriate explanation for their twist-on-the-Monday effect.

Cross (1973) introduced the existence of the twist-of-the-Monday effect. He discovered that the S&P Composite Stock Index increases on 48.8% of all Mondays after an increase of the S&P Composite Index on Friday. After a decline of the index on Friday, the index only increases on 24% of the Mondays. He also stated that the stock price changes on Monday and Friday are significantly different from the stock price changes observed on other successive days. Therefore, similar to Jaffe, Westerfield and Ma (1989), Cross found that there is no significant correlation between returns on other days of the week in the same way as the effect observed in the return on the stock market on a Friday and a Monday.

Van der Sar (2003) found a twist-on-the-Monday effect on the Amsterdam Stock Exchange between 1981 and 1998. He addressed this twist-on-the-Monday effect to a delayed reaction to information by investors. The results indicate that investors do not only react to bad information in the weekend, as suggested by French (1980), but also show a delayed reaction to information released on Fridays. This could be the reason why some researchers tend to find a Monday effect, while the researchers that look at the relationship between last week's Friday and Monday tend to find a twist-on-the-Monday effect.

January effect

Rozeff and Kinney (1976) displayed the existence of seasonality in the monthly rates of return on the New York Stock Exchange. They did this over the period of 1904 until 1974. These monthly differences are mostly due to January showing very large returns. They stated that their findings do not necessarily contradict market efficiency, as the higher return in January seems to come with a higher degree of risk as well. They did however state that market equilibrium models may need to incorporate seasonality effects.

Keim (1983) discovered that the January effect is strongly related to abnormally high returns on stocks of small firms. These abnormally high returns on the stocks of small firms had previously been observed by both Banz (1981) and Reinganum (1981). Keim additionally finds that over fifty percent of the January effect is earned in the first week of trading and especially on the first trading day. He proposed the idea of an unknown risk variable as an explanation for this pattern. However, he argues that this cannot fully explain the January effect, as solely risk cannot explain that a certain return premium is earned in the same month every year. This unknown risk variable could be present in multiple years, but it is highly unlikely that it would return the same days every year.

Gultekin and Gultekin (1983) examined stock market seasonality in sixteen countries. In 15 of these countries they found a very large January effect. Many countries even displayed a larger January effect than the U.S., adding to the relevance of this paper's European examination of stock market seasonality. Gultekin and Gultekin used value-weighted market indices to examine stock market seasonality. This way large and small firm stocks are equally represented in the index, implying that a "small-firm effect" could be found sooner. They added that tax-loss selling could be a valid explanation for the existence of the January effect. This tax-loss selling leads to a sell-driven market in December, allowing investors to make use of tax benefits at the turn of the tax year. In January, many positions in stocks that bear a higher degree of risk are retaken, leading to a buy-driven market in January. Their empirical results support this possible explanation, as in all countries observed, with the exception of Australia, the abnormally large returns are observed around the turn of the tax year.

Ritter (1988) found that the ratio of stock purchases to sales by individual investors is relatively low in December. This buy/sell ratio is above average in the start of January. This means that in December, individual investors' actions are more sell-driven, while in January their actions are more buy-driven. Similar to the reasoning of Lakonishok and Maberly (1990) for the Monday effect, this buy-driven mentality in January by individual investors could partially explain the abnormally high returns over the month of January.

Haugen and Jorion (1996) stated that, in an efficient market, the exploitability of the January effect should have been priced away since its first discovery. This means that the January effect could still exist, but that its profitability should have drastically decreased or even ceased to exist. Transaction costs are the reason the anomaly does not have to disappear completely for the anomaly to lose its profitability. Even though this explanation works theoretically, their empirical evidence indicates otherwise. Haugen and Jorion found that the January effect still existed after all these years. Not only does did still exist, the effect's magnitude has not changed significantly, and neither is there a visible trend that the effect will ever disappear. This has large implications for the EMH. As a possible reason for its persistence, they state that the January effect can only be exploited while exposing yourself to a considerable amount of risk. Maybe markets are slow to arbitrage away market inefficiencies that come with a considerable amount of risk. The possibility also exists that markets do not arbitrage these risk-bearing inefficiencies away at all.

Halloween Effect

Bouman and Jacobsen (2002) mentioned that the European press repeats a similar message every year around the month May. They say, "sell in May and go away". According to this statement, May is the start of a bearish market with low average returns. "But remember to come back in September" is usually how the saying ends. This pattern of low returns after May, and high returns after September has come to be known as the Halloween effect/indicator. Bouman and Jacobsen found this Halloween effect to be present in 36 out of the 37 countries in their sample. This means that in 36 out of the 37 countries examined, the summer months were outperformed by the winter months. Maybe even more interestingly, they found no evidence that factors like risk and correlation between markets are responsible for this Halloween effect. Even correcting for the January effect, which could have a large outcome on the post September returns yields no explanatory power. Another interesting finding is that apparently, a trading strategy based on the Halloween effect outperforms a simple buy and hold strategy, making the Halloween effect relatively exploitable, questioning the Efficient Market Hypothesis.

Jacobsen and Visaltanachoti (2009) continued researching the effect by examining the Halloween effect in the U.S. stock markets. In a sample period of roughly 80 years, they found that in more than two thirds of the sectors examined, the summer stock returns are outperformed by the winter stock returns. A striking discovery is the difference between sectors. Production sectors show the strongest Halloween effect, whereas the effect is negligible in consumer consumption sectors. Yet again, risk based explanations provide no solution to the Halloween puzzle. Additionally, Jacobsen and Visaltanachoti discovered that liquidity changes provide no explanatory power for the Halloween effect.

Maberly and Pierce (2003) continued the research of the Halloween effect by examining the Japanese stock market. They questioned the robustness of the research performed by Bouman and Jacobsen (2002). They found that, in the Japanese market, the Halloween effect is concentrated in a period before 1986. After this period, Japanese markets internationalised, which brought the disappearance of the Halloween effect. The reason that they found different results than the researchers before them is, according to the authors, that the previous studies did not take alternative models and effects into consideration as effectively as they should have. For this paper, that could mean that a Halloween effect will not be observed at all, or that it could completely disappear when examining the effect over time.

Decrease of the calendar anomalies

Calendar anomalies have been a topic of large interest in the financial world over the years. In recent years, besides trying to find calendar anomalies in financial markets, a lot of attention has been focussed on the decrease and disappearance of calendar anomalies. Chan, Leung and Wang (2004) found that low returns on Mondays are due to relatively high trading activity by individual investors, who are believed to be less sophisticated than institutional investors. They stated that the increased trading volume of institutional investors on Mondays could be one of the key factors that led to the disappearance of the Monday effect in their sample. Similar to Chan, Leung and Wang (2004), Chen and Singal (2003) showed that the weekend effect has disappeared in their sample. They found that the general trading volume of stocks has explanatory power for the disappearance of the Monday effect.

Marquering, Nisser and Valla (2006) found evidence for the disappearance of several anomalies, under which the Monday effect and the January effect. They stated that the knowledge of the existence of the anomalies among investors will increase investor attention and trading volume, leading to a decrease or disappearance of the anomaly. This statement is supported by the fact that they found the disappearance of the anomalies to coincide with the timing of the publishing of academic papers regarding these calendar anomalies.

Barber and Odean (2007) described the effect of news and attention on the stock market. They found that individual investors are very news driven, and buy stocks that have been reported in news outlets recently. Considering this, it is very likely that due to a high degree of information spreading in recent times, there is a larger variety of stocks that catch the eyes of individual investors. This added information spreading makes the market more accessible for individuals, thus increasing the general trading volume of many stocks. As mentioned by Marquering, Nisser and Valla (2006), this increased attention and trading volume is one of the most prolific explanations for the decrease and disappearance of the calendar anomalies.

Data and Methodology

Data

To test for a decrease in these specific calendar anomalies over time in Europe, the most important indices of Germany, the United Kingdom, France and Switzerland will be used. The indices used for these countries are the DAX, the FTSE 100, the CAC 40 and the SMI respectively. Daily closing prices of each of these indices have been obtained from Yahoo! Finance and Google Finance.

Naturally, due to closed markets during the weekend (Saturday and Sunday), share prices on those two days of the week have not been incorporated in the data sets. However, each country has its specific holidays where the stock exchanges are closed. If these days are incorporated into the data sets, it would affect the average daily returns of the indices observed, as the daily return on those days are 0%. To retrieve a more accurate estimate of the average daily returns, these specific holiday dates have been removed from the data sets.

Working with just closing prices, it is nearly impossible to execute the desired research. The reason for this is that the closing price does not comply with the standard rules to perform an Ordinary Least Squares regression. Closing prices will most definitely show a clear trend upwards over time. This trend is not due to the continuing rise in company valuation however. It is much more likely that due to a continuous inflation over time, the stock prices have moved along with the inflation trend. This trend needs to be removed to be able to examine the factors causing stock price movements that are of interest in this research. This can be reached through differencing. Simply put, you compare each closing price to the closing price the day before, leading to a percentage change in closing price. This change is called the return of the stock or index.

To obtain the daily returns of the indices from the daily closing prices, the following formula has been used:

$$R_t = \ln(P_t) - \ln(P_{t-1})$$

Where:

R_t = return on day t

P_t = closing price on day t

P_{t-1} = closing price on day t – 1

Technically, the returns computed are not general returns, but logarithmic returns. Making use of logarithmic returns poses several advantages compared to using regular returns. Firstly, the properties of logarithmic returns allow them to be added together, something that is mathematically more complicated if done with regular returns. Secondly, an assumption is made that prices are distributed log normally. This would mean that using the logarithmic returns helps to move the distribution closer to a normal distribution, making the OLS estimates more accurate.

Considering dividends is important when examining stock market seasonality. This is because stock prices usually drop when dividends are released. This could have a big impact on the accuracy of the test results if not corrected carefully. Consider the Monday effect, that states that stock returns on Mondays are significantly lower than the returns on the other days of the week. If proof can be found that most companies issue dividends on Mondays, leading to a fall in stock prices, the Monday effect could be reduced to nothing more than an effect of dividend pay-out policy. To test if the Monday effect still holds correcting for dividend pay-out policy, the adjusted closing price will be used to compute daily returns instead of the regular closing price. The adjusted closing price corrects for dividend pay-out policy by directly reinvesting the paid-out dividend back into the stock. Furthermore, the adjusted closing price also accounts for stock splits, which obviously have a big impact on the value of a stock as well.

To test for a possible decrease in the existence of the mentioned calendar anomalies, simply testing for its existence once does not suffice. A control period is needed where the degree of existence is established, followed up by a test of existence in a second period. According to the logic and theory mentioned earlier in this paper, the effect should have decreased or disappeared altogether in the second period. The data set of each index contains the daily returns ranging from the 27th of November 1990 to the 22nd of June 2017. For each index, the data set will be split up into two periods; the control period and the test period. Google opened its first office in 1998, marking a milestone in their ability to store and spread information across the world. Google launched their IPO in 2004, creating a strong foothold for further growth of the company. Given the impact and growth of Google on the spreading of information about calendar anomalies, the control period will range from the 27th of November 1990 to the 31st of December 2004, right after Google's IPO. The test period therefore will range from the 1st of January 2005 to the 22nd of June 2017. The IPO of Google will not serve as an explanatory variable for a possible decrease or disappearance of the calendar anomalies. Instead, it will serve as an indication of a period in time were investor attention might have increased significantly. As mentioned in the Literature Review section, investor attention and trading volume are the main causes of the disappearance of calendar effects. Google's influence on information spreading might have had a big influence on the spreading of information and the increase of investor attention, hence these time periods are chosen.

To obtain a more accurate representation of the daily returns over the two periods, extreme variables will be altered. Extreme observations in the data can influence the data tremendously, even though the observation itself is only one in thousands. However, deleting the data could create a bias in the results, as the largest and smallest observations in the data would be eliminated. Therefore, these extreme observations will not be deleted, but replaced accordingly. An upper and lower boundary will be created. These boundaries will equal the mean return plus (minus) three times the standard deviation, respectively. Each observation above (below) this boundary will be replaced by the upper (lower) bound value. This method ensures that the nature of the high (low) observation is preserved, but ensures that the impact of this extreme observation is limited.

Important factors to consider to ensure the efficiency of the OLS estimates are heteroskedasticity and serial correlation. These two cannot be present in the data set, as homoscedasticity and no serial correlation are important conditions for and OLS approach. To test for the presence of heteroskedasticity and serial correlation, each subsample will be subjected to a White-test and a Breusch-Godfrey test.

Descriptive Statistics

Table 1 displays the descriptive statistics of the daily returns for the total time period, the control period and the test period. All indices seem to have a small positive daily return in both subsamples on average. The lowest standard deviation off all indices is roughly over 1.01%, and belongs to the FTSE 100 in the control period. The FTSE 100 is also the index with the lowest average standard deviation across the total sample. The DAX shows the highest mean returns as well as the highest standard deviation in the total sample period. Striking is that the daily returns seem to be negatively skewed in all indices across all sub samples. The returns observed are frequently small positive returns, with a few large negative returns. Negative skewness implies that the chance of extremely negative returns is relatively large compared to a positive skewed distribution. The kurtosis of all indices in each period is above 4. For reference, a normal distribution has a kurtosis of 3, making 4 a relatively high kurtosis. This means that the chance of extreme observations is more likely than normal., which is in line with the negative skewness of the distributions.

The majority of the indices show White-test statistics significantly different from zero at a significance level of at least 5%. This means that in those indices in those periods, the null hypothesis of homoscedasticity can be rejected. Additionally, table 1 shows that the Breusch-Godfrey test statistics are significantly different from zero at a significance level of at least 10% in all sub periods. The Breusch-Godfrey test is executed to test for the existence of serial correlation up to five lags. Five lags were chosen, as it is very reasonable that today's returns are influenced by the returns of five trading days ago[1]. Adding any more lags is of little value, since that would tend to forcing the test statistic to find serial correlation where none might exist. Considering the results of both tests, all regressions will be corrected using Newey-West standard errors.

[1] The returns on a Monday were assumed to influence the returns of the next Monday, which equals to five lags.

Table 1: Descriptive statistics of daily returns in all subsamples. The table displays the number of observations (N), the mean, standard deviation, skewness, kurtosis and the outcomes of the White test and the Breusch-Godfrey test.

Index *Period*	**N**	**Mean**	**Std. Dev**	**Skewness**	**Kurtosis**	**White Test**	**Breusch-Godfrey**
DAX	6714	.000346	.0133356	-.1827181	4.386383	16.33492***	15.532***
CAC 40	6737	.000187	.0131273	-.1421229	4.253749	36.08055***	30.771***
FTSE 100	6703	.0002053	.0103899	-.1123517	4.442179	5.171626	29.230***
SMI	6681	.0003074	.0106158	-.2110561	4.466025	18.76581***	46.077***
DAX *Control period*	3547	.0003236	.0138757	-.1548525	4.317766	15.7538***	13.333**
CAC 40 *Control period*	3548	.0002481	.0131907	-.0969685	4.027752	11.5127**	22.991***
FTSE 100 *Control period*	3562	.0002404	.0101027	-.0639071	4.181835	5.720168	27.545***
SMI *Control period*	3543	.0004231	.0109536	-.1846667	4.3000274	21.6998***	25.382***
DAX *Test period*	3167	.0003713	.0127085	-.2214761	4.432357	3.065538	9.372*
CAC 40 *Test period*	3189	.0001189	.0130603	-.194662	4.519282	28.51715***	14.337**
FTSE 100 Test period	3141	.0001643	.0107265	-.1604636	4.715305	3.160578	10.595*
SMI *Test period*	3138	.000177	.0102218	-.2517844	4.669001	3.216113	27.844***

*N.B. *** stands for significance at a 1% level, ** at a 5% level, and * at a 10% level*

Methodology

Monday Effect

To test if Mondays show significantly lower returns than other trading days, the following formula will be used:

$$R_t = \alpha + \beta D_{monday} + \epsilon$$

The variable D_{monday} is a dummy variable that equals one if the day is a Monday, and equals zero if the day is a Tuesday, Wednesday, Thursday or Friday. The constant α is a constant that equals the average daily returns of Tuesday to Friday. The variable D_{monday} is excluded from the constant α in order to examine the existence of the Monday effect. β Is the coefficient that displays what effect Monday has on the daily return R_t. This regression was introduced by Cross (1973) to test for the Monday effect in different regions, which is the reason this regression will be used in this paper. For all indices and subsamples this regression will be corrected using Newey-West standard errors. The null- and alternative hypotheses are as follows:

H0: Monday does not show significantly lower returns than other trading days

H1: Monday shows significantly lower returns than other trading days

If the coefficient β is significantly different from zero, the null hypothesis can be rejected. This can be done at a significance level of 1%, 5% and 10%. To illustrate, rejecting at a significance level of 1% implies that there is a 1% chance that the null hypothesis is rejected when it should not have been rejected.

Twist-on-the-Monday Effect

The formula used for the twist-on-the-Monday effect is largely similar to the formula used for the Monday effect. The dummy variable for the Monday is replaced by a dummy variable that displays a twist. To create this dummy variable, the return of the week prior to the week of interest needs to be defined. This return will equal the average return of the five trading days before Monday. Doing this will lead to the following formula:

$$R_t = \alpha + \beta D_{Twist} + \epsilon$$

The variable D_{Twist} will equal one if the average return of the last five trading days is negative. It will be equal to zero if the average return of the last five trading days is positive. Considering this, the constant α equals the average daily returns on Monday after a positive week. To derive the returns of Monday after a negative week, β needs to be added. This regression regarding the twist-on-the-Monday effect, which exists if the return on Mondays after a negative week differs from the return on Mondays after a positive week, will also be corrected using Newey-West standard errors. Since Jaffe, Westerfield and Ma (1989) found that a negative week is followed up by negative returns on Mondays, the coefficient of the dummy variable D_{Twist} is expected to be negative in the control period. The null- and alternative hypotheses are as follows:

H0: Mondays after a week of negative average returns do not show significantly lower returns than Mondays after a week of positive average returns

H1: Mondays after a week of negative average returns show significantly lower returns than Mondays after a week of positive average returns

The null hypothesis can be rejected if the coefficient β is significantly different from zero at a 1%, 5% or 10% significance level.

January Effect

The January effect considers the anomalous returns in the month January. Specifically, January should show significantly higher returns than the other months. To test for this anomaly, the following formula will be used:

$$R_t = \alpha + \beta D_{January} + \epsilon$$

The dummy variable $D_{January}$ will be equal to one if the month in question is January. For all other months, the dummy variable will equal zero. The intuition behind interpreting the model is similar to the model for the Monday effect. The only difference naturally is that the Monday effect regression considers a model of days in a week, whereas the regression for the January effect considers months in a year. Therefore, the constant α equals the average daily returns of the months February to December. Adding the coefficient β yields the average daily returns in the month January. Like the previous models, the model for the January effect will also be corrected with Newey-West standard errors to correct for heteroskedasticity and serial correlation. The null- and alternative hypotheses are as follows:

H0: January does not show significantly higher returns than other months of the year

H1: January shows significantly higher returns than other months of the year

The null hypothesis can be rejected if the coefficient β is significantly different from zero at a 1%, 5% or 10% significance level.

Halloween Effect

To test if the saying “Sell in May and go away” is becoming less true over time, and if the summer months of the calendar year are outperformed by the winter months, the following model will be used:

$$R_t = \alpha + \beta D_{Halloween} + \epsilon$$

The dummy variable $D_{Halloween}$ will be equal to one for the months November to April. For the rest of the months, the variable will equal zero. If the Halloween effect exists, we would expect the coefficient β to be positive, implying that the months November to April have a positive effect on the daily returns of the indices examined, thus outperforming the months May to October. The constant α equals the average daily returns in the months May to October (summer months). Adding the coefficient β will result in the average daily returns of the months November to April (winter months). All regressions will be corrected for serial correlation and heteroskedasticity with the use of Newey-West standard errors. The null- and alternative hypotheses are as follows:

H0: The months November to April do not show significantly higher returns than the months May to October (the winter months do not outperform the summer months).

H1: The months November to April show significantly higher returns than the months May to October (the winter months outperform the summer months).

The null hypothesis can be rejected if the coefficient β is significantly different from zero at a 1%, 5% or 10% significance level.

Differences between periods

The regressions models mentioned above are used to determine whether or not a certain calendar anomaly was present in the control or test period. However, simply testing for the existence in these periods separately is not sufficient to determine a decrease over time of the day-of-the-week effect and the month-of the-year effect. To test for a decrease over time, a t-test comparing the means of the two periods will be used. The average return of the control period will be compared with the average return of the test period. The null- and alternative hypotheses are as follows for each anomaly:

For the Monday effect:

H0: The difference between the average return on Monday of the control period and the test period is zero.

H1: The average return on Monday of the control period is significantly smaller than the average return on Monday of the test period.

For the twist-on-the-Monday effect:

H0: The difference between the average return on “Mondays with a twist” of the control period and the test period is zero.

H1: The average return on “Mondays with a twist” of the control period is significantly smaller than the average return on “Mondays with a twist” of the test period.

For the January effect:

H0: The difference between the average return in January of the control period and the test period is zero.

H1: The average return in January of the control period is significantly larger than the average return in January of the test period.

For the Halloween effect:

H0: The difference between the average return in the winter months of the control period and the test period is zero.

H1: The average return in the winter months of the control period is significantly larger than the average return in the winter months of the test period.

The t-tests executed are one-sided t-tests. The main focus lies on a decrease of the calendar anomalies. A two-sided test would test for both an increase and a decrease of the anomalies, therefore a one-sided test is more suitable. For the Monday- and the twist-on-the-Monday effect, the t-test will determine if the average return of the control period is significantly smaller than the average return of the test period, because this would indicate a decrease of the anomaly. For the January- and the Halloween effect, the t-test will determine if the average return of the control period is significantly larger than the average return in the test period, since in this case that would indicate a decrease of the anomaly.

The null hypotheses can be rejected if the at a 1%, 5% or 10% significance level. Rejecting the null hypotheses implies that the average return of the control period and the test period are significantly different from each other, in the direction mentioned above. After concluding whether or not a difference exists between the two periods, the results of the regression analyses will be used to explain where this difference, is applicable, originates from.

Results

Monday Effect

Table 2 displays the results of the regression of the Monday effect in the control period. What stands out is the lack of coefficients that are significantly different from zero. In the control period, none of the coefficients are significantly different from zero, implying that the null hypothesis, that states that Mondays do not show significantly lower returns than the other days of the week, cannot be rejected. Despite the lack of significance, three out of four indices display the expected trend of the coefficient. Only the DAX displays a positive trend, meaning that in the control period in this sample, the average daily returns on Mondays were positive rather than negative. The constants all display a positive trend, implying that the average daily returns for Tuesday to Friday were positive in this sample. However, only the SMI displays a significant constant.

The results of the regression for the Monday effect in the test period can be found in table 3. Again, none of the four indices display a coefficient for the Monday effect that is significantly different from zero at a significance level of at least 10%, implying the null hypothesis cannot be rejected one again. Despite the failure to reject the null hypothesis, it is striking that the coefficients all display a negative trend, implying that Mondays showed negative daily returns in the control period on average. This also means that the positive trend of the DAX in the control period has reversed and changed to a negative trend in the test period. The constant values of all four indices display a positive trend. However, none of these constants are significantly different from zero.

In both the control period and the test period, the Newey-West standard errors are relatively high. Some are even higher than the coefficient itself. This is no cause for problems, as it could simply indicate that the distribution of the confidence interval is relatively broad, something that was already established in the descriptive statistics section.

Table 4 displays the results for the t-test to test for a difference in the average Monday returns of the control period and the test period for the Monday effect. Striking is the statistical significance of all T-statistics at a 1% level, implying that, considering the Monday effect, the null hypothesis that states that the difference of the average Monday returns of the two periods is zero can be rejected. However, the data in the regression analyses display some unexpected results. The average returns on Monday in the control period are larger, or in most cases less negative, than the average returns on Monday in the test period for all four indices. Therefore the alternative hypothesis cannot accepted. This indicates that the average Monday returns of the two periods are indeed significantly different, but in the unexpected direction. This could indicate a possible reappearance of the Monday effect in the test period. However, since no proof regarding the existence of the Monday effect was found in either period for all indices, this difference is due to other factors.

Table 2: The Monday effect in the control period

	N	Coefficient	Constant	Newey-West std. error of coefficient	Newey-West std. error of constant	R-squared
DAX	3547	.000664	.0001925	.0006285	.0001925	.0004
CAC 40	3548	-.0004589	.0003369	.0005841	.0002355	.0002
FTSE 100	3562	-.000056	.0002509	.0004614	.0001812	.0000
SMI	3543	-.0002295	.0004681**	.0004942	.0002007**	.0001

Table 3: The Monday effect in the test period

	N	Coefficient	Constant	Newey-West std. error of coefficient	Newey-West std. error of constant	R-squared
DAX	3167	-.0001188	.0003945	.0005908	.0002467	.0000
CAC 40	3189	-.0009556	.0003073	.0006068	.0002466	.0008
FTSE 100	3141	-.0004154	.0002417	.0005133	.0002047	.0002
SMI	3138	-.0003173	.0002386	.0004771	.0002033	.0002

Table 4: T-test for difference in means for the Monday effect

	T-statistic
DAX	-52.506***
CAC 40	-34.213***
FTSE 100	-30.187***
SMI	-7.366***

*N.B. *** stands for significance at a 1% level, ** at a 5% level, and * at a 10% level*

Twist-on-the-Monday effect

Table 5 displays the results for the twist-on-the-Monday effect in the control period. The SMI shows a negative coefficient that is significantly different from zero at a 5% significance level, implying that the null hypothesis of no twist-on-the-Monday effect can be rejected for the SMI in the control period. The DAX, the CAC 40 and the FTSE 100 all display coefficients that are not significantly different from zero, which means the null hypothesis cannot be rejected in their case. Even though three out of four indices fail to reject the null hypothesis, it is striking that three out of four indices do find the negative trend that is associated with the twist-on-the-Monday effect, one of which is significantly different from zero. Three out of four constants show a positive trend, implying that the average daily returns on Mondays after a positive week are positive in this sample. The constant of the DAX is significantly different from zero at a 10% level, and the constant of the SMI is significantly different from zero at a 5% level. The FTSE 100 displays results that are opposite to the results of the DAX, the CAC 40 and the FTSE 100.

The results of the twist-on-the-Monday effect in the test period can be found in table 6. The twist-on-the-Monday effect for the SMI found in the control period is no longer present in the test period, as the coefficient for the SMI is no longer significantly different from zero. The other three indices display coefficients that are not significantly different from zero as well. This implies that the partial twist-on-the-Monday effect in the control period, that was found in one out of four countries, has completely vanished in the test period. What stands out besides the disappearance of the effect, is that all trends have reversed from the control period to the test period. Additionally, the constants of all four indices are now negative, implying that Mondays after a positive week now show negative daily returns on average.

Again, in both the control period and the test period, the Newey-West standard errors are relatively high. Some are even higher than the coefficient itself. This is no cause for problems, as it could simply indicate that the distribution of the confidence interval is relatively broad and that most observations are relatively close to zero, something that was already established in the descriptive statistics section.

Table 7 displays the results for the t-test to test for a difference in the average return of the control period and the test period for the twist-on-the-Monday effect. Similar to the t-test for the Monday effect, proof for significantly different average returns for the control and test period is found at a 1% level. The significant T-statistic implies that the null hypothesis, that states there is no difference between the periods, must be rejected. For the DAX, the CAC 40 and the SMI this means that the average returns on Mondays with a twist in the control period are significantly smaller than in the test period. For the FTSE 100 however, the data shows that the average in the control period is actually larger, or less negative, than the average in the test period. This unexpected result is similar to the unexpected results for the Monday effect. For the SMI, one of these factors causing the difference between the two periods could be the disappearance of the twist-on-the-Monday effect in the test period, since the effect was found in the control period, but not in the test period. For the other indices, the significant difference must be due to other factors, as no proof for a twist-on-the-Monday effect was found in either period.

Table 5: The twist-on-the-Monday effect in the control period

	N	Coefficient	Constant	Newey-West std. error of coefficient	Newey-West std. error of constant	R-squared
DAX	700	-.0007832	.0012056*	.0011927	.0006735*	.0006
CAC 40	686	-.0013347	.0005123	.001072	.0006444	.0023
FTSE 100	666	.0008091	-.0001939	.0008205	.000506	.0014
SMI	694	-.002198**	.0012172**	.000964	.000523**	.0079

Table 6: The twist-on-the-Monday effect in the test period

	N	Coefficient	Constant	Newey-West std. error of coefficient	Newey-West std. error of constant	R-squared
DAX	619	.0009025	-.0001106	.0011276	.0005817	.0011
CAC 40	629	.0002726	-.0007709	.0011283	.0006021	.0001
FTSE 100	585	-.0003942	-.00000122	.0009607	.0005146	.0003
SMI	609	.0000934	-.0001182	.0008977	.0004745	.0000

Table 7: T-test for difference in means for the twist-on-the-Monday effect

	T-statistic
DAX	26.280***
CAC 40	26.486***
FTSE 100	-23.892***
SMI	44.203***

*N.B. *** stands for significance at a 1% level, ** at a 5% level, and * at a 10% level*

January effect

Table 8 shows the results for the regressions testing the January effect as described in the methodology section. Similar to the results of the Monday effect, none of the coefficients for the January effect are significantly different from zero at a significance level of at least 10%. This means that the null hypothesis, that states that January does not show significantly higher returns than the other months of the year, cannot be rejected. However, the DAX and the CAC 40 both show a positive trend, implying that the average daily returns in January were positive in the control period. For the FTSE 100 and the SMI, this trend is negative, which is exactly the opposite of what would be expected if a January effect were to be observed. The constant values show a positive trend for all four indices, two of which are significantly different from zero at a significance level of at least 10%.

The results for the January effect in the test period can be found in table 9. Again, none of the indices display coefficients that are significantly different from zero. This means that the null hypothesis, which states that January does not show significantly higher returns than the other months of the year, cannot be rejected again. The January effect was not present in the control period, and has not returned in the test period. The negative trend in all four indices in the test period is perhaps the most striking result regarding the January effect. This negative trend implies that in this sample, the average daily returns in January are negative. This is the exact opposite of what the January effect describes. Implications of these negative trends will be discussed further in the conclusion of this paper. Similar to the control period, the constant values in the test period are all positive. The only difference is that this time, the only constant that is significantly different from zero can be assigned to the DAX.

Table 10 displays the results for the t-test to test for a difference in the average January returns of the control period and the test period for the January effect. Again, all T-statistics show significance at a 1% level. Considering this, it can be concluded that the average January return in the control period is significantly larger, or less negative, than the average January return in the test period. However, the difference of the average returns in the two periods cannot be assigned to a disappearance of the January effect, as in both periods no evidence for the existence of the January effect was found. Therefore other unknown factors are likely be the reason of the difference between the average January returns of the two periods.

Table 8: The January effect in the control period

	N	Coefficient	Constant	Newey-West std. error of coefficient	Newey-West std. error of constant	R-squared
DAX	3547	.0003329	.0002954	.0008049	.0002405	.0000
CAC 40	3548	.000474	.0002082	.0007679	.0002256	.0001
FTSE 100	3562	-.0004846	.0002808*	.0005764	.0001678*	.0002
SMI	3543	-.0001902	.0004387**	.0007171	.0001959**	.0000

Table 9: The January effect in the test period

	N	Coefficient	Constant	Newey-West std. error of coefficient	Newey-West std. error of constant	R-squared
DAX	3167	-.0008472	.0004454*	.0008586	.0002294*	.0004
CAC 40	3189	-.0005013	.0001626	.0008283	.000226	.0001
FTSE 100	3141	-.0006367	.0002195	.0006578	.0001881	.0003
SMI	3138	-.0002667	.0001999	.0006695	.0002865	.0001

Table 10: T-test for difference in means for the January effect

	T-statistic
DAX	-58.111***
CAC 40	-50.146***
FTSE 100	-10.090***
SMI	-4.489***

*N.B. *** stands for significance at a 1% level, ** at a 5% level, and * at a 10% level*

Halloween effect

Table 11 displays the results of the regression concerning the Halloween effect in the control period as described in the methodology section. The coefficients of the DAX, the CAC 40 and the SMI are all different from zero at a significance level of at least 5%. The CAC 40 even displays a significant coefficient at a 1% level. For these three indices the null hypothesis, that states that the winter months do not outperform the summer months, can be rejected. Additionally, all indices display a positive trend, which is in line with the expectations regarding the Halloween effect. However, the coefficient of the FTSE 100 is not significantly different from zero, implying that the null hypothesis cannot be rejected. None of the constant values are significantly different from zero. For the DAX and the CAC 40, the constants are negative, implying that the average daily returns in the summer months were negative in this sample. The FTSE 100 and the SMI show positive constants, pointing to positive average daily returns in the summer months.

The existence of the Halloween effect in the control period could provide an argument against the EMH, since the returns of a stock should not be predictable for a certain time period. To illustrate, in theory one could buy the DAX index in the winter months, and proceed to short it in the summer months to make profit on average. However, in practice this is not as simple. Buying ETFs of these indices often come with large transaction costs, which could mean that the strategy described previously would not necessarily work. However, if an investor would possess the knowledge of the existence of the Halloween effect, the investor could time his trades accordingly to profit from the Halloween effect, making it valuable nonetheless.

The results for the Halloween effect in the test period can be found in table 12. The most striking about these results is that none of the four coefficients are significantly different from zero, unlike the coefficients in the control period. This means that for the test period, the null hypothesis cannot be rejected for all four indices, indicating the disappearance of the Halloween effect in the test period. Despite this, the coefficients still display the same positive trend as before, indicating that the average daily returns in the winter months were higher than the average daily returns in the summer months in this sample. Furthermore, three out of the four constants are positive, implying that the summer months showed positive returns on average for the DAX, the FTSE 100 and the SMI. For the CAC 40, the summer months showed negative returns on average. However, similar to the control period, none of the constants are significantly different from zero.

Table 13 displays the results for the t-test to test for a difference in the average winter returns of the control period and the test period for the Halloween effect. All T-statistics show significance at a 1% level, implying that the null hypothesis, which states that the difference between the average winter returns of the two periods is zero, has to be rejected. Therefore, the average winter returns of the control period are significantly larger than in the test period. This finding is supported by the results of the regression analyses.

The regression analysis displays the existence of a Halloween effect in the control period for three out of four indices, but does not display the existence of the effect in the test period for any of these indices. The difference in coefficients in the two periods provides a strong argument that the Halloween effect has in fact disappeared in the test period.

Table 11: The Halloween effect in the control period

	N	Coefficient	Constant	Newey-West std. error of coefficient	Newey-West std. error of constant	R-squared
DAX	3547	.0010267**	-.0001836	.0004536	.0003299	.0014
CAC 40	3548	.001093***	-.0002953	.000426	.0003135	.0017
FTSE 100	3562	.0004662	.00000925	.0006204	.0002371	.0005
SMI	3543	.000742**	.000057	.0003717	.0002768	.0011

Table 12: The Halloween effect in the test period

	N	Coefficient	Constant	Newey-West std. error of coefficient	Newey-West std. error of constant	R-squared
DAX	3167	.0004581	.0001443	.0004387	.0003175	.0003
CAC 40	3189	.0003933	-.0000762	.0004294	.0003149	.0002
FTSE 100	3141	.0002124	.0000582	.0003552	.0002621	.0001
SMI	3138	.000133	.0001107	.0003546	.000256	.0000

*N.B. *** stands for significance at a 1% level, ** at a 5% level, and * at a 10% level*

Table 13: T-test for difference in means for the Halloween effect

	T-statistic
DAX	-52.074***
CAC 40	-67.057***
FTSE 100	-20.194***
SMI	-68.294***

*N.B. *** stands for significance at a 1% level, ** at a 5% level, and * at a 10% level*

R-Squared

The R-squared of all models is reviewed separately, because the same applies for all models. All the R-squared values found in this paper were below .01. This is a very low value for the R-squared, as it states that, in the best case scenario, only 1% of the total variance of the returns is explained by this model. It is often argued that low R-squared values are always bad, and high values are always good. However, a low R-squared value could have been expected for this paper. Since R-squared stands for the percentage of the total variance of the returns explained by the model, naturally the R-squared would be very low, because the models in this paper only take calendar related explanatory variables into account. It would be shocking to see a high R-squared of .7, for example, because that would mean that 70% of the returns variance could be assigned to calendar related explanatory variables. Naturally there are explanatory variables that are far more important when explaining stock returns, like revenue, profit and cashflows. Therefore, it is very reasonable that calendar dates only explain about 1% of the movements of stock returns at the most.

Conclusion

This paper has covered the day-of-the-week effect and the month-of-the-year effect, split up into two smaller effects per anomaly. The four specific effects that were covered, the Monday effect, the twist-on-the-Monday effect, the January effect and the Halloween effect, have been examined for Germany, France, England and Switzerland. The indices used to generalize the effect for each country were the DAX, the CAC 40, the FTSE 100 and the SMI respectively. The period 1990-2017 was covered in this paper. This period has been split up into two sub periods to examine a possible decrease of the calendar anomalies over time.

The results show that the Monday effect is not present in the control period nor in the test period. However, despite the lack of significant results, there is a negative trend to be observed between Mondays and the stock returns. This trend is observed in the control period as well as the test period, meaning that in the entire sample, Mondays showed a lower return on average than the other weekdays. Because the coefficients are not statistically different from zero, the null hypothesis of no Monday effect would be rejected unfairly more than 10% of the time. However, the fact that this negative trend is found calls for further research regarding the Monday effect in Europe, since a negative trend that stretches across a period of over 25 years is definitely worth investigating.

The results concerning the twist-on-the-Monday effect show that the twist-on-the-Monday effect is significantly present for the SMI in the control period. The coefficients of the other three indices are not significantly different from zero, meaning that the null hypothesis cannot be rejected for these indices. The control period shows that, like the rest of the indices, the SMI now also displays a coefficient that is not statistically different from zero, leading to the conclusion that the null hypothesis cannot be rejected. This means that the twist-on-the-Monday effect, which was present in one out of four indices in the control period is not present in the test period. An interesting finding is that in the control period, three out of four indices displayed a negative trend, which would be expected according to the theory of the twist-on-the-Monday effect. In the test period, these three negative trends changed to a positive trend. This could point to a possible reversal of the effect. No significantly present effect is found in this paper, but finding a trend that reversed over time is an interesting side avenue for new research.

Overall, considering the day-of-the-week effect, it is possible to draw the conclusion that the effects were not present during the control period, and continued to do so in the test period. In the single case where the twist-on-the-Monday effect was present in the control period, this effect was not present anymore in the test period. Despite not finding proof for the existence of the anomalies, the trends found regarding the Monday effect and the twist-on-the-Monday effect provide a possibility to continue research regarding these topics.

The results regarding the January effect are conclusive. The January effect is not significantly present in the control period as well as the test period. Despite this conclusion, an interesting side avenue regarding the January effect has been opened. In the control period, two out of the four indices showed a negative trend between the month January and the daily stock returns. In the test period, all indices showed this trend. This implies that over a period of at least 10 years, the average daily returns in January were lower than the rest of the months on average, even though January typically is the best month of the year for stock prices. This trend contradicts the January effect, and continues to build on the claims of Marquering, Nisser and Valla (2006), who stated that the January effect had completely disappeared due to more investor attention and a higher trading volume. Following the results in this paper, a trend was found towards the reversal of the January effect, something that could provide an interesting topic for further research.

The Halloween effect was significantly present in three out of four indices in the control period. However, the effect disappeared completely in the test period. This is in line with the expectations of this paper. Despite the effect not being present in the test period, the trend between the winter months and stock returns continued to stay positive, meaning that in a period of over 10 years, the average return in the winter months was higher than the average return in the summer months. Despite the fact that the null hypothesis, that states that a Halloween effect is not present, cannot be rejected, the persistence of this trend could still be interesting for further research.

Overall, considering the month-of-the-year effect, some interesting results have been found. The January effect was not present over the entire data sample, while the Halloween effect showed to be present in the control period, but not in the test period. This means that, overall, the month-of-the-year effect has disappeared in the test period, providing it was present in the control period period.

Have the day-of-the-week effect and the month-of-the-year effect decreased over time in Europe?

Looking at the regression analyses, many effects have shown not to be present in the control period, and any effect that was found in the control period has not been found in the test period. However, simply finding an effect in two separate periods is not enough to conclude that the day-of-the-week effect and the month-of-the-year effect have decreased over time. The fact that in all cases, the average returns of the control period are significantly different from the average returns of the test period at a 1% significance level does create the possibility to draw this conclusion. Since any effect that was found in the control period had disappeared in the test period, a conclusion can be made that the day-of-the-week effect and the month-of-the-year effect have decreased over time in Europe. However, the t-test for the difference in means executed for the Monday effect showed that the average return of the Monday effect was significantly different in the two periods, but this difference was displayed in the opposite direction as expected. This relates back to the trend mentioned earlier in this section, and could call for further observation of the effect over time.

Because certain trends were found where no significant effect was found, a possibility exists that certain events have clouded the data, making it unable to find a significant effect where there might be one. An example is the Economic crisis that started in 2008. This crisis covers a large part of the test period, possibly leading to results that are not representative of regular circumstances. This could be combined with the challenge of explaining the trends that were found regarding these calendar anomalies. However, since testing for origin of these trends and correcting for economic cycles is beyond the scope of this research, that will be left as a possibility for future research.

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